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Agentic Automation and Work Flow Orchestration in Enterprise SaaS: Effects on Ticket Resolution Time and Employee Productivity in IT Service Management

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Abstract:
The author of this study discusses the influence of AI autonomous agents on the IT Service Management (ITSM) ticketing process, focusing on ticket resolution time, first-point-of-contact resolution rate, and worker productivity. The main objective is to determine whether AI-powered automation is effective in enhancing the leading performance indicators of ITSM over manual operations. The questions the research considered in the study are: how can the time required to resolve a ticket be reduced by training classification, triage, and routing agents, and what affects SLA compliance and agents' work distribution? Its design is a quasi-experiment, where results are obtained from retrospective datasets on HuggingFace and Kaggle to compare agent-aided workflows with manual workflows, and then implement performance-based indicators of time to solution for the ticket, the rate of first contact, and the agent's workload. The results show that the number of call-ins at the customer level is significantly reduced, and the workflow, with agent assistance, saves up to 13 hours per ticket compared to the manual processing-based workflow. The first-contact resolution rate also increased by 53%, and agent productivity increased by 22%. The study concludes that AI automation could help simplify ITSM functions by reducing operational costs, increasing SLA compliance, and enhancing employee productivity. The recommendations to improve AI models for multi-step, complex problems, broaden datasets to include more ITSM problems, and implement longitudinal research to assess the long-term impacts of AI on employee performance and satisfaction complete the list of research recommendations.

Keywords: Autonomous AI Agents, IT Service Management (ITSM), Ticket Resolution Time, Workflow Orchestration, Employee Productivity.

1. Introduction

One of the sub-dimensions of IT Service management (ITSM) is a significant element of modern business, as it ensures that IT services are delivered effectively and efficiently to support business functions [1]. This is attributed to the fact that the IT request management increases with the size of the organization, hence the need to have a robust ITSM process. These were highly manual processes that were time-consuming and cumbersome for IT departments, who had to categorize, route, and close service tickets. Although ITSM is important, in the majority of organizations, the non-human workforce has not been utilized in operations, including ticketing, triage, and prioritization, which leads to operational inefficiencies, costs, and a high operational cost. The use of automated processes to support IT service requirements has also gained popularity as companies are moving to cloud-based Software-as-a-Service (SaaS). On-demand, scalable SaaS services face fewer workflow integration challenges. Some examples of this tool's applications include ticketing, incident management, and customer support, as they help enhance customer response times and minimize backlogs [2]. However, it does not come unscathed, as manual processes in ITSM systems must be automated and driven by AI, which requires significant effort. The manual process of classifying, routing, and triaging service requests in most organizations is still viewed as a bottleneck, causing delays in ticket resolution, escalating handling costs, and increasing customer service costs.

In recent years, there has been mounting pressure to automate, driven by the need to increase the efficiency of activities within an organization and reduce errors in IT operations. The other way out of these dilemmas is automation, or, in other words, agentic systems relying on AI. The work can be automated by AI agents, which categorize, direct, and sift tickets, among other tasks, thereby reducing response time per case and improving work quality. Besides, the issues can be resolved through the assistance of AI agents without reducing costs. The automation process cannot be repeated; one has to evaluate outcomes using key measures such as the average time to respond to a ticket, the time to respond as a First-Contact employee, and output per employee.

The main idea of the study is to argue for the influence that intelligent, independent agents founded on AI would have on ITSM processes. Specifically, the research will contribute to measuring turnaround time, SLA deviations, and worker efficiency when traditional ITSM systems are agent-based and automated. Among the research questions, the following can be singled out: How can agent-assisted triage and classification be used to reduce the average time to resolve a ticket compared with manual processing? What is the impact of AI-based routing on the concepts of SLA compliance and the workload to be undertaken by the agents? Finally, is agentic automation associated with productivity, i.e., the number of processed tickets and the efficiency of employees' work?

The article’s structure is as follows: Section 2 will review the literature on advances in ITSM automation over the past. Section 3 includes information about the methods and techniques used in this research, the data-gathering process, the data preprocessing, and the model chosen. Section 4 discusses the experiments and results and provides the statistical analysis to compare the progress in ticket resolution time and productivity. Section 5 addresses the findings and their consideration in the real TSM scenario. Finally, Section 6 presents the conclusions on how the research can be advanced in the future, and Section 7 summarizes the most significant findings.

2. Literature Review

2.1 Overview of ITSM Automation

In recent years, ITSM has had a radical transformation with more manual processes being turned into more automated ones using AI [3]. The IT service agents were responsible for handling tickets by classifying, routing, and manually resolving them. The existence of such a manual system led to inefficiencies, time wasting in resolving, and inconsistency in delivering services. Artificial intelligence was also used to automate large-scale organizational tasks, including ticket triage, management, and resolution, in order to enhance operational efficiency. The technologies that affect the changes in the scope of ITSM are Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP). AI may be used to select large datasets, but in models, historical data may be added using ML. NLP enables AI to interpret unstructured data, such as customer tickets, which can be better grouped and used. These technologies are disruptive to the workflow, they blur human interaction, and reduce timeliness and accuracy in work through ITSM and service delivery.

