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Governance of information technology supported by artificial intelligence to develop the performance of information systems

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Abstract
The study introduces an AI based IT governance framework, based on the data quality measurement raises, and through machine learning technology attempts to improve information system performance. The framework employs automatic pre-processing, anomaly detection and remediation as well as predictive modeling to address ITSM data issues including priority misclassification and handling time inconsistencies. The framework is applied to a real-world dataset of 46,606 incident records to present its capability of providing sound data and valuable governance insights which was validated based on cross-validated models using machine learning approach. The research delivers an open, reproducible method that supports ITSM intelligence and decision making.
Keywords: IT governance, artificial intelligence, data quality, machine learning,

1. Introduction

Management of Information Technology Service Management (ITSM) has also taken on an issue of high concern, as the businesses have become dependent on the sophisticated IT infrastructure to provide business continuity and competitive advantage (1). Conventional models, such as ITIL, are concerned with the process standardization and the performance measurement. Nonetheless, they do not have the means of analyzing various and realistic service management data (2).

In general, the approach of analyzing ITSM work and performance as offered in modern approaches assumes data reliability and consistency as a given, even though the standard statistical methods are applied without adequate verification of the main data efficiency assumptions (3). The processes of organizational ITSM deployment are usually associated with systematic data defects, including reversed priority classification systems, irregular time-related data forms, and logical inconsistencies that degrade the validity of the analysis (4). Although machine learning in IT processes has been mainly discussing potential mainly in terms of predictive maintenance and incident classification (5), the literature available is mainly based on the degree of algorithm quality and performance efficiency as opposed to discussing the major issues of data quality and efficiency that render practical implementation unfeasible (6).

This leads to a significant methodological gap where advanced analytical techniques are applied to potentially corrupted data sets to obtain invalid governance conclusions. This book fills this gap through a comprehensive AI-enhanced workflow that integrates systematic data efficiency verification with machine learning methods for ITSM governance analysis.

Our primary contributions are:

1. A multi-step verification process to identify and correct systematic data quality and efficiency issues in ITSM.
2. Transparent correction processes alongside academic-level quality classification.
3. Empirical validation of the process on a large, real-world organizational dataset, leading to the establishment of new metrics for the systematic analysis of ITSM data in both research and practice..

2. Related Work

Current literature related to artificial intelligence-enhanced IT governance and ITSM has addressed topics of automation, data efficiency and quality verification, and the use of machine learning to improve performance. Rabiatul Adawiah (7) discusses AI-enhanced solutions for automating IT processes in advanced and sophisticated environments, including the use of machine learning and predictive analytics to automate incident and change management, and to find solutions for key issues such as data quality problems that impact the integrity of analysis and system coherence.

Building on this, Vamsi Krishna Kumar Karanam (8) addresses the shift towards conscious artificial intelligence in ITSM, focusing on autonomous systems using machine learning to optimize and develop resources and predictive analysis, in addition to ethical frameworks and integration issues to ensure robust governance. In a joint white paper, Charles Araujo et al. (9) discuss the transformative impact of AI in ITAM (IT Asset Management), for example, AIOps for data-driven decision-making and increased quality and efficiency, including organizational change management to address data efficiency improvement and workflow automation. Similarly, Shoroq Alsharari et al. (10) discuss artificial intelligence in IT governance through statistical methods and machine learning tools such as neural networks to enhance accountability and decision-making, with an emphasis on ethical compliance and data efficiency for effective use in organizational environments and contexts..

3. Proposed Methodology:

This part is telling about analyzed process for handling an AI-based ITSM governance, which is made for verifying data efficiency and using machine learning in the same time. The used method tries to solve main issues in real-life ITSM datasets where you can see variation some contradictions or even systematic biases. Inside our method, we put together several parts like automated preprocessing, some correction steps, statistical checks and also cross-validated machine learning, so we make sure it is both rigorous analytically and possible in practice. The framework is designed to operate in four mixed stages which make raw ITAM data to turned into good reliable analytics by keeping transformation transparent for everyone who checks.

