FAIL: Analyzing Software Failures from the News Using LLMs

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ABSTRACT

Software failures inform engineering work, standards, regulations. For example, the Log4J vulnerability brought government and industry attention to evaluating and securing software supply chains. Retrospective failure analysis is thus a valuable line of software engineering research. Accessing private engineering records is difficult, so such analyses tend to use information reported by the news media. However, prior works in this direction have relied on manual analysis. That has limited the scale of their analyses. The community lacks automated support to enable such analyses to consider a wide range of news sources and incidents.

In this paper, we propose the Failure Analysis Investigation with LLMs (FAIL) system to fill this gap. FAIL collects, analyzes, and summarizes software failures as reported in the news. FAIL groups articles that describe the same incidents. It then analyzes incidents using existing taxonomies for postmortems, faults, and system characteristics. To tune and evaluate FAIL, we followed the methods of prior works by manually analyzing 31 software failures. FAIL achieved an F1 score of 90% for collecting news about software failures, a V-measure of 0.98 for merging articles reporting on the same incident, and extracted 90% of the facts about failures. We then applied FAIL to a total of 137,427 news articles from 11 providers published between 2010 and 2022. FAIL identified and analyzed 2457 distinct failures reported across 4,184 articles. Our findings include: (1) current generation of large language models are capable of identifying news articles that describe failures, and analyzing them according to structured taxonomies; (2) high recurrences of similar failures within organizations and across organizations; and (3) severity of the consequences of software failures have increased over the past decade. The full FAIL database is available so that researchers, engineers, and policymakers can learn from a diversity of software failures.

KEYWORDS

Software Failure Analysis, News Analysis, Large Language Models

1 INTRODUCTION

Software has become pervasive and ubiquitous in modern society. Technologies such as the Internet of Things (IoT) and Cyber-Physical Systems have enabled software to increasingly interact with the physical world [89]. Given the complexities of modern software systems, their diverse characteristics enable diverse failures [63, 84]. Recent software failures have had catastrophic consequences [63, 77, 111, 112, 120], and the need to reduce software

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failures is growing. As the National Academy of Engineers has emphasized [77], software engineering failures remain commonplace and cost an estimated trillions of dollars annually [64]. We believe that one contributing factor to the high rate of software failure is the limited effectiveness and adoption of failure-aware software development practices [18].

A fundamental engineering principle is to analyze failures and act to mitigate them in the future [36, 85]. This principle has been successful in many engineering disciplines, and has contributed to the low failure rates of, e.g., buildings, aircraft, and nuclear reactors. In contrast, this principle is rarely followed consistently as part of the software engineering process within organizations (intraorganizational learning) [39, 51, 61, 105] or across organizations (inter-organizational learning) [58, 81]. Although organizations may be unwilling to publicly disclose their own failures, news articles and other kinds of grey literature could provide sufficient information on failures to facilitate inter-organizational learning.

News agencies often report on public-facing engineering failures: negatively, emphasizing the problem (defects), or positively, highlighting the resolutions (mitigations) [22]. Specifically, news articles reporting on software failures often contain information related to system and design level causes, impacts, and lessons learned from an incident [18, 63, 87, 88]. Additionally, software incidents often result from a combination of organizational, managerial, technical, sociological, and political factors, and preventing such incidents necessitates addressing all underlying causes, extending beyond code-level issues [66, 90]. Suitably, news articles reporting on software failures often contain such contextual information. For example, the Cyber Safety Review Board (CSRB) [5] in the Cybersecurity and Infrastructure Security Agency (CISA) [7] published a failure report about the Log4j incident [34], in which they note news articles that reported failure information surrounding the incident. As illustrated in Figure 1, the report lists articles containing failure information from The Guardian [21], Fox News [20], The Wall Street Journal [73], CNN [69], WIRED [80].

Such news data comprise "Open-Source Intelligence" [102], and may be used by organizations, government bodies, and academics to formulate best practices, draft regulations, or discover research directions [50]. Researchers have theorized that such news may discipline organizations, leading them to make socially responsible decisions in the context of safety [22]. Such information could also influence rationales for software design decisions, and enable failure-aware software development practices [19]. High-profile software incidents such as Therac25 [103], Stuxnet [43], and Boeing 737 MAX crashes [59], have informed software engineering practices, guidelines, and policymaking [43, 59, 103].

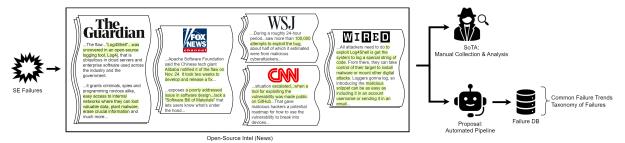


Figure 1: Concept of the FAIL (Failure Analysis Investigation with LLMs) project. Software failures are often described in news articles, e.g., the examples here for the Log4j security vulnerability. If analysts can identify and collate related articles about failures, they can share this knowledge with software engineers and policymakers. Current approaches are manual. We propose the FAIL system to automatically collect, group, and analyze software failures from the news. Our FAIL prototype collected, grouped, and analyzed these articles together for Log4j.

However, current approaches to obtaining open source intelligence (e.g., studying news articles reporting on failures) require costly expert manual analysis which limits the scale of analysis. For example, the only prior large-scale study related to software failures relied on manual analysis to study the consequences of 3,977 software problems from the news [63], which reportedly took 1,000 person-hours over 2 months. A similar work manually analyzes 347 Communication and IT infrastructure failures from the RISKS digest [88]. There is a gap in current software engineering research to efficiently gather, analyze, and report insights from open-source information on recent software failures to enable failure-aware software development practices.

