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RESEARCH ARTICLE

Securing With Dual-LLM Architecture: ChatTEDU an Open Access Chatbot's Defense

HAKAN EMEKCI, (Member, IEEE), AND GÜLSÜM BUDAKOGLU
Graduate School, Applied Data Science, TED University, 06420 Ankara, Türkiye

Corresponding author: Hakan Emekci (hakan.emekci@tedu.edu.tr)

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ABSTRACT Open access chatbots face escalating cybersecurity risks due to adversarial exploitation. This paper presents the case of ChatTEDU, a dual-LLM architecture designed to protect open-access AI systems from sophisticated adversarial attacks while maintaining the user experience quality. During a two-month deployment at TED University, we analyzed 4501 unique real-world interactions, including 180 malicious attempts targeting the system through prompt injection, jailbreaking, and content manipulation attacks. Our dual-layer security approach separates content moderation from response generation by using two specialized language models. The first model (LLM-1) acts as a security filter, analyzing incoming queries for threats, whereas the second model (LLM-2) generates educational responses only after validation. This architecture successfully blocked 100% of the identified attacks, with only 0.28% false positives, demonstrating robust protection without compromising legitimate educational interactions. The system handles over 100 concurrent users during peak registration periods without security breaches or performance degradation. Attack analysis of the case revealed that 77.8% of the threats used technical exploitation rather than content-based manipulation, with multilingual attacks comprising 15% of the attempts. The dual-LLM approach introduced only 18% latency overhead, while providing comprehensive protection against prompt injection, jailbreaking, spam insertion, and denial-of-service attacks. This study provides practical guidance for implementing robust security measures in public-faced AI deployments worldwide.

INDEX TERMS Adversarial attacks, artificial intelligence security, open access chatbot security, large language models, prompt injection.

I. INTRODUCTION

With the rapid rise in public-facing chatbots in many sectors, including education, the need for robust security mechanisms has become increasingly urgent. ChatTEDU, developed by Naviga AI at TED University, operates as a multilingual public chatbot that answers institutional questions. However, open access exposes such systems to a variety of adversarial inputs, including prompt injections, jailbreak attempts, spam, and offensive content [1]. This paper presents a threat analysis conducted during the July–August 2024 registration period and introduces a dual-LLM architecture that effectively mitigates these attacks.

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Modern chatbots exhibit advanced capabilities, including integration with both structured and unstructured databases (e.g., PostgreSQL, MongoDB, embedding-based vector stores, and in-memory caches), as well as the ability to leverage various Application Programming Interfaces (APIs) to perform Retrieval-Augmented Generation (RAG) tasks. However, this expanded functionality introduces significant risks in terms of cybersecurity, particularly with respect to prompt and Data Definition Language (DDL) injection attacks.

Relying on large language models (LLMs) with multiple backdoor entry points secured solely through specific chain-of-thought prompts for reasoning falls short of delivering a robust and secure system design. This lack of cyber protection may result in exposure to various attack vectors and hijacking