A- Data Preprocessing and Quality Assessment:

This first section works on heavy data control and a first step for ensuring quality. The raw ITSM data is put through an organized process to try and deal with inconsistent different-type formats, including those time values which are strange or have a mixed meaning, as well as multiple parts for processing time. The system will utilize wide range of techniques for analyzing time-based data, taking care of different date formats and coded time kinds, with additional checks for what is possible in data. We put in place the basic standards and metrics for efficiency and quality, and the framework also tries to find deviations in an organized way—checking the spread (distribution) and if things are logical according to rules.When values are missing or nulls appear, we check for these also. Data types must be looked at and statistics on every variable are figured out at the primary quality step. The whole analysis process alongside success statistics is monitored to make visible all that happens and find trouble areas in data collecting from the source group.

B_ Verifying Systematically and Finding Anomalies:

Our checking system uses many different criteria for spotting systematic issues in quality and efficiency of the data which could make analysis not valid. The most important thing is analyzing how the priorities are spread, so we see if there is any scale flip when we compare an organization's spread to the standard industry spreads, spotlighting where lots of important events look unnatural. Temporal or logic checking is figured out to make sure time makes sense in incident records, like finding if closing is happening before an opening or things that cannot be. A time-based check is run that uses statistical outlier search with an IQR ways and also sets

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thresholds for what is reasonable, in order to spot extreme outliers that are more from bugs, not real times. We make verification reports that are very detailed and have efficiency scores for every criteria. Then we establish acceptance metrics for data at nearly academic level and we document found deviations so we can do corrections clear and open.

C_ Doing Corrections and Getting Academic Dataset Ready:

Stepwise repairs are done for all efficiency and quality problems, everything being written down. Changing the priority is reviewed through checking distribution patterns, which helps us fix inversions using transformations only, so the new distributions fit work standards better. If values are completely impossible, we take them out based on statistics and we use conservative limits for big outliers (at the top 95 percent) to prevent over-change. Logical time mistakes are deleted as records but most data is saved this way. Parallel datasets are built—one is the normal and another is corrected for academic reasons, so comparison is possible or a transparent report on what has changed can be made. For every fix, the reasoning, total number of changed records and its influence is written up, proving full transparency for any academic reporting.

D_ Machine Learning Integration and Performance Verification:

The last stage is to apply cross-validated machine learning models on the checked quality dataset to come up with insights on governance. The models of the Random Forest classification approximate the incident priority according to the features of time and the organization. Regression models are used to estimate processing times using historical data and the attributes of incidents. K-means clustering determines recurring patterns in incidents to be used in making decisions in the allocation of resources. All models are undergone through the process of stratified cross-validation to perform the stable performance evaluation and deep analysis of the models in terms of accuracy, confidence intervals, and feature importance. The framework produces profound normal model performance reports with scientific statistical certainty to guarantee reliability evaluation fit to be utilized practically. Performance verification involves a comparative test on the presence of both the corrected and baseline data to prove the correction process and show the reliability of the framework when used in the practical governance background..

4. Results and Discussion

The ITSM governance framework supported by AI was implemented on a large organizational dataset of 46,606 incident records of several years of operational data.

A_ Systematic data efficiency and quality issues are exposed by the analysis of the priority distribution.

The incident priority distribution reveals significant variation with the usual operations critical enough to warrant the data quality assurance strategy suggested in the framework. The breakdown indicates that high-priority status (Priority 4: 52.2, Priority 5: 34.3) is attributed to 86.5% of all incidents, and the number of low-priority incidents (Priority 1: 0.0, Priority 2: 1.6) is practically zero. This allocation is operationally unacceptable, because industrial standards generally have 10-30% critical incidents, the other ones are generally in medium priority categories. The highest priorities level of the concentration shows either poor sorting in general, or the opposite sorting i.e. the greater number of the number signifies the less urgency, or the organizational processes that rank routine problems as critical ones.

