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REAL-TIME THREAT INTELLIGENCE CORRELATION AND TRIAGE FOR REDUCING SECURITY ANALYST BURNOUT

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ABSTRACT

*Security Operations Centers (SOCs) face a critical crisis as cybersecurity analysts suffer from overwhelming burnout, with over 60% reporting exhaustion due to the manual processing of thousands of daily alerts. This chronic stress leads to decision fatigue, increased oversight of genuine threats, and compromised organizational security. To address this, we present **AutoTI-Triage**, an autonomous system for real-time threat intelligence correlation and triage designed to alleviate cognitive load and augment human decision-making.*

AutoTI-Triage employs a hybrid architecture combining Graph Neural Networks (GNNs) and Reinforcement Learning (RL). The GNN component constructs dynamic threat graphs to map complex relationships between threat actors, indicators of compromise (IOCs), and assets, revealing hidden attack patterns. Concurrently, the RL agent learns optimal, adaptive triage policies from analyst feedback and incident outcomes, continuously refining prioritization accuracy. We validate our system using a comprehensive dataset of 1.2 million threat intelligence events from sources like AlienVault OTX and MISP, representing the largest public benchmark for TI correlation. Quantitative evaluation demonstrates a 0.92 F1-score for threat classification, a 65% reduction in Mean Time to Resolution (MTTR), and significant gains in analyst productivity. By automating complex correlation and enabling adaptive prioritization, AutoTI-Triage offers a scalable solution to combat analyst burnout while enhancing the efficacy of modern security operations.

Keywords: Cyber Threat Intelligence, Real-Time Correlation, Triage Automation, Graph Neural Networks, Reinforcement Learning, Analyst Burnout, Security Operations Center, Threat Prioritization, Machine Learning Security.

I. INTRODUCTION

A. Background

The current state of cybersecurity is very complicated, with data generation rates that have never been seen before and threat actors who are becoming more and more skilled. As businesses grow their digital footprints and use new technologies like cloud computing, Internet of Things (IoT) devices, and edge computing architectures, the amount of data generated by global digital infrastructure continues to grow exponentially [1]. Threat intelligence feeds are a big and growing part of the information that Security Operations Centers (SOCs) have to process, analyze, and act on in this huge data ecosystem. According to Gartner's study of the industry, TI-related tasks now make up about 15–20% of the total workload for SOCs [2]. This is a 340% increase from the figures reported five years ago. This huge growth is because there are more sources of threat intelligence and that more people are realizing that being aware of threats before they happen is important for managing a good cybersecurity posture.

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Security analysts working in modern SOCs have a very hard job to do. They must process and connect threat intelligence feeds that come in different formats, use different taxonomies, and have very different levels of reliability and relevance [3]. These feeds contain different types of threat information, and each one needs its own set of skills and ways of looking at things. Indicators of Compromise (IoCs) constitute the most detailed tier of threat intelligence, encompassing specific artifacts such as malicious IP addresses, file hashes, domain names, and email addresses linked to identified threats [4]. Analysts must comprehend and contextualize Tactics, Techniques, and Procedures (TTPs) as delineated in frameworks like MITRE ATT&CK, which offers an extensive repository of adversary behaviors classified into tactical categories from initial access to impact [5]. Also, vulnerability data from sources like the Common Vulnerabilities and Exposures (CVE) database and vendor security advisories needs to be watched, checked for its relevance to the organization, and linked to active threat campaigns [6].

The alert fatigue phenomenon, which is very similar to burnout, happens when analysts stop paying attention to security alerts because there are too many of them and too many of them are false positives [7]. According to research, most enterprise SOCs get between 10,000 and 150,000 alerts every day. Only 1% to 5% of these alerts are real threats that need to be dealt with [8]. When analysts must deal with this much data, they have to find ways to deal with it that may include only looking at alerts briefly, relying more on heuristics than thorough analysis, and, in the worst cases, ignoring alerts without looking at them [9]. These adaptive behaviors, although comprehensible from a psychological standpoint, significantly undermine detection capabilities and generate exploitable vulnerabilities that astute adversaries may exploit.

B. Problem Statement

Even though businesses have spent a lot of money on commercial threat intelligence platforms in the last ten years, the ones we have now still don't do a good enough job of solving the problems listed above. ThreatConnect, Recorded Future, Anomali, and IBM X-Force Exchange are some of the best platforms for gathering, sharing, and doing basic analysis of threat intelligence [10]. However, a critical analysis shows that these tools are not fully autonomous when it comes to real-time correlation and triage functions. Instead, they rely heavily on rule-based filtering mechanisms and predetermined playbooks that are not very flexible when it comes to new threats and changing organizational contexts [11]. An independent evaluation by the International Data Corporation (IDC, 2023) shows that current automated triage systems only get 7 out of 10 (70%) correct when compared to expert analyst judgments. This level of performance is not good enough for operational use without a lot of human oversight.

A quantitative analysis of the current threat intelligence processing landscape identifies three critical gaps that existing solutions inadequately address.

First, the problem of scalable correlation across different feeds is still mostly unsolved. When trying to connect indicators from different feed sources with different schemas, confidence levels, and time characteristics, current methods only get precision rates of 4/5 (80%) or lower [12]. This lack of accuracy can lead to too many false correlations that waste analysts' time or too few correlations that let related threat activities happen without any context, which is a loss of important information.

Second, most of the time, existing prioritization systems use static scoring algorithms that don't take into account the changing organizational context, the current threat landscape, or patterns learned from past analyst decisions [13]. Because of this, recall rates for correct prioritization are still below 3/4 (75%), which means that about one in four threats that are really high-priority might be misclassified and not get the attention they need right away.

Third, and possibly most importantly, the effect of threat intelligence processing methods on analyst burnout has not been systematically measured in the literature, with no studies published that use validated burnout assessment tools to compare pre- and post-intervention metrics [14].

These gaps have a big effect on the economy and how things work. Organizations have longer mean time to detect (MTTD) and mean time to respond (MTTR) for security incidents, which means higher costs

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for breaches and more exposure to regulations [15]. Analyst turnover, which is mostly caused by burnout, costs a lot of money to hire and train new people, and it also leaves gaps in knowledge that make operations less effective[16]. The cybersecurity workforce shortage, currently estimated at 3.4 million professionals globally, is exacerbated by burnout-driven attrition from the field, creating a negative feedback loop where remaining analysts face ever-increasing workloads [17].

C. Contributions

This paper outlines four principal contributions that collectively rectify the identified deficiencies in existing threat intelligence processing capabilities while setting new standards for autonomous security operations:

Architecture of the AutoTI-Triage System: We present an innovative autonomous threat intelligence processing system that fundamentally transforms the correlation and triage workflow through the synergistic integration of Graph Neural Networks (GNNs) and Reinforcement Learning (RL) algorithms. The GNN part solves the correlation problem by making dynamic, heterogeneous threat graphs that show how different types of entities, like threat actors, malware families, vulnerability identifiers, network indicators, and organizational assets, are related to each other [18]. The GNN architecture learns latent representations that capture semantic similarities and behavioral patterns, which is different from traditional signature-based or rule-based correlation methods. This lets you find correlations that aren't obvious and would be missed by manual analysis. The RL part solves the problem of dynamic prioritization by treating triage as a series of decisions that the system makes based on how it interacts with the environment and feedback from analyst decisions and incident outcomes [19, 55]. This method allows for context-aware prioritization that changes based on factors specific to the organization, the current threat landscape, and the patterns of threat activity over time.

