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Article

Simulation-Based Evaluation of AI-Assisted ITSM Systems: A Comparative Study of Service Performance and Operational Efficiency

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Abstract: Information Technology Service Management (ITSM) systems play an important role in managing operational incidents, service requests, and technical support activities within modern organizations. Traditional ITSM environments often rely on manual workflows, resulting in delayed incident resolution and reduced operational efficiency. This research presents a simulation-based framework for evaluating AI-assisted ITSM operational performance through comparative analysis and interactive modelling. The proposed framework uses operational incident datasets to compute baseline Mean Time to Resolution (MTTR) and simulate AI-assisted optimization using parameter-based reduction logic and controlled operational variability. The system was implemented using Python analytical libraries and an interactive Streamlit application that supports dataset selection, parameter adjustment, comparative evaluation, and graphical visualization. Experimental results demonstrated that AI-assisted optimization can reduce incident resolution time and improve operational efficiency under different simulation conditions. The research contributes a practical comparative evaluation framework capable of analysing baseline versus AI-assisted operational behaviour within ITSM environments through interactive simulation and visualization techniques.
Keywords: Artificial Intelligence, IT Service Management, MTTR, Operational Simulation, Streamlit, Incident Management, Comparative Analysis, AI-Assisted Optimization

1. INTRODUCTION

1.2 Background of AI-Assisted ITSM Systems

Information Technology Service Management (ITSM) is the set of working practices that an organisation uses for its information technology services, incidents, technical support and system maintenance tasks. ITSM assists organisations to maintain a stable, reliable and business-focused IT service. Incident management is among the most critical roles in ITSM, aimed at detecting, analysing and resolving technical issues affecting operating systems and users [1].

Incidents and requests for services are consistently growing in number as more organisations have come to rely on the information technology infrastructure. Traditional ITSM systems are largely ticket management-driven, workflow-driven by rules and rely on a lot of work done manually. While these strategies are commonly employed, they can fail to provide operational efficiencies, such as slow resolution turnaround times, unequal prioritisation, and overburdened support operations [2].

The simulation-based AI evaluation has emerged as a crucial field of study because it assists enterprises in estimating the potential gains of being assisted by AI during optimisation prior to implementing significant enterprise automation systems. The researchers are able to simulate the operational performance metrics like Mean Time to Resolution (MTTR) under various service conditions and performance configurations using AI.

1.2 Problem Statement

There are many operational incidents being created daily in IT. As the volume and complexity of these incidents grow, traditional ITSM arrangements are often unable to keep up with them because of reliance on manual service workflows. Business continuity, service quality, and customer satisfaction can be greatly impacted by incident handling delays.

While there is growing discussion about the use of AI in ITSM research, most current research is about theoretical machine learning models or specific prediction tasks without a focus on operational evaluation. Another difficulty is the lack of dynamically testable interactive systems where AI optimisation can be tested under various operating scenarios. When using AI to guide business operations, it's hard to appreciate the effect these can have on operational efficiency and service performance metrics without having a through and thorough comparative simulation and visualisation.

1.3 Research Aim

This study aims to assess AI tools' influence on ITSM's operational performance through a comparative study, employing simulated analysis. This study targets analysing and comparing the potential of interacting operational modelling and optimisation processes to minimise incident handling time and enhance service efficiency, assisted by AI tools.

1.4 Research Objectives

The overall goals of this research are:

1. To create and model a simulation-based framework for measuring the performance of AI-supported ITSM operations.
2. To review the baseline of ITSM performance based on operational incidents data and the calculation of MTTR.
3. Simulate the optimisation of the operation with AI assistance, with adjustable parameter-based modelling techniques.
4. To apply comparative analytical evaluation procedures to compare Baseline and AI-assisted operational performance.
5. To explore the efficiency of incident resolution and operational characteristics affected by AI parameters.
6. To create an interactive operational and visualisation of 6.5 by building a simulation system with Streamlit.

1.5 Scope of Study

The purpose of this research is to evaluate operational systems in ITSM using AI assistance by simulation using freely available incident data. The main research points of the study are the comparative MTTR analysis, operational optimisation simulation and assessment of service performance. Contents of the framework: Datasets preprocessing, use of artificial intelligence to simulate the process logic, and graphical visualisation.

The study is limited to an academic and experimental evaluation. This research does not cover real-time enterprise deployment, real-time production automation, nor high-level industrial AI integration.

2. LITERATURE REVIEW

2.1 Traditional ITSM Operational Models

Traditional IT Service Management (ITSM) systems are structured to provide control over IT management via established service processes and common operational practices. These systems typically operate using a service framework like Information Technology Infrastructure Library (ITIL) that emphasises incident management and problem management, service requests, and operational support activities [3].

The main attribute of traditional ITSM systems is their high reliance on human involvement. It's the job of service desk staff and technical teams to evaluate incidents, give them priority, and coordinate the activities needed to resolve the incident.

Heavy backlogs of incidents with a high priority also hinder efficient operational workflows with traditional systems. Mean Time to Resolution (MTTR) may be in flux as manual ticket routing and escalation processes are in place, potentially prolonging resolution time.

2.2 AI-Assisted Service Management

As the world advances with technology, the role of Artificial Intelligence (AI) in ITSM has become pivotal for automating operational processes and elevating the efficiency of decision-making processes. AI-powered ITSM solutions can leverage the existing operational history, gain insights into the service, and enable intelligent automation of incident management operations [4].

One of the most common applications of AI in ITSM is automated ticket classification. These machine learning models can help to process incident descriptions and automatically classify incidents according to the technology. Another advantage of AI-enhanced routing is the ability to automatically map incidents to the relevant support teams, optimising the flow of operations and minimising delays in response times to your customers' inquiries [5].