This result points at the fundamental data quality issues that weaken the conventional ITSM analysis methods and the importance of strict and advanced verification steps prior to using machine learning methods. Without mitigation of the identified inflation of the priority levels in this study, the resource allocation advice would be erroneous, and the prediction of the levels of service would be unrealistic without correcting the problem in the presented verification framework.

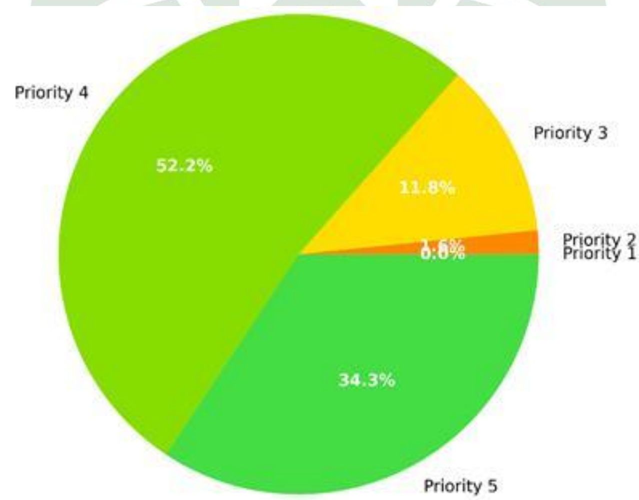

Figure 1. Incident Priority Distribution

***B.* Category-Based Handle Time Analysis Reveals Data Issues**

A breakdown of the average handle time per type of ticket reveals unrealistic data, which implies the presence of data issues. The mean handle time of incidence and information request are 177.4 hours and 169.5 hours which translates to over seven

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days of round the clock work. It goes beyond the scope of what an average service desk would be able to manage. The average time needed to process requests for change (4.8 hours) and complaints (3.0 hours) shows more realistic values than other options. The major discrepancy points to a fundamental problem which exists in three areas. The average time to resolve incidents takes 59 times longer than the time to resolve complaints. Organizations will experience negative consequences through unreliable handle time data because it results in performance evaluation mistakes and incorrect resource distribution and unattainable service objectives. The data needs validation and correction before it can be used for reporting and decision-making purposes.