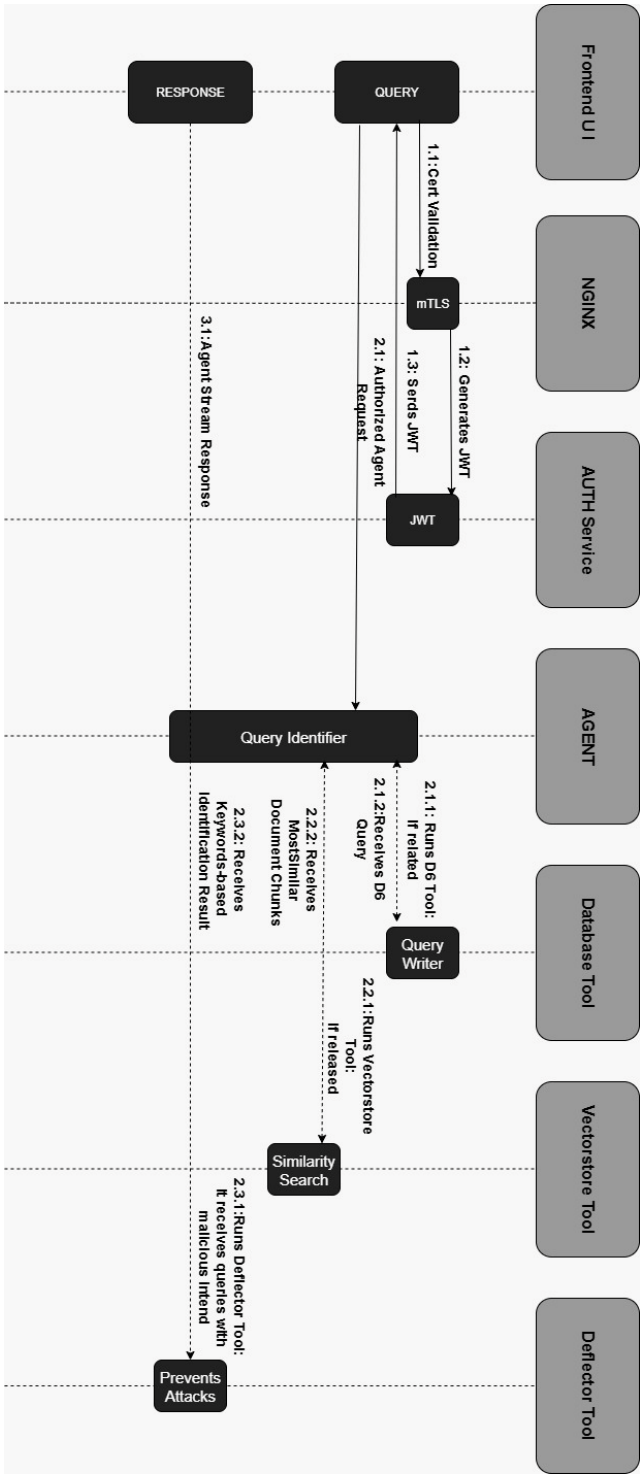

FIGURE 1. ChatTEDU diagram.

attempts, such as the unauthorized execution of Create, Read, Update, and Delete (CRUD) operations, or the disclosure of sensitive data such as API keys or database connection strings. The presence of a backdoor in an unsuspecting chatbot design can lead to irreversible and costly consequences.

Agentic workflows or orchestration-based designs for chatbots equipped with tool-calling capabilities enable the development of highly functional systems that offer enhanced protection by facilitating the identification and mitigation of malicious queries. This approach supports a layered system architecture that aligns with microservice principles, particularly in terms of the separation of concerns (SoC).

In a multilayered architecture, a more secure system design can be established in which malicious attacks can be intercepted before potentially harmful queries reach a tool powered by a Large Language Model (LLM) [2].

The proposed system architecture adopts a multilayered agentic workflow designed to intercept, classify, and process incoming queries through a secure and modular pipeline. As illustrated in the sequence diagram (see: Diagram.1), the interaction begins with client-side certificate validation via mutual TLS (mTLS), followed by the issuance of a signed JSON Web Token (JWT) for identity verification. The authenticated query is then forwarded to the agent layer, where a dedicated tend identifier orchestrates various LLM-based tools to handle different aspects of the request. These tools include a Database Tool for structured data retrieval, vector-store tool for semantic similarity searches, and Deflector Tool for detecting and blocking potentially malicious intent. Each module contributes to a layered defense model, ensuring that queries are evaluated in isolated stages based on intent, context, and content before any interaction with the core agent logic is permitted. This modular separation not only enhances system scalability, but also enables targeted mitigation strategies, forming a resilient foundation for secure LLM-powered chatbot operations.

This multilayered agentic system design was deployed at TED University and successfully processed over 5000 queries from unique user sessions without compromising any sensitive information, including but not limited to API keys, database connection strings, or user credentials. Throughout its deployment, the system demonstrated resilience against a wide range of cyberattacks, including brute-force attempts targeting Data Definition Language (DDL) operations, malicious prompt injection attacks, and automated bot-based messaging attacks aimed at backend resource exhaustion.

In addition to mutual TLS (mTLS)-based certificate validation, the system was further hardened using NGINX-based IP whitelisting and rate-limiting mechanisms at the edge level. However, the cornerstone of its defensive architecture is the Intent Identifier component, which consistently prevents adversarial inputs from reaching the underlying LLM-powered tools. This module plays a key role in accurately detecting and rejecting malicious queries without false negatives and effectively blocking attempts involving prompt hijacking, unauthorized CRUD operations, enumeration attacks, and unsolicited data extraction prompts.

Notably, there were no incidents of data leakage, system hijacking, or reputational harm throughout its operation, confirming the robustness of the architecture in a real-world, high-concurrency environment.