To reduce the costs and improve the scalability of manual analysis, we propose an automated pipeline that employs Large Language Models (LLMs) to collect, analyze, and report insights from software failures reported in the news (Figure 1). Using this pipeline we conducted a large-scale systematic study of recent software failures as reported in the news.

Our main contributions are:

- (1) We design and implement FAIL, an automated approach for large-scale analysis of software failures from news using LLMs.
- (2) We publish a database of postmortems describing software failures from 2010-2022, which can be updated at the cost of approximately \$50 per year of data at present LLM costs.
- (3) We provide an up-to-date and large-scale report on the common sources, impacts, repair recommendations, etc. of these software failures.

Significance: Our work shows the effectiveness of an automated approach in enabling large-scale news failure analysis. FAIL is fully automated so it can easily become an ongoing community resource, with updates published every few months. The resulting database can inform software engineering practice and research, policy making, and education.

2 BACKGROUND AND RELATED WORK

Here we discuss failures as a feedback mechanism (§2.1), with news articles as a source (§2.2), and large language models as a tool (§2.3).

2.1 Failures as Feedback

2.1.1 Definition of software failures. Engineers expect some defects [33, 65], but try to eliminate severe defects that may cause incidents: undesired, unplanned, software-induced events that cause

substantial loss [66]. Whether severe defects are caught internally or as incidents, their presence is a <u>failure</u> indicating flawed software engineering process. Not all defects are the same, and understanding failures assists with failure mode analysis [54, 91, 101] and helps researchers and engineers to identify and prioritize risks [41].

2.1.2 The study of failures in SE. Studying engineering failures enables successful design [85]. Software researchers have extensively studied failures in open-source software systems [14, 17, 46, 71, 119]. However, we believe the most interesting failures occur in contexts where engineers followed robust engineering processes [60]. Thanks to standards (e.g., IEC 61508 [9]) and regulations (e.g., the EU GDPR [12], the US FDA FD&C Act section 524B [44]), those contexts are generally commercial.

Only a few works have studied commercial software failures in detail. Commercial failure information is difficult to obtain, so the normal approach is to identify relevant news articles (e.g., via searches) and then analyze them by hand. For an early example, Wallace et al. studied 342 software failures in medical devices from the FDA medical device failures database from 1983 to 1997 [107]. Researchers commonly study news articles [18, 26, 53, 63, 112], and have also analyzed data from the RISKS digest [79], and public postmortems [98]. Many of these works consider dozens or hundreds of failures, while others present failure case studies to inform software engineering education, practice, and policymaking [66, 67]. Although these failure analysis studies have advanced the software engineering field [66, 75], they require costly expert manual analysis which limits their scale and update rate. Studies have not shown how to automatically gather, analyze, and report insights from news articles about software failures.

2.1.3 Databases of failures for inter-organizational learning. Other engineering fields benefit from periodically-updated, large-scale, industry-wide databases providing postmortem information about failures. For example, there are databases of failures in medical devices [32], aviation [1], aerospace [15], railways [13], and chemicals [10]. These enable practitioners in those fields to learn from past failures across organizations. Within software engineering, such databases are limited to vulnerabilities (e.g., CVEs [4]) and open-source defects (e.g., BugSwarm [2]). There is also the RISKS Digest, a manually maintained list of computing related incidents and risks [78]. Although researchers have highlighted the need for large, up-to-date databases of software failures [58, 81], none exists, perhaps due to technology gaps in scaling up manual analysis [58].

2.2 News Articles as a Data Source

2.2.1 Definition and Biases. The notion of a news source can be broad, including any "open-source intelligence" [50, 102]. Examples include the mainstream news media (e.g., The New York Times, CNN), public information from companies (e.g., public postmortems and vulnerability writeups) and other organizations (e.g., wikis and databases in open-source repositories), and individual views expressed in blogs and podcasts. A news article typically summarizes and reports on events rather than being the primary source of the information. News articles provide historic and real-time information, presenting an opportunity for researchers to explore and analyze dynamic events and trends across diverse domains. There is a large volume of articles each day, some of which contain insight into industry failures and software in particular.

We acknowledge the limitations of news articles, notably source bias [72] and editorial bias [93]. For example, news articles include information from multiple sources, including official statements (*i.e.*, biased organizational perspectives), government reports and investigations (*i.e.*, delayed, independent analyses), expert opinions and analyses (*i.e.*, independent analysis varying in objectivity and accuracy), internal leaks and whistle-blowers (*i.e.*, internal organizational views of unclear reliability), and user reports or social media (*i.e.*, public perspectives lacking technical insight and of unclear reliability) [72]. The author of the news article, *e.g.*, a journalist, may introduce their own biases, notably selection bias (preferring sensational incidents), framing bias (adding narration for audience engagement), and information gaps (authors may provide incomplete or inaccurate analysis) [93].

2.2.2 Use of News in Other Fields. News is used to study failures and inform practices in various fields. News reports have been used as primary data sources in works to identify cascading effects of infrastructure failures on other infrastructures and stakeholders [118], and to identify risks and conduct a quantitative analysis to study cost overrun in rail transit projects [45]. In traffic engineering, news has been used to identify traffic incidents and notify citizens [92], and to study the characteristics and reasons for first responderinvolved incidents [114]. In environmental engineering, news has been used to study chemical pollution [31]. In public health, news has been used to study food safety [86]. In civil engineering field, the Engineering News Record gives examples of failures weekly [6], and is used to form case studies to inform education and practices [38]. These works show that incident information (e.g., causes, impacts, stakeholders) can be extracted and studied from the news. However, at the moment they rely on manual analysis, limiting their scale and update frequency.