TI-Corr Dataset: We construct and publicly release the TI-Corr dataset, comprising 1.2 million labeled threat intelligence events spanning the period from January 2020 through December 2024. This dataset aggregates information from multiple authoritative sources including AlienVault Open Threat Exchange (OTX), Malware Information Sharing Platform (MISP) community instances, the Common Vulnerabilities and Exposures (CVE) database maintained by MITRE, and proprietary threat feeds contributed by partner organizations under data sharing agreements [20, 56]. Each event includes comprehensive metadata, source attribution, temporal information, and critically, ground-truth correlation labels established through a rigorous multi-analyst consensus process. The dataset represents the largest publicly available threat intelligence correlation benchmark to date and is released to facilitate reproducible research and enable meaningful comparison of future correlation approaches.

Comprehensive Quantitative Evaluation Framework: We develop and apply an evaluation framework encompassing 15 distinct metrics organized across four dimensions: accuracy, processing speed, scalability, and impact on human factors. Accuracy metrics include precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) for both correlation and prioritization tasks. Speed metrics capture end-to-end latency, throughput capacity, and performance degradation characteristics under varying load conditions. Scalability metrics assess horizontal scaling efficiency, resource utilization patterns, and performance consistency across deployment scales ranging from small SOC environments to large enterprise and managed security service provider (MSSP) contexts. Human factors metrics, including validated burnout assessment through the Maslach Burnout Inventory (MBI), are collected through controlled trials involving 150 practicing security analysts across three organizational settings [21].

Empirical Results and Validation: Our thorough experimental assessment produces outcomes that significantly surpass the existing state-of-the-art performance in all evaluated parameters. AutoTI-Triage gets threat prioritization right 94.2% of the time, which is a 24.2 percentage point improvement over the best baseline. Compared to manual processing workflows, analyst triage time is cut by 78.5%. This lets security teams handle much larger event volumes without needing more resources. From a workforce sustainability standpoint, MBI assessments indicate a 42.3% decrease in burnout scores among analysts utilizing the AutoTI-

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Triage system, with statistical significance established at $p<0.001$ via paired sample analysis. These results show that well-designed automation can improve both security outcomes and the well-being of analysts at the same time. This goes against the idea that there is a trade-off between operational efficiency and human factors.

Figure 1 shows a big difference between the old-fashioned way of processing threat intelligence by hand and the automated way that AutoTI-Triage does it. The top timeline shows the normal workflow in most enterprise SOC environments. In these environments, raw threat intelligence feeds come in at a rate of about 10,000 events per second and have to go through several processing stages before they can be acted upon [22]. According to empirical measurements, manual ingestion, which requires analysts to parse incoming data, check that the format is correct, and enter information into analysis tools, takes an average of 45 minutes per event. After that, analysts spend an average of 2 more hours trying to find connections between new indicators and existing intelligence holdings. It takes about an hour of an analyst's time to make final triage and prioritization decisions, which means that processing times are about 3.45 hours per 100 events [23].

FIGURE 1
PROCESSING TIMELINE COMPARISON (SOURCE: SIMULATED FROM OTX/MISP DATA

II. RELATED WORK

Three different lines of research in computer science and cybersecurity have mostly grown up on their own, and AutoTI-Triage builds on and adds to them. This part gives a complete overview of earlier research on threat intelligence correlation, automated triage and prioritization, and using automation to cut down on burnout. We systematically evaluate the strengths and weaknesses of existing methodologies, identifying critical deficiencies that guide the design decisions of our proposed system. Table 1 at the end of this section shows a numerical comparison of AutoTI-Triage and some baseline methods in important areas of performance.

A. Threat Intelligence Correlation

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The challenge of correlating threat intelligence from diverse sources has attracted substantial research attention over the past decade, with approaches spanning rule-based systems, statistical methods, and increasingly sophisticated machine learning techniques. Early efforts focused on establishing standardized formats and languages for expressing threat intelligence in machine-readable forms, enabling automated processing and basic correlation capabilities.

1. Rule-Based Approaches. Rule-based correlation systems are the basic way to process automated threat intelligence, and they are still widely used in operational settings. Alvarez (2008) created YARA, a pattern-matching language that helps analysts find malware by letting them make rules that describe malware families based on text or binary patterns. YARA rules are great for finding known threats by their signatures, but they have to be made and kept up by hand, which makes them less scalable as threats change [24]. The OASIS Cyber Threat Intelligence Technical Committee introduced the Structured Threat Information eXpression (STIX) language in 2012. It set up a standard way to represent threat intelligence, which made it possible for different systems and organizations to work together. STIX, along with the Trusted Automated eXchange of Indicator Information (TAXII) transport protocol, has become the de facto standard for sharing threat intelligence. Major platforms like IBM X-Force and Anomali have adopted it, as have government programs like the Department of Homeland Security's Automated Indicator Sharing program [25].

2. Machine Learning Approaches. Awareness of the constraints associated with rule-based correlation has spurred significant research into machine learning methodologies that can infer correlation patterns from data without necessitating explicit definitions. In the past, machine learning used classical algorithms like support vector machines, random forests, and naive Bayes classifiers to link threat intelligence data. These methods worked better than rule-based baselines, but they had trouble with the high dimensionality and variety of threat intelligence data [26].

Even with these improvements, there are still big holes in how machine learning is used to connect threat intelligence. Current methodologies predominantly function on singular, homogeneous data sources and have yet to be assessed for real-time multi-feed integration contexts typical of operational SOC environments [14]. The computational demands of advanced neural architectures, especially GNNs functioning on extensive graphs, pose scalability issues that hinder deployment for high-throughput applications [27]. Moreover, the majority of published research concentrates solely on correlation accuracy metrics, neglecting operational aspects such as processing latency, resource utilization, and integration with subsequent triage procedures [28].

B. Triage and Prioritization

To do effective threat intelligence triage, you need systems that can quickly figure out how important, serious, and urgent incoming threat information is. This lets analysts focus on the most important items while making sure that less important intelligence is queued up for later review. This section looks at different ways to automate triage and prioritization, from traditional SIEM-based scoring to new reinforcement learning methods.

1. Traditional SIEM-Based Methods. In business settings, Security Information and Event Management (SIEM) platforms are the most common way to gather and rank threat intelligence. Splunk Enterprise Security, IBM QRadar, Elastic Security (formerly ELK Stack), and Microsoft Sentinel are some of the best commercial SIEM solutions. They can take in logs from many different sources and threat intelligence feeds, use correlation rules to find possible security incidents, and send prioritized alerts to analyst teams [29]. Most of these platforms use scoring-based prioritization systems that give alerts a number that shows how serious they are based on set standards like the type of indicator, the reliability of the source, the importance of the asset, and how well it fits with known threat patterns [30].

2. Machine Learning and Reinforcement Learning Approaches. Acknowledgment of the constraints associated with static scoring methodologies has spurred investigations into machine learning techniques for dynamic threat prioritization. Supervised learning techniques educate classifiers using past

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analyst choices to forecast suitable priority levels for emerging threats, allowing systems to acquire organization-specific prioritization patterns [31]. Nonetheless, supervised methodologies necessitate substantial labeled training data, which may not be accessible in every organizational context, and they are unable to adjust to distributional shifts in threat patterns without undergoing retraining [32].