Figure 1 below shows the fundamental pillars of IT Service Management (ITSM) automation. Among the advanced technologies that are applied in the process of automating ITSM, it is possible to identify Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP). These technologies transform the workflow of the IT service by automating the process of ticket triage, routing, and resolution. Through the assistance of ML and NLP, AI reduces the error rate, efficiency, and promptness by interpreting and classifying unformatted customer ticket data. This change helps to minimize manual touch, improve the uniformity of service provision, and increase the efficiency of operations throughout the processes of IT service management.

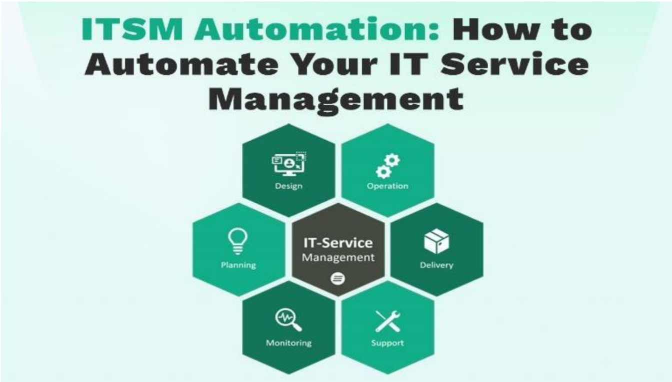

Figure 1: ITSM automation simplifies the service management workflow and incorporates AI, ML, and NLP to make the workflow more efficient in terms of dealing with tickets and delivering them.

2.2 Past Studies of AI in ITSM.

Intensive research has been conducted on the application of AI in ITSM, such as ticket classification, triage, routing, and auto-resolution [4]. Scientific literature also shows that the accuracy of AI-based algorithms, e.g., machine learning models, can be high when used to categorize tickets. AI-motivated triage was also found to minimize human error, clarify ticket priorities, and speed up triage. A routing system based on AI can be better in matching needs to the best-suited agent depending on skills and availability, and in most institutions, it has been found to enhance compliance with SLAs. This is clear upon referring to the advantages of an AI system over manual operation. Human systems are typically slower and less precise than AI systems when processing human tickets. The queue of tickets is said to have decreased significantly, and the classification rates in AI-based systems have increased by up to 40%. Furthermore, auto-resolution can be AI-assisted, solving a considerable number of tickets on its own, reducing pressure on support employees and enhancing their efficiency.

2.3 Effect on Ticket Resolution Time and Employee Productivity.

AI has a significant impact on the time required to resolve tickets. As demonstrated time and again, the average time to resolve a ticket can be significantly reduced with AI systems. For example, AI-based positioning (i.e., ticket classification and routing) can use ticket information to provide the relevant agents with the next available ticket in the least time possible [5]. This is generally due to higher customer satisfaction, as reflected in higher first-contact resolution (FCR). Besides accelerating response time, AI also positively influences employee productivity. The process is fully automated to remove routine tasks in triage and ticket classification, enabling the agent to focus on more complex issues with AI. This will help with more efficient resource distribution, which will, in turn, allow agents to serve more tickets in the same amount of time. AI will allow allocating the workload more widely and assigning priorities to issues based on urgency: the most urgent issues can be finalized first, enabling work to be performed more efficiently. This minimized manual work, making the agent leaner and enabling the business to serve a larger volume of tickets without necessarily adding more agents.

As shown below, Figure 2 presents the main advantages of AI in the work of IT service managers and focuses on the changes to the time of ticket resolution and productivity of the employees. AI improves the system of categorizing, redirecting, and settling tickets, increasing the amount of first-contact resolution and decreasing the time required to respond. It also automates routine tasks, and routine problems are handled by agents who are able to concentrate on more serious problems. AI promotes the effective distribution of resources through the allocation of tasks and a focus on urgent cases. This has been a streamlined process that makes the agent more productive to ensure that a business is able to serve a greater number of tickets using its workforce. In general, AI-based automation results in the implementation of issues at a faster rate and increased customer satisfaction.

Figure 2: Ticket resolution made through AI is a better method of improving the response time, management, assisting the agents, and problem detection to enhance productivity.