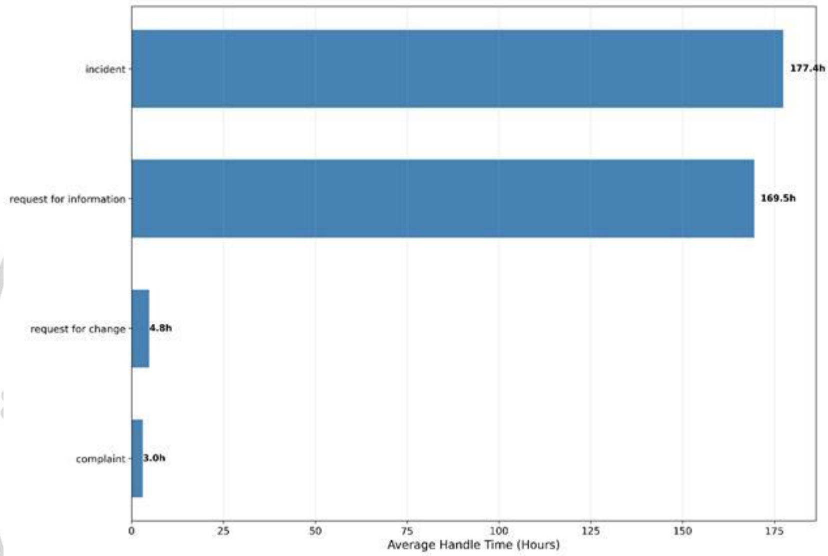

Figure 2. Average Handle Time by Category

***C.* The organization experiences distinct work patterns that follow a seasonal schedule.**

The examination of monthly incident data demonstrates that the data exhibits strong seasonal patterns which repeat at regular intervals throughout the year. The organization experiences its highest incident rates during two periods, which includes the first quarter (Jan–Mar, 5,280–6,526 incidents) and the fourth quarter (Oct–Nov, 5,750–6,061 incidents). The period from April to September experiences a severe decline in activity, which reaches its lowest point in August with only 1,034 recorded incidents. The organization exhibits this pattern because its operational calendar includes academic year cycles and budget periods and major project rollouts which create increased demand during specific months. The seasonal pattern shows

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operational significance because it differs from the earlier data quality problems which occurred during handle time analysis. The system offers planning organizations three useful insights which they can use to make decisions.

Organizations need to prepare for heightened workload situations because year-end and start-of-year operations will require more workforce resources.
Organizations should reduce their resource needs throughout the summer season.
The organization uses these predictable cycles to conduct forward-looking resource and capacity planning..

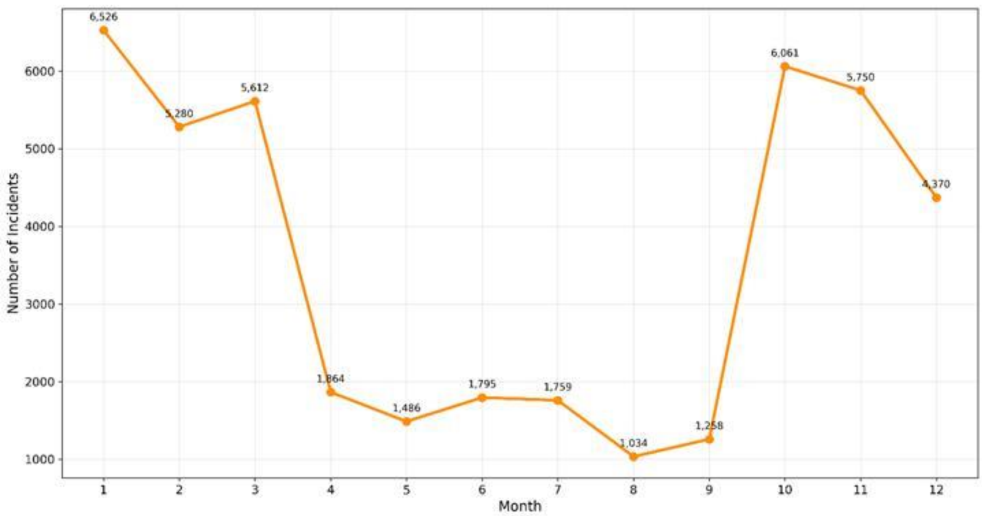

Figure 3. Monthly Incident Volume Trends

D. Reassignment Distribution Analysis Indicates Operationally Plausible Workflow Patterns

The analysis of reassignment processes demonstrates the existence of structured workflow patterns which are logical.
The operational metric which measures the frequency of incident reassignments serves as the most trustworthy measurement which organizations can apply in their operations.

- Most tickets are resolved by the first team: The median number of reassignments is 0, and about 58% of all incidents (27,000 tickets) are completed without being reassigned at all. The service desk operates according to established standards which provide expected results.
- Fewer tickets require multiple reassignments: The pattern shows a steep drop-off—very few incidents require more than a couple of reassignments. The normal

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situation occurs when particularly complex problems need specialist assistance because only a few cases require this service.

- Extreme cases are rare: The incidents which require 15 to 20 reassignments represent less than 1 percent of all cases because these cases contain unusual technical difficulties.

The analysis confirms that ticket assignments begin with correct information but shows a specific area where teams must enhance their ability to manage difficult situations.