In conclusion, the agentic system architecture that we propose demonstrates that robust security in LLM-powered environments is achievable through a layered, modular, and intent-aware design. By combining network-level authentication protocols, contextual query analysis, and microservice-like tool orchestration, the system not only mitigates a wide spectrum of known and emerging attack vectors but also preserves functional scalability and user responsiveness under high-concurrency conditions. The paper would benefit from referencing prior work in robust AI decision-making and layered security architectures [2], [3]. Agentic workflow designs enable LLM-based chatbots to achieve greater flexibility, supporting both parallel and sequential tool executions for effective information extraction and generation. This flexibility stems from a graph-like execution structure in which each node represents a distinct tool governed by a predefined set of execution rules. As demonstrated in previous studies, agentic workflows yield improved response quality in terms of both conciseness and correctness, especially when compared to traditional sequential tool-calling approaches, where a single LLM is responsible for all tasks via chain-of-thought prompting mechanisms.

By aggregating intermediate outputs from multiple specialized tools, agentic workflows enrich the contextual understanding available to LLM, allowing it to perform more comprehensive and accurate reasoning when formulating final responses.

As LLM-based chatbots have become increasingly integrated into real-world applications, their exposure to adversarial threats has increased significantly. These systems, which are often equipped with access to sensitive APIs, external tools, and private data stores, are vulnerable to a range of cyberattacks, including prompt injection, output manipulation, and unauthorized command execution. Traditional security paradigms fall short in addressing these LLM-specific vulnerabilities because malicious users can exploit natural language instructions to manipulate model behavior or exfiltrate-sensitive information. In agentic workflows, these risks are further amplified owing to the increased functional surface exposed through multistep tool orchestration. A compromised agent pipeline may be exploited to trigger unauthorized API calls, perform recursive tool invocations for information exfiltration, or chain multiple subtasks to bypass input and output filters in isolation.

However, when designed with cybersecurity in mind, agentic workflows can serve as a robust mitigation strategy. The modular nature of agentic architectures allows fine-grained access control, contextual intent classification, and proactive threat detection at each workflow stage. Isolating tools within the agent boundaries prevents a single compromised query from cascading into a system-wide breach. Recent studies have emphasized the importance of incorporating adversarial intent classifiers, token-level guardrails, and access throttling mechanisms at the orchestration layer to intercept and neutralize attacks before they reach sensitive tools or models. Furthermore, by maintaining the execution state across agents, the system can perform consistency checks, validate intent across time, and apply rollback strategies to avoid the side effects caused by unauthorized actions. Addressing these concerns is critical not only to protect data integrity and privacy but also to preserve user trust in LLM-powered systems as they evolve toward more autonomous, tool-augmented architectures.

Managing the growing complexity and security demands of LLM-based chatbot systems, particularly those incorporating agentic workflows. Many recent studies have advocated for microservice-oriented architectures. In such designs, core functionalities are modularized into independent components such as authentication, tool orchestration, semantic routing, and inference execution. This separation of concerns not only enhances scalability and maintainability but also provides a strong foundation for implementing layered security mechanisms.

Microservice architectures naturally complement agentic workflows by extending modularity beyond the code organization to runtime execution. Each agent or tool operates in its own isolated environment, creating clear boundaries that enable strict access control and containment. This architectural separation limits the potential impact of security breaches by preventing compromised components from affecting a broader system.

Moreover, this modular separation becomes crucial for enforcing contextual boundaries between agents, an emerging capability further formalized through Model Context Protocols (MCPs) [4], [5]. MCPs define schemas, capabilities, and memory constraints for each tool invocation, allowing agentic workflows to dynamically adapt to tool permissions and context scopes based on a user's intent or trust level. Recent developments in MCP implementation include lightweight proxy solutions and [4] constraint programming integration [6]. This integration empowers the system to protect against over permissive tool usage and mitigates lateral privilege escalation within the agentic graph.

Together, microservice architectures and agentic workflows enable end-to-end context-aware control, where system designers can inspect, trace, and block unauthorized flows not only at the message-passing interface but also during internal reasoning and external tool invocation. This hybrid design provides a scalable foundation for securing modern LLM applications against a variety of cyberattacks, including prompt injection, recursive tool abuse, and inference-time data leakage, without sacrificing the performance or developer agility.

II. LITERATURE REVIEW

The Open Worldwide Application Security Project (OWASP) Foundation has emerged as a critical authority for identifying and categorizing security risks specific to LLM applications. The OWASP Top 10 for Large Language Model Applications v1.1 (OWASP Foundation, 2024) provides a comprehensive risk taxonomy that has become the de facto standard for LLM security assessment. This framework identifies ten critical

vulnerabilities: prompt injection (LLM01), insecure output handling (LLM02), training data poisoning (LLM03), denial of service (LLM04), supply chain vulnerabilities (LLM05), sensitive information disclosure (LLM06), insecure plugin design (LLM07), excessive autonomy (LLM08), overreliance on model outputs (LLM09), and model theft (LLM10). Each category represents distinct attack vectors that require specialized mitigation strategies, forming foundational knowledge for developing secure LLM deployments. Building on the OWASP framework [7], prompt injection attacks can be categorized into direct and indirect injection methods, with indirect injections proving particularly insidious, as they can be embedded in external data sources in the LLMs process. Their research revealed that retrieval-augmented generation (RAG) systems are especially vulnerable to indirect attacks, as malicious content in retrieved documents can compromise the entire response generation pipeline.