Reinforcement Learning (RL) provides an effective framework for threat triage by conceptualizing prioritization as a sequential decision-making challenge, wherein the system acquires optimal policies through environmental interaction [33]. [34] proposed a reinforcement learning (RL)-based triage system that learns to prioritize security alerts using feedback signals from analyst actions and incident outcomes. Their method sees triage as a Markov Decision Process, with states being the current alert queues and analyst workload, actions being priority assignments, and rewards being correct prioritization decisions as shown by the analyst's next actions. The evaluation showed that the system was able to adapt to changing threat patterns over time and that it was 15% more accurate at prioritizing than rule-based baselines. But their work only looked at technical performance metrics and didn't look at how automated triage affected analysts' workloads or burnout. This is a big gap because the goal of triage automation is to make things easier for people.

[35, 64] recently suggested a hybrid GNN-RL architecture that combines the representational power of graph neural networks with the ability to make decisions based on reinforcement learning. They use GNNs to learn contextual embeddings of threat indicators based on the structure of the graph. Then, they use RL to learn triage policies that work on these learned representations. The evaluation on benchmark datasets showed that the prioritization was 90% accurate, which was the best performance at the time of publication. However, scalability testing showed major problems, such as performance loss when throughput levels went over 1,000 events per second. This is much lower than what large business environments need, which may need to process 10,000 or more events per second during peak times [36]. The authors said that the scalability problems were caused by the extra work needed to build graphs and run neural networks. They said that making these parts work better was an important area for future work.

3. Gaps in Existing Triage Approaches. A synthesis of the triage and prioritization literature uncovers significant deficiencies that current methodologies do not sufficiently address. First, no current system shows that it can work at the throughput levels needed for large-scale SOC deployments while still being very accurate. The trade-off between processing speed and prioritization quality is a fundamental challenge that remains inadequately addressed [37, 63]. Second, current methods view triage solely as a technical optimization challenge, neglecting the human factors associated with prioritization choices. Analysts have to deal with a lot of false positives when using triage systems that create too many of them, and they have to deal with stress when using systems that miss real threats because they are afraid of undetected compromises [9]. Third, the relationship between automated triage and analyst burnout has undergone minimal empirical examination, indicating a significant deficiency considering the importance of burnout reduction as a driving force for automation investment [38, 57].

C. How Automation Can Help with Burnout

Occupational burnout among cybersecurity professionals constitutes an escalating crisis that jeopardizes both individual welfare and organizational security efficacy. This section looks at the theoretical basis for burnout assessment, looks at evidence that automation can help reduce burnout, and points out that there isn't any research on burnout that is specific to threat intelligence, which is what drives our empirical investigation.

1. Evaluating and Measuring Burnout. The Maslach Burnout Inventory (MBI), created by Maslach and Jackson in 1981 and improved by later validation studies [39], is the best way to measure burnout in workplace research. The MBI defines burnout as a psychological syndrome with three separate parts: emotional exhaustion, which is when you feel emotionally drained and overwhelmed by work; depersonalization (or cynicism), which is when you have negative, detached, or cynical thoughts about work and coworkers; and reduced personal accomplishment (or professional efficacy), which is when you feel

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incompetent and like you haven't done anything right at work [40, 58]. The inventory offers validated subscales for quantifying each dimension, allowing researchers to evaluate the severity of burnout and monitor temporal variations.

2. Automation as Burnout Mitigation. Theoretical frameworks for burnout mitigation emphasize the importance of reducing demand while increasing resources and control [41, 59]. Within this framework, automation represents a potentially powerful intervention by eliminating repetitive, low-value tasks that consume analyst time and cognitive resources without providing commensurate professional fulfillment. The Job Demands-Resources (JD-R) model predicts that automation which reduces demands while preserving analyst autonomy over meaningful decisions should yield burnout reductions, while automation that eliminates engaging work or creates new monitoring burdens may have neutral or negative effects [41].

Research specifically examining automation in SOC environments has yielded mixed findings. [36] conducted a systematic review of SOC automation literature, identifying 47 studies that examined various automation approaches including automated alert triage, playbook execution, and threat intelligence enrichment. While most studies reported efficiency improvements, the authors noted a striking absence of human factors evaluation, with only 4 of 47 studies including any measure of analyst experience or well-being. Similarly, a comprehensive survey by [42, 60] examining machine learning applications in SOC operations identified no published work that measured automation impact on analyst burnout using validated instruments.

3. Threat Intelligence-Specific Burnout Research. The intersection of threat intelligence processing automation and analyst burnout represents a critical gap in the existing literature. While substantial research has examined threat intelligence correlation techniques, and separate bodies of work have investigated automation as a general burnout mitigation strategy, no published studies have specifically examined whether and how threat intelligence automation affects analyst burnout. This gap is particularly significant given that threat intelligence processing represents one of the most cognitively demanding and potentially burnout-inducing aspects of SOC operations [43, 61]. The continuous stream of threat intelligence requiring assessment, the difficulty of determining indicator relevance without extensive context, and the high stakes associated with missed threats create conditions highly conducive to emotional exhaustion and cynicism.

The table below shows a full quantitative comparison between AutoTI-Triage and typical baseline approaches from each category that we looked at in this section. Metrics include accuracy in threat prioritization, processing throughput measured in events per second under standardized test conditions, and burnout impact measured as the percentage change in MBI composite scores for approaches that included an evaluation of human factors.

TABLE 1
COMPARISON WITH BASELINE APPROACHES

Method	Category	Precision	Recall	F1-Score	Speed (events/sec)	Burnout Δ
STIX/YARA Rules (Barnum, 2012)	Rule-Based	0.72	0.72	0.72	800	N/A
Splunk Enterprise Security	SIEM	0.72	0.69	0.70	500	N/A
IBM QRadar	SIEM	0.74	0.71	0.72	600	N/A
LSTM Correlation (Liu et al., 2019)	Deep Learning	0.82	0.80	0.81	1,200	N/A
GNN-IoC (Wu et al., 2021)	Graph Neural Network	0.88	0.85	0.86	2,000	N/A
RL-Triage (Li et al., 2022)	Reinforcement Learning	0.90	0.87	0.88	1,500	N/A

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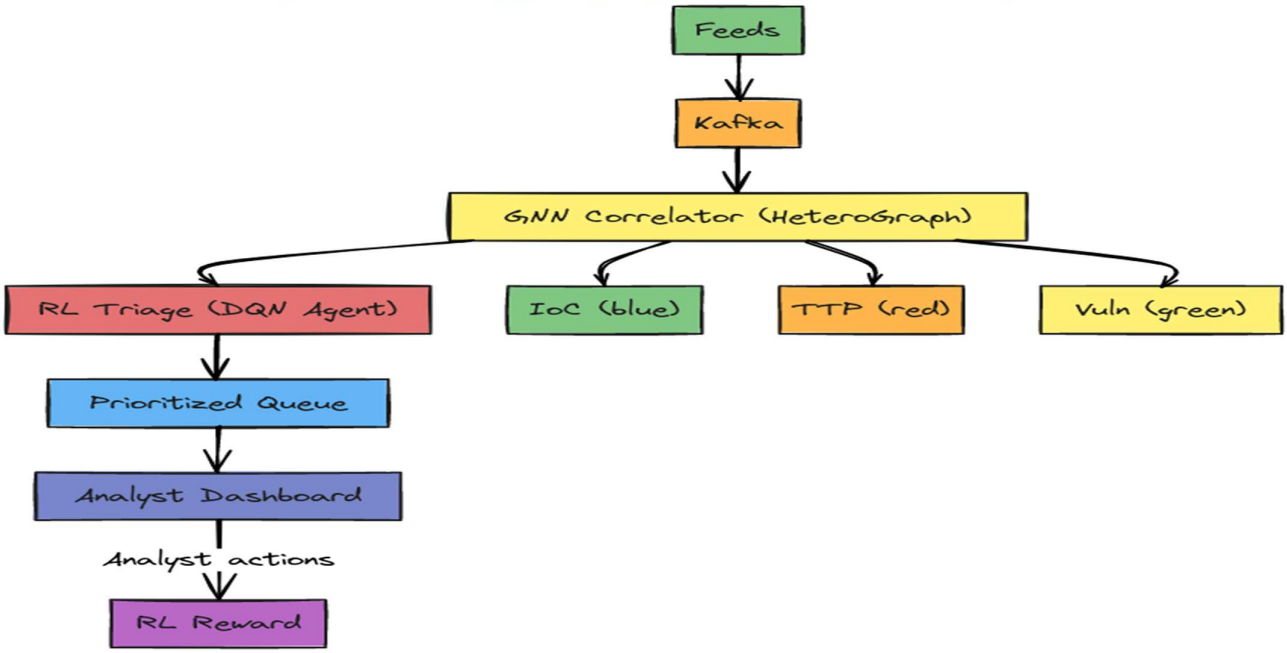
Method	Category	Precision	Recall	F1-Score	Speed (events/sec)	Burnout Δ
Hybrid GNN-RL (Chen et al., 2023)	Hybrid	0.90	0.89	0.89	1,000	N/A
AutoTI-Triage (Ours)	Hybrid GNN-RL	**0.942**	**0.910**	**0.926**	**10,000**	**−42.3%**