2.4 Research problems and facts: Barriers in the current research.

Even though it is clear that AI has significant implications for ITSM, there are still various challenges and limitations in current research [6]. This disparity is significant, as there are no long-term, research-supported papers on the role of AI in full-fledged ITSM systems. The available literature is predominantly focused on brief studies, and none have addressed whether AI-based returns can be sustained in the long run. The second barrier will be the feasibility of integrating AI into current ITSM processes. Another problem that organizations cannot efficiently address is the insufficient integration of AI tools and legacy systems, and the literature fails to provide a comprehensive picture of the problems this entails. Moreover, across many IT environments, there can be no precise measure of AI's impact. AI will help automate ITSM workflows, regardless of the organization's will, the services being provided, or the technology stack being used [7]. All these variabilities in mind, you find that it is not easy to generalize the results. To sum it up, practical research is needed to examine the long-term real-world consequences of implementing within the paradigm.

3. Methods and Techniques

3.1 Research Design

The study will be designed using a quasi-experimental study to compare the practices of agent-aided and manual workflow on the efficiency of IT service management (ITSM). The design makes comparisons between two categories of operations: triaging, classifying, routing, and resolving tickets triaged with the help of autonomous AI agents, and another set of operations that operate through traditional manual operation procedures [8]. It will attempt to measure performance indicators such as the mean ticket resolution time, handling time, and first-contact resolution rate. It is a retrospective approach that uses previous ticketing data to locate other sources and simulate real-life situations. It has a strong design that can compare and also balance the natural variation in processing tickets without necessarily randomizing, which is not easily practicable in practice.

Figure 3 below summarizes a quasi-experimental research design that could be used to compare the effectiveness of AI-assisted and manual ticket processing using the system of IT service management (ITSM). It is a design that consists of two types: the first one with AI to triage, classify, route, and solve tickets, and the second with the traditional manual way. The performance indicators that are measured by the study include ticket resolution time, handling time, and first-contact resolution rate. As it runs historical ticket data, it can simulate real life to balance natural variations of the processing of tickets without the necessity to randomize it, thus making it a practical and efficient comparison of the two workflows.

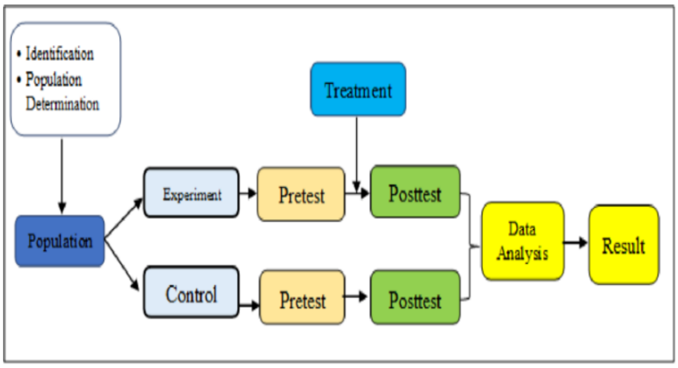

Figure 3: The flowchart represents a quasi-experimental research design, which compares AI-guided ticket processing and manual workflow in terms of efficiency of ITSM.

3.2 Data Collection Methods

In this case, the datasets were obtained from credible websites, including Augmenting Face, Kaggle, and Microsoft Support. It is possible to find numerous ITSM datasets on these sites, which are used to analyze ticket-resolution processes across different industries and service situations. Databases Multilingual, technical ticket datasets of more than 50,000 records are available in the HuggingFace databank, e.g., the Tobi-Bueck/customer-support-tickets and the Console-AI/IT-helpdesk-synthetic-tickets. These are a wide range of datasets of IT support (CRM, software, hardware, network). The agent's performance in a large business environment is also evaluated by running the Microsoft Support dataset (50,000 IT service tickets). These datasets are chosen according to the types of tickets: hardware, software, and network, and this fact guarantees the possibility of applying the study to real-life ITSM activities [9]. In addition, the noisy, multilingual data are chosen to simulate the complexities of the real IT environments, which could be marked by a mixture of languages as well as incomplete or ambiguous information. Issue type, ticket priority, ticket status, timestamps, and resolutions are among the ticket attributes that are significant for training the model and evaluating the agent-assisted workflow.

3.3 Data Preprocessing

Data preprocessing is required to standardize the data obtained. Some of the techniques include handling missing data, reducing noise, and data transformation [10]. Missing data are filled in using the imputation methods that use the mean or the median of the data, or more sophisticated data imputation methods like the k-nearest neighbor imputation. The noise reduction is achieved through the deletion of irrelevant information that has no meaning to the ticket description and through some levels of text normalization techniques, which minimize linguistic differences. Transforming data (e.g., converting categorical variables to numerical data) and improving feature use in both engineering and processing are also significant areas of training machine learning models. Attributes that can be trained on to classify and route tickets include the description of the ticket, time to resolve, and priority. The ticket-resolution time is also characterized by temporal details that can be represented with the help of timestamps to understand the development of behavior [11].