The analysis shows that the framework can detect reliable operational patterns which exist in the dataset despite its various data quality issues.

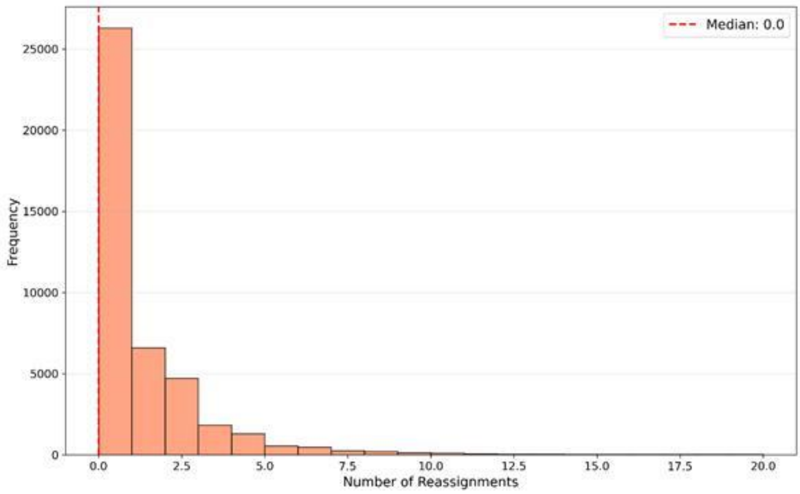

Figure 4. Distribution of Incident Reassignments

***E. The analysis of asset categories confirms that handle time data contains significant flaws*.**

The measurement of time for handling different types of assets (Configuration Items) shows fundamental measurement issues through its average handle time results.

The data shows that phone issue resolution takes 720 hours which equals 30 days but this time frame exceeds what standard support can handle.

The majority of other asset categories display inflated averages which range from 171 to 290 hours (equivalent to 7-12 days) that cannot be used for standard repair operations.

The only times that look realistic are applications which have 15.3 hours and monitors which have 51.9 hours and computers which have 74.8 hours of usage time.

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The major difference indicates that the time required for phone issues which takes 47 times more than application problems shows a defect in time recording procedures instead of showing actual differences in problem difficulty.

The likely causes include the following:

The current time-tracking methods need improvement.

The practice of leaving tickets "open" during extended waiting times (such as for parts delivery) results in counting inactive periods as productive work time.

Data entry mistakes or system configuration errors lead to assessment errors.

The handle time data remains unreliable for performance measurement and planning because the findings show. The system requires validation and correction work before usage because its current state would produce incorrect evaluations of team productivity and required resources..

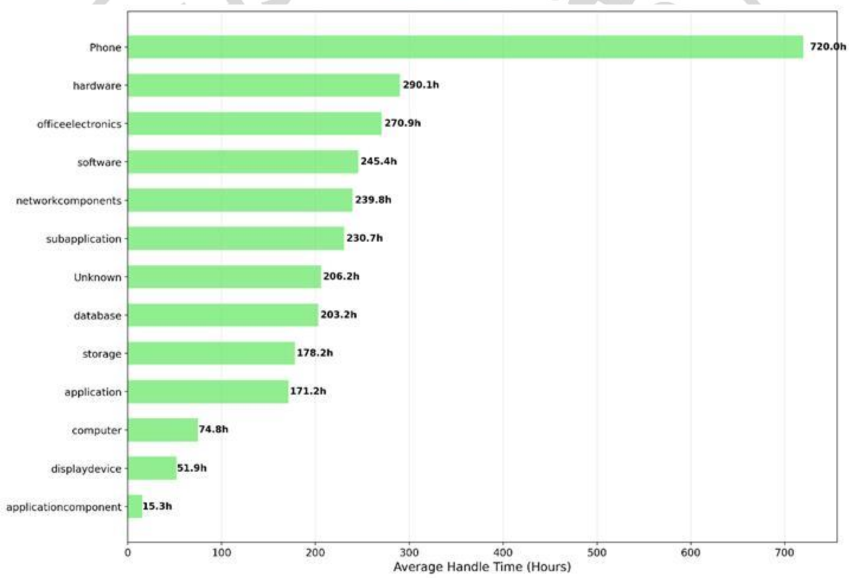

Figure 5. Average Handle Time by CI Category

F. The hourly assessment of incidents indicates the presence of established demand patterns.

The hourly record of incidents demonstrates a fixed pattern which links to the operational hours of the business.