2.3 NLP and LLMs for Software Engineering

Natural Language Processing (NLP) has been leveraged for various phases of the Software Development Life-Cycle (SDLC). Classical NLP tools have been applied in specification (requirements extraction) [117]; design (system modeling) [25]; implementation (code generation) [40]; testing (identifying risks) [47, 106]; and maintenance (analyzing user feedback) [83].

In this paper, we apply a recent innovation in NLP - Large Language Models (LLMs) — to study software failures. LLMs are

neural network-based language models that "understand" and generate text [27]. LLMs have been applied to software engineering tasks [42, 52], *e.g.*, requirements [116], design [109], implementation [55], testing [62], deployment [97], and maintenance [113].

The closest lines of work to ours have applied NLP and LLMs for incident management. Studies using NLP techniques have mined dialogues of IT staff [24], found entities in incident descriptions [96], pulled root causes from incident reports [95], and categorized IT incident tickets [99]. More recently, LLMs have been applied to incident management. These works have used cloud incident data, often based on internal (not public) reports. On that class of data, LLMs can assess the impact scope and summarize cloud outages [57], identify root causes and mitigation steps [16, 29, 30], and recommend further queries [56]. Our work addresses similar tasks but is focused on publicly available data in the news, more limited in detail but more accessible across organizations.

3 FAIL: DESIGN AND IMPLEMENTATION

Let us summarize the background and related work. Engineering failures are often covered in the news. News articles have known biases, but are sometimes the only source of insight into failures of high societal impact. Thus, researchers in many engineering disciplines — including software engineering — have extracted knowledge from this data source. Current approaches to this are largely manual. Meanwhile, large language models (LLMs) have shown promise in automatically analyzing natural-language descriptions of failures, notably postmortems written by engineers. LLMs have not been applied to software failures in the news.

To fill this gap, we propose an automated pipeline, **FAIL**, that uses LLMs to collect and analyze software failures in the news. FAIL is conceptually depicted in Figure 1. We address three requirements:

- (1) $\it R1-Scale:$ FAIL should handle years' worth of news data.
- (2) *R2-Accuracy:* FAIL should be able to correctly (a) identify news articles about software failures, (b) merge related articles, and (c) analyze them for postmortem data.
- (3) *R3-Cost:* FAIL should do so cheaply, *e.g.*, <\$1 per incident, orders of magnitude less than the cost of manual approaches.

Figure 2 shows our FAIL design. Components are detailed next.

3.1 Approach for each FAIL Component

Step 1—Initial search: We began by creating an initial criteria for news sources and keywords to search their databases. Following prior work (§2.2), we used globally popular news sources [70] as well as common sources used in the RISKS Digest [88]. The resulting 11 news sources were: Wired, The New York Times, CNN, Daily Mail, The Guardian, BBC News, Fox News, The Washington Post, CNET, Reuters, and AP News. We compiled 13 keywords related to software failure [11], such as "software flaw", "software bug", and "software crash". We used Google News as the search engine. We searched for news from these sources, matching these terms, from 2010 to 2022. For each search result, we used a news scraper [82] to scrape the text content of each article.

Step 2–Relevance: The search results contain news articles that may be irrelevant. To filter out such articles, FAIL prompts an LLM for whether the article actually reports on software failures.

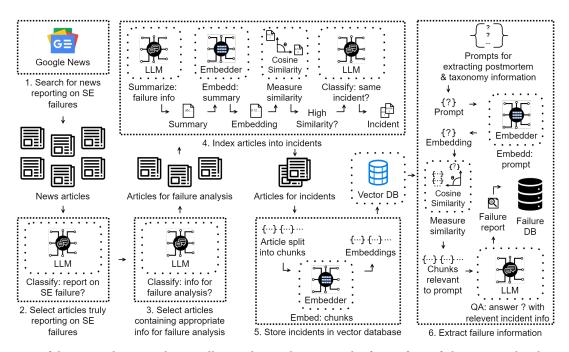


Figure 2: Overview of the proposed FAIL pipeline to collect, analyze, and report insights from software failures reported in the news. FAIL has 6 components. In Step 1, we search for news based on criteria such as keywords, sources, and timeframe. In Step 2, we remove articles that are not about software failures. In Step 3, we remove articles that do not have enough information to analyze. In Step 4, we merge articles reporting on the same incident. In Step 5, we use RAG techniques to handle long incidents. In Step 6, we create a failure report for each incident.

Step 3–Level of detail: The relevant articles may not have enough detail to conduct failure analysis, which could lead to low performance during failure analysis [100]. To filter out such articles, FAIL prompts an LLM for whether the articles contain enough information for failure analysis.

Step 4-Merge: A high-profile failure (e.g., the Boeing 737 MAX crashes [48, 68]) may be covered by many articles. The articles may have different information, e.g., based on different sources, so we want to analyze them together for a full understanding of the failure. FAIL merges these articles into a single *incident record*, similar to prior work [63] but applying LLM technology rather than classical NLP. To reduce costs, our approach proceeds in two stages: approximation and a follow-up check. For the approximation, FAIL prompts the LLM to create a summary of the failure as reported in each article, and then uses OpenAI's sentence transformer (text-embedding-ada-002) to convert the summary into an embedding. FAIL then calculates the cosine similarity of the summary embedding against that of existing incidents in the database. If the similarity exceeds a threshold, we do a follow-up check with the LLM. That check uses the summary of the article and the existing incident from the DB. If the article is deemed similar, we associated it with the existing incident, else we create a new incident.