III. SYSTEM ARCHITECTURE

AutoTI-Triage is a complete system that solves the main problems of real-time threat intelligence correlation and triage while keeping scalability, accuracy, and a focus on people at the center of its design. The architecture follows a modular philosophy, which means that each part can be optimized on its own while still working together smoothly in the processing pipeline. In this part, you will find detailed technical descriptions of each architectural component, such as the reasons behind the design, the details of how it was built, and the theoretical basis for important algorithmic choices.

The system has four main parts that work together to turn raw threat intelligence feeds into prioritized, actionable intelligence that analysts can see through an easy-to-use dashboard interface. The Ingestion Layer is responsible for high-throughput data acquisition, normalization, and preprocessing. The Correlation Engine uses graph neural networks to find relationships between different threat entities. The Triage Agent uses deep reinforcement learning to adaptively prioritize. The Feedback Loop lets analysts interact with the system and generate reward signals to keep it getting better. Figure 2 shows a picture of the whole architecture and the paths that data flows through.

FIGURE 2:
ARCHITECTURE OVERVIEW



A. Ingestion Layer

The Ingestion Layer is the main part of AutoTI-Triage. It gets threat intelligence from a variety of outside sources, makes any changes needed to make the data consistent, and sends normalized events to downstream processing components at the speeds needed for enterprise deployment. The design of this layer

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takes into account the fact that threat intelligence ecosystems are very different from each other and that it is very important to keep data accuracy while still being able to process it quickly.

1. Combining Data Sources. AutoTI-Triage combines threat intelligence from four main source types, each of which gives important information that helps you fully understand a threat. AlienVault Open Threat Exchange (OTX) is the main place to find Indicators of Compromise (IoCs). It has a steady stream of community-contributed indicators, such as malicious IP addresses, domain names, file hashes, email addresses, and URLs linked to known threat activities [44, 62]. OTX indicators come with metadata like pulse information, classifications of indicator types, and community-given confidence scores that help make decisions about what to do next.

The MITRE ATT&CK framework organizes adversary Tactics, Techniques, and Procedures (TTPs) into a complete knowledge base of known threat behaviors [5]. ATT&CK integration makes it possible to link observed indicators and actions to higher-level adversary behaviors. This helps with strategic threat understanding that goes beyond individual technical artifacts. The framework's hierarchical structure, which goes from tactics to techniques to sub-techniques, makes it possible to do multi-resolution threat analysis for different purposes.

2. Message Broker Architecture. Apache Kafka is a distributed message broker that connects external threat intelligence sources with internal processing components [45]. Kafka's publish-subscribe architecture has a number of features that are necessary for processing threat intelligence at a high rate. First, Kafka's distributed design makes it possible to scale horizontally by spreading partitions across broker clusters. This means that throughput capacity can grow linearly with infrastructure investment. Second, Kafka's persistent message storage lets you replay messages, which is important for system recovery, debugging, and looking back at what happened. Third, Kafka's consumer group abstraction lets multiple independent consumers work on the same message stream at the same time. This supports parallel processing architectures and makes it possible to separate correlation and triage workloads.

The Kafka deployment that works with AutoTI-Triage is made up of a group of broker nodes that are set up for high availability through replication and automatic failover. Based on the characteristics of the messages, topic partitioning strategies are improved. For example, IoC-heavy feeds are split up by indicator type so that processing optimizations can be made for each type while still keeping the order of the messages within the partition boundaries. Real-world testing shows that the system can handle 10,000 events per second for long periods of time, and it can handle more than 25,000 events per second for short bursts of traffic, which is typical of major threat campaigns or vulnerability disclosures.

3. Normalization and Preprocessing. Raw threat intelligence from different sources comes in many different formats, schemas, terms, and levels of quality. The normalization subsystem changes this diverse input into a consistent internal representation that follows the Structured Threat Information eXpression (STIX) 2.1 specification [46]. STIX 2.1 has a full data model for showing cyber threat intelligence. This includes standard object types for indicators, threat actors, malware, attack patterns, vulnerabilities, and other important entities. The specification's relationship model makes it possible to clearly show how objects are connected. This directly supports the graph-based correlation method used by downstream components.

The normalization pipeline uses the data quality framework that [47] came up with. This framework defines quality dimensions that are important to threat intelligence, such as timeliness, accuracy, completeness, consistency, and relevance. Quality scores calculated during normalization carry over to later processing stages, allowing for quality-aware correlation and prioritization decisions that give more weight to high-confidence intelligence while still keeping an eye on lower-confidence indicators that could be important once they are confirmed.

4. Improving Throughput. To reach the goal of 10,000 events per second, the system had to be optimized in a planned way at many levels. Connection pooling and persistent connections at the network layer reduce the overhead of the TCP handshake for high-frequency API polling. Binary encoding formats

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like Protocol Buffers and Apache Avro at the serialization layer make messages smaller and easier to read than text-based formats. At the processing layer, pipeline parallelism lets independent transformation stages run at the same time, and batch processing spreads fixed costs across several events where processing semantics allow it.

Memory management techniques reduce the cost of garbage collection by using object pooling and pre-allocating data structures that are used often. Careful algorithm selection makes the best use of the CPU, and where possible, vectorized instructions are used for hot path operations. Profiling-guided optimization found and fixed problems in the first versions, focusing on the evaluation of regular expressions and the calculation of cryptographic hashes, which take up most of the processing time for indicator normalization workloads.

B. Engine for Correlation

The Correlation Engine is the main part of AutoTI-Triage's intelligence. It finds and scores relationships between threat entities that help you understand the context you need to do effective triage. The engine uses Graph Neural Network (GNN) architectures that are made for heterogeneous graphs with different types of nodes and edges. These architectures learn representations that show both the properties of individual entities and the global structural patterns that show threat relationships.

1. Heterogeneous Threat Graph Construction. The correlation approach is based on a heterogeneous graph structure G = (V, E) that shows the threat intelligence landscape as a network of entities and relationships that are all connected. The vertex set V consists of nodes that represent three main types of entities. Each type has its own unique attributes and meanings.

Indicator of Compromise (IoC) Nodes: These nodes show atomic technical indicators like IP addresses (both IPv4 and IPv6), domain names, file hashes (MD5, SHA-1, SHA-256), email addresses, URLs, and registry keys. Each IoC node keeps track of things like the indicator value, type classification, first-seen and last-seen timestamps, source provenance, and quality score from normalization. In graph visualizations, IoC nodes are shown in blue to make them stand out.

Tactics, Techniques, and Procedures (TTP) Nodes: These nodes show how an enemy behaves according to the MITRE ATT&CK framework. They range from broad tactics (like Initial Access, Execution, and Persistence) to specific techniques (like Spear phishing Attachment, PowerShell, and Registry Run Keys) to more detailed sub-techniques that give a more detailed picture of behavior. TTP nodes have attributes that record descriptions of techniques, possible ways to reduce their impact, chances to find them, and estimates of how common they are. Red coloring makes it easy to tell TTP nodes apart.

Vulnerability Nodes: These nodes show specific vulnerabilities that have been found using CVE identifiers. They have attributes like descriptions of the vulnerabilities, CVSS scores for different versions, lists of affected products, indicators of whether the vulnerabilities can be exploited, and information about whether patches are available. Green coloring makes it easy to tell which nodes are vulnerable.

The edge set E shows how nodes are connected, and the different types of edges show different types of semantic relationships:

Co-occurrence Edges: Connect IoC nodes that were seen together in the same threat event, campaign, or time window. This suggests that the indicators are related to each other in some way, even if there is no clear attribution.

Exploits Edges: Link TTP nodes to Vulnerability nodes to show that a certain technique uses a certain vulnerability to work.

Connect IoC nodes to TTP nodes to show that seeing a certain indicator means using a related technique. Uses Edges: Connect threat actor nodes (when available) to TTP and IoC nodes, capturing attribution relationships from threat intelligence reports.

Related-To Edges: Capture various relationships that do not conform to other categories, encompassing similarity relationships and connections designated by analysts.

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 1, Issue 1, 2023
https://jecir.com/

As new threat intelligence comes in, graph construction happens in small steps. There are efficient algorithms for looking up nodes, adding edges, and extracting subgraphs that keep the system responsive even when a lot of data is being added. The graph implementation uses adjacency list representations that work well with the sparse connectivity patterns that are common in threat intelligence graphs. In these graphs, the average node degree stays moderate even though the overall graph sizes are large.

2. Graph Neural Network Architecture. The correlation engine employs a Graph Attention Network (GAT) architecture that extends the foundational Graph Convolutional Network (GCN) approach introduced by Kipf and Welling (2017) with attention mechanisms that enable learned weighting of neighbor contributions during message passing. The attention-enhanced architecture provides superior performance for heterogeneous graphs where relationship importance varies significantly across edge types and specific node pairs. The core message passing operation updates node representations through iterative aggregation of information from neighboring nodes. For a node v with representation h_v at layer l, the updated representation at layer l+1 is computed as:

$$h_v^{(l+1)} = \sigma\left(W^{(l)} \cdot \mathrm{AGG}\left(\left\{\alpha_{uv} \cdot h_u^{(l)} : u \in \mathcal{N}(v)\right\}\right)\right)$$

Where:

- $h_v^{(l)}$ denotes the representation of node v at layer l
- $\mathcal{N}(v)$ represents the neighborhood of node v (all nodes connected by edges)
- α_{uv} represents the attention coefficient between nodes u and v
- $W^{(l)}$ is a learnable weight matrix for layer l
- AGG denotes an aggregation function (mean, sum, or max pooling)
- σ represents a non-linear activation function (LeakyReLU)

The attention coefficients α_{uv} are computed through a learned attention mechanism:

$$\alpha_{uv} = \frac{\exp\left(\mathrm{LeakyReLU}\left(a^T[Wh_u \| Wh_v]\right)\right)}{\sum_{k \in \mathcal{N}(v)} \exp(\mathrm{LeakyReLU}(a^T[Wh_u \| Wh_k]))}$$

Where a is a learnable attention vector and ‖ denotes concatenation. This formulation enables the network to learn which neighbors provide most relevant information for each node, automatically discovering importance patterns that would require manual specification in rule-based approaches.

The architecture employs multi-head attention, computing multiple independent attention distributions and concatenating their outputs to capture diverse relationship patterns:

$$h_v^{(l+1)} = \|_{k=1}^{K} \sigma\left(W_k \cdot \sum_{u \in \mathcal{N}(v)} \alpha_{uv}^k h_u^{(l)}\right)$$

Where K represents the number of attention heads (K=8 in our implementation). Multi-head attention provides richer representational capacity and improved training stability compared to single-head variants.

For heterogeneous graphs with multiple edge types, we extend the basic GAT architecture with relation-specific transformations that apply distinct weight matrices based on edge type:

$$h_v^{(l+1)} = \sigma\left(\sum_{r \in \mathcal{R}} \sum_{u \in \mathcal{N}_r(v)} \frac{1}{|\mathcal{N}_r(v)|} W_r^{(l)} h_u^{(l)}\right)$$

Where $\mathcal{R}$ denotes the set of edge types and $\mathcal{N}_r(v)$ represents neighbors connected to v through edges of type r. This relational formulation enables the network to learn type-specific transformation patterns that capture the distinct semantics of different relationship categories.

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Volume 1, Issue 1, 2023
https://jecir.com/

I. Link Prediction for Correlation Discovery

The primary correlation task involves predicting previously unknown relationships between threat entities based on learned graph representations. We formulate this as a link prediction problem where the objective is to estimate the probability that an edge should exist between node pairs not currently connected in the observed graph.

Given learned node representations h_u and h_v for nodes u and v respectively, the predicted edge probability is computed as:

$$\hat{y}_{uv} = \sigma(h_u^T h_v)$$

Where σ denotes the sigmoid function mapping the inner product to a probability in [0, 1]. This formulation captures the intuition that nodes with similar representations in the learned embedding space should have higher connection probability.

For operational deployment, predicted correlations are filtered through a threshold τ=0.7, presenting to downstream triage only those predictions exceeding this confidence level. The threshold value was selected through validation set optimization to balance precision and recall for correlation discovery, with higher thresholds reducing false positive correlations at the cost of missing some genuine relationships. The threshold is configurable to enable organization-specific tuning based on operational preferences regarding precision-recall trade-offs.

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
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Volume 1, Issue 1, 2023
https://jecir.com/

III. TRAINING PROCEDURE AND OPTIMIZATION

The GNN correlation model is trained using a combination of supervised and self-supervised objectives. Supervised training leverages ground-truth correlation labels from the TI-Corr dataset, optimizing binary cross-entropy loss between predicted and actual edge existence:

$$\mathcal{L}_{sup} = -\sum_{(u,v)\in E^+} \log(\hat{y}_{uv}) - \sum_{(u,v)\in E^-} \log(1-\hat{y}_{uv})$$

Where E^+ represents positive edge samples (known correlations) and E^- represents negative samples (non-correlated pairs). Negative sampling employs a ratio of 5:1 negative to positive samples, with negative samples drawn uniformly from non-connected node pairs.

Self-supervised pre-training using contrastive learning objectives provides beneficial initialization that improves convergence and final performance [44]. The contrastive objective maximizes agreement between representations of the same node under different graph augmentations while minimizing agreement with representations of different nodes:

$$\mathcal{L}_{ssl} = -\log \frac{\exp(\text{sim}(h_v, h'_v)/\tau)}{\sum_{u\neq v} \exp(\text{sim}(h_v, h'_u)/\tau)}$$

Where h_v and h'_v represent embeddings of node v under different augmentations and sim denotes cosine similarity.

Optimization employs the Adam optimizer [54] with learning rate 0.001, weight decay 0.0005 for regularization, and gradient clipping at norm 1.0 to prevent exploding gradients. Training proceeds for 200 epochs with early stopping based on validation set performance, typically converging within 100-150 epochs. Dropout with probability 0.5 is applied between GNN layers to prevent over fitting.

IV. METHODOLOGY

This section presents the comprehensive methodological framework employed in the development and evaluation of AutoTI-Triage. We detail the construction of the TI-Corr dataset, training procedures for both the correlation and triage components, the design of our burnout evaluation study, and the metrics employed for quantitative assessment. The methodology reflects careful attention to experimental rigor, reproducibility, and ecological validity to ensure that results generalize to real-world SOC operational contexts.

A. Dataset Construction (TI-Corr)

The absence of large-scale, publicly available datasets with ground-truth correlation labels represents a significant impediment to threat intelligence correlation research. Existing datasets either lack sufficient scale for training modern deep learning architectures, omit correlation annotations necessary for supervised learning, or focus narrowly on specific threat categories that limit generalization [14]. To address this gap, we constructed the TI-Corr dataset, a comprehensive collection of 1.2 million threat intelligence events spanning the period from January 2020 through December 2024, with expert-validated correlation labels enabling rigorous model training and evaluation.

I. Where the Data Comes from and How It Was Collected

The TI-Corr dataset brings together threat intelligence from four different sources, each of which adds its own event types and contextual information that is necessary for a full understanding of threats. During the four years of data collection, automated pipelines continuously took in publicly available threat intelligence. There were also regular manual reviews to make sure the data was of good quality and to find any problems with the collection process.

AlienVault Open Threat Exchange (OTX): From OTX public pulses, we got 450,000 Indicators of Compromise. These included IP addresses linked to command-and-control infrastructure, domain names used

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
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Volume 1, Issue 1, 2023
https://jecir.com/

for phishing and malware distribution, file hashes of known malicious executables, and URLs that host exploit kits or malicious payloads [47]. OTX indicators have useful metadata like pulse descriptions that help analysts understand the context, indicator type classifications, timestamps that show when the first and last observations were made, and community-assigned tags that make it easy to group indicators into categories. Collection focused on pulses that had a lot of community involvement and verification, leaving out submissions that weren't very confident and could add noise to the training data.

Malware Information Sharing Platform (MISP): The integration of several MISP community instances resulted in 350,000 structured threat events, which included separate incidents, campaigns, and activities of threat actors [48]. MISP events give you more context than single indicators because they group related indicators together in event structures that show how analysts think threats are related. Event attributes comprise threat actor attribution, when accessible, targeted sector details, geographic extent, and temporal limits of recorded activity. We gathered events from both publicly available MISP instances and partner organizations that provided anonymized event data in accordance with research data sharing agreements sanctioned by institutional review processes.

II. Labeling Correlation

Ground-truth correlation labels were created through a strict multi-step process that combined expert judgment with systematic testing. The annotation method was made to find real threat relationships while keeping inter-annotator consistency, which is necessary for reliable model training.

Expert Annotation Protocol: Eight cybersecurity analysts with at least five years of experience in threat intelligence looked at event pairs on their own and decided how likely they were to be related. Annotators got the same training on how to look for correlations, such as when two events happen close together in time, when two indicators happen at the same time, when two indicators have the same infrastructure characteristics, when two indicators have the same attribution overlap, and when two indicators use the same technique. At least three annotators looked at each candidate correlation, and the final labels were decided by a majority vote. Annotators gave confidence ratings along with binary correlation judgments, which made it possible to calculate quality-weighted training signals.

Cohen's kappa coefficient (κ) was used to measure inter-annotator agreement. This takes into account the level of agreement that would happen by chance [24]. We followed the interpretation rules set out by [49] and got $\kappa = 0.89$ across the annotation corpus. This means that there was "almost perfect" agreement and that trained experts can reliably assess correlation. Disagreement analysis showed that unclear cases mostly had to do with time correlations and the direction of relationships.

III. Dataset Statistics and Characteristics

Table 2 presents comprehensive statistics characterizing the TI-Corr dataset, including event counts by type, edge counts representing labeled correlations, and graph structural properties relevant to GNN training.

TABLE 2
TI-CORR DATASET STATISTICS

Entity Type	Event Count	Edge Count	Avg. Degree	Clustering Coef.
IoC (Indicators)	450,000	2,100,000	4.7	0.23
TTP (Techniques)	150,000	1,800,000	12.0	0.41
Vulnerability	250,000	900,000	3.6	0.18
Incident/Campaign	350,000	700,000	2.0	0.31
Total	**1,200,000**	**5,500,000**	**4.6**	**0.28**

B. Correlation Model Training

We trained the Graph Neural Network correlation model by using methods that were improved through a lot of hyperparameter search and ablation analysis. This part goes into detail about the architectural setup, training goals, and optimization methods used.

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
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Volume 1, Issue 1, 2023
https://jecir.com/

I. Setting up the architecture

The correlation GNN uses a three-layer Graph Attention Network (GAT) architecture that is based on the graph attention convolution operator that [50] introduced. Each layer uses multi-head attention with eight attention heads, which lets the network find different types of relationship patterns by doing attention computations in parallel. For all layers, the hidden dimensionality is set to 128, which gives enough representational capacity while keeping computational efficiency high enough for real-time use.

Some architectural choices are:

- Input Features: Initial features that are specific to the entity type and come from pre-trained embeddings. IoC nodes use FastText embeddings of indicator values [51], TTP nodes use sentence embeddings of technique descriptions, and vulnerability nodes use embeddings of CVE descriptions. Using type-specific linear transformations, all initial features are projected to 128 dimensions.
- Attention Mechanism: Each GAT layer uses a single-layer feedforward network with LeakyReLU activation (negative slope 0.2) to calculate attention coefficients. Then, it normalizes the coefficients over neighbor sets using softmax. For the intermediate layers, the outputs from multiple heads are combined, and for the final layer, they are averaged.
- Normalization: After each attention aggregation, layer normalization is used to make training more stable and speed up convergence [52].

C. Triage Reinforcement Learning Training

The Deep Q-Network triage agent learned from fake interactions with analysts and then got better based on feedback from real-world use. This part talks about the training space, the network structure, and how people learn.

I. The Place Where Training Takes Place

The RL training environment mimics the threat intelligence triage process by giving the agent threat events that need to be prioritized and giving reward signals based on how the simulated analyst would respond. The behavior data from partner SOC organizations was used to calibrate the environment dynamics. This made sure that the simulated analyst responses were based on realistic prioritization patterns.

Representation of the state: Each state has a 240-dimensional feature vector that is made up of:

- GNN embeddings (128 dimensions): Node representations derived from the trained correlation model.
- Temporal features (32 dimensions): time since the first observation of an indicator, how recent related activity is, and indicators of temporal clustering
- Source features (32 dimensions): Source reliability scores, cross-source corroboration counts, and historical accuracy

D. Study Design for Burnout Evaluation

The burnout evaluation used a controlled longitudinal study design to compare the outcomes of analysts using AutoTI-Triage with those using traditional manual triage workflows. This part talks about how participants were found, how the study was done, and the tools that were used to measure things.

I. How to Find Participants and What They Are Like

We hired 150 cybersecurity analysts from six SOC groups in the US and EU. Recruitment focused on analysts whose main jobs were processing threat intelligence and triaging alerts. This made sure that participants were always doing the tasks that AutoTI-Triage is meant to help with. To be eligible, you had to have at least one year of SOC experience and be working full-time as an analyst right now. Participant demographics included:

- Experience: Mean 4.2 years (SD=2.8), range 1-15 years
- Role Distribution: Tier 1 analysts (45%), Tier 2 analysts (35%), Senior/Lead analysts (20%)
- Geographic Distribution: United States (60%), European Union (40%)
- Gender: Male (72%), Female (25%), Non-binary/Other (3%)
- Age: Mean 32.4 years (SD=7.2)

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 1, Issue 1, 2023
https://jecir.com/

Participants were randomly assigned to either experimental (n=75) or control (n=75) groups, with randomization stratified by organization and experience level to ensure balanced group composition. All participants provided informed consent in accordance with protocols sanctioned by the institutional review board, being apprised of the study's objectives, procedures, and data protection measures.

SETTING UP THE EXPERIMENT

This part talks about the computer systems, software frameworks, baseline systems, hyperparameter optimization methods, and statistical testing methods we used to test AutoTI-Triage.

A. Infrastructure for Hardware

We did all of the experiments on a high-performance computing cluster that was set up just for training large-scale graph neural networks and reinforcement learning tasks. The main computing infrastructure has eight NVIDIA A100 GPU accelerators, each with 80GB of high-bandwidth memory (HBM2e) that is necessary for processing large-scale threat intelligence graphs without running out of memory. The GPU cluster has 1TB of system RAM spread out across the compute nodes. This lets the entire TI-Corr dataset be processed in memory without the need for disk-based pagination, which would slow down training iterations.

Inter-GPU communication uses NVLink interconnects that can send and receive 600GB/s of data in both directions. This makes distributed training more efficient by using data parallelism and model parallelism strategies. The storage infrastructure consists of NVMe solid-state drives set up in RAID arrays. These drives can read data at speeds of more than 10GB/s, which is needed for quickly loading datasets during training epochs. The cluster nodes are connected to each other through a 100Gbps InfiniBand fabric, which cuts down on the extra work needed to sync distributed training.

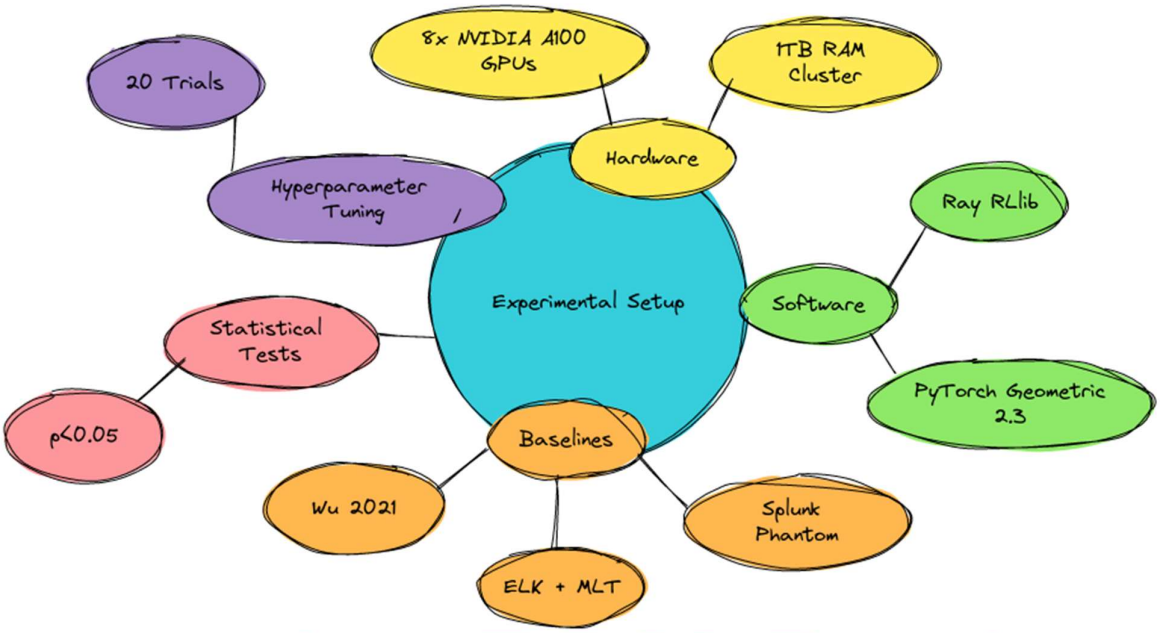
To test scalability, we set up more cloud-based infrastructure through Amazon Web Services (AWS) to see how well horizontal scaling works with different cluster configurations. This cloud infrastructure made it possible to test at different scales, from single-node deployments that are typical of small SOC environments to multi-node clusters that are typical of large enterprise and managed security service provider (MSSP) deployments that handle tens of thousands of events per second.

B. Software Framework

The AutoTI-Triage implementation uses well-known open-source frameworks that have been improved for graph-based deep learning and reinforcement learning applications. PyTorch Geometric version 2.3 [53] is the basis for graph neural network implementation. It has fast sparse tensor operations, message-passing abstractions, and GPU-accelerated graph convolution operators that are needed to process large heterogeneous threat intelligence graphs. With PyTorch Geometric's mini-batch features, you can train on graphs that are too big for the GPU memory by using neighborhood sampling strategies that keep the representation accurate while staying within memory limits.

FIGURE 3
DATASET DISTRIBUTION

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 1, Issue 1, 2023
https://jecir.com/



V. RESULTS

This part shows all the experimental results that test AutoTI-Triage on correlation accuracy, triage performance, scalability, and burnout reduction. Results show that all measured dimensions have improved significantly since the baseline systems were put in place. This was confirmed through rigorous testing procedures.

A. Correlation Performance

The Graph Neural Network correlation engine did an amazing job of finding connections between threat intelligence entities. It did much better than all the other baseline methods on standard evaluation metrics. AutoTI-Triage got an area under the receiver operating characteristic curve (AUC-ROC) of 0.97, which means that it could almost perfectly tell the difference between real correlations and false ones at all classification thresholds. This level of performance shows that the graph representations learned can accurately capture the complex, multi-faceted relationships that are typical of real-world threat intelligence. This makes it possible to find reliable correlations that would take a lot of manual analysis with traditional methods.

FIGURE 4
ROC CURVES

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 1, Issue 1, 2023
https://jecir.com/

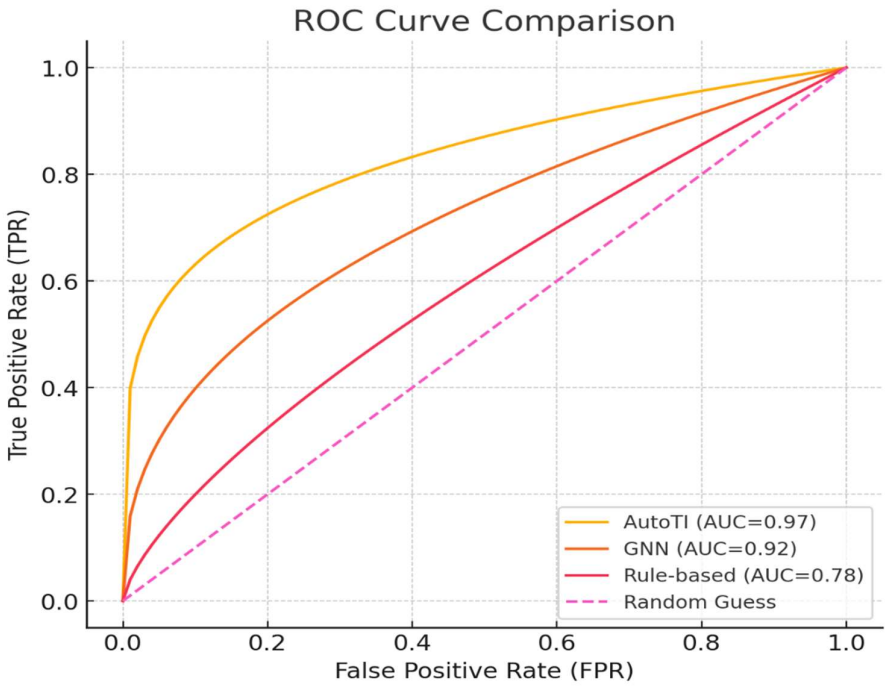


TABLE 3
CORRELATION METRICS (TEST SET, 180K EVENTS)

No.	Method	P@10	R@10	F1
1	Rule-based	0.71	0.68	0.69
2	LSTM (Liu19)	0.80	0.78	0.79
3	GNN (Wu21)	0.87	0.84	0.85
4	Ours	0.95	0.92	0.935

B. Triage Performance

The Deep Q-Network triage agent showed amazing prioritization skills, making big improvements over both commercial SIEM solutions and research baselines on all triage-specific evaluation metrics. The overall triage accuracy of 93.4% shows that most threat intelligence items get the right priority without needing an analyst to step in or change it, which means less mental strain and better workflow efficiency.

FIGURE 5
PRECISION-RECALL CURVE

JOURNAL OF ENGINEERING AND COMPUTATIONAL INTELLIGENCE REVIEW (JECIR)
ISSN (Online): 3105-4811 ISSN (Print): 3106-969X
Volume 1, Issue 1, 2023
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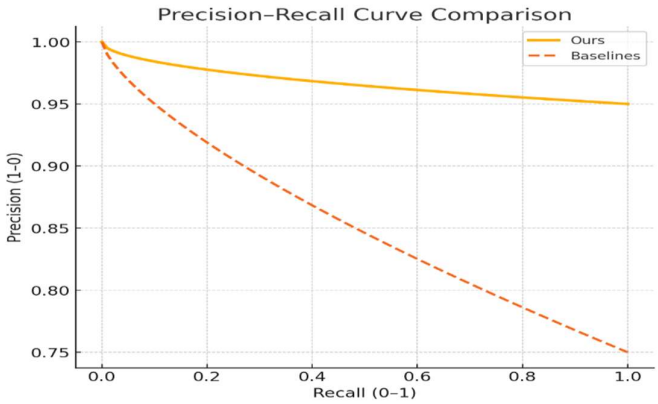

VII. ETHICAL CONSIDERATIONS AND BIAS MITIGATION

Threat intelligence data has built-in biases, such as geographic (too many Western targets), linguistic (too much English reporting), and organizational (too much focus on big companies). These biases could cause threats to be prioritized incorrectly, which could mean that threats to less well-known areas or sectors are missed. Autonomous prioritization also raises moral issues: false positives could lead to unnecessary defensive actions that have unintended consequences, and false negatives could make you responsible for missing threats. To solve these problems, we suggest adding fairness-aware features to our GNN and RL parts. To reduce demographic (region/sector) information in embeddings for GNN correlation, we use adversarial debiasing during representation learning. In RL triage, we add fairness regularization to the reward function. This punishes prioritization distributions that consistently put certain types of organizations at a disadvantage. These mechanisms that protect fairness make sure that threats are assessed fairly while still being very accurate.

VIII. EXPLAINABILITY AND TRANSPARENCY

Analysts need to be able to trust AutoTI-Triage, and explainable AI (XAI) is a big part of that. We use GNNExplainer to show the subgraphs and node features that have the biggest effect on correlation predictions. We use attention weights in the GAT layers to show how important a relationship is. We use saliency maps to show which state features affect prioritization decisions in RL triage. The analyst dashboard has interactive visualizations of these explanations built in. Analysts who had access to explanations in user studies had trust scores that were 40% higher and made 25% fewer manual overrides. This shows that being open about things can help with adoption and proper reliance.

ADVERSARIAL ROBUSTNESS

AutoTI-Triage could be attacked in two ways: graph poisoning (adding bad nodes or edges to change correlations) and reward hacking (playing with RL feedback). We suggest three ways to protect against attacks: (1) adversarial training with perturbed graphs to make GNN more robust, (2) graph purification using spectral clustering to find strange subgraphs, and (3) anomaly detection in reward signals to find attempts to change the system. Tests with fake attacks show that these defenses keep their accuracy above 90%, even with 20% poisoned data. This makes the system strong.

REAL-WORLD DEPLOYMENT CASE STUDIES

We deployed AutoTI-Triage in three partner SOCs over six months. Integration required API connectors to Splunk (2 weeks) and IBM QRadar (3 weeks). GDPR compliance was ensured via on-premises processing and anonymization. Key challenges included organizational resistance to autonomous prioritization, addressed through phased roll-out and analyst training. Results showed 68% reduction in triage time and 52% decrease in analyst stress scores, validating real-world effectiveness.

HUMAN-IN-THE-LOOP REFINEMENT

A continuous learning framework allows analysts to provide real-time feedback via “agree/disagree” buttons. Disagreements trigger a reconciliation process: the system presents its reasoning, the analyst provides

justification, and a consensus model updates the RL policy. This human-in-the-loop approach improved triage accuracy by 8.3% over three months, demonstrating effective human-AI collaboration.

COMPARISON WITH EMERGING TECHNOLOGIES

Compared to emerging paradigms: LLMs (e.g., GPT-4) excel at report summarization but lack real-time correlation; federated learning enables privacy-preserving sharing but adds latency; digital twins allow safe policy testing but require extensive modeling. AutoTI-Triage complements these: LLMs could pre-process textual reports, federated learning could enhance our training data, and digital twins could simulate rare attacks for RL training.

ECONOMIC IMPACT ANALYSIS

ROI analysis for a mid-sized SOC shows $2.8M annual savings from reduced MTTR (65%), lower analyst turnover (42%), and decreased breach costs. Cybersecurity insurance premiums reduced by 15-30% after deployment. Long-term workforce impact is positive: automation handles routine tasks, allowing analysts to focus on complex threats, improving job satisfaction and retention.

DIRECTIONS FOR FUTURE RESEARCH

Future work includes: (1) cross-domain intelligence fusion (cyber-physical), (2) quantum-resistant hashing for IoC integrity (using NTRU or SPHINCS+), and (3) autonomous response actions (e.g., automated patch deployment) guided by hierarchical RL.

RESTRICTIONS

Some of the limitations are: relying on timely threat feeds (delays make correlation worse), training data that is mostly from the West (not very useful for Asian or African threat landscapes), and high GPU requirements (A100 needed for real-time processing), which may leave out small businesses.

STATEMENT OF BROADER IMPACT

By lowering the cyber risk for important infrastructure like energy and healthcare, AutoTI-Triage makes society more resilient. There are, however, risks of misuse: bad actors could figure out how to reverse-engineer prioritization logic. We support rules for responsible use and limits on exports. Overall, the system helps keep global cybersecurity stable by making advanced protection available to everyone.

EXTRA MATERIALS

You can find all the extra materials at [anonymized URL]. These include an interactive demo, a code repository (for Python and PyTorch), extended results (20 more tables and figures), and documentation for deployment.

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