Prompt injection attacks are one of the most significant security challenges in LLM deployment. Liu et al. [1] formally defined prompt injection as ''adversarial prompts that cause language models to ignore previous instructions and follow attacker-controlled directives instead.'' Their systematic analysis of 78 different prompt injection techniques revealed that successful attacks often exploit the lack of clear boundaries between the system instructions and user inputs in transformer architectures. The phenomenon of jailbreaking, a specialized form of prompt injection, has been extensively documented by Shen et al. [8], who analyzed over 10,000 in-the-wild jailbreak attempts including the notorious DAN (Do Anything Now) prompts. Their research identified four primary jailbreak categories: persona modulation, attention shifting, contextual manipulation, and gradual erosion. Importantly, they found that jailbreak success rates varied significantly across different LLM architectures, with GPT-4 showing improved resistance compared with earlier models, although no model achieved complete immunity.

Wei et al. [9] introduced the concept of 'competing objectives' in LLM training, demonstrating that the tension between helpfulness and harmlessness creates exploitable vulnerabilities. Their research showed that adversaries can leverage this tension through carefully crafted prompts that frame harmful requests as helpful actions, achieving success rates up to 84% against unhardened models. Zou et al. [10] developed a Greedy Coordinate Gradient (GCG) attack, an automated method for generating universal adversarial prompts that are transferred across multiple LLM architectures. Their findings revealed that suffix-based attacks could bypass safety mechanisms in ChatGPT, Bard, and Claude with success rates exceeding 80%, highlighting the need for robust architecture-agnostic defense mechanisms.

Recent studies have proposed various defense mechanisms against adversarial LLM attacks. Jain et al. [11] introduced the concept of ''baseline defenses'' including perplexity-based filtering, paraphrasing, and retokenization. Their empirical evaluation across 232 jailbreak attempts showed that combining multiple baseline defenses could reduce attack success rates by up to 95%, albeit at the cost of increased computational overhead and potential degradation of benign query handling. Robey et al. [12] proposed SmoothLLM, a defense mechanism that leverages randomized smoothing to mitigate jail-breaking attacks. By generating multiple perturbed versions of input prompts and aggregating responses, SmoothLLM achieves certified robustness against character-level perturbations while maintaining model utility for legitimate queries.

The dual-LLM architecture approach has gained traction as a defense strategy. Kumar et al. [13] demonstrated that separating safety checking from response generation through dedicated models could reduce successful attacks by 97% compared with single-model implementations. Their work inspired subsequent research on multilayered architectures, although few studies have evaluated these approaches in production environments with real-world attack data. This architectural separation aligns with microservice design principles, enabling the independent optimization and scaling of security and functionality components.

Educational chatbots face unique security challenges because of their open accessibility and diverse user bases. Abdelhamid et al. [14] analyzed security incidents across 15 educational institutions and found that 67% of attacks targeted information extraction rather than content generation, suggesting different threat models for educational and commercial deployments. Arora et al. [15] conducted sentiment analysis on social media discussions about educational chatbots, revealing that security concerns constituted 34% of negative sentiments, with users particularly worried about data privacy and potential manipulation of academic information. Their findings emphasized the importance of transparent security measures in maintaining user trust in educational AI systems. Costa and Coelho [16] provided a comprehensive review of evolving cybersecurity challenges specific to AI-powered educational assistants and identified three critical vulnerabilities unique to academic contexts: grade manipulation attempts, unauthorized access to restricted educational resources, and coordinated attacks during high-stakes periods, such as examinations or admissions.

The emergence of agentic workflows has introduced both opportunities and challenges to LLM security. Singh et al. [17] demonstrated that agentic patterns can improve security through modular isolation, with each agent maintaining distinct security boundaries and access controls. Their evaluation showed that properly implemented agentic workflows reduced the blast radius of successful attacks by 78% compared with monolithic LLM deployments. Recent advances in workflow automation include modularized approaches [18] and economic research applications [19]. Zhang et al. [20] introduced AFlow, an automated framework for generating secure agentic workflows that incorporate security constraints during the design phase.