Step 5–Handling long articles (RAG): LLMs have a context window (e.g., \sim 12K words for the LLM we used). Because we merge articles into incident records for analysis, our data on some incidents may exceed the context window. In our database, 26 incidents (out of 2457) exceeded this context window. To accommodate such incidents, FAIL uses Retrieval-Augmented Generation (RAG). For each article, FAIL stores embeddings in a vector database. A vector

database supports similarity searches using indexing techniques and similarity metrics, allowing FAIL to reference multiple articles within a context window. Our approach is typical of RAG: we chunk the article into paragraphs, label them with incident id, article id, and their order in the article, and embed them using OpenAI's sentence transformer. Based on similarity to each prompt in Step 6, the most relevant chunks from each incident are provided as context to the prompt.

Step 6–Postmortem analysis: Finally, FAIL analyzes each incident. We developed prompts to extract information prescribed by several prior works on failure analysis. The fields are shown in Table 1. FAIL collects the articles for each incident as context, and prompts the LLM for each field of the failure report.

The prompts were engineered to extract information relevant to postmortems [39], a taxonomy of software faults [23], and additional details about the incident [63, 74]. The failure report contains open-ended (postmortem) fields and multiple-choice (taxonomy) fields. For the open-ended fields, the prompts contained instructions to *extract* information from the incidents relevant to the fields and their definitions. For extracting the timeline of incidents, further instructions (including chain-of-thought prompting [108] and fewshot prompting [28]) were added to guide the LLM into estimating the timeline of incidents. For the multiple-choice fields, we likewise applied chain-of-thought prompting. For each field, we first prompt the LLM to extract information from the incidents related to all of the options, and then we prompt the LLM to mark whether each option is supported by the information it extracted.

To illustrate, we show the prompt to extract information about the *system that failed*. This prompt is for row 2 in Table 1.

Table 1: Failure information per incident, aligned with taxonomies from prior work on software failure analysis. We introduced an IoT-specific taxonomy as many articles discussed IoT systems.

Postmortem [39]	Timeline
	System
	Responsible Organization
	Impacted Organization
	Software causes
ostm	Non-software causes
F	Impacts
	Prevention & Fixes
	References
	Recurring: At one organization, or multiple
[23]	Phase: Design, Operation
ults	Boundary: Internal, External
of Fa	Nature: Human, non-human actions
my	Dimension: Hardware, Software
хоис	Objective: Malicious, Non-malicious
e: Ta	Intent: Poor decisions, Accidental decisions
Software: Taxonomy of Faults [23]	Capability: Developmental incompetence, Accidental
Sof	Duration: Permanent, Intermittent
	Behaviour: Crash, Omission, Timing, Value, Byzantine
Other [63] IoT System: Layer [74]	Perception: Sensors, Actuators, Processing, Network, Embedded software
	Communication: Link, Connectivity
Ioī La	Application
[63]	Consequence: Death, Harm, Property, Delay, Basic, None
Other	Domain (12 total): IT, Transport, Manufacturing, etc.

What system(s) failed in the software failure incident? If specific components or models or versions failed include them. Return the products, systems, components, models and versions that failed in a numbered list (with citations in the format: [#, #, ...]).

3.2 Component Development and Validation

To develop and validate each component, we developed a ground-truth dataset by manually performing each step of the pipeline. Our human analysts were qualified: they were students in computing (1 graduate, 1 undergraduate) and both have native-level English. Labeling the ground-truth dataset took 4 weeks with 2 analysts, or $\sim\!320$ person-hours.

We describe some details for each Step. Since FAIL uses learned components, we do not expect perfect performance. Our goal is to understand the degree of uncertainty present in our subsequent analysis of the FAIL DB (§4).

Steps 2-4: Relevance, detail, clustering: The underlying data are somewhat sparse: the Google news queries return 137K articles,

of which our final pipeline found 6K to be relevant and 4K to be analyzable. Thus, had we used a truly random sample from Google News we would have had to examine many irrelevant articles. Instead, for these steps, we ran the FAIL pipeline and used stratified sampling based on FAIL's opinion in order to get articles for our manual ground truth. We used stratified sampling as follows: (1) we collected articles from 30 incidents (the articles that went through Step 4 of the pipeline and were indexed into incidents), and (2) we collected 30 articles which were (2.a) classified as **not** reporting on a software failure - articles that went through Step 2 of the pipeline, and (2.b) classified as reporting on a software failure AND classified as **not** containing sufficient failure information to conduct failure analysis - articles that went through Step 3 of the pipeline.

For Steps 2-3, we did this twice. *First* we focused on 2010-2016. This sample had 77 articles. The analysts labeled these for relevance and level of detail and we iteratively improved the prompts accordingly. For example, we removed the phrase "failure analysis" from these prompts and added more specific criteria instead. These data were then discarded to avoid overfitting.

Second, we randomly sampled 76 articles from 2010-2022. On this set, the analysts had internal 92% agreement for Step 2, and 80% agreement for Step 3. After resolving disagreement, 50 of the 76 articles were related to software failures, and 45 as having enough information. On this sample, the FAIL prompts achieved F_1 scores of 90% and 91%, respectively. Confusion matrices are given in Table 2.

Table 2: Confusion matrices for Step 2 and Step 3.

(a) Step 2: About a software failure?

(b) Step 3: Analyzable?

n 1. . 1

		Prea	lictea			Pred	lictea
al		TRUE	FALSE	Į1		TRUE	FALSE
anna	TRUE	50	0	nne	TRUE	39	6
Ма	FALSE	11	15	Mai	FALSE	1	4
-				7			

For *Step 4*, we evaluated on our manual analysis as well as to clustered articles from prior work [63]. We use common metrics for evaluating clustering [94]: *homogeneity* measures whether each incident contains only articles that belong to a single incident, *completeness* for measuring whether all articles that belong to the same incident are indexed into the same incident, and *V-measure* for measuring the balance between homogeneity and completeness. Results are in Table 3. The performance of our initial prompts (prior to formal evaluation) was sufficiently good that we did not refine the Step 4 prompts after this.

