Understanding Primary Fault Types of IT Failures

An Analysis of Public Incident Reports Using Large Language Models

1 Introduction

- Modern organisations increasingly operate as software-defined businesses, relying on fast-paced agile methodologies [1, 2].
- This transformation, while beneficial, raises the risk of operational incidents, e.g. unplanned service interruptions or degradations.
- Research shows 70% of outages stem from changes to live systems, highlighting the need for effective incident analysis [3].
- AlOps promises improvement, but is limited by inconsistent, manual reporting [4, 5].
- · Rise of cloud-native architectures introduces new fault patterns.
- Lack of cross-organizational analysis on fault types, severity, and evolution.

Research Questions:

- 1. What taxonomy of primary fault types can be established for modern IT incidents, and how reliable is automated classification of these categories?
- 2. What is the relative frequency of different primary fault types across incident reports?
- 3. Are there correlations between specific primary fault types and the duration of incidents?
- 4. Has the frequency of specific fault types changed over time, particularly with the adoption of cloud-native architectures?

2 Methodology

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Scrape incident reports from the Verica Open Incident Database API [16]

- Filter out incomplete reports with missing descriptions or duration data, exclude years with not enough reports, resulting in 7,804 incident reports from years 2014 to 2022
- Classify incident reports using the Athene V2 72B large language model (LLM) [18] on the Delft Blue supercomputing infrastracture [19]
- Evaluate model's performance using a manually labelled ground truth, sampled via a population-proportional stratified design to ensure coverage across fault types.
- Use Scikit-learn, Pandas, and NumPy to measure fault category frequencies, analyze correlations with incident duration, and evaluate time trends.
- Develop clear, insightful visualizations using Matplotlib and Seaborn, e.g. bar charts of fault type distributions, line plots of temporal changes

3 Results

Taxonomy of Primary Faults and Classification Performance

Technical	Human/Organizational	External/Environmental	Other
Infrastructure Failure Software Bug Misconfiguration/Deployment Failure Capacity Issue	Human/Process Error (operator mistakes, inadequate procedures, monitoring/alerting failures, etc.)	External Dependency Failure Security Incident Environmental Hazard (power, fire, fiber cut, etc.)	Scheduled Maintenance Unknown

Overall metrics: Accuracy: 92%, Macro F1-score: 0.89

Analysis of Primary Fault Types Frequency, Severity, and Evolution







Upward trend **小**

Software Bug, Misconfiguration/Deployment Failure, Environmental Hazard

Downward trend ψ

Infrastructure Failure, Capacity Issue **No trend** –

External Dependency Failure, Security Incident, Human/Process Error

4 Conclusions

- · Automation improves speed but introduces new risks, configuration management is critical
- External dependencies need stronger resilience strategies, shifting from traditional infrastructure concerns, as they extend beyond organizational boundaries.
- Rise of software bugs calls for more testing, security incidents are rare but highly disruptive
- · Cloud technologies successfully reduce infrastructure failures and capacity issues
- LLM-based classification is viable for large-scale analysis, but can be improved via fine-tuning.



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