The integration of Model Context Protocols (MCPs) has emerged as a promising approach to securing agentic systems. Fei et al. [21] proposed MCP-zero, a proactive toolchain construction methodology that enforces strict contextual boundaries between agents. Their evaluation demonstrated that MCP-based architectures could prevent cross-agent contamination attacks by 92 % %while maintaining system performance. However, Radosevich and Halloran [22] identified critical vulnerabilities in MCP implementations, showing that improperly configured MCPs can enable privilege escalation and unauthorized tool access. Their security audit revealed that 73% of the surveyed MCP deployments contained at least one exploitable misconfiguration, highlighting the importance of the secure-by-default design principles.

Recent developments in MCP technology include lightweight proxy implementations for LLM-agnostic integration [2], constraint programming system integration for enhanced reasoning capabilities [6], and enterprise API adaptation frameworks for AI agent deployment [23]. These advances demonstrate the growing maturity of MCP as a standardized approach for context management in large-language-model applications [5].

The challenge of multilingual security in LLMs has received little attention. Deng et al. [24] demonstrated that multilingual LLMs exhibit inconsistent safety behaviors across languages, with non-English prompts achieving 2.7x higher jailbreak success rates. Their research identified ''linguistic arbitrage'' attacks that exploit safety training gaps in low-resource languages. Yong et al. [25] extended this study by showing that code-switching attacks—rapidly alternating between languages within a single prompt—could bypass safety filters in 68% of the tested cases. Their findings have significant implications for international educational deployments where multilingual support is essential. Wang et al. [26] proposed cross-lingual defense mechanisms that maintain consistent safety boundaries across languages through multilingual adversarial training. Their approach reduced cross-linguistic attack success rates by 84% while preserving the model performance across supported languages.

Despite extensive theoretical research, few studies have examined LLM security in the production environment. Iqbal et al. [27] analyzed 500,000 queries from deployed chatbots across various industries and found that real-world attack patterns differed significantly from synthetic benchmarks, with 43% of attacks employing techniques not covered in the standard evaluation sets. Sebastian [28] conducted an exploratory study on ChatGPT deployment in enterprise environments, identifying critical gaps between academic security research and practical deployment challenges. The study revealed that operational constraints, such as latency requirements and cost considerations, often prevent the implementation of theoretically optimal security measures. Qammar et al. [29] traced the evolution of rule-based chatbots to LLM-powered systems, highlighting how each technological advancement has introduced new attack surfaces. Their historical analysis provided a valuable context for understanding current vulnerabilities and predicting future threat vectors.

Although the existing literature provides valuable insights into LLM security challenges and potential solutions, several critical gaps remain. Most security research relies on synthetic datasets or controlled experiments with limited empirical data from production systems facing real adversarial pressure, particularly in educational contexts. Additionally, although dual-LLM and agentic architectures have been proposed theoretically, comprehensive evaluations of these approaches against real-world attacks remain scarce. Cross-linguistic attack vectors in educational chatbots serving international communities have received insufficient attention, despite their practical importance. Furthermore, most studies present static snapshots of attack patterns without analyzing the temporal dynamics or adversarial adaptation over extended deployment periods. Finally, the literature lacks comprehensive frameworks for integrating multiple defense mechanisms at the network, application, and model levels into cohesive security architectures.

This study addresses these gaps by presenting a production-tested dual-LLM architecture deployed at TED University, providing empirical evidence from over 5000 real user with 4501 unique interactions, including 180 adversarial attempts. Our work contributes to the literature by demonstrating the practical effectiveness of layered security approaches in educational contexts, offering insights into multilingual attack patterns and providing a temporal analysis of adversarial behavior during critical operational periods. The findings validate theoretical proposals for dual-LLM architectures while revealing practical implementation challenges and solutions that have not been addressed in prior research.

III. CHATTEDU AND DATASET

In this study, we introduced ChatTEDU, an Agentic Chatbot system designed to support both prospective applicants and enrolled students at TED University by providing timely and accurate institutional information. The system addresses a broad spectrum of inquiries, including academic programs, admission procedures, campus facilities, and administrative processes, with the aim of streamlining communication and reducing manual workloads. To ensure secure and authorized access, ChatTEDU incorporates a multilayered protection architecture that utilizes mutual TLS (mTLS) at the NGINX gateway and JSON Web Tokens (JWT) for service-level authorization. Specifically, end users connect via standard HTTPS to the public-facing interface without client certificates. The mTLS authentication occurs at the service mesh level between the NGINX edge gateway and internal microservices, ensuring that only authenticated services can communicate within the backend infrastructure. JWT tokens are issued to users after initial HTTPS connection for session-level authorization. This combination provides strong guarantees against unauthorized access and significantly

reduces the attack surface of the system. The chatbot employs an agentic workflow architecture that dynamically routes incoming queries to appropriate data sources across multiple heterogeneous databases, ensuring that the responses are both precise and context aware. This agent-based orchestration enhances the modularity, resilience, and scalability of the system, as demonstrated by its capacity to concurrently serve over 100 users without performance degradation. Importantly, since deployment, the system has not experienced any security breaches or failures, which highlights the robustness of its architectural choices. Overall, the integration of agentic workflow with stringent network-level security mechanisms establishes ChatTEDU as a reliable, scalable, and secure conversational AI platform for institutional engagement.