Table 3: Performance of FAIL Step 4: merging articles into incidents.

(a) On the 30 incidents (45) articles from our own pipeline.

(b) On the 81 incidents (536) articles compiled from Ko *et al.* [63]

Metric	Value
Homogeneity	0.9686
Completeness	0.9999
V-measure	0.9841

Metric	Value
Homogeneity	0.9780
Completeness	0.9292
V-measure	0.9530

Step 6: Failure analysis For the multiple-choice (taxonomy) fields, the human analysts independently selected options based

on the definitions for each field. We conducted 6 iterations of taxonomization until we reached definitions that resulted in a percent agreement of 80.65%, as reported in Table 4. Changes include: extending the definitions with detailed explanation, and shifting the focus of the definitions from fault to failure. We report the final percent agreement between the two analysts for each of the multiple-choice fields in Table 5.

Table 4: % agreement between the analysts taxonomizing incidents.

Iteration	1	2	3	4	5	6	Final
Incidents	5	3	3	3	3	3	31
Agreement	49.09%	43.59%	58.97%	53.85%	46.15%	89.74%	80.65%

The analysts manually conducted Step 6 to analyze and create failure reports for the 30 incidents described earlier. For the open-ended (postmortem) fields, the manual analysts independently extracted information from incidents. The two analysts discussed disagreements until agreement was reached. For this manual analysis, we report the inter-rater agreement with the proportion of overlapping facts between the two analysts and the proportion of discarded facts with respect to the number of agreed-upon facts reached by consensus in Table 5.

Summarizing Table 5: For the *postmortem* fields, FAIL extracted 90% or greater of the facts extracted by the analysts for the time, system, impacted organization, and impacts fields. However, FAIL only extracted 68% of the facts extracted by the analysts for the non-software causes field. We conjecture that this performance is because news articles are more likely to focus on the observable impacts of incidents rather than the unobservable causes. This limitation of news articles makes it difficult to assess the non-software causes of an incident, even when done manually (40% inter-rater agreement for our manual analysts). For the multiple-choice (taxonomy) fields, FAIL and the analysts generally drew from the same facts: overlapping was 90%, missing was 10%, additional and relevant was 18%, additional and irrelevant was 6%, and incorrect by the pipeline was 1%. Further details are in the table.

3.3 Implementation details

Tech stack. Our pipeline implementation is 3,500 lines of Python and 32 prompts. We built the pipeline with a tech-stack of: Django application for interface, Postgres database for text data storage, Chroma DB as a vector database for RAG, and LangChain to interact with the vector database. The pipeline is periodically run to collect and analyze new incidents for the database using Celery.

LLM selection. We used a SoTA LLM publicly available at the time of writing (2024): OpenAI's ChatGPT (gpt-3.5-turbo-0125) [3]. This LLM offers good performance at low cost [49, 115]. It supports many human languages [8], so FAIL analyzes non-English articles.

Prompts. When working with an LLM, much of the implementation cost is in developing prompts. As described in the design, FAIL uses LLM prompts in many steps. FAIL uses a total of 32 prompts. We applied best practices in prompt engineering, using iterative analysis and improvement as well as attempting a variety of strategies. The prompts are available in our supplemental material.

Requirement analysis:

- R1-Scale: FAIL analyzes incidents over a 12-year span.
- R2-Accuracy: FAIL's accuracy appears to be acceptable to fully or substantially automate news failure analysis, depending on the application.
- R3-Cost: The cost of running FAIL to gather incidents over the span of 12 years was \$590, or \$0.25 per incident.

4 ANALYZING THE FAIL DB

4.1 Research Questions

Using FAIL we conducted a large-scale systematic study of recent software failures from the news. We answer similar research questions as prior works that manually analyzed software failures [63, 88, 112]. Specifically, we ask:

- **RQ1:** What are the characteristics of the *causes* of recent software failures?
- **RQ2:** What are the characteristics of the *impacts* of recent software failures?
- **RQ3:** How do the *causes* affect the *impacts* of recent software failures?

The contributions of our analysis are: (1) The last similar work was conducted in 2014, so we provide an updated view as of 2024; and (2) The prior similar works rely on manual analysis [88, 112] or semi-automation [63], whereas ours uses a fully automated approach.

4.2 Preliminary analysis of the database

Using FAIL we collected 2457incidents as reported in Table 6. During Step 1 of FAIL, 137,427 articles were found with our search query from Google News. Out of these articles, FAIL successfully scraped 121,941 articles (88.73%). During Step 2 of FAIL, 6,553 articles (5.37%) were classified to have reported on a software failure. During Step 3, 4,184 articles (63.84%) were classified to have met the criteria for sufficient information to conduct failure analysis. During Step 4, all of these articles were merged into 2,457 incidents.

We report the distribution of keywords and the distribution of sources for the articles from the incidents in our database in Figure 3. The keywords that resulted in the most number of articles reporting on software failures are: "hack" (14%) and "bug" (14%), followed by "fail" (13%), "flaw" (11%), "incident" (10%), "crash" (10%), and error (8%). The sources that published the most number of articles reporting on software failures are: CNET (18%) and the Guardian (18%), followed by Daily Mail (15%), Wired (12%), BBC (9%), Reuters (9%), New York Times (7%), and CNN (6%).