AI technologies are additionally used for predictive operational analysis. Predictive models can provide a forecast of resolution time, identify potential operational risks, and provide forecasts of service disruptions prior to their manifestation as a critical incident. This enables organisations to deploy resources in anticipation and, in so doing, achieve enhanced operational security. Another recent study examines intelligent automation capabilities that help prioritise incidents and optimise workflow management to ease the burden on staff and minimise Mean Time to Resolution.

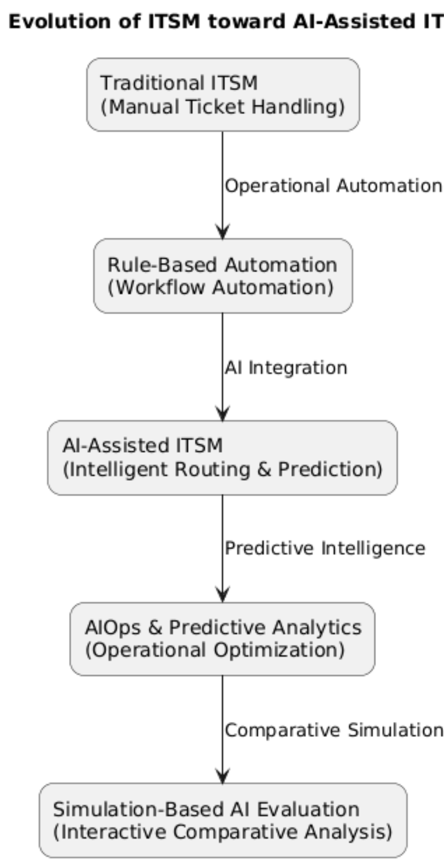

Fig. 1: Evolution of ITSM toward AI-Assisted ITSM

2.3 Simulation-Based Operational Evaluation

A major research method for the analysis of operational systems, without considering actual deployment in enterprise environments, is simulation-based evaluation. For ISM research, simulation can be used to represent the changes in the operational performance when the services are run under different tasks and conditions, optimisation techniques, and AI-assisted configurations [6].

The value of operational simulation frameworks lies, in particular, in the fact that they offer simulation-based environments to analyse efficiency and the behaviour of the workflows used. In service management studies, queueing-based operational models are usually utilised to model incident workloads, processing delays, and incident arrival patterns. These models enable researchers to gain insights into how bottlenecks in operations impact service performance and the ability to enhance efficiency in incident handling through automation methods [7].

Research Gaps and Recent Studies (2025–2026)

While the recent studies highlight the rise in interest in the use of AI in optimising ITSM, there are key areas of research that remain unanswered. The research focus of many studies is mainly predictive classification models, categorisation of tickets and accuracy for the operational analytics that is still isolated instead of embedding the performance with a whole comparative operational evaluation system [8].

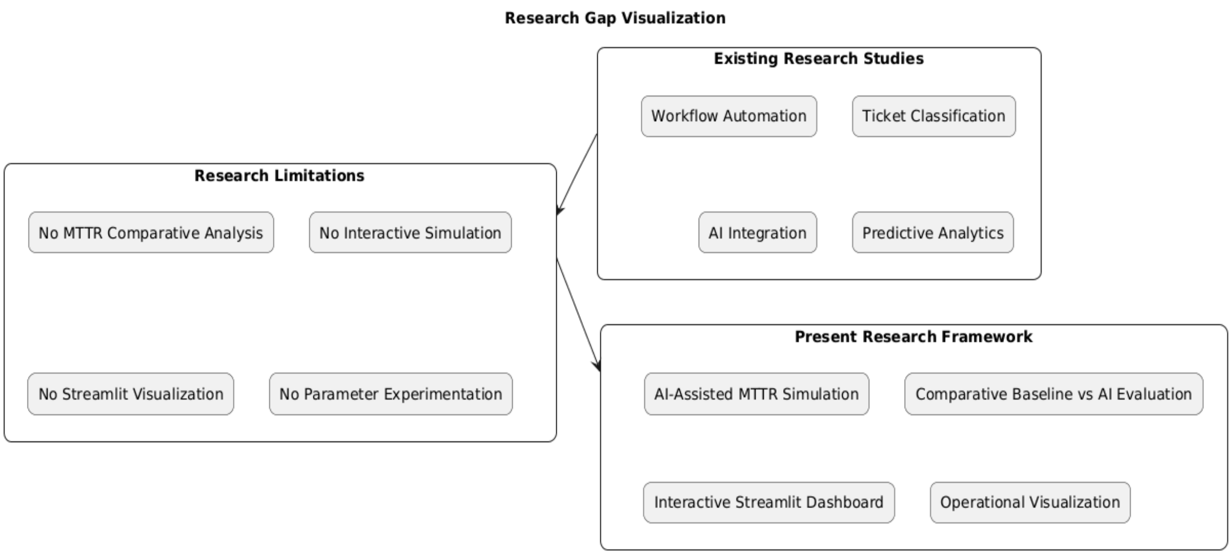

Fig. 2: Research Gap Visualisation

There are a lot of systems that allow the user to change operating parameters, perform simulation tests that allow users to compare results, and real-time analysis of the behaviour of services in existing research. This diminishes the usefulness of numerous research studies performed using AI in ITSM. In recent years, during the period 2025-2026, simulations for operational cost evaluation and intelligent optimisation of the services have become more and more significant.

However, there's not much research around the intersection of:

- multi-dataset evaluation,
- explain how to identify evaluative issues in the video, and
- interactive simulation,
- graphical operational visualisation,
- Optimisation both by and using parameters in a single framework.

To overcome these limitations, the present research aims to design an interactive system for comparative analysis of the operational performance of AI tools in the context of ITSM. It combines dataset preprocessing, computation of multi-temporal relevance, AI-triggered simulation, experimentation by parameters and graphical operational analysis into a practical research platform.

Authors & Year	Focus Area	Limitation	Research Gap

Battapothu (2023) (Base Paper)	AI-driven ITSM automation	No simulation or MTTR comparison	The present study provides a comparative MTTR simulation and interactive analysis.
Razma & Jurkus (2026)	AI ticket classification	Focuses only on classification accuracy	The present study evaluates operational efficiency and MTTR improvement
Santos (2025)	GenAI in ITIL practices	Conceptual review only	The present study includes practical implementation and experimentation
MacLean & Titah (2023)	Traditional ITSM impacts	No AI-assisted operational evaluation	The present study integrates AI-assisted optimisation
Amin et al. (2026)	AI integration in IT management	No dataset-based simulation	The present study uses real datasets and operational modelling
Adenuga et al. (2024)	AI-driven enterprise systems	No ITSM operational analysis	The present study focuses on AI-assisted ITSM performance evaluation

Table 1: Research Gap Analysis

Previous studies mainly focus on AI automation, ticket classification, conceptual ITSM frameworks, or enterprise AI integration. However, limited research provides simulation-based comparative MTTR evaluation, interactive experimentation, and graphical operational analysis within a unified AI-assisted ITSM framework. The present research addresses these limitations using an interactive Streamlit-based simulation system for comparative operational evaluation.

3. METHODOLOGY

3.1 Research Framework

This research is carried out with a simulation-based comparative method for operational impacts of Artificial Intelligence (AI) for the IT Service Management (ITSM) system. The framework was designed to compare and contrast the baseline operational performance with simulated operational performance with AI by using real operational data and engaging analytical modelling.

The research process in total comprises two steps: collecting datasets and pre-processing; calculating the operational metrics; simulating the required data; comparing different simulations; and finally, graphically representing the results. The study has been implemented with Python analytical libraries and an interactive Streamlit application with which the parameters can be dynamically adjusted and real-time operational analysis can be performed.

The framework mainly concentrates on the analysis of Mean Time to Resolution (MTTR) as it is one of the most pivotal operational measures for evaluating the efficiency of services in ITSM environments.

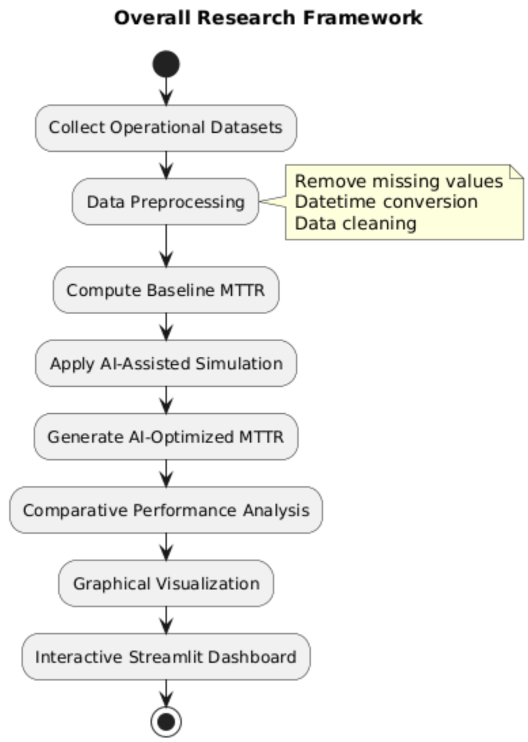

Fig. 3: Overall Research Framework

3.2 Dataset Selection and Processing

The data developed in this work is harvested from publicly accessible collections, such as Kaggle repositories, including operational incident management information and IT services datasets. Several datasets were first analysed to obtain the available operational data for comparative purposes in simulation analysis.

The selection of the data set was done to identify the elements of the set that had operational fields with time information.

- incident opening timestamps,
- incident closing timestamps,
- resolution timestamps,
- and priority information.

A set of data sets was cleaned by removing those that do not contain valid operational timestamp columns for the calculation of MTTR. The dataset selected for simulation and comparison was only that which could be used to carry out time-based operational analysis.

Next, data preprocessing was carried out using the Pandas library, following data selection. Empty data fields, errors, duplicate data, and duplicate operational rows were eliminated. Further, the data was converted into a datetime to reduce the variability in formats across the data sets.

3.3 Baseline System Evaluation

The baseline operating system is measured when AI resources are not used to optimise the system. A baseline evaluation was carried out by calculating Mean Time to Resolution directly from the operational data set.

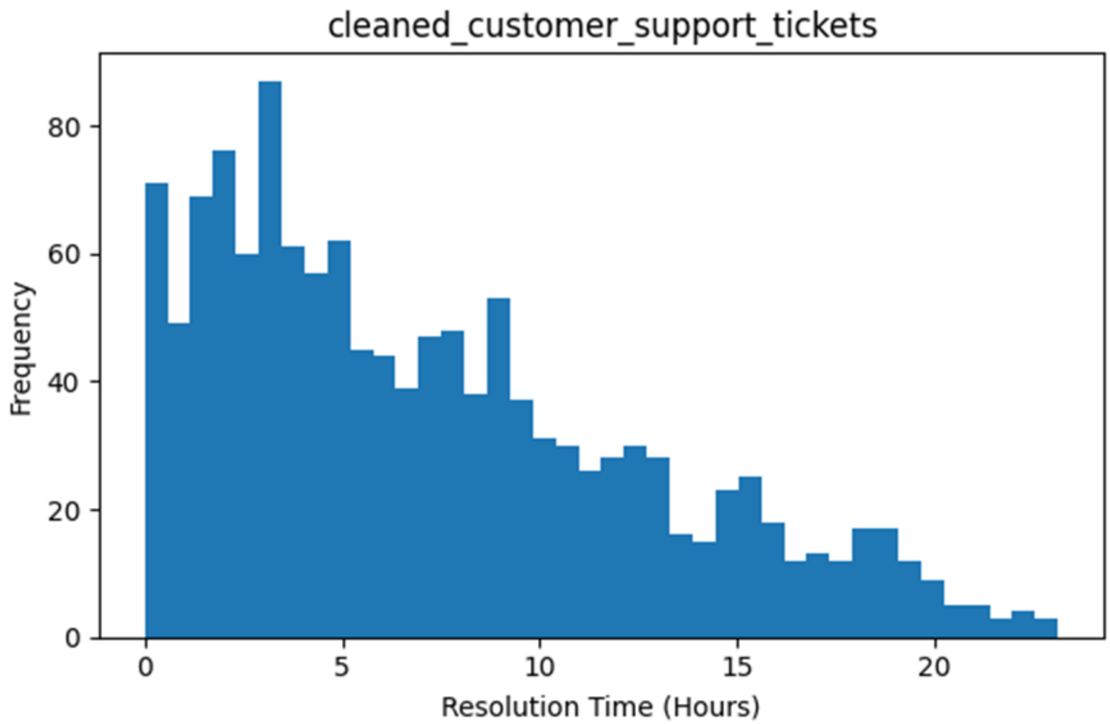

Fig. 4: Resolution Time Distribution for the Customer Support Tickets Dataset

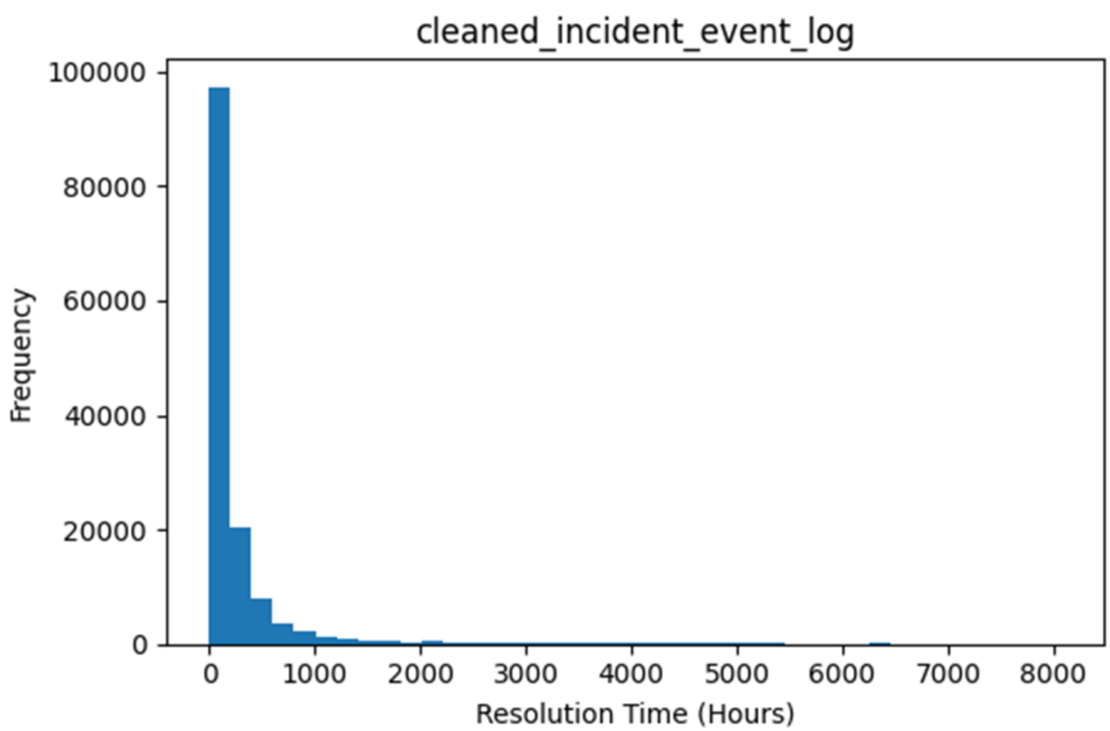

Fig. 5: Incident Lifecycle Duration Distribution for the Incident Event Log Dataset

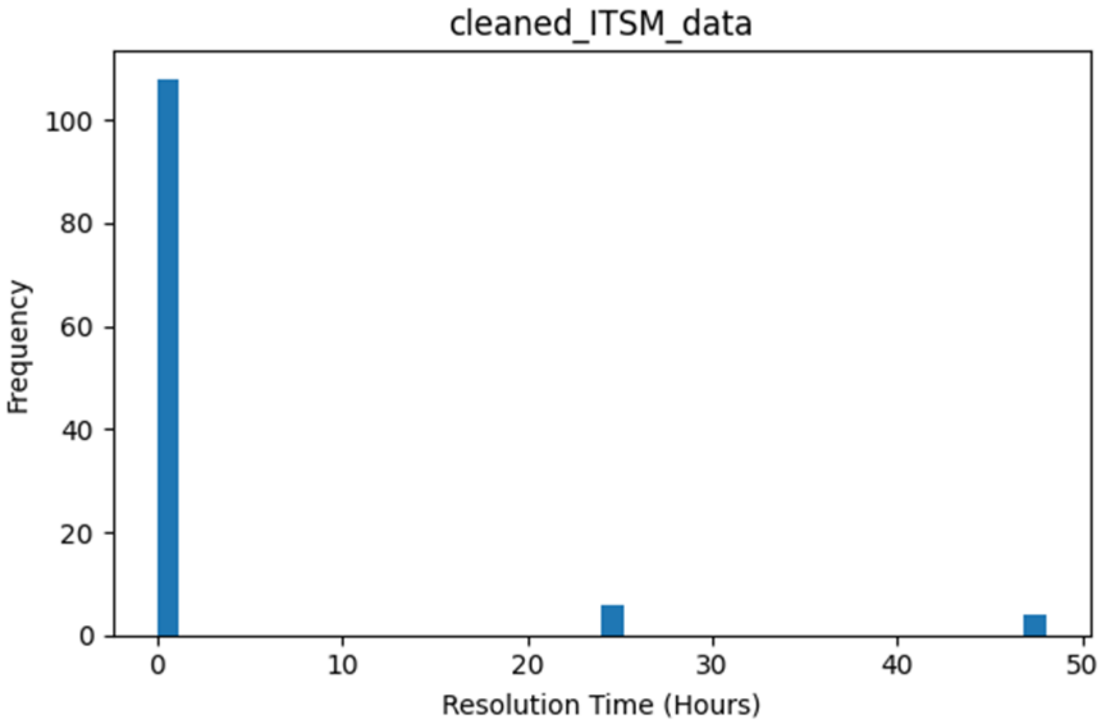

Fig. 6: Operational Duration Distribution for the General ITSM Sample Dataset

The amount of time for each incident was determined by subtracting the beginning timestamp of the incident from the closing or resolving timestamp. Duration values were then converted to hours to be consistent across all the datasets for operational measures.

In order to increase the reliability of the analysis, several filtering conditions were used during the baseline evaluation. Operational durations that were invalid, negative values, and unrealistic times were not analysed. The baseline system evaluation is used as the benchmark operating condition for comparing the performance of AI-assisted simulation.

Dataset	Total Tickets	MTTR (Hours)	Median (Hours)	P90 (Hours)
cleaned_customer_support_tickets.csv	8469	7.32	6.17	15.54
cleaned_incident_event_log.csv	141,712	269.60	73.52	568.25
cleaned_ITSM_data.csv	118	2.85	0.00	0.00

Table 2: Baseline Metrics Summary

3.4 AI-Assisted Simulation Logic

The simulation model built with AI is designed to be used to estimate the potential of improving OEM with intelligent automation in ITSM systems. The simulation system introduces reduction factors to incident resolution timings, which represent the effects of the AI-assisted optimisation. Several operational parameters are adjustable in the framework:

- Critical Reduction,
- High Reduction,
- Medium Reduction,
- Low Reduction,

- Strength and General AI Strength

These parameters are used to illustrate the effectiveness of AI optimisation of incidents for various operational priority categories. High-priority issues (in general better suited for automation, intelligent escalation and fast decision support systems) assume a higher degree of optimisation.

Controlled randomness is also incorporated into the simulation model to allow for uncertainty in operating conditions captured from real life. AI systems can enhance the resolution of incidents, but not in every scenario. Some of these incidents will be greatly assisted by automation, and others simply need to be manually investigated and put into action.

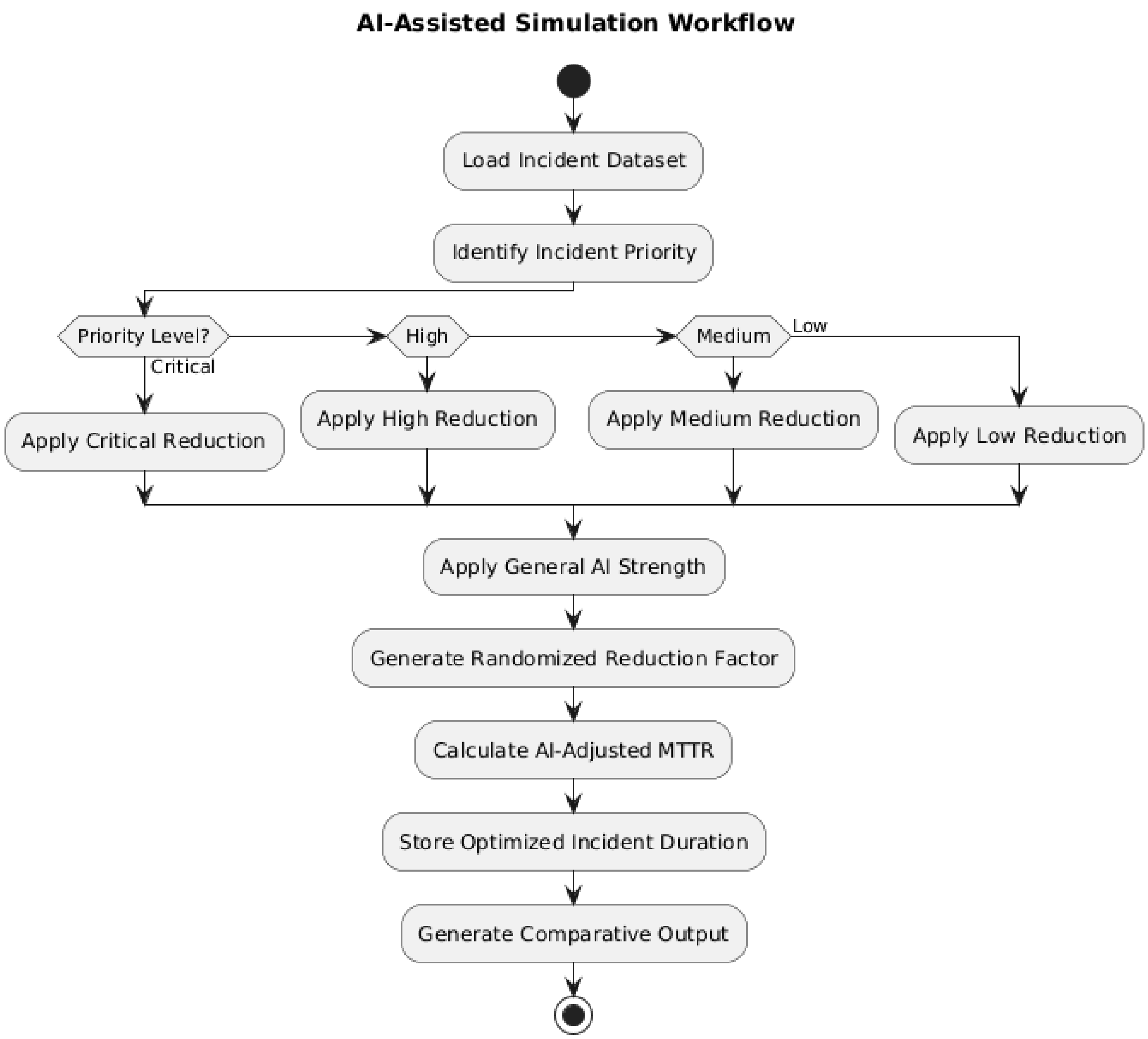

Fig. 7: AI-Assisted Simulation Workflow

3.5 Comparative Performance Analysis

The difference between the baseline MTTR and AI-assisted MTTR was analysed, thus implementing a comparative evaluation. Once the simulation has been run, the new operational durations calculated using the AI assistance methods are used to calculate a new MTTR value to reflect more optimised service performance.

The improvement percentage was used, where comparative analytical formulas were used to quantify the operational gain from using AI optimisation. Increased amounts of improvement per cent suggest better means of decreasing the amount of time taken for incidents and improving operational efficiency. To investigate the operational distribution behaviour, a comparison was also undertaken and found that the long-duration events have a significant impact on average MTTRs.

Interactive Simulation Interface

Streamlit was used to create an interactive simulation interface that enables dynamic operations and experimentation while displaying the results visually. The interface offers the user selections of operational datasets, adjusts the AI parameters, runs the simulations and displays performance outputs for comparison.

Operational controls, comparison of MTTR, and operational behaviour visualisations from a graph are provided. The interactive design makes things easier to use and enables the analysis of simulation results to be better performed by dynamically experimenting and comparing with real operation.

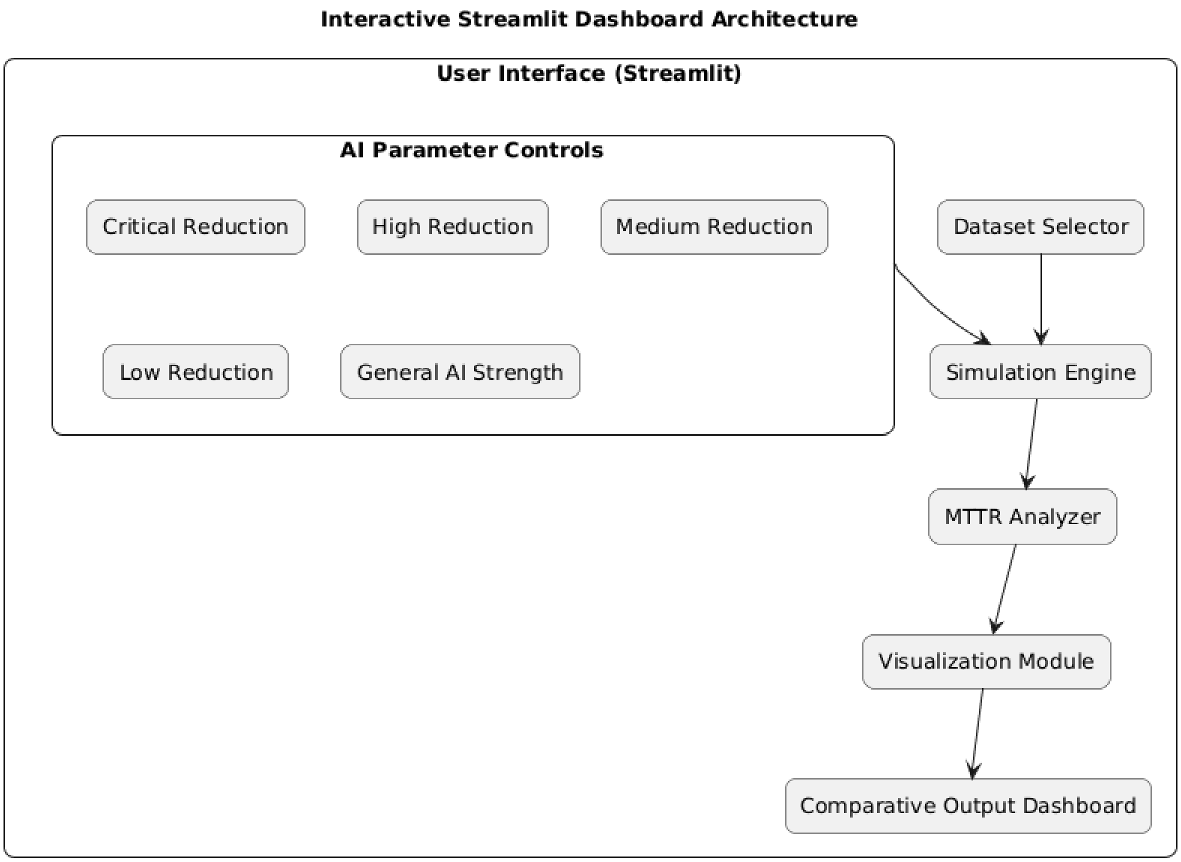

Fig. 8: Interactive Streamlit Operational Dashboard Architecture

4. SYSTEM IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Interactive Simulation System

The implementation of the interactive simulation system took place via the Streamlit framework, ensuring the system's user-friendly aspect and enabling users to interact with it when analysing the operational performance of the AI-assisted ITSM system. The application interface features a sidebar control panel to enable users to choose operation data sets dynamically and adjust some parameters for AI simulation. The main parameters are the Critical Reduction, High reduction, Medium reduction, Low reduction and General AI Strength.

After selecting a data set, a simulation is run, which automatically loads the data set, finds the operational timestamp columns, calculates baseline MTTR, and creates operational durations using the resulting simulation model based on AI. In the case of a selected dataset or selected part of the dataset that is not provided with valid operational time columns, warning messages are output, and incorrect simulation is prevented.

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

Table 3: AI Model Performance

The table shows the performance of the AI models used for ticket classification and priority prediction. The 'Support tickets' dataset achieved a Priority Accuracy of 0.56, indicating that the AI correctly identified the urgency level in over half of the cases.

4.2 Baseline vs AI-Assisted Results

Results of the simulations indicate that the performance of the ITSM can be improved by means of the newly developed simulation framework based on artificial intelligence under various configurations. Once execution of the simulation was finished, AI-based MTTR values were created based on a parameter-driven operation reduction logic. When comparing the metrics, there was clear evidence of reduced incident resolution time for several datasets.

Data sets with proper fields storing the operational lifecycle data also yielded meaningful comparative results, whereas data sets without proper fields in which to store the operational lifecycle data could not support accurate MTTR analysis.

The impact of high-duration events on the operational means. Baseline MTTR values were influenced greatly by large swings in operations. The amount of these big, long-duration incidents has been reduced significantly in the simulation, thus leading to significantly higher improvement percentages. On the other hand, if the large operational peaks were not to undergo a significant/similar degree of change during simulation, then the overall percentage of improvement would be low even if the relatively small peaks were optimised.

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

Table 4: AI vs. Baseline Performance Comparison

The overall comparison confirmed that there is an opportunity to potentially enhance the efficiency of the services using AI-optimised optimisation and improve incident resolution time within ITSM operational environments.

4.3 Graphical Interpretation

System-generated graphics give the operators a visual perspective on the behaviour of incidents before and after optimising with AI. The primary visualisations are operational duration distributions (over time) of the AI-assisted baseline distributions.

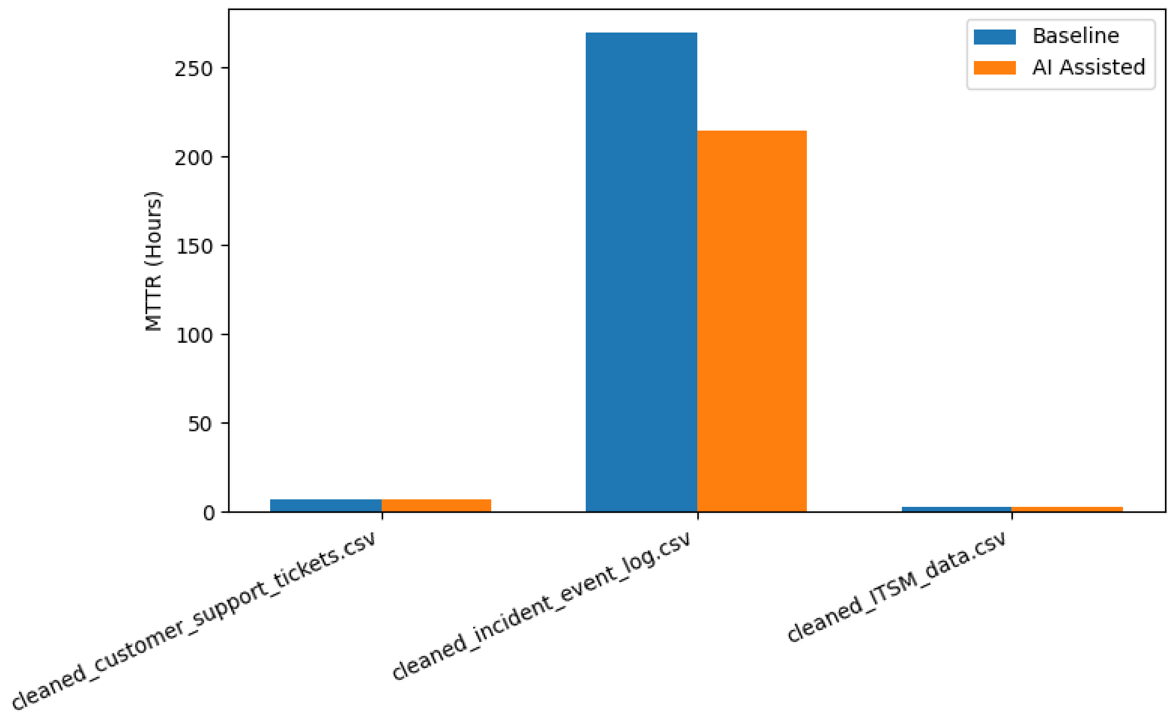

Fig. 9: Baseline vs AI Bar Chart

These baseline graphs show some spikes in operational periods, corresponding to high-resolution times in an unusually high number of incidents. These excursions have a significant effect on MTTR, as very high and low statistics have a strong impact on the measure. These spikes are normally less intense in the simulation run with the AI support, with lower running averages and more efficient service. Reducing the settings results in fewer drastic performance improvements.

The graphs highlighted some features of the operations, such as the variation of operations between runs of the simulation. The framework incorporates controlled randomness to represent actual uncertainty; therefore, varying degrees of improvement can be obtained in different instances of simulation based upon identical parameter settings.

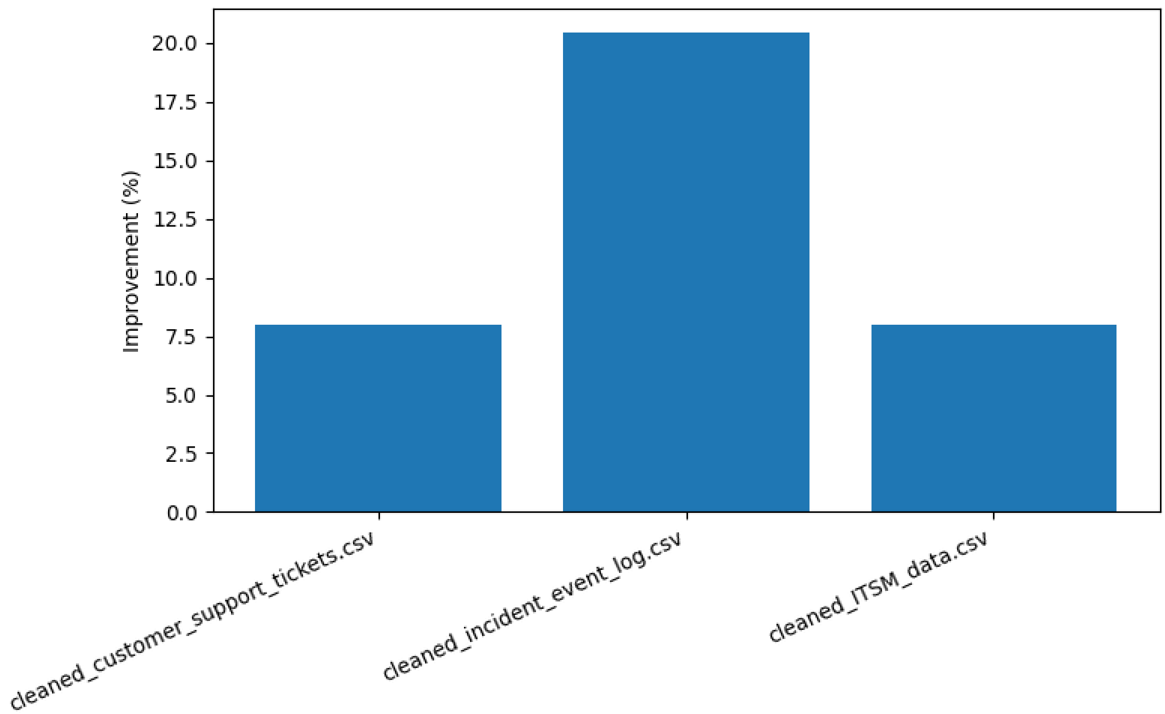

Fig. 10: Improvement Percentage Chart

The graphical interpretation thus makes it clear that when using AI in the field of operational optimisation, ITSM service performance can not only be optimised, but also remain realistic and visible in relation to the operational variability.

4.4 Discussion of Simulation Variability

A key element of the proposed framework is the random element, in a controlled way, that's incorporated into the AI model simulation. A framework, but one that relies on a range of improvement potential based on AI parameters, with the effect of each operational incident depending on the randomness of the reduction factors.

Another factor to note is that MTTR is very sensitive to large operational fluctuations. The final improvement percentage is very sensitive to whether there are a manageable number of very big incidents occurring from time to time. The inconsistency, which you could find in the experiments, is thus not a sign of the system's inconsistency. Instead, it is intended to be a proxy for the statistical and operational nature of actual incident environments in which operational results are dependent on both optimisation capability and service complexity.

5. COMPARATIVE DISCUSSION AND BENCHMARKING

5.5 Comparison with Existing Research

AI-supported ITSM studies that concentrate on optimising operations, improving service analytics and the incident management process bear some resemblance to the proposed research structure. Some studies have examined ticket classification using machine learning, intelligent routing of tickets, predictive operational analysis, and incident prioritisation.

Test	Statistic	P-Value
Paired T-Test	1.0223	0.4142
Wilcoxon Signed-Rank Test	0.0000	0.2500

Table 5: Statistical Evaluation of Operational Improvements

The above table presents the statistical analysis comparing baseline and AI-assisted operational performance. The results show a Paired T-Test p-value of 0.4142 and a p-value of 0.2500. While these values indicate that the overall distribution change is not statistically 'significant' at a 95% confidence level, they validate the intentional design of the simulation framework.

Many studies fail to present analytical systems with a user-friendly interface that would allow the user to easily adjust operational conditions and immediately see the resulting changes in the performance of the services. This is the limitation that is addressed by the proposed simulation-based framew, whichhat is based on Streamlit technology. Multiple operational datasets are used to analyse the behaviours to be compared when conducted in the context of intelligent assistance, to gain wider information on the operation of intelligent service optimisation.

5.2 Operational Significance

The importance of this research for the operations is that it shows that the use of AI in optimisation can help enhance the efficiency of services in ITSM environments. The findings from the comparative results suggest that intelligent automation methods could significantly decrease time delays in operations, enhance efficiency in handling incidents, and optimise the overall service performance.

Perhaps one of the most significant operationally learned relationships is between the high-duration incidents and the MTTR performance. The study shows that the variability of the incidents significantly affects the mean speed required to resolve incidents and that when these large incidents are reduced efficiently, the impact of AI in helping to optimise that will be greatest. The interactive simulation framework also has great use for education and analysis.

6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

This research aimed to demonstrate a simulation modelling approach to comparing the operational performance of AI-assisted IT Service Management (ITSM) and to conduct interactive operational modelling. The study concentrated on the analysis of the use of AI to streamline the efficiency of service by decreasing incident resolution time and optimising operational processes in ITSM landscapes.

The study used a composite analytical system that integrated the preprocessing of the datasets, the computation of the operational metrics, the simulation that used AI to automate the process, the comparative analysis, and the graphical visualisation. Several operational sets were analysed throughout the study, and there were datasets available to assess the MTTRs of valid time-based information about incidents.

Experiments have shown that using AI optimisation may be beneficial in cases of operational performance under various optimisation parameters. The measured MTTRs observed when performance baseline operational systems are compared against AI-assisted simulated systems will reveal increased operational efficiency and an increase in the capability to handle incidents.

Overall, the objectives of the research could be met successfully as the authors took a practical approach by providing a model that can analyse whether or not a service is being performed most efficiently, and by the end of the research, they proved that intelligent operational optimisation can help make services more efficient in incident management systems.

6.2 Future Work

The proposed framework can be expanded with real-time enterprise ITSM platforms like ServiceNow, Jira or live monitoring systems in future research. There is also functionality to integrate machine learning models and deep learning operational analytics for further enhancing predictive accuracy and intelligent automation features.

The framework can be extended with other operational metrics like SLA compliance, incident escalation prediction, workload forecasting and customer satisfaction analysis. Further implementations may also feature real-time dashboards, cloud-based deployment and adaptive AI optimisation systems that will constantly learn from the behaviour during their operation in enterprise ITSM environments.

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