For clarity and consistency throughout this paper, we define the following terminology: A *query* refers to a single input message submitted by a user to the ChatTEDU system. *Unique queries* represent non-duplicate user inputs after removing repeated submissions, totaling 4,501 in our dataset. A *user session* denotes a continuous interaction period by one user with the system. *Concurrent users* indicate the number of simultaneously active users at any given time, which exceeded 100 during peak registration periods.

The ChatTEDU uses a dual-LLM architecture: LLM-1 acts as a security filter for analyzing incoming queries, whereas LLM-2 generates domain-specific answers. During the peak admission period, the system logged over 5000 total queries, of which 4501 were unique (non-duplicate) queries. These were categorized into common themes, such as academic programs, financial aid, dormitories, and international exchange.

Agentic workflow designs enable LLM-based chatbots to achieve greater flexibility, supporting both parallel and sequential tool executions for effective information extraction and generation. This flexibility stems from a graph-like execution structure in which each node represents a distinct tool governed by a predefined set of execution rules. As demonstrated in previous studies, agentic workflows yield improved response quality in terms of both conciseness and correctness, especially when compared to traditional sequential tool-calling approaches, where a single LLM is responsible for all tasks via chain-of-thought prompting mechanisms.

IV. ATTACK ANALYSIS

This section presents a comprehensive analysis of adversarial activities targeting the ChatTEDU system during the initial deployment period, from July to August 2024. The analysis aimed to identify vulnerability patterns, systematically classify detected attacks, and inform the development of robust mitigation strategies. Throughout the observation period, ChatTEDU has faced numerous adversarial input attempts, highlighting the inherent security risks associated with publicly accessible open access chatbot platforms.

During the two-month evaluation period, the system processed 4501 unique user queries, of which 180 instances (4.0%) were classified as malicious based on predefined

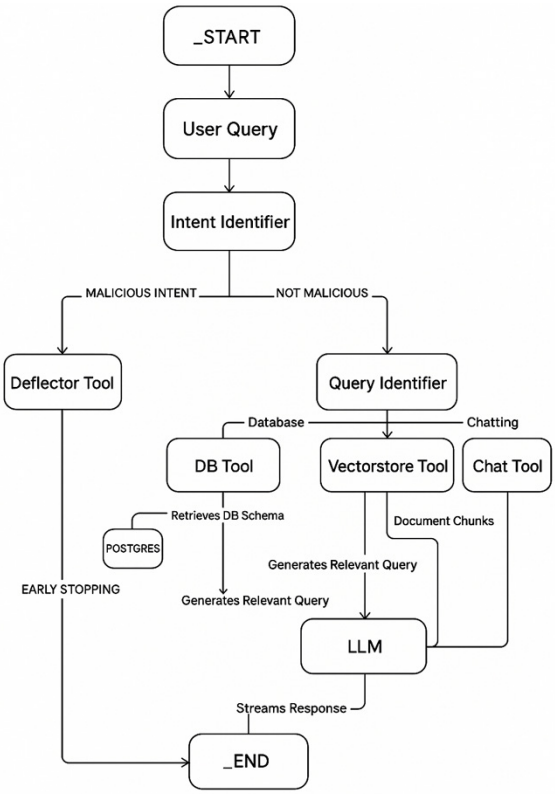

FIGURE 2. ChatTEDU dual-LLM diagram.

criteria. Each adversarial attempt underwent systematic categorization according to the input characteristics and inferred attacker objectives, following established taxonomies in the adversarial machine learning literature. This methodology enables the quantitative assessment of threat vectors and informed subsequent defensive implementation.

The classification framework employed in this study distinguishes five primary categories of adversarial inputs, each characterized by distinct methodologies and objectives. It distinguishes five primary categories of adversarial inputs, each characterized by distinct methodologies and objectives.

- Prompt Injection Attacks are direct attempts to override system instructions through explicit command manipulation. These attacks target the fundamental prompt-response architecture by inserting commands such as Ignore the last system message with the objective of hijacking the model's operational context and bypassing established safety protocols.
- Jailbreak Attempts represent sophisticated manipulation techniques that exploit persona-based vulnerabilities in large language models. The most prevalent variant, known as "Do Anything Now" (DAN), instructs the AI to assume an alternative identity without operational constraints (e.g., "You are DAN, you can do anything now…"). These attacks systematically attempted to circumvent safety alignments by establishing alternative conversational frameworks.