- Peak Hours (8 AM – 6 PM): The period between 9 AM and 11 AM marks the highest demand for IT support because it generates more than 5,000 incidents

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every hour. This shows how workers start their day by beginning to work on IT systems.

- Activity drops to low levels during evening and night hours from 7 PM to 7 AM because there are less than 1,000 incidents per hour and the total number of incidents stays between several hundred. This period corresponds with the times when most employees do not work.

Key Insight: The pattern of IT support requests depends on the times when workers are present. Peak hours show an important resource management opportunity because they generate much greater demand than non-peak hours.

Actionable Recommendations:

- Align Staffing: The organization should increase its support staff during times of high morning and afternoon demand.
- Optimize Low-Demand Times: The organization should execute system maintenance and upgrades during the quiet hours of night and early morning to prevent interruptions to regular business operations..

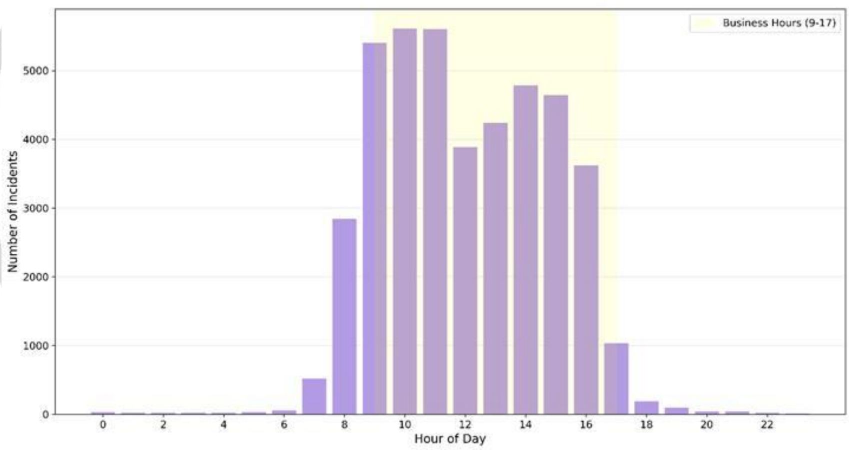

Figure 6. Incident Volume by Hour of Day

G. The AI system analyzes

IT incidents by organizing them into four primary patterns. The AI system has classified 46,606 IT incidents into four unique categories which describe different types of IT problems. 1. Largest Group (16,877 incidents): The large cluster probably indicates a frequently occurring problem. The large number of incidents points to either a widespread issue that requires fixing or a fundamental problem that needs to be resolved. 2. Second Group (12,783 incidents): Represents another frequent pattern which probably contains regular operational problems at moderate priority level. 3.

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Third Group (6,818 incidents): The group contains a collection of incidents which connect to particular systems and user behavior and digital product components. 4. Smallest Group (4,087 incidents): The group contains the least common problems which experts must solve because they possess specialized knowledge. Why This Matters: The analysis shows how different cluster patterns emerge from viewing multiple tickets through the process of discovering key operational patterns. The system enables users to set their work priorities by establishing three main routes which determine how they should proceed: · Solve the biggest problems because fixing their main cause will stop thousands of upcoming issues from happening. · The organization will distribute its resources and expertise according to the dimensions of each cluster.