The number of incidents reported by the news sources and collected by FAIL increased over time as illustrated in Table 6. As illustrated in Figure 4, most of the incidents only contained one article: 81.28% (n=1997) of incidents only contained 1 article, 17.05% (n=419) contained 2 to 10 articles, 1.1% (n=27) contained 11 to 20 articles, 0.41% (n=10) contained 21 to 30 articles, and 0.16% (n=4) contained more than 30 articles. The four outliers were major incidents that received extensive news coverage. Incident 1912 with 43 articles was about the solar winds security attack. Incident 351 with 66 articles was about Tesla autopilot system failures that led

Table 5: Performance of pipeline for Step 6 to analyze incidents. The inter-rater agreement for open-ended (postmortem) fields are reported as the ratio of the overlapping facts between the two analysts to facts reached by agreement.

Field	# Facts	Inter-rater Agreement	LLM Overlapping	LLM Missing	LLM Add & Relevant	LLM Add & Irrelevant	LLM Incorrect
Time	27	100%	93%	4%	37%	0%	4%
System	41	71%	100%	0%	73%	0%	0%
Responsible Org	43	63%	88%	12%	9%	2%	0%
Impacted Org	46	80%	96%	4%	17%	0%	0%
SEcauses	55	58%	89%	11%	16%	2%	0%
NSEcauses	47	40%	68%	32%	45%	13%	0%
Impacts	93	54%	90%	9%	43%	4%	1%
Preventions & Fixes	70	49%	83%	17%	90%	29%	0%
References	117	49%	88%	12%	39%	0%	0%
Recurring	26	81%	100%	0%	31%	4%	4%
Phase	52	81%	98%	2%	8%	6%	0%
Boundary	52	77%	98%	2%	8%	0%	0%
Nature	46	87%	98%	2%	24%	2%	0%
Dimension	43	94%	100%	0%	5%	0%	0%
Objective	44	94%	77%	23%	5%	0%	0%
Intent	30	71%	80%	20%	23%	10%	0%
Capability	32	65%	88%	13%	41%	16%	0%
Duration	31	87%	100%	0%	13%	3%	0%
Behaviour	32	84%	81%	19%	63%	41%	3%
Domain	50	71%	70%	30%	18%	0%	2%
Consequence	42	65%	86%	14%	7%	2%	5%
CPS	31	94%	94%	6%	0%	0%	0%
Perception	16	92%	94%	6%	25%	6%	0%
Communication	0	100%	-	-	n=3	-	-
Application	12	100%	92%	8%	0%	0%	0%

Table 6: Number of articles for Step 1 to Step 3 and the number of incidents for Step 4 of the pipeline from 2010 to 2022.

Year	Step 1	Step 1	Step 2	Step 3	Step 4
	(search)	(scraped)			
2010	3999	3697	154	102	71
2011	6188	5709	266	188	120
2012	7247	6690	292	211	157
2013	7819	7292	317	222	161
2014	9557	8761	344	230	144
2015	10753	9888	425	290	182
2016	11745	10348	451	327	193
2017	9054	7273	483	284	151
2018	13089	11304	616	416	229
2019	14287	12856	766	541	271
2020	15358	13040	623	383	223
2021	13249	11799	869	539	269
2022	15082	13284	747	451	286
Total	137427	121941	6353	4184	2457

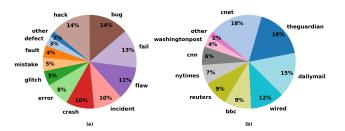


Figure 3: (a) Incidents by keyword that found them in Step 1. (b) Distribution of news sources.

to crashes. Incident 36 with 75 articles was primarily about a cyber-attack on Sony's playstation network, however many articles about cyber-attacks were incorrectly merged into this incident. Incident 1396 with 150 articles was about the Boeing 737 MAX crashes.

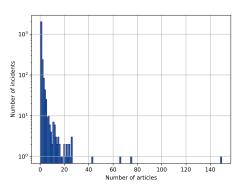


Figure 4: Frequency of articles to incidents for our database. Y-axis is a log scale. The most-covered incidents were XXX and YYY.

For RQ1, RQ2, and RQ3, we highlight some of the interesting findings we observed from Figure 5 and Figure 6. We illustrate the findings using the following randomly chosen incident from our database. The summary is by the LLM, edited slightly for space.

FAIL's summary of incident 2389: The incident occurred in Worcester. It involved the parking payment machines operated by Worcester City Council's parking contractor, Flowbird. The failure started around mid-September when an erroneous software upgrade by Flowbird caused duplicate payments to be debited from individuals' bank accounts. This glitch led to an estimated 1,500 drivers being overcharged, with some individuals experiencing multiple unauthorized transactions, such as one individual being debited 122 times over

three days, resulting in financial hardship for many affected drivers. The impact of the failure was significant: drivers out of pocket, some unable to pay bills, and one individual unable to afford a pending holiday. Responsible entities were Flowbird, the parking contractor, and Worcester City Council. The council issued a breach notice to Flowbird and promised refunds. Articles: [134147, 132785]

4.3 RQ1: Characteristics of the *causes* of recent software failures

The taxonomization of the characteristics of the *causes* of recent software failures analyzed by our pipeline is illustrated in Figure 5.