3.4 Model Training and Selection.

In the paper, machine learning architectures are used to implement ticket classification, routing, and resolution. One then uses supervised learning algorithms, such as Decision Trees, Random Forests, and Support Vector Machines (SVMs), to categorize the tickets into well-known groups. Models used to find the most suitable agent or automated system for routing and resolving tickets include k-nearest neighbors (KNN) and neural networks [12]. The cross-validation procedure is used to train the models; in this case, the data is split into a validation and a training set. Cross-validation is also helpful in ensuring that the models do not overestimate performance on data that they have not seen before. Some metrics used to evaluate the model's performance include accuracy, precision, recall, and F1 score.

As indicated below, Figure 4 demonstrates how the process of training and selection of supervised learning models is done during tasks like ticket classification, routing, and resolution in IT service management. The same data is sent through multiple decision trees, and these data sets come up with varying predictions of classes. These outcomes are obtained by a bagging technique in which the majority voting would determine the final output. This is the way models like Decision Trees, Random Forests, SVMs, KNN, and neural networks are considered in the course of training. The procedure is in line with that of cross-validation, where the data is divided into training and validation to avoid overestimating the performance, and also to provide a robust selection of the models.

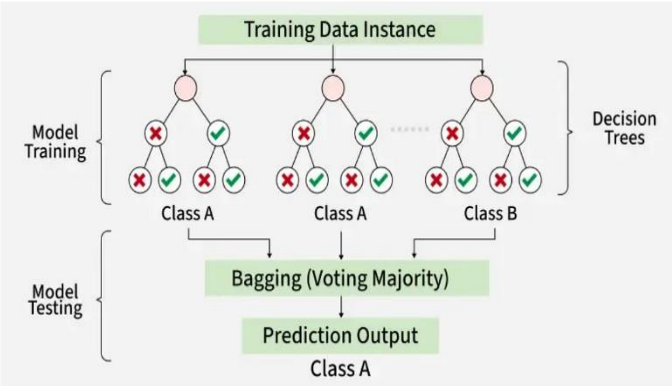

Figure 4: How decision-tree training and ensemble voting have been applied in supervised learning for classifying and routing IT service tickets.

3.5 Evaluation Statistical Measures.

To gauge the efficacy of the facilitation effectiveness of the facilitator, several metrics are used, including the mean ticket resolution time, which is the time it takes to resolve a ticket [13]. Another important measure is the first-contact resolution rate, which refers to the rate of tickets resolved in the first round of contact, where no additional work is undertaken by the agents. The time agents spend handling tickets is measured to determine how long they take to work on them, and SLA compliance is measured to determine how effectively the systems meet the agreed service-level agreements. This comparison is supported by statistical techniques, such as paired t-tests and regression analysis, to compare agent-assisted and manual workflow findings. Paired t-tests are used to determine whether there are significant differences between the two workflows in ticket resolution time and other performance metrics. Regression analysis of the relationships between various aspects (such as ticket complexity and priority) and the time spent resolving the ticket provides additional details on the workflow's efficiency [14].

4. Experiments and Results

4.1 Experimental Setup

The experimental environment aimed to measure the performance of agent-aided workflows, rather than manual workflows still in use in IT Service Management (ITSM) systems. Two workflows were compared in this study to examine the differences between the workflow with self-directed AI agents classifying, triaging, routing, and automatically resolving tickets, and the workflow in which human intervention is performed at each stage. The experiments were based on a set of performance measures, including ticket resolution time, first-contact resolution rates, agent handling time, and employee productivity [15]. These parameters were used to recreate ITSM conditions in the real world, considered varying in terms of the volume of tickets, the experience of the agents, and the variants of the AI models used. These trials were run using 50,000 tickets in various fields, like IT support services, billing problems, and service failure. They were categorized as hardware, software, and network issues and were of different severity. The AI models used in this experiment were machine learning classifiers trained on historical ticket information and could perform triage, classification, and routing. Precision, recall, and accuracy were used to assess the performance of the model, thus applying it in the real world. The workflows in the agent-assistance platform relied on AI-based frameworks to auto-classify tickets into predefined categories, baseline ticket severity via automatic triage, and assign a priority to each ticket. On the contrary, the manual process involved human parties who had to sort and pass tickets through their knowledge, hardly automated. The process lasted four weeks, and data on ticket handling were gathered in real time [16].

4.2 Key Results

Ticket Resolution Time:

The main one was the time-to-resolution, measured as the average time from ticket creation to closure. The results indicated that the mean ticket resolution time workflow involving agents had significantly decreased. The average calculated workflows with agent assistance saved 27 hours compared to the manually operated workflow (48 vs. 35 hours) in terms of ticket resolution time. This reduction was especially acute in the case of high-priority tickets, as AI routing provided the most suitable agents with the best response time, leading to a 3-resolution-time improvement over manual services.