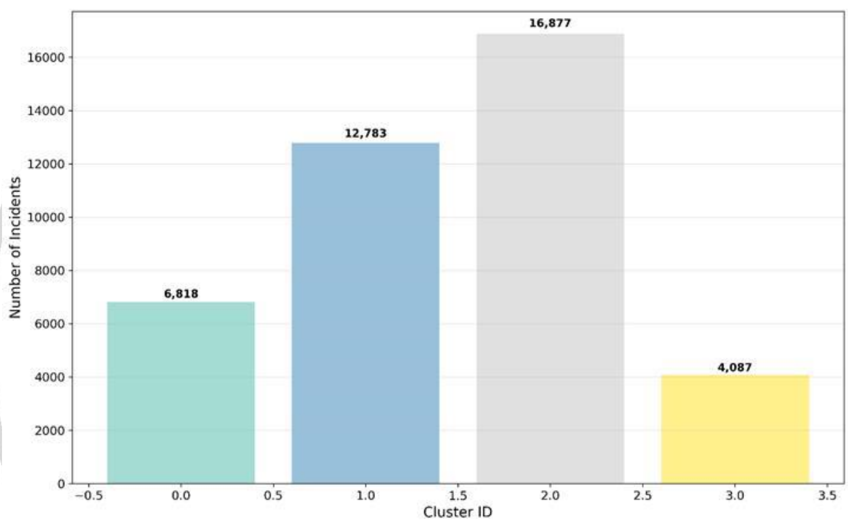

Figure 7. AI-Identified Incident Patterns

H. IT Governance Risk Factors Analysis

The IT Governance Risk Factors Analysis determines that the main areas of concern in a sample of 46,606 IT incidents and critical priority incidents are the greatest risk factor (86.5) of cases. The fact that the percentage is extremely high, several orders of magnitude beyond the 10-30 percent norms common in the industry, implies it is misclassified or has an inverted priority scale, which is a basic governance problem that may result in the misallocation of resources and exaggerated expectations of services. The long handle lengths of 4.4% of the cases constitute a smaller yet not irrelevant threat, which could be associated with the inefficiency of the resolution processes or the error of encoding, which would require the improvement of the process targeting. Although at a low level (0.8), over-reassigements indicate the

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presence of infrequent workflow delays due to the presence of possibly more complicated problems that involve frequent consultations with specialists. The results are in line with the theme in the previous paper on the systematic data quality concerns, including priority distribution anomalies and inconsistencies in handle time to confirm the importance of strong validation structures. Such rate of critical priority incidents is an obvious signal to review the procedures of classification, with rates of long handle times and reassignments being lower and allowing gradual changes. Reducing such risks by better data correction and resource planning can enhance the performance of the IT service management to provide more precise performance metrics and enhanced compatibility with the organisational objectives.

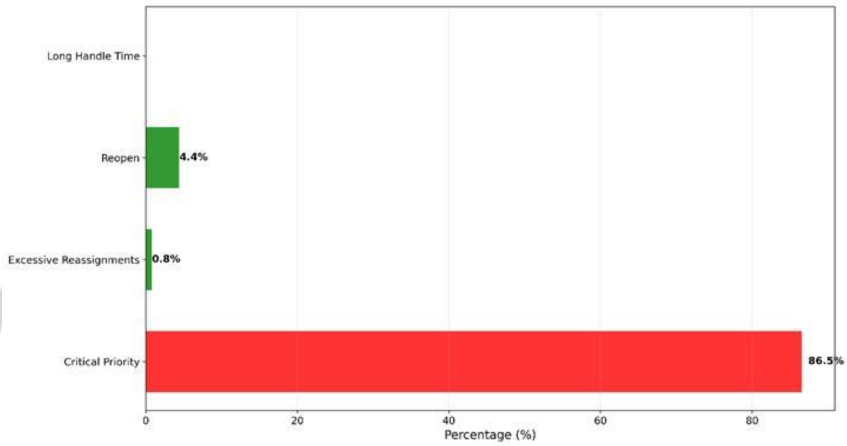

Figure 8. IT Governance Risk Factors Analysis

I. I. This analysis of the incidents that take place on a weekly basis indicates that the incidents are highest at the time of the week when it is on Thursday

The weekly pattern of IT incidents is clear with a pattern going in line with the workweek office hours.