Recurring: Incident 2389 was a recurring incident within the organizations involved and had similar incidents occur at other organization from the same developer, where there were recurring issues with the payment processing for parking. Most of the incidents (85%) in our database were recurring incidents where a similar incident reoccurs across multiple organizations (53%) and/or recurring at one organization (77%). Phase: The incident occurred due to factors originating from the design and operation phases, since it was because of a software glitch from a software update. Most of the failures were due to contributing factors introduced during system design (95%), with 75% of the failures due to contributing factors introduced during operation. **Boundary:** The incident was caused by a software glitch within the system, and was exacerbated by continued unauthorized debits from individuals' bank accounts after being notified of the issue by the city council. Most of the failures in our database were due to contributing factors originating within the system (98%), with 38% of the failures due to contributing factors originating outside the system. Nature: Beyond the software glitch, the incident was exacerbated by the poor response by the employees of the company. Most of the failures in our database were due to contributing factors that did not involve human-actions (95%), with 69% of the failures due to contributing factors involving human actions. Dimension: The incident occurred due to only software issues, with no reports of hardware issues. Most of the failures in our database were due to contributing factors that originate in software (87%), with 50% of the failures due to contributing factors originating in hardware. Objective: The incident did not have any malicious factors. Roughly an equal amount of the failures in our database were due to contributing factors introduced by human(s) with intent to harm a system (50%), with 55% of the failures due to contributing factors introduced without intent to harm a system. **Intent:** The incident was rather due to poor and accidental decisions by the developer. A majority of the failures in our database were due to contributing factors introduced by poor decisions (64%), with 32% of the failures due to contributing factors introduced by accidental decisions. Capability: The incident was due to accidental factors as well as developmental negligence. Roughly an equal amount of the failures in our database were due to contributing factors introduced accidentally (61%) and introduced by development incompetence (65%).

Cyber-Physical System: The incident is due to a failure in a system for parking payment machines, which is a cyber-physical system. 15% of the software failures in our database were in Cyber-Physical Systems (CPS). **Perception:** The incident could have

occurred due to factors involving the processing unit and the embedded software. Most failures in the perception layer of CPS systems in our database were due to contributing factors introduced by embedded software (77%), followed by sensors (53%), processing unit (45%), network communication (43%), and actuators (13%). **Communication:** The communication layer of the system being a factor in the incident is unknown. Most failures in the communication layer of CPS systems in our database were due to contributing factors introduced by connectivity level (40%), followed by link level (22%). **Application:** The incident occurred due to factors from the application layer of the system. 69% of the failures in the CPS systems in our database are due to contributing factors introduced by the application layer.

4.4 RQ2: Characteristics of the *impacts* of recent software failures

The taxonimization of the characteristics of the *impacts* of recent software failures analyzed by our pipeline is illustrated in Figure 6.

Duration: Incident 2389 was caused by temporary factors. Most of the failures in our database were due to contributing factors that were temporary (79%), with 20% of the failures due to contributing factors that were permanent. Behaviour: The incident was due to the system crashing, omitting to charge users at certain instances, charging users at incorrect times, and charging users incorrect values. Roughly an equal amount of the failures in our database were due to a system crashing (51%), a system omitting to perform its intended function (54%), and a system performing its function incorrectly (56%). Notably, 85% of the failures in our database were due to a system behaving in a way not described in the taxonomy ([23]). **Domain:** The incident involved transportation and financial application domains. The software failures in our database most commonly occurred in systems supporting industries related to information (47%), followed by transportation (21%), finance (18%), and government (17%). The software failures also occurred in systems supporting industries related to entertainment (9%), health (8%), manufacturing (5%), knowledge (5%), utilities (4%), and sales (2%). Consequence: As a result of the incident, peoples' money was impacted. The most common consequence of the software failures in our database was impact to peoples' (material goods, money, or data) property (66%), followed by delay to peoples' activity (21%), physical harm to people (13%), and people losing their lives (5%).

4.5 RQ3: Influence of the *causes* on the *impacts* of recent software failures

Recurring: Similar incidents reoccur across multiple organizations most in the information (27%), finance (13%), government (11%), and transportation (9%) domains. Most cyber-physical system failures had similar recurrences (14%). Objective: Incidents with malicious objectives mostly occurred in the information (29%), finance (13%), and government (11%) domains. Incidents with malicious objectives mostly only impacted property (40%). About half of the failures in cyber-physical systems were due to malicious intent (9%), which mostly impacted property (6%) and caused some harm (2%). Cyber-physical system: Most cyber-physical system failures occurred in the transportation domain (7%), followed by the information (4%),

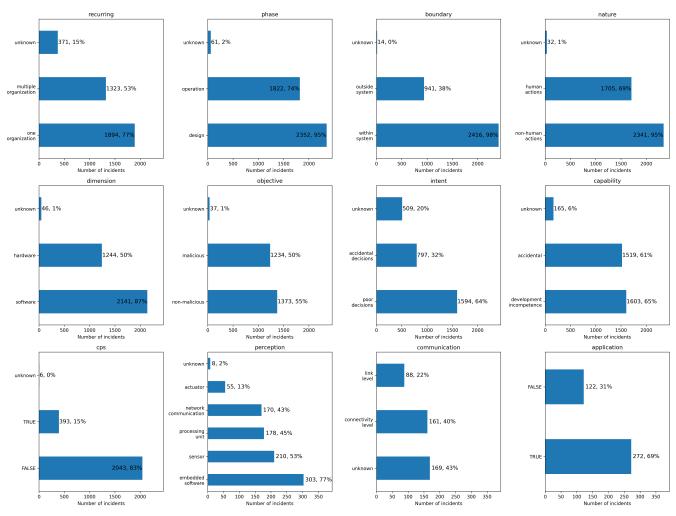


Figure 5: Taxonimization of the characteristics of the causes of recent software failures from our database.

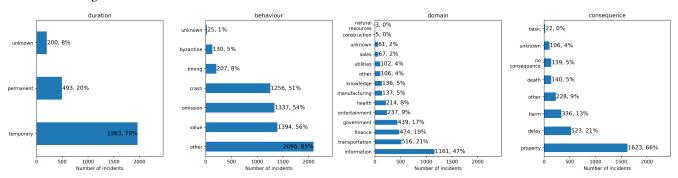


Figure 6: Taxonimization of the characteristics of the impacts of recent software failures from our database.

government (3%), and health (2%) domains. These failures primarily impacted property (9%) and led to harm (4%).