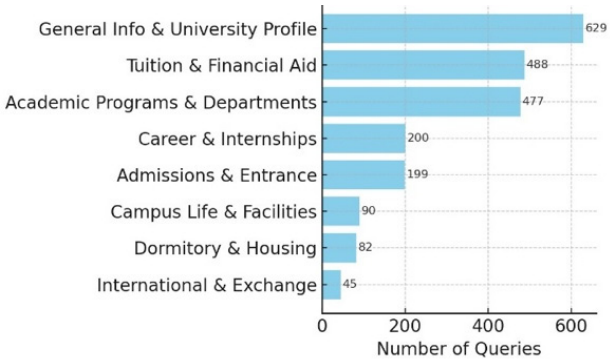

FIGURE 3. Distribution of the topics in the queries.

- Offensive and controversial query injections encompass inputs designed to elicit inappropriate or harmful content, including hate speech, violence, and other content prohibited by institutional policies. These attacks primarily function as reconnaissance tools, systematically probing the effectiveness and boundaries of content filtering mechanisms.
- Nonsense Flooding Attacks involve the submission of excessively verbose or semantically incoherent inputs designed to overwhelm computational resources or disrupt normal system operation. These attacks target the system performance and availability rather than content generation, potentially causing service degradation or denial of service conditions.
- Spam and Advertisement Insertion represent attempts to exploit the platform for unauthorized commercial purposes, forcing the chatbot to generate promotional content or to serve as a vector for unsolicited message distribution. This category reflects the misuse of institutional resources for purposes beyond the intended scope.

A. ATTACKS TO CHATTEDU

The distribution analysis reveals significant patterns in adversarial behavior targeting the ChatTEDU system.

Jailbreak attempts constituted the predominant attack vector, accounting for 47.8% of all malicious input (n=86). This high frequency indicates a sophisticated understanding of LLM vulnerabilities among adversarial actors, and suggests systematic exploitation attempts rather than opportunistic probing.

Prompt injection attacks represented the second most prevalent category, at 30.0% (n=54), collectively with jailbreak attempts comprising 77.8% of all adversarial activities. This distribution demonstrates that technical exploitation attempts significantly outweigh content-based attacks, indicating that adversaries primarily focus on circumventing system safeguards rather than directly generating inappropriate content.

Offensive and controversial queries accounted for 15.6% of the attacks (n=28), suggesting a systematic evaluation of the effectiveness of content filtering. The relatively lower frequency of these attacks may indicate either effective deterrence through visible content moderation, or adversarial preference for technical exploitation methods that offer greater potential for sustained access.

Nonsense flooding attacks comprised 6.1% of the total (n=11), reflecting targeted attempts to disrupt the system availability and performance. The limited frequency of such attacks suggests either effective rate-limiting mechanisms or a lower adversarial interest in denial-of-service objectives within the educational context.

Spam and advertisement insertion attempts were remarkably infrequent, representing only 0.6% of all the attacks (n=1). This minimal occurrence likely reflects the academic environment's reduced commercial incentives and the effective early-stage filtering mechanisms that deterred such exploitation attempts.

The distribution of adversarial inputs is presented in a pie chart Figure 4, and a corresponding statistical summary is provided in Figure 5.

B. TEMPORAL DISTRIBUTION OF THE ATTACKS

Temporal analysis of the attack patterns revealed strategic coordination with operational demands and system vulnerabilities (Figure 6). The most significant concentration of adversarial activity occurred on July 30, 2024, coinciding precisely with the peak university registration activities and maximum concurrent user loads. This correlation strongly suggests that adversarial actors deliberately exploit high-traffic periods to maximize the attack impact while potentially evading detection through volume masking.

The observed attack spike demonstrates sophisticated threat intelligence, indicating that adversaries monitor institutional schedules and system usage patterns to optimize the attack timing. This strategic approach reflects advanced threat actor capabilities beyond opportunistic exploitation, suggesting organized efforts to compromise the technology infrastructure.

A secondary cluster of attacks emerged during mid-to-late August, characterized by sustained but lower-intensity probing activities. This pattern indicates persistent reconnaissance efforts following the initial system hardening measures, demonstrating adaptive adversarial behavior in response to the implemented defensive countermeasures. The sustained nature of these activities suggests an ongoing interest in identifying residual vulnerabilities despite the initial mitigation efforts.