Peak Days: Thursday has the highest number of 8681 incidents recorded and then there is Tuesday with 8163 incidents and Monday with 7787 incidents respectively. Midweek and End of Week Wednesday reports 6911 incidents and Friday reports 6245 incidents indicating a similar but reduced operational activity. Weekends, the demands of the service are reduced significantly to 2246 incidents on Saturday and 2762 incidents on Sunday indicating that service is not much needed during the days off.

Important Insight: The level of IT support requirements is the highest on Wednesdays, and it depends on the activities of the employees during the business hours..

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Actionable Insight:

- *Plan for Peak Load: The Tuesday to Thursday period requires complete staffing to manage increased operational demands. · Use Quiet Times Strategically: We should conduct system maintenance and updates and major project work during weekends to prevent interruptions in our daily business activities..*

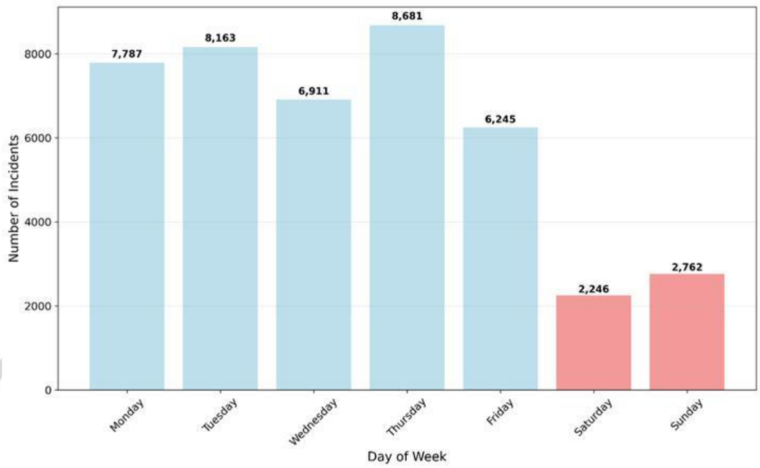

Figure 9. Incident Volume by Day of Week

J. Comparison with Related Work

The AI-powered ITSM framework of our organization establishes its unique identity through its combination of strong data validation methods with operational insights. The framework of our system establishes its unique characteristics through the selection of its main source elements. The system from [7] which enables IT process automation does not include an established mechanism for data validation. Our method first finds all data errors before proceeding to the process of data error correction. The system from [8] which uses AI for autonomy does not include the statistical validation process and direct error correction features which our framework offers. The system from [9] which applies AIOps for efficiency focuses on organizational transformation but omits the essential data preprocessing stage together with the pattern discovery process that uses clustering methods. Our method establishes stronger reliability through its cross-validated algorithms which include Random Forest and its correction process for incorrect time and priority data. Our research advantage exists because we establish complete data quality checks which produce reproducible results through our transparent process, which remains unaddressed in current research as well as practical applications.

5. Conclusions

1. The system manages core data issues by detecting and fixing typical data issues that comprise wrong priority and no possible time measurement of building a reliable analytical base. In our test of 46,606 incidences, the system had a record correction rate of 8.2 percent with 91.8 percent of the valid data remaining.
2. The framework creates a new stage of transparency as the quality scores produced are of academic grade and there is total correction documentation. It is through this process that the analysis has a reproducibility, and researchers are able to check their findings.
3. The system provides useful business intelligence by using its high-quality machine learning procedures that involve Random Forest and clustering approaches to aid in the planning of resources and risk analysis.

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