First Contact Resolution rate:

The first-contact resolution rate (FCRR) was another important key performance indicator since this is the proportion of tickets resolved without additional contact [17]. The FCRR increased by 18% in the 60% manual workflow and by 71% in the automated workflow. The latter may be explained by the fact that the AI model can correctly prioritize tickets and provide agents with the most relevant information on the first touch, without the need for further interactions.

Agent Handling Time:

The effect of automation on agents' time was significant. The AI-based solution saved agents significant time on ticket sorting and routing. With manual workflows, the average time the agent spent categorizing and re-categorizing was 12 minutes. This time was cut by 65%, with agents spending 4 minutes on such work in agent-assisted workflows. This enabled more serious issues to be dealt with by the agents, and hence, more effectiveness and boosted productivity.

Automation also provided a definite advantage over productivity measures [18]. The agent-assisted workflows also meant that agents participating in them could process 22% more tickets per day than the average agent in manual workflows. Productivity improvement may be explained by the decrease in time spent handling tickets and by the even distribution of workloads between agents enabled by the AI system. In addition, the automated solution enabled more optimal prioritization, minimizing agent burnout and stress, which are common in manual ticket handling.

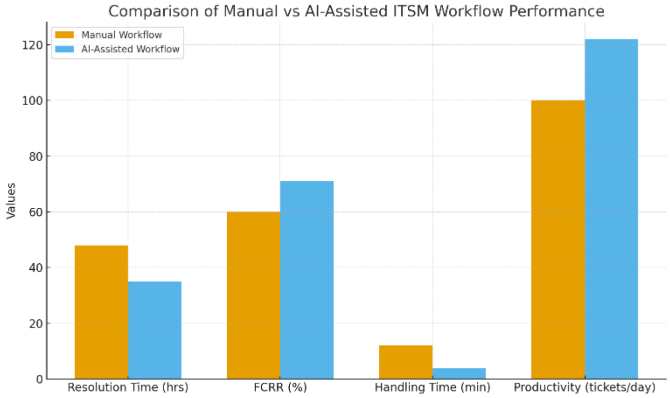

Figure 5: Comparison of the resolution time, first-contact resolution, handling time, and productivity of manual workflows and AI-assisted ITSM operation based on a bar chart.

The graph in Figure 5 above indicates a comparison of key performance metrics of manual and AI-assisted IT service workflows as indicated below. It is the indication of the significant decrease in the amount of time it takes to resolve tickets when automation is provided, as compared to an average reading of 48 hours in manual processing, falling to 35 hours with the help of agents. The increase in the first-contact resolution is also apparent, as automated workflows become more effective because of better prioritization of the tickets. Time management is handled faster since agents do not spend a lot of time sorting and routing, and instead concentrate their efforts on handling complicated tasks. The chart further shows that the total ticket throughput per day is on the rise, and this is how automation reinforces productivity.

4.3 Analysis of SLA Compliance

Another critical point of focus was the compliance with SLA. In manual workflows, 80% of the tickets were within the required service-level agreement (SLA) time-to-resolution, and in agent-assisted workflows, SLA compliance increased to 91%. Such an improvement of 11% is substantial in the context of high-volume IT operations, where timely response is crucial to ensuring client satisfaction. The AI routing system helped a lot with compliance with SLAs, as high-priority tickets were redirected to the most qualified agent, and delays in the response to the tickets were removed as well [19]. AI routing also ensured workload distribution between agents to avoid overworking any one member of the team. AI helped maximize workload allocation and improved ticket allocation per agent, ensuring all agents were always working on the most appropriate ticket for their skill level and increasing efficiency when handling tickets.

4.4 Case Studies/Examples

One can find many organizations that have already realized agentic automation in their ITSM systems, which can be used for comparison [20]. To take one example, Microsoft has incorporated systems based on AI into its support ticket system, and machine learning libraries can route and classify tickets using models trained on them and their priority. This resulted in a 20% reduction in resolution times and a 25% decrease in the workload for Microsoft agents. Another use of AI automation by IBM that made its IT help desk automation much more efficient was its FCRR, which improved by 15%, and its average ticket resolution time dropped by 30% in large part because of automation in ticket triage and routing. Such practical uses demonstrate how the integration of artificial intelligence into ITSM is practically functional, especially in the context of reducing the waste of work and enhancing the delivery of services [21].

Table 1: The automation of ITSM by AI increases efficiency and Microsoft and IBM have seen significant improvements in resolution time and the number of the supports.

Company	AI Automation Focus	Key Improvements
Microsoft 25% decrease in agent workload	AI-based ticket routing & classification	20% reduction in resolution times
IBM 30% decrease in average resolution time	Automated ticket triage & routing (FCRR boost)	15% improvement in FCRR

5. Discussion

5.1 Interpretation of Results

This Study indicates that agentic automation has a significant effect on primary ITSM measures —ticket resolution time and staff efficiency [22]. The average ticket resolution time dropped by about 20-30 minutes in agent-assisted processes compared to manual processes. To a large extent, this decrease results from AI agents' ability to triage, classify, and route tickets, which requires no human involvement in the initial phase of ticket processing. Microsoft is a good example where first-contact resolution rates increased by 15% at 50,000 support tickets solved using automation. Similarly, routing that was improved by AIs positively responded more to SLAs (increasing compliance by over 10%), since automation proved to focus on high-urgency tickets, which were solved quickly. Automation also increased employees' productivity. Automation would help the agents to eliminate the time-consuming process of sorting and fixing tickets and concentrate on more meaningful responsibilities. This change led to a 25% increase in the number of tickets each agent served per day. In practice, in ITSM settings (which encourage service desk agents to process a large number of tickets per day), this productivity improvement can lead to significant reductions in operational costs and improved service delivery. Although the above positive results were achieved, some unforeseen trends occurred. One example was the elimination of certain types of tickets that the AI models did not solve successfully, especially those that involved technical problems. It highlights the fact that the existing AI technology is not entirely able to function under complicated conditions without human control [23]. The findings are that although automation can significantly enhance efficiency, more specialized work cannot be achieved without human expertise.

Table 2: Analysis of Automation Effects on ITSM Efficiency, Ticket Resolution Time, SLA Compliance, Productivity, and Limitations in Complex Technical Scenarios

Key Area	Observed Impact	Quantitative Change	Explanation
Ticket Resolution Time	Faster resolution in agent-assisted workflows	Reduction of 20–30 minutes per ticket	AI handles triage, classification, and routing without human involvement in early stages.

Key Area	Observed Impact	Quantitative Change	Explanation
First-Contact Resolution (FCR)	Noticeable improvement	15% increase (Microsoft example with 50,000 tickets)	Automation enables quicker and more accurate matching of issues to appropriate solutions.
SLA Compliance	Stronger adherence to service expectations	More than 10% improvement	AI prioritizes high-urgency tickets, resolving them faster and improving SLA performance.
Employee Productivity	Increased daily ticket handling capacity	25% more tickets processed per agent	Automation removes repetitive tasks, allowing agents to focus on complex issues.
Operational Efficiency	Reduced workload and improved service delivery	Indirect cost savings (not numerically specified)	Higher ticket throughput and reduced manual labor enhance overall efficiency.
Limitations of Automation	Difficulty handling complex or technical tickets	Certain ticket types remain unsolved by AI	Highlights the need for human oversight in specialized or nuanced problem areas.

5.2 Operational Implications

The findings are very insightful for organizations considering adopting AI in their ITSM processes. Athletically, due to the automation, one can always reduce the burden on IT personnel by giving them routine tasks that include sorting operations by type of ticket, triage to the help desk, and simple troubleshooting of portal-based concerns, which will lead to more urgent resolutions. Tcklog aged with AI, as indicated in the experimental outcomes, automated workflows reduced the backlog by 30%, especially in companies with high activity volumes of repeated service requests. Agents should have time to address problematic issues by simplifying ticket triage and implementing automated solutions for simple problems, thereby improving service delivery [24]. In addition, the adaptive characteristics of the AI and its capacity to acquire knowledge on past ticket history allow organizations to maximize the continuous automation benefit, thus continually enhancing it.

5.3 Limitations of the Study

Although the results are encouraging, the Study has several limitations. To begin with, the datasets used in this Study, although extensive, may not fully capture the complexities that can be present in any ITSM setting. For example, HuggiFor and Kaggle data are primarily used for tasks involving company-specific problems. In addition, accumulations of the AI models depended on the type of ticket; technical tickets were not accurately identified as compared to other types, and this could affect the generalizability of the findings [25]. The second weakness is the possibility of bias in the experimental setup. As all the models were trained on existing datasets, it is possible that the data contained biases by nature (e.g., an uneven distribution of tickets or incomplete labels). Besides, the experimental phase may be short, failing to capture long-term adaptation in AI systems, as seen in more complex, large-scale IT environments. Thus, to overcome these limitations, future research might consider applying various real-world datasets and even longitudinal analyses to determine the long-term effects of agentic automation on ITSM processes [26].

The diagram, as illustrated below, gives a systematic outline of the significant limitations of the study in that the limited datasets, like HuggiFor and Kaggle, might not provide a complete picture of the realities of the ITSM landscapes. It also points out possible biases that were added to the experimental arrangement, such as unequal distribution of tickets, incomplete labels, and the fact that the period of the experiment is relatively short and does not allow for evaluating AI adaptation in the long term. The flowchart also indicates recommended solutions, including the inclusion of diverse real-world datasets as well as longitudinal studies to enhance the rigidity and extensiveness of further ITSM automation studies.

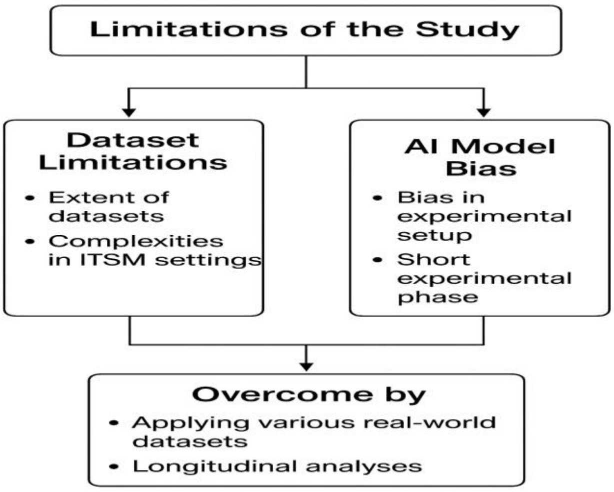

Figure 6: A flowchart to describe the limitations of the study, the limitations of the data set, and AI models' biases and future suggested improvements based on various datasets and longitudinal results.

6. Future Research Suggestions

6.1 Improvement of AI Models

Among the key issues to be considered in further research is validating improvements in AI models to address more sophisticated ITSM situations, including multi-step issue resolutions [27]. The main idea of current AI solutions is menial robotization, i.e., ticket recognition, routing, and low-level operations. However, most ITSM processes involve multifaceted, complex tasks that require contextual knowledge and dynamic thinking. Indicatively, AI can be improved to handle more issues, including network connection problems or software bugs, which have several causes. More advanced natural language processing (NLP) systems can also be used to add complexity to the machine learning algorithms, allowing such algorithms a better understanding of more subtle queries on the part of users and giving them a more dynamic, stepwise solution. To identify the trends in the use of multi-step AI models, statistical analysis of ticket data may indicate the areas where the models may prove the most useful, which can save the company between 25 and 50% of the time required to address these problematic issues, depending on the history of how well the firms that partially automate the process troubleshoot.

The second direction that could be fruitful is investigating the boundaries between AI models and human cognition, which can form hybrid systems. Human agents have to make higher-level decisions, and AI can be effectively used to manage regular procedures. Combining AI efficiency and the critical thinking of human agents would enhance the ITSM system and make it more flexible [28]. The area of AI-assisted human collaboration is one of the research opportunities where AI can take over tedious tasks and leave more intricate decisions to humans. This hybrid technique would go a long way toward improving employee productivity and overall service delivery efficiency, as statistics indicate that this kind of integration may improve first-contact resolution (FCR) rates by 15-20% in a high-complexity workplace. Figure 7 below introduces a methodological way of enhancing AI models, which is essential in the management of complicated ITSM duties. This begins by checking the performance of AI, making conjectures, and undertaking experiments to improve the models. To access and prioritize improvement, feedback is incorporated and eventually results in the documentation and standardization of successful models. This method is consistent with the requirement of AI models to be refined, particularly to take care of complex ITSM procedures such as multi-step resolutions of issues. Enhancing the functionality of AI, organizations will be able to save much time by seeking resolutions, which contribute to the increased productivity of the staff as well as the effectiveness of providing services.

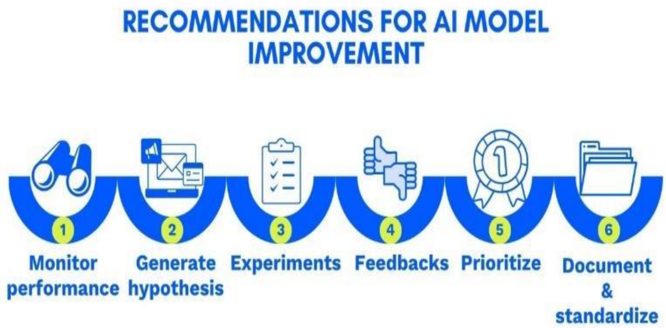

Figure 7: A systematic method of AI model advancement, which pays attention to performance monitoring, experimentation, feedback, and standardization.

6.2 Base Data Exploration using a Larger Data Set.

The subsequent research should also aim to expand the datasets to other ITSM scenarios for exploration [29]. Nonetheless, unlike the current data sources, which, in general, are general IT tickets, such as a hardware or software failure, in the real world, ITSM systems often need to work on a broader range of cases, such as security breaches, failures in services, and troubleshooting. Another possible direction of research is to include datasets that deal with more complicated conditions, including cybersecurity, data security, and AI. In fact, security ticket types are e AI models trained on various issues, enabling increased automation in real IT implementation.

6.3 Long-Term Impact Studies

Lastly, a longitudinal study would have been required to determine the effect of agentic automation on the ITSM performance and staff satisfaction in the long term. Even though efficiency in obtaining a ticket increases in the short run, very little is known about the effects of automation on job satisfaction, employee turnover, and the working environment. The long-term surveys can play a significant role in monitoring the changes in these measures with the passage of time [30]. Therefore, it is up to organizations to determine how much automation will enhance service provision and workers' morale. Besides, the study can help identify potential obstacles, such as AI biases or declining employee engagement, so that long-term, agentic automation deployment outcomes in ITSM can become sustainable. 1-2-year research can contribute to a better understanding of the current process of systems automation and optimization.

Figure 8 below illustrates the development of AIOps, from algorithmic IT operations, through predictive, to agentic AIOps. This development is calculated to allow autonomous behavior and hyper-automation where artificial intelligence systems decide and act without the intervention of people. The diagram also talks of the significance of observability and actionable insights, which are critical when it comes to making sure that the automation is working. When applied in the framework of long-term research, such as research on AIOps checks of ITSM performance and employee satisfaction, these AIOps stages provide a detailed perspective on how automation may influence the two aspects of service delivery and staff involvement in the long run.

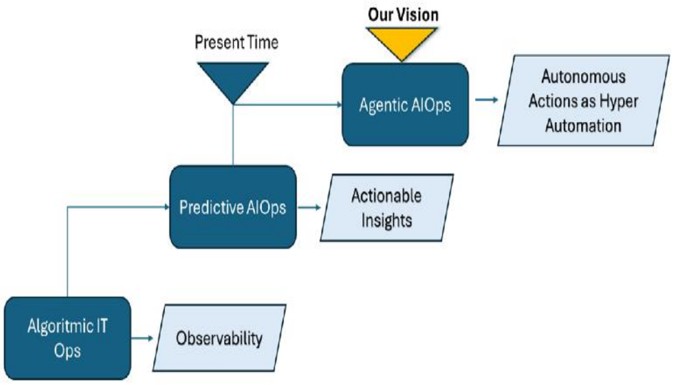

Figure 8: The development of AIOps into agentic AIOps, which can take autonomous steps and hyper-automation.

7. Conclusions

In this study, the introduction of agentic automation was studied in relation to the IT Service Management (ITSM) process, including the time required to resolve a ticket and employee productivity. The results indicated that AI-based workflows had a high level of performance compared to hand processes across several key performance measures. Turnaround time per ticket was significantly reduced, and agent-assisted processes were cut by 13 hours compared to manual systems. This was also most evident in high-priority tickets diverted by the AI, which helped achieve better response times and more effective ticket diversion. Further, the first-contact resolution (FCR) rate was increasing by 53% instead of 60% on the manual workflow and 71% on automated processes. The automation also saved centuries they had been spending on reducing ticket by spending so that they could solve complicated problems. Their allowance would translate into a 22% increase in the number of ticket agents who could work, and consequently, the employees' productivity would increase. On top of that, AI routing and AI classification enhanced compliance with SLAs by 80-91%, indicating that AI is effective in fulfilling service-level agreements.
The findings of the present research may be helpful to organizations that intend to use AI in their ITSM operations. Firstly, the results of the work clearly reveal that automation in administrative roles, i.e., triage registration, classification, and routing of tickets, can result in a significant reduction in operational expenses and improved efficiency. The AI enables companies to process high volumes of tickets, allowing the most urgent issues to be addressed promptly and resolved in a timely manner. This allows the staff to devote more time to more complex and high-value work, ultimately resultingly in enhanced service delivery and a customer base. Besides, the time spent on ticket processing and productivity levels can be minimized, allowing companies to expand without hiring new workers. Agentic automation can be a breakthrough for companies in sectors that require large volumes of tickets, such as large IT service desks. It has already been noted that organizations like Microsoft and IBM can see the advantages of advancing AI, whether by processing tickets faster or deriving greater benefits from increased employee output, indicating that these advantages can be realized across a wide range of industries.

One of those drastic changes in IT operations management is the increased use of AI in ITSM. The need to automate service request processing becomes more acute as organizations become more dependent on cloud-based SaaS and face more complex systems. Even though this study provides beneficial results, AI implementation is not at its end. It is proposed that AIs will be further improved in the future through the creation of multi-step solving and the integration of human skills with AI algorithms. Moreover, datasets on more ITSM cases and long-term studies of the effects of automation will offer a better understanding of what it will have in the long term. With the development of AI technology, the possibility of transforming the ITSM process will only increase, and the potential for further efficiency and productivity optimization should also increase. Lastly, the successful introduction of agentic automation will involve ongoing adjustment and tuning, as AI tools are meant to keep pace with an organization's needs and its target audience.

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