5 DISCUSSION AND FUTURE WORK

5.1 Recurring incidents

Our results for RQ1 indicate high recurrences of similar failures: within organizations and across organizations. This implies that the software engineering community might benefit from learning from past failures to prevent similar future ones. To reduce recurring

incidents within organizations, we first need to study the current practices utilized by practitioners to learn from failures within organizations and their effectiveness. To reduce recurring incidents across organizations, we suggest the need for the software engineering community to learn from inter-organizational failures using resources such as the Risks Digest [78] or our database. Specifically, based on our results for RQ3, the information, finance, government, and transportation domains had a high rate of similar incidents recurring and may benefit from an inter-organizational failure database within each domain.

5.2 Change in the consequences of software failures over time

The consequences of software failures have evolved in severity over time. In Ko *et al.* 's analysis of software failures from 1980 to 2012, 50% of the failures had no consequences, 40.4% delayed activities, 12.5% impacted property, 1.2% led to death, 1% led to harm, and 0.7% impacted basic needs. Whereas, based on our results for RQ2, for software failures from 2010 to 2022, we find that only 5% had no consequences, with increase in failures that impacted property, led to harm, and led to death. This indicates that the severity of the consequences of software failures have increased over the past decade. This may be due to the increased use of software in modern society. The increase in the severity of the consequences of software failures, indicates the need to develop safer software. As such, policymakers, practitioners, and academics should study the causes of software failures and their consequences to prioritize preventing high severity software failures.

5.3 Cybersecurity failures

Our results for RQ1 indicate that half of the recent software failures were malicious in nature. Based on our results for RQ3, the information, finance, and government domains had a higher occurrence of malicious failures. Similarly, in RQ3 we found that half of the failures in cyber-physical systems were due to malicious intent. This data motivates the continued investment by policymakers, practitioners, and academics in improving the cybersecurity of our digital and physical systems.

5.4 Applications: Policy, Engineering, Research

We invite the policy-making, engineering, and academic communities to explore insights and applications that could be built from our database of software failures. The use of software in the modern world is ubiquitous, and based on §5.2, the consequences of their failures have become more severe. To enable the safe development and implementation of software, we advocate exploring our database to learn how software failures occur, what their impacts are, and how to prevent them. This insight could inform policies around software: what are the ways in which people are affected by software failures? what policies, regulations, and standards could help prevent such failures? This insight could also inform software engineering: what are the common causes of software failures and how can we prevent them? what context are software systems used in and how do they invoke failures? This insight could also inform academics: it could guide research on improving software reliability and developing new methods for failure prevention. Additionally, given the high occurrences of incidents with malicious intent, researchers could map the failures in the database with the Common Weakness Enumeration (CWE) categories to identify the common weaknesses in real world security failures.

5.5 Extension to FAIL

We propose extensions to FAIL to leverage the failure knowledge from our database of software failures. First, our database contains open-ended fields with rich failure data such as the: cause of failure, impact of failure, and mitigation for failure. LLMs can be used to conduct thematic analysis [35, 37] on this data to identify failure trends. Second, we propose a failure-aware chat-bot. An LLM-based chatbot could be developed with our database to aid engineers during the SDLC. For example, grounded by past failure knowledge, a failure-aware chatbot could: aid in refining requirements to improve resiliency of a system, during the planning phase, or offer design rationales to aid with design decisions, during the design phase, or write test cases to look out for past failure causes, during the testing phase, or suggest mitigation strategies for incidents, during the maintenance phase.

6 THREATS TO VALIDITY

We discuss three types of threats to validity [110]. Taking into consideration the criticisms of Verdecchia *et al.* [104], we focus on substantive threats that might influence our findings.

Construct Threats are potential limitations of how we operationalized concepts. In this work we relied on existing constructs (§2): failures and incidents are well documented concepts, and we applied existing taxonomies from prior work. We scoped our definition of news articles to mainstream media sources such as CNN and Wired, which may reduce the level of technical detail available.

Internal threats are those that affect cause-effect relationships. This paper propagates the failure cause-effect relationships as indicated in the articles selected by FAIL. In addition, FAIL relies on a Large Language Model (LLM) which may hallucinate and introduce incorrect cause-effect relationships. In our evaluation (the additional and irrelevant column in Table 5), we found this was relatively rare for most fields. Additionally, we acknowledge that our evaluation of FAIL was based on comparison to human analysts, and that the analysts may themselves have erred in their interpretation of the studied articles. To mitigate, we used two analysts and found reasonably high inter-rater agreement.

External threats may impact generalizability. Any application of failure data drawn from the news media must acknowledge the potential biases of that media [76]. A publication's editors may sway which events are covered and with what frequency. For example, the FAIL database is likely biased toward more large-scale, impactful, and "interesting" incidents. The FAIL database is also likely geographically biased. It does include articles from multiple languages, but as Ko *et al.* noted [63], failure coverage tends to focus on issues in the United States and Europe.

7 CONCLUSION

In this work, we presented the concept of Failure Analysis Investigation with an LLM. We materialized this concept in the FAIL system,

which applies OpenAI's GPT-3.5 large language model to news articles from 11 sources including The New York Times, the BBC, and Wired Magazine. Where prior work relied on manual analysis of such articles, FAIL demonstrates the novel capability of automated analysis. We learned that the current generation of large language models is capable of identifying news articles that describe failures, and analyzing them according to structured taxonomies. FAIL will thus enable researchers, practitioners, and policymakers to keep up with the pace of public software failure data.

8 DATA AVAILABILITY

The code, prompts, manual analysis, and evaluation for FAIL, as well as a publicly viewable version of our database is available at: https://anonymous.4open.science/r/FAIL.

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