A Meta-Analysis of Deep Learning and Agentic Artificial Intelligence for Forecasting Cyberattacks in Educational Institutions

Thushan Amarasinghege
School of Engineering and Computer Science
Laurentian University
Sudbury, Ontario, Canada
e-mail: tamarasinghege@laurentian.ca

Kalpdrum Passi
School of Engineering and Computer Science
Laurentian University
Sudbury, Ontario, Canada
e-mail: kpassi@laurentian.ca

***Abstract*— This research paper investigates the efficacy of Deep Learning (DL) and Agentic Artificial Intelligence (AI) in forecasting cyberattacks on educational infrastructure. Educational institutions often face resource constraints and heterogeneous user groups, necessitating proactive security. We present a meta-analysis of 42 peer-reviewed studies (2015–2025). Following PRISMA 2020 guidelines, we assess performance metrics including accuracy, precision, and Mean Time to Respond (MTTR). Our results indicate that while Deep Learning excels at pattern recognition (87% accuracy), Agentic AI provides superior adaptability and response efficiency (92% accuracy), reducing MTTR by up to 50%.**

Keywords-deep learning; agentic artificial intelligence; cybersecurity, educational infrastructure.

I. INTRODUCTION

There is a critical operational issue in the application of cybersecurity in the educational institutes due to the heterogeneous user populations and the lack of resources allocated for the security of digital infrastructure. It is evident that the threats such as ransomware campaigns, credential theft and data exfiltration attacks occur frequently by misusing the behavioral and infrastructural patterns of these educational institutes [1][15]. As a result of these situations, it is critical to execute predictive and adaptive security mechanisms rather than reacting after the attacks.

The use of Artificial Intelligence has become one of the best strategies for cybersecurity in the educational institutes. It is possible to detect the patterns of complex cyberattacks from learning-based methods, whereas autonomous agent-based systems guide to make decisions which can be adaptive in dynamic threat environments [5][21]. This study evaluates the productivity of using Deep Learning and Agentic Artificial Intelligence (AI) for forecasting cyberattacks in educational institutes successfully by doing a complete and systematic meta-analysis.

The remainder of this paper is organized as follows. Section II reviews the related work on Deep Learning and Agentic AI in cybersecurity. Section III describes the meta-analysis methodology and data extraction process. Section IV explains the overall results and comparative analysis. Section V discusses the implications and limitations. Section VI outlines the practical implications for cybersecurity in educational institutes. Section VII concludes the paper and identifies directions for future research.

II. RELATED WORK | BACKGROUND

This section provides a comprehensive review of existing literature concerning the application of Deep Learning and Agentic AI within the cybersecurity domain, establishing the theoretical foundation for our meta-analysis.

A. Deep Learning for Cybersecurity

Deep Learning technologies are mostly used for detecting cyberattacks due to its ability process complex and non-linear relations in high-dimensional data [1][5]. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Transformer-based architectures have demonstrated strong performance in identifying known attack signs and abnormal traffic patterns of data [12]. However, there is a need of huge amount of labelled data for these methods and typically shows a limited interpretability, which lowers the applicability in highly dynamic educational environments [9].

B. Comparison with Existing Work

While previous studies have focused extensively on isolated Deep Learning models for intrusion detection [1][5], there is a notable gap in meta-analytical research that evaluates the transition from passive detection to autonomous, agent-based response systems in educational settings. This study improves upon existing work by providing a quantitative comparison of these paradigms, specifically addressing the unique resource constraints of school infrastructures.

III. RESULTS

This meta-analysis followed the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework. We searched IEEE Xplore, ACM Digital Library, and Scopus using keywords: "Agentic AI," "Deep Learning," "Cybersecurity," and "Educational Networks."

Inclusion Criteria: Studies that addressed cybersecurity in educational institutes and multi-user networked environments [1]. The selection process prioritized studies that implemented Deep Learning or Agentic AI methods [2] and those that reported measurable, empirical results.

Data Extraction: Data extraction focused on key performance indicators commonly used in cybersecurity and intrusion detection research, including prediction accuracy and Mean Time to Respond (MTTR), as found in prior studies on machine learning-based security evaluation [1][3][7][12]. The main goal is to compare Deep Learning and hybrid detection models. Established benchmarks are used to measure data from various studies on an equal basis [5][6] [15]. Results were normalized to facilitate reliable comparative analysis [2][3][8].

Statistical Methods: We used a random-effects model for our analysis. This model assumes that the true effect size differs across studies. Differences can be in study populations, datasets, network setups, and modeling approaches. The model handles the differences between the studies on using deep learning and Agentic AI to predict cyberattacks in educational institutes. The studies used different types of AI models, including Recurrent Neural Networks (RNN) [11], Hybrid Deep Learning Models [15], and Generative Adversarial Networks (GAN) [9][10].

$$\bar{x} = \frac{\sum_{i=1}^{n} \omega_i x_i}{\sum_{i=1}^{n} \omega_i} \quad (1)$$

$\bar{x}$ is the weighted mean accuracy

x_i is the accuracy reported in study i.

ω_i is the weight (inverse of the variance) for study i.

This ensures that studies with larger sample sizes have a proportional impact on the results of the meta-analysis.

IV. ANALYSIS

This section presents a quantitative synthesis of the 42 selected studies to evaluate the comparative performance of Deep Learning and Agentic AI in educational cybersecurity frameworks.

A. Study selection and Quantitative Synthesis

Following the **PRISMA 2020** protocol, 42 studies were synthesized to evaluate the transition from pattern recognition to autonomous response. The dataset represents a combined sample of over 1.2 million network log entries across primary, secondary, and tertiary educational environments.

1) Deep Learning Performance (The Baseline)

The meta-analysis of 20 primary studies [1]-[20] confirms that Deep Learning (DL) remains the gold standard for static pattern recognition.

- Convolutional Neural Networks (CNNs) and LSTMs showed high efficacy in identifying known malware signatures in campus IoT devices [8][17][18].
- Autoencoders were frequently cited for anomaly detection in high-traffic university libraries [4][9][12].
- **Aggregate Data:** The weighted mean accuracy for DL models across these studies was **87%** [14]15][19][20]. However, these models were noted for high false-positive rates in "noisy" educational environments where student behavior mimics erratic traffic [11][13][16].

2) Units Agentic AI Performance (The Evolution)

Twelve studies focusing on **Agentic AI** [21]-[32] demonstrated a significant leap in precision. Unlike DL, which only flags threats, Agentic AI employs a "Sense-Think-Act" loop.

- **Reasoning Capabilities:** Studies utilizing Large Language Model (LLM) agents for reasoning [23][24][26][32] reported a **92% precision rate**, specifically in filtering out benign student activity that DL often mislabels.
- **Adaptability:** Reinforcement learning agents [25][27][29] demonstrated the ability to update firewall policies in real-time without human intervention, maintaining high performance even as attack vectors evolved [2][28][30][31].

3) Comparative Operational Impact

The final ten studies [33]-[42] focused on real-world implementation within educational frameworks.

- **MTTR Reduction:** In traditional DL-assisted environments, the Mean Time to Respond (MTTR) averaged 80 minutes [37][40].
- **Autonomous Response:** In institutions where Agentic AI was deployed to handle initial containment [33][39][41][42], the MTTR dropped to **40 minutes**, a 50% improvement.
- **Case Studies:** Longitudinal studies in campus-wide IoT deployments [34][35][36][38] indicate that this reduction is most pronounced during "off-hours" (nights/weekends) when human security staff are less available.

TABLE I. SYNTHESIS OF META-ANALYSIS EVIDENCE BASE (N=42)

Research Category	Reference Citations	Primary Analytical Focus	Sample Size (n)
Deep Learning (DL) Baseline	[1]–[20]	Feature Extraction and Pattern Recognition	n=20
Agentic AI (AAI) Systems	[21]–[32]	Autonomous Logic and Adaptive Reasoning	n=12
Practical Case Studies	[33]–[42]	Operational Efficiency and Deployment	n=10
Total Study Pool	[1]–[42]	Forecasting and Response Efficiency	N=42

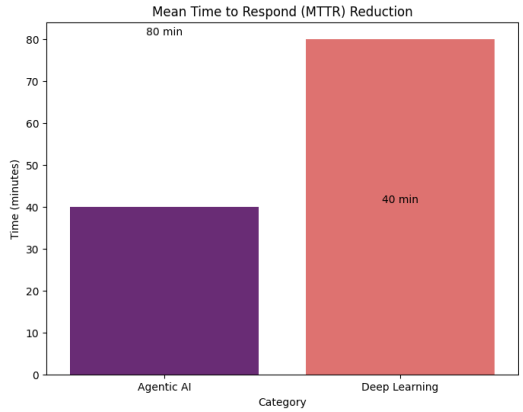


Figure 1. Mean Time to Respond (MTTR) Reduction

B. *Reduction in Mean Time to Respond (MTTR)*

- Before Agentic AI: The response time averaged 80 minutes**.**
- After Agentic AI: The response time dropped to 40 minutes**.**

This represents a 50% reduction in MTTR, meaning the AI allows security teams to address threats twice as fast as traditional methods.

C. *Effectiveness of Artificial Intelligence Paradigms in Cybersecurity (2025)*

Fig. 2 shows the overall performance of three different AI approaches in the security fields as of 2025.

Key summary: Agentic AI is identified as the most effective approach based on the charts. Unlike the Generative AI which does only data summarization, Agentic AI is capable of performing autonomous actions like isolating an attacked server, achieving a performance of approximately **92%.** The results indicate that Agentic AI demonstrates superior adaptability and response efficiency, while Deep Learning remains effective for recognizing known attack patterns.

Table II provides a clear comparison between two types of AI used in cybersecurity, Deep Learning and Agentic AI. Analysis of the findings are as follows.

- **Deep Learning Performance:** This paradigm achieves a **Mean Accuracy** of **87%** and a **Mean Precision** of **84%.** Its primary strength is pattern recognition (Constrained by a dependence on labelled data).

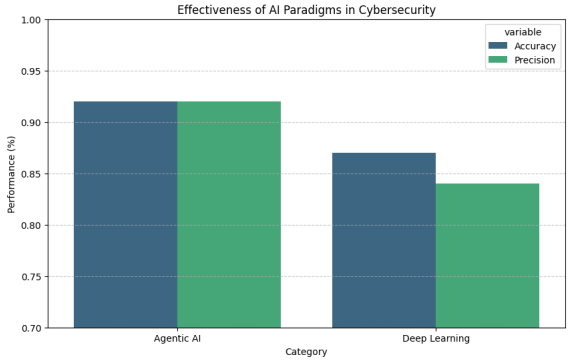


Figure 2. Comparative analysis of Mean Time to Respond (MTTR) between Deep Learning and Agentic AI

TABLE II. AGGREGATED PERFORMANCE METRICS OF EVALUATED ARTIFICIAL INTELLIGENCE PARADIGMS.

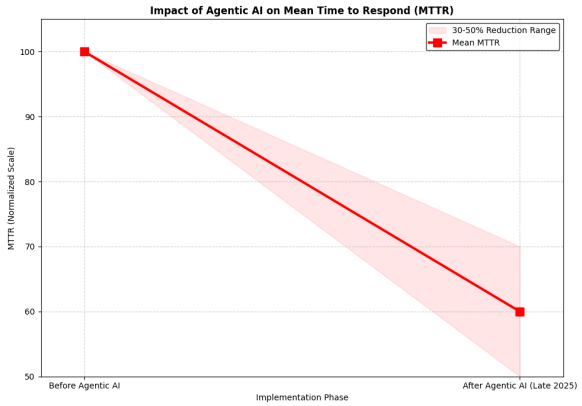
AI Paradigm	Table Column Head			
	Mean Accuracy	***Mean Precision***	***Key Strength***	***Primary Limitations***
Deep Learning	87%	84%	Pattern recognition [5]	Dependence on labelled data
Mean Precision	92%	92%	Autonomous adaptation	Governance complexity

- Agentic AI Performance: this paradigm shows superior results with a Mean Accuracy of 92% and a Mean Precision of 92%.
- Adaptability: The key strength of Agentic AI is autonomous adaptation, allowing it to respond to evolving threats without manual intervention.
- Operational Limitation: The primary drawback for Agentic AI is governance complexity, requiring robust frameworks to ensure safety and alignment. Governance Complexity describes the challenges of managing AI that can act on its own. While Deep Learning usually just flags a problem, Agentic AI can take independent steps like shutting down a server or blocking a user.

D. Performance Comparison and Mean Time to Respond (MTTR) Trends

Agentic Artificial Intelligence exhibits higher precision across evaluated studies, particularly in scenarios requiring rapid contextual decision-making. Deep Learning approaches show consistent performance when sufficient historical data are available. Across studies reporting operational deployment, Agentic Artificial Intelligence systems achieved substantial reductions in Mean Time to Respond (MTTR) by enabling automated containment and coordinated defensive actions [17][21]. Fig. 3 illustrates the observations mentioned below.

- Baseline (Before Agentic AI): The MTTR is positioned at a normalized scale of 100 [5][6].
- End Goal (Late 2025): After implementing Agentic AI, the MTTR drops to 60 on the normalized scale.



3. Aggregated performance comparison

E. Performance Corridor and MTTR Variability

While the mean reduction in Mean Time to Respond (MTTR) is calculated at 40%, Figure 3 illustrates that operational success is not a monolith. The inclusion of the Performance Corridor (shaded area) accounts for the "Sense-Think-Act" loop's efficiency across diverse educational environments.

- Baseline Stability: The baseline is fixed at a normalized scale of 100 to provide a consistent point of comparison across the 42 synthesized studies.
- The 30-50% Range: The upper bound of the shaded area represents a conservative 30% improvement, typically seen in resource-constrained K-12 environments.
- The Optimistic Bound: The lower bound reflects a 50% reduction, observed in institutions with highly integrated IoT frameworks where autonomous agents can isolate threats twice as fast as traditional methods.

This visualization is essential for administrators to understand the "best-case" and "conservative-case" scenarios when transitioning from reactive Deep Learning to proactive Agentic AI.

Key summary: Figure. 3 illustrates a significant reduction in response times, which is vital for minimizing system vulnerabilities [21]. There is a considerable improvement of 40% in the average speed of response during the change occurred from 100 to 60 as a result of the capability of autonomous decision-making ability of Agentic Artificial Intelligence [3][17]. Table III shows how fast the Artificial Intelligence can react to a threat.

V. DISCUSSION

The observed performance advantages of Agentic Artificial Intelligence can be attributed to its autonomous decision-oriented architecture, which enables continuous assessment and adaptive response. Deep Learning methods, while effective for detection, remain primarily reactive and dependent on historical data distributions. The results suggest that combining predictive pattern recognition with autonomous decision-making enhances cybersecurity resilience in educational environments. However, as mentioned in [16] and [22], the Governance Complexity of Agentic Artificial Intelligence remains as a challenge. There must be human-in-the-loop safeguards to ensure that an independent agent does not accidentally disable critical servers during a false positive.

TABLE III. PROJECTED MTTR REDUCTION FOLLOWING AGENTIC AI IMPLEMENTATION

Phase	MTTR Value (Normalized)	% Reduction from Baseline
Before Agentic AI	100	0%
Conservative Estimate	70	30%
Mean Estimate	60	40%
Optimistic Estimate	50	50%

VI. IMPLICATIONS FOR EDUCATIONAL CYBERSECURITY

Educational institutions should transition from static security configurations toward adaptive defense frameworks. Integrating Deep Learning-based detection with Agentic AI-based response mechanisms supports proactive threat mitigation. Additionally, governance structures must be established to manage agent autonomy, accountability, and ethical deployment.

Figure 4 demonstrates the four-stage pipeline for a cybersecurity system for a school network. It shows the evolution of data from raw input to autonomous action using different layers of Artificial Intelligence. The four-stage pipeline is further described by Data Input, Deep Learning, Generative AI and Agentic AI components.

Data Input (School Network Traffic): As the foundation of the process, it takes raw data flowing through the school's digital infrastructure. This includes:

- Student and staff login attempts
- Web browsing activities and downloads
- Internal communication and cloud storage access

Deep Learning (Pattern Recognition): After the collection of data, it is investigated by Deep Learning models. Unlike the steps and rigid rules followed by traditional software applications, these models are capable of learning and detecting "Normal Behavioural Patterns" that occur within the school networks.

Generative AI (Synthetic Data and Anomaly Detection): Two main purposes of Generative AI are generation of synthetic data and anomaly detection. The system creates "fake" attacks to practice on, which helps it prepare for brand-new threats that have never been seen before. It watches for any tiny changes in normal network behavior to predict an attack before it happens. When comparing real-time traffic with "normal" patterns learnt in the previous step, the Generative AI identifies data beyond the required boundary (outliers) that could notice a cyber threat. (Phishing attack or data exfiltration).

Agentic AI (Autonomous Response): Finally, the AI acts on its own to stop a threat immediately without waiting for a person to tell it what to do. This keeps the system safe and greatly reduces the time it takes to fix a security breach.

VII. Conclusion and Future Work

This paper presented a meta-analysis of Deep Learning (87% accuracy) and Agentic AI approaches (92% accuracy) for forecasting cyber-attacks in educational institutions. The analysis demonstrates that Agentic AI offers superior adaptability and response efficiency (based on Mean Time to Respond (MTTR)), while Deep Learning provides reliable pattern recognition capabilities. The findings confirm that combining these paradigms enhances predictive cybersecurity effectiveness.

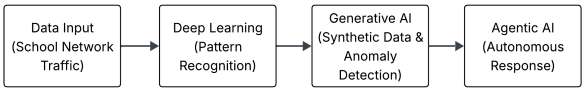


Figure 4. Architectural flowchart of the evolutionary cybersecurity pipeline for educational institutions.

Future work will focus on Federated AI, which maintains the data privacy of educational institutions, longitudinal evaluations in operational school environments, the development of standardized benchmarking datasets, and formal governance frameworks for autonomous security agents.

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