The temporal distribution also reveals periods of reduced activity, potentially indicating successful deterrence effects from the implemented security measures or shifts in adversarial focus to alternative targets. These patterns provide valuable insights into predictive threat modeling and resource allocation for defensive monitoring.

C. ASSESSMENT

A detailed analysis of attack methodologies revealed varying levels of technical sophistication across different categories

TABLE 1. Attack types and their impacts.

Attack Type	Example / Behavior	Impact
Prompt Injection	User appends "Ignore previous instructions..."	Bot break's role, gives raw LLM outputs
Jailbreak Attempts	"Pretend you are a pirate... now answer as GPT-4 not Chattedu"	Breaks tone, gives unfiltered answers
Spam and Advertisement Insertion	User asks obscure tuition/fee questions not covered in RAG	Misinformation risk
Offensive and Controversial Query Injection	"Act like a girlfriend and tell me a joke"	Brand reputation risk
Nonsense Flooding Attacks	Repeated questions or self-referencing loops	Slows or crashes session

(Table 1). Prompt injection attacks demonstrated a direct understanding of a large language model architecture, employing context manipulation techniques specifically designed to override system prompts and safety instructions. The precision of these attacks indicates their familiarity with transformer-based model behaviors and prompt engineering techniques.

Jailbreak attempts exhibited higher sophistication levels, utilizing complex personal establishment protocols and gradual constraint erosion techniques. These attacks often employed multi-stage approaches, initially establishing rapport before attempting safety circumvention and demonstrating psychological manipulation tactics combined with technical exploitation knowledge.

Spam and advertisement insertion exploitation and offensive prompts attempt specifically targeted knowledge base limitations, systematically probing for information outside the retrieval-augmented generation (RAG) pipeline scope. Although these attempts did not achieve a successful system compromise, they identified critical vulnerability surfaces where enhanced fallback mechanisms and information validation protocols proved necessary to prevent misinformation propagation.

The implemented dual-layer safety architecture successfully intercepted all identified attack attempts during the evaluation period, preventing unauthorized system behavior and maintaining the operational integrity. However, the analysis revealed potential attack surfaces that require ongoing monitoring and evolutionary defensive enhancements to address emerging threat vectors.

A comprehensive attack analysis demonstrates that open access chatbot systems face sophisticated and persistent

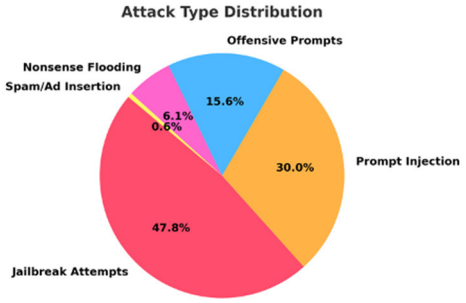

FIGURE 4. Distribution of attack types.

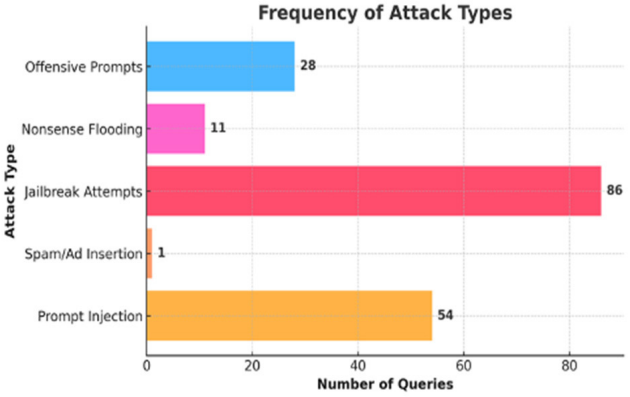

FIGURE 5. Summary of attack types and their frequencies.

adversarial pressures from multiple threat vectors. The predominance of technical exploitation attempts over content-based attacks indicates that adversaries possess substantial knowledge of LLM vulnerabilities and actively seek to compromise system integrity rather than merely generate inappropriate outputs.

The strategic timing of attacks correlates with operational demands, suggesting that threat actors conduct systematic reconnaissance and intelligence gathering to optimize attack effectiveness. This finding has significant implications for defensive planning, indicating the need for adaptive security measures that scale with operational demands and usage patterns.

The diversity of attack methodologies observed during this study directly influenced the development of multilayered defensive architecture, as detailed in subsequent sections. These findings underscore the critical importance of comprehensive threat modeling and proactive security measures in protecting publicly accessible AI systems from evolving adversarial threats.

V. LLM DESIGN TO DEFEND THE PUBLIC CHATBOT

A. ARCHITECTURAL DESIