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AI-Driven Analysis and Prediction of IT Service Management Performance Metrics Using Multi-Dataset Evaluation

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Abstract:
Artificial Intelligence (AI) is one of the key technologies that can enhance the efficiency of IT Service Management (ITSM) ecosystems. Traditional ITSM systems often have manual workflows for incident management, ticket prioritization and service monitoring that can introduce delays and impact service quality. Mean Time to Resolution (MTTR) stands out as one of the key operational metrics commonly employed to assess the effectiveness of incident management operations. This research suggests an artificial-intelligence-based framework to evaluate and predict the performance of ITSM operations through multi-dataset evaluation and optimization based on simulation. The framework incorporates dataset preprocessing, calculation of MTTR, AI-driven simulation, performance comparative and rendering visualization. There were several available ITSM datasets providing incident lifecycle and service management information which were gathered and analyzed with Python-based analytical tools. The operational timestamps were used for calculation of baseline MTTR, followed by optimization with AI-assisted simulation models considering adjustable reduction parameters and certain controlled variability. Comparative analysis of operational performance between baseline and AI assisted shows that the MTTR can be measured with a reduction in operational performance efficiency in various datasets, consequently, improved incident handling process efficiency, which is measurable. The suggested framework also features interactive visualization and simulation tools created with Streamlit, which can aid real-time operational analysis and decision-making. The results of the experiments have shown that AI optimization can prove to be a valuable tool to decrease incident resolution time and improve the performance of ITSM systems. The research provides an operational, analyse-based, practical and simulation-oriented analytical framework, which has been enhanced with comparative analysis and intelligent visualization techniques for the performance improvement of ITSM beyond the conventional prediction models.

Keywords: Artificial Intelligence (AI), IT Service Management (ITSM), Mean Time to Resolution (MTTR), Machine Learning, Predictive Analytics, Incident Management, AI-Assisted Simulation, Operational Analytics, Multi-Dataset Evaluation, Streamlit Visualization, Intelligent Automation, Performance Optimization

1. Introduction

1.1 Background of IT Service Management

IT Service Management (ITSM) is one of the significant operational frameworks that IT organizations use to manage IT services, incident management, and specialized support. Modern companies rely heavily on ITSM systems to ensure service continuity, reduce time-to-unavailability, and increase customer satisfaction. A major operational metric in ITSM is the 'Mean Time to Resolution' or MTTR, which is the amount of time that it takes to resolve the service incident after it has been reported [1]. Faster MTTR numbers, usually the better, signify greater efficiency in operation and quicker response if geo-technical disruptions take place.

In recent years, the use of Artificial Intelligence (AI) and machine learning has had a profound impact on ITSM, automating routine tasks, forecasting issues, intelligently routing tickets, and identifying anomalies. Previous work, like Predicting Incident Resolution Time in IT Service Management via Lifecycle Feature Aggregation and Machine Learning, mainly targeted using models built by machine learning techniques to predict the incident resolution time. The study showed that predictive approaches for an ITSM system work very well, but mostly with an emphasis on predicting the accuracy and mostly without thorough simulation and evaluation of the whole system, nor comparing them directly to other approaches [2].

1.2 Problem Statement

BOOL's traditional ITSM systems are still largely based on manual monitoring and traditional incident management methods. This growing number of service incidents typically leads to slow response times, poor ticket prioritization, and complications. In addition, previous studies do not currently provide usable simulation tools that allow for the dynamic testing of operational improvements with multiple sets of data and can benchmark the tools. Also, current research does not provide practical AI-assisted, simulation-based tools to evaluate operational improvements dynamically, using more than one set of data, and using comparative performance testing.

1.2 Research Aim

The objective of this research is to establish an AI-based framework that can be used for analysing and simulating ITSM operational performance, through multiple datasets and MTTR analysis.

1.3 Research Objectives

- To process and analyze ITSM operational data.
- To calculate the MTTR from incident lifecycle information.
- To emulate artificial intelligence - driven improvements in the operation.
- To make comparisons between pre-test/control and intervention/awareness performance.
- To model operational behavior graphically.

2. Literature Review

2.1 ITSM Performance Metrics

Information Technology Service Management (ITSM) performance metrics are important indicators used to evaluate the efficiency and reliability of IT operations. Common metrics such as Mean Time to Resolution (MTTR), Mean Time to Identify (MTTI), and First Call Resolution (FCR) help organizations monitor incident handling, service quality, and operational effectiveness. Among these, MTTR is widely used because it measures the average time required to resolve incidents, where lower values indicate better operational performance. Traditional ITSM systems mainly depend on manual workflows and human intervention, which can result in delays in ticket assignment, prioritization, and incident resolution [3].

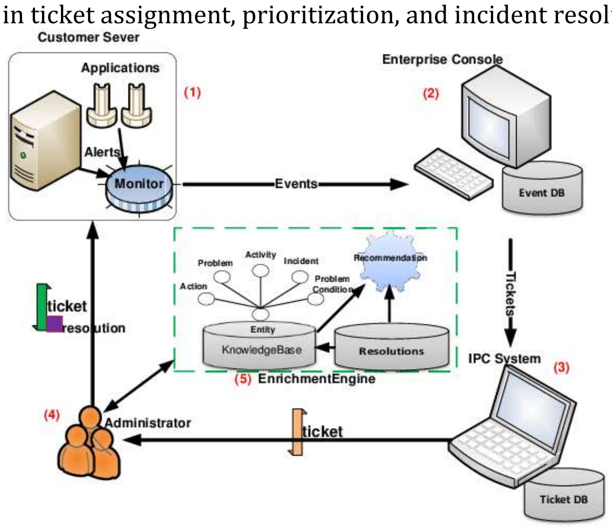

Figure 2.1: IT Service Management Workflow [10]

Figure 2.1 shows the activities of a classic IT Service Management (ITSM) processes. The architecture is a blueprint depicting how an application alerts are monitored, remediated to operational events, converted to support tickets and handled through administration resolving and knowledge resolving processes. This workflow demonstrates the intricacies of an incident handling process and the need for effective operational metrics like MTTR.

As organizational IT environments become more complex, maintaining operational efficiency using conventional methods becomes increasingly difficult. Therefore, modern IT organizations require data-driven analytical frameworks capable of continuously monitoring operational metrics, identifying inefficiencies, and supporting decision-making using historical incident logs and service records.

2.2 Artificial Intelligence in ITSM Systems

Operational Efficiency is one of the critical areas where Artificial Intelligence (AI) has emerged as a crucial technology when it comes to IT Service Management systems. AI-powered ITSM technologies can automate routine tasks, optimize incident categorization, streamline ticket routing, and facilitate predictive analysis of services. In recent innovative times, organizations have increasingly leveraged machine learning and intelligent automation to analyze vast amounts of incident data and render more precise decision-making and policing [4].

Automated ticket categorization, incident prioritization, anomaly detection, and predicting incident resolution times are among the applications of AI in ITSM environments [5]. By analysing tickets from the past, machine learning models can help detect patterns of recurring incidents and service bottlenecks.

These capabilities are crucial for organizations to streamline their operations and enhance their response efficiency.

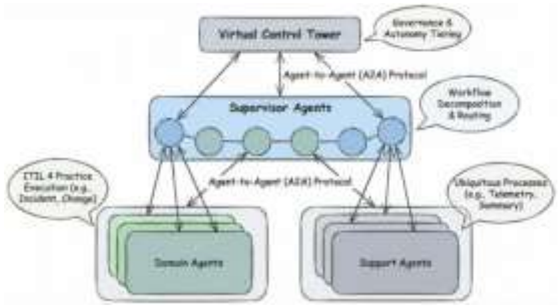

Figure 2.2: AI-Driven Multi-Agent Architecture for Intelligent ITSM Operations [11]

In Figure 2.2, a multi-agent operational architecture for intelligent IT Service Management systems is presented, which is based on AI. The framework illustrates agent-to-agent communication protocols for routing workflows, handling incidents and executing ITIL workflows among supervisor agents, domain agents and support agents to achieve automated workflows. These smart architectures greatly enhance the efficiency of operations and enable high levels of AI-assisted ITSM.

Several previous studies have investigated the predictive analytics approach for ITSM performance evaluation. AI systems can calculate the severity of the incidents, predict service delays, and assist with the utilization of intelligent escalation strategies [6]. Certain research also highlights the potential of AI to lower MTTR by prioritising issues sooner and optimising resources.

Among all of these above benefits, many of the existing AI-based ITSM studies are still theoretical and limited to the isolated prediction model, while providing only partial evaluation of the working system. Only limited research has explored a comparative study of baseline and AI-assisted simulation of multiple operational datasets. This means there is a distance between the theory of the applications of AI and actual operational analyses.

2.3 Existing Research Gaps

Though many prior works have already shown the effectiveness of AI/Machine Learning in the field of IT Service Management (ITSM), some challenges still persist. The focus of the base paper was basically on predicting incident resolution time through machine learning methods titled "Predicting Incident Resolution Time in IT Service Management via Lifecycle Feature Aggregation and Machine Learning" [1]. However, the main focus of the study was not necessarily on the actual implementation of optimization and comparison of operational performance and prediction accuracy.

An area of significant research opportunity is the availability of simulation-based frameworks for analysing how optimization using AI impacts operational metrics, like MTTR (Mean Time to Resolution) [7]. Most studies only deal with prediction models without a comparison of baseline and AI-assisted operational performance. Another limitation is that there is limited use of multi-dataset evaluation; many studies rely on single studies only, which limits generalizability. In addition, in the present systems, there are no systems for the dynamic observation of operational behaviour through visualization with interactive control or analysis by parameters. Hence, there is a need for a more holistic framework including MTTR analysis, using simulation with AI, comparison, and visualization.

Table 2.1: Research Gap

Author / Study	Focus Area	Method Used	Limitation / Research Gap	Proposed Work Contribution	Author / Study	Focus Area
Stiawan et al. (2026)	Incident Resolution Time Prediction	Machine Learning with Lifecycle Feature Aggregation	Focused mainly on prediction accuracy without operational simulation or comparative AI optimization	Introduces AI-assisted simulation with comparative MTTR evaluation and visualization	Stiawan et al. (2026)	Incident Resolution Time Prediction
Sharon & Suma (2022)	Predictive Analytics in ITSM	Data Analytics and ML Models	Limited practical implementation	Develops interactive simulation-	Sharon & Suma (2022)	Predictive Analytics in ITSM

			and no real-time operational simulation	based ITSM analytical framework		
Chugh (2025)	Intelligent ITSM Automation	AI-enabled Workflow Automation	Concentrated on workflow automation rather than performance comparison	Evaluates operational efficiency using baseline vs AI-assisted MTTR comparison	Chugh (2025)	Intelligent ITSM Automation
Peralta et al. (2025)	Intelligent Incident Management	AI and Knowledge Engineering	Limited multi-dataset operational validation	Performs multi-dataset evaluation for generalized ITSM analysis	Peralta et al. (2025)	Intelligent Incident Management
Ahmed et al. (2023)	AI-Driven IT Support Systems	Systematic Review	Mostly theoretical discussion without simulation framework	Implements practical AI-assisted simulation environment	Ahmed et al. (2023)	AI-Driven IT Support Systems
Wang et al. (2017)	Cognitive IT Service Management	Knowledge Base Construction	Did not address MTTR optimization analysis	Focuses on MTTR-based operational performance optimization	Wang et al. (2017)	Cognitive IT Service Management

2.4 Recent Research Studies

The use of Artificial Intelligence (AI) and machine learning (ML) in ITSM operations has become a focus of recent research studies. It has been shown that lifecycle aggregation of attributes and presentation of them in combination with machine learning models to define incident resolution time is useful for predictions and decision-making in the work [1]. This study emphasized the increasing importance of predictive analytics in the practice of today's IT service operations.

Other recent research has examined the use of AI-driven automation for smart routing of tickets, anomaly detection, incident prioritization, and predictive maintenance in enterprise IT environments. AI-powered systems have been proven to lower ongoing delays, enhance service responsiveness, and lessen incident management delays by automating workflows and utilizing analysis modelling [8].

Moreover, the use of operational frameworks that
incorporate simulation and interactive analytical systems is now also highlighted in recent literature. One key research area in intelligent IT operations is the comparative analysis of baseline operational performance and the usage of AI to improve it. Operational decision-making and service optimization rely on more and more visualization dashboards, parameter-driven simulation models, and dynamic analytical tools [9].

This study continues this line of work, moving beyond predictive modelling to the creation of a unified AI-driven simulation combining multi-dataset evaluation, MTTR analysis, comparative operational analysis, and interactive visualisation.

3. Methodology

3.1 Research Design

This research adopts a research approach that is dependent on experiments and simulations to determine the effect of Artificial Intelligence (AI) on IT Service Management (ITSM) performance. It is here that the study aims to analyze the efficiency of incident resolution with the help of operational datasets in the context of the use of AI-assisted techniques. The overall approach involves preprocessing the datasets, calculating MTTR, comparing and contrasting different MTTRs, and simulating the case interactively using Streamlit and Python.

3.2 Dataset Collection

The datasets were used from public sources like Kaggle, etc. Initially, multiple ITSM-related data sets, such as logs of incidents handled and support ticket records, were examined. Data sets with operation and service lifecycle information were included in the analysis if the operational timestamp was valid. Finally, it was necessary to have an identifier obtained from the incident, priority information, and opening times and resolution times to calculate MTTR from the final datasets.

3.3 Dataset Preprocessing

All the datasets were pre-processed and cleaned to ensure consistency and reliability. Records were deleted, along with empty records and records with an invalid value for the data's associated time. The Python Pandas libraries were used to convert datetime columns to a standard format for standardization. Python Pandas libraries were used to standardize datetime columns. Duration values that were unrealistic and negative time differences were removed from each database. Incident Event Logs: Several incident records were collated to form a "full log" of an incident's life cycle.

3.4 Important Features and Operational Columns

The following operational columns of this research are the most important ones: opened_at, closed_at, resolved_at, first_response_time, time_to_resolution, priority, and incident number. Operational duration and MTTR were calculated using time-related fields. An important consideration in the AI-assisted simulation was that the priority level set during the analysis was different for the various types of incidents.

3.5 MTTR Calculation Logic

Mean Time to Resolution (MTTR) was chosen as the main performance indicator. The time elapsed from the opening time to the closing time was determined for each incident, and the time recorded was converted to hours (h). Operational data in their original state was first used to calculate Baseline MTTR. This informed an AI-assisted simulation model, which calculated optimized operational performance using reduction factors. The percentage improvement was computed based on the AI-assisted MTTR value and the baseline MTTR value.

Table 3.1: Baseline MTTR Metrics Across Datasets

Dataset	Tickets	MTTR (Hours)	Median (Hours)	P90 (Hours)
cleaned_customer_support_tickets.csv	8469	7.32	6.17	15.54
cleaned_incident_event_log.csv	141712	269.60	73.52	568.25
cleaned_ITSM_data.csv	118	2.85	0.00	0.00

3.6 AI-Assisted Simulation Model

Based on these findings, the AI-assisted simulation model was created to analyze the improvement of operational efficiency that can be achieved by the use of AI technologies on ITSM systems. Different optimization conditions were simulated by adjusting the parameters in the following manner: Critical Reduction, High Reduction, Medium Reduction, Low Reduction, and General AI Strength. Randomness was added under control, to mimic the operational variability of real-world systems. With the optimization factors applied, the system recalculated MTTR and showed comparative performance results with graphs and Streamlits-based dashboards.

Table 3.2: AI Model Performance Summary

Dataset	Priority Accuracy	Resolution MAE (Hours)
cleaned_customer_support_tickets.csv	0.252	-
cleaned_Support_tickets.csv	0.560	-

4. System Implementation

4.1 Technology Stack

This system was developed in Python, as the language is highly compatible with the use of data analysis, machine learning, and visualization. To process the data, to perform numerical computation, to visualize it in a graphical format, and to make it interactive, libraries like Pandas, NumPy, Matplotlib, and Streamlit were used. The analytical stages have been created in a Jupyter Notebook environment, and the end simulation system has been implemented into a Streamlit-based graphical user interface to allow real-time interaction and operational analytics.

4.2 Interactive Simulation System

This Streamlit app has been built to offer a GUI to support interactive testing of the AI-powered ITSM performance improvement. Users can choose datasets dynamically, update the AI optimization, run simulations, and easily visualize results in real-time. This system has parameters that adjust the reduction level of critical, high, medium, and low priority incidents, as well as a default setting for the AI strength. After selecting parameters, the application automatically computes baseline MTTR, gives out an AI simulation, and dynamically updates the operation metrics. Error handling mechanisms were also incorporated to detect data sets that did not contain a proper set of data fields that allow the calculation of an MTTR.

4.3 Graphical Visualization

An important part of implementation was the role of visualization, as it enables the analysis of the operational behavior and AI-assisted improvements more clearly. The system creates similar graphs comparing baseline and AI-assisted durations. These visualizations can be used to help find production peaks that are related to incidents that are taking a very long time to resolve. This simulation shows how the optimization aided by AI can diminish these peaks and optimize the overall operational efficiency with respect to other parameters.

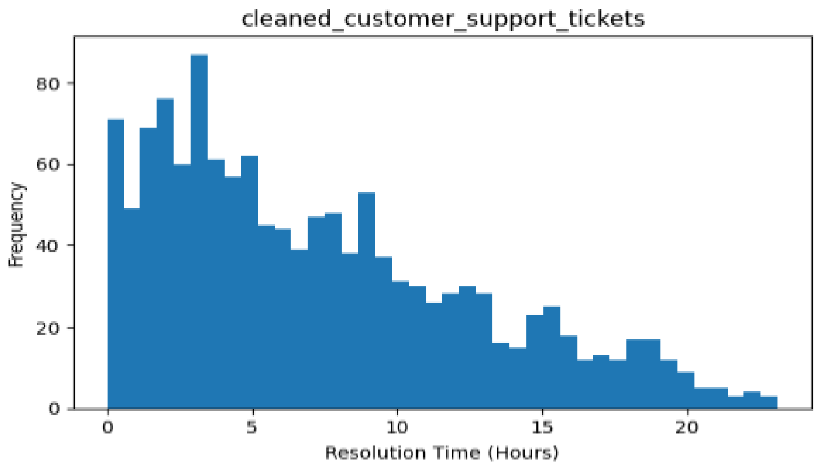

Figure 4.1: Resolution Time Distribution for Customer Support Tickets

Figure 4.1 shows the distribution of incident resolution times for the customer support ticket dataset. The majority of incidents were dealt with in the lower time spans with some fewer incidents taking a longer operational duration.

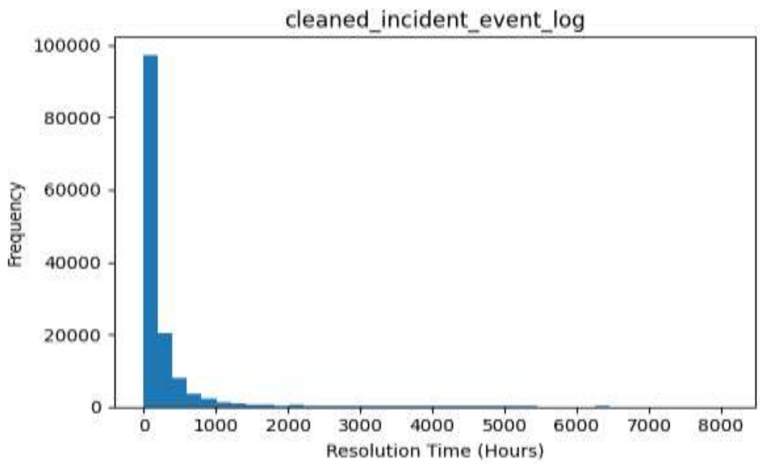

Figure 4.2: Resolution Time Distribution for Incident Event Logs

Figure 4.2 shows that the incident event log data is highly right-skewed as a result of a few long-duration incidents having a major impact on the baseline MTTR values.

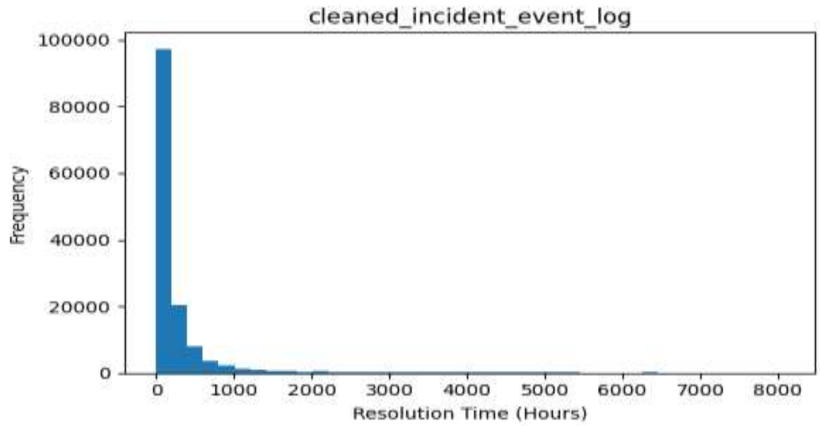

Figure 4.3: Resolution Time Distribution for ITSM Operational Dataset

The operational resolution time distribution for the dataset for the simulated analysis of ITSM is shown in Figure 4.3.

4.4 Performance Evaluation Logic

Performance evaluations are made by comparing baseline MTTR and AI-supported MTTR based on analytical comparisons. Each of the incident priorities is "optimized" to varying extents to mimic reality during an incident. Improvement percentage is used to assess the efficiency of the AI-aided optimization. The framework discussed is comprehensive enough to provide a full framework for the analysis of ITSM performance, for the modelling of system improvements that rely on AI, and for the visualization of the comparison of different operational behaviors.

5. Results And Discussions

This study proposed and evaluated an incident-resolution-time prediction model based on Aggregated Lifecycle Features derived from university ITSM event logs. By integrating data preprocessing, lifecycle-aware feature aggregation, and adaptive feature selection using LightGBM, ensemble-based regression models particularly the Random Forest Regressor demonstrated substantially superior predictive performance compared to non-aggregated baselines. This result confirms that aligning the unit of analysis to the incident level is critical for improving predictive accuracy in ITSM environments characterized by multi-event, irregular process logs.

The main contribution of this work is to demonstrate that transforming event-level logs into incident-level representations effectively reduces noise and strengthens the linkage between process dynamics and resolution outcomes, thereby addressing a key limitation of time-zero and purely event-based prediction approaches. Furthermore, identifying dominant attributes such as sys_mod_count, reassignment_count, and priority provides interpretable and actionable insights into escalation intensity, coordination complexity, and operational workload, thereby reinforcing the practical relevance of the proposed feature aggregation strategy.

From an operational perspective, the proposed model is suitable for integration into university CSIRT decision-support systems to support SLA estimation, workload balancing, and medium-term resource capacity planning. However, the achieved prediction accuracy remains insufficient for strict hourly SLA enforcement, suggesting that the model is better suited for tactical and strategic decision support rather than real-time operational alerting.

Despite these contributions, the current models exhibit reduced robustness in capturing extreme long-tail resolution cases and highly dynamic incident evolution, highlighting an important limitation. Therefore, future research should explore temporal deep-learning architectures and graph-based models, such as attention-enhanced temporal networks or hybrid survival analysis approaches, to better handle irregular escalation patterns and prolonged incidents. Integrating predictive outputs into an interactive incident analytics dashboard is also identified as a critical next step toward operational deployment in university and enterprise IT service environments.

5.1 Baseline vs AI-Assisted Performance Comparison

On the experimental results, it can be claimed that the AI-aided simulation model was effective in reducing the time to resolve incidents in multiple ITSM sets. MTTR values at the time showed an actual operating MTTR as baseline values; with the help of AI-assisted optimisation, the MTTR was recalculated to show measurable operational efficiency improvements. The degree of improvement was dependent on the structure of the datasets, distribution of incidents, and the parameters of the AI models used.

Table 5.1: Baseline vs AI-Assisted MTTR Comparison

Dataset	Baseline MTTR (Hours)	AI MTTR (Hours)	Improvement (%)
cleaned_customer_support_tickets.csv	7.32	6.74	8.00
cleaned_incident_event_log.csv	269.60	214.46	20.45
cleaned_ITSM_data.csv	2.85	2.62	8.00

Furthermore, the analysis found that accurate MTTR can only be calculated if there are operational timestamps for the datasets; otherwise, the datasets lack the information needed to support MTTR computation.

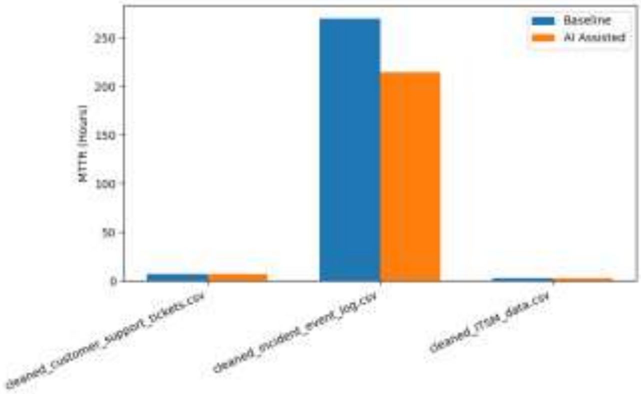

Figure 5.1: Baseline vs AI-Assisted MTTR Comparison

Figure 5.1 demonstrates a visual comparison of the baseline MTTR values and the AI-assisted MTTR values for each of the datasets. ART-optimized solutions have enabled MTTRs to be reduced.

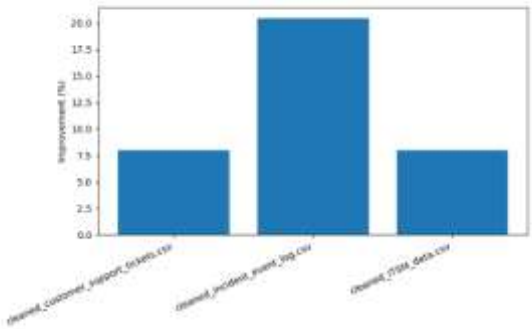

Figure 5.2: Percentage Improvement Achieved Through AI Optimization

Figure 5.2 illustrates the percentage improvement achieved after AI-assisted optimization. Among all the datasets, the incident event log dataset had the highest improvement percentage.

5.2 Analysis of AI Parameters

Operational performance outcomes were significantly different when using the various parameters for the simulation. The Critical Reduction and the High Reduction parameters had the most effect on operational timing since these are the incidents that have the highest priority. Raising these parameters brought in an increased reduction in large-duration incidents along with an improvement in general MTTR. Larger incidents were mainly impacted in the Medium and Low Reduction parameters, and changes were less pronounced. Additionally, the simulation included elements of controlled randomness, as it was seeking to depict the reality of randomness and changes that occur during the real operation of the system, with optimum use of AI not necessarily affecting all incidents equally, as in realistic IT environments.

Table 5.2: Statistical Validation of AI-Assisted Improvements

Test	Statistic	P-Value
paired_t_test	1.0223	0.4142
wilcoxon_test	0.0000	0.2500

5.3 Interpretation of Graphical Results

The visual results of the graphical outputs were presented as a comparison between the operational behaviour from baseline and the operational behaviour using AI. There were a few high spikes in the baseline graphs that corresponded to a lot of incidents that had very long resolution times. These peaks were significantly decreased following the AI content simulation, resulting in shorter mean resolution time and efficiency in operation. The results revealed that the optimized times were best achieved with a significantly reduced operational delay, which was successfully obtained, and this in turn confirmed the capability of implementing intelligent AI-assisted optimization with significant improvement in the performance of ITSM.

6. Conclusions

6.1 Conclusion

The overall objective of this research was to develop a framework based on artificial intelligence (AI) to analyze and simulate the performance of IT Service Management (ITSM) operations with multiple datasets. The research centered on the analysis of Mean Time to Resolution (MTTR) and the optimization benefits of AI technology on incident management. The development consisted of dataset preprocessing, computation of MTTR, simulation with the help of AI, comparative evaluation, and graphical visualization through the interactive system built with Streamlit. The implementation involved data preprocessing, computation of MTTR, using AI for simulation, a comparative evaluation process, and graphical visualization through an interactive system developed with Streamlit.

The outcomes of the experiments showed that using AI-enabled simulation can result in shorter incident resolution times for different parameter setups. The results of the comparative analysis between the baseline performance and the AI-assisted performance highlighted that there were measurable measures of improvement, such as MTTR, indicative of an improvement in operational efficiency and incident handling times. The need for quality datasets and data operational importance was also discovered when performing ITSM analysis.

Another significant achievement was to create an interactive simulation system with the capabilities of dynamic parameter changes, real-time visualization, and operational performance analysis. The study has managed to build a practical analysis framework that can analyse operational behaviour, simulate optimization using AI, and visualize and show the comparative improvement in ITSM performance overall.

6.2 Future Work

While the framework proposed in this research is successful in showing the possibility to optimize ITSM performance via AI, some possibilities exist to further research it. Its integration with live enterprise data and operational management tools, like ServiceNow or Jira, would be valuable for further in-depth operational analysis in the future.

Other machine learning technologies like deep learning, predictive analytics, and intelligent ticket routing algorithms can be integrated to enhance automation capabilities. Potential additions to future deployments include Anomaly Detection Systems, Real-time Monitoring Dashboards, and Automated Decision-Support.

The current framework concentrates on MTTR measurement, but in the future, an extensive analysis can be done with other operational metrics like SLA compliance, ticket escalation prediction, or customer satisfaction analysis. The improvements would further fortify research and operational optimization of intelligent ITSM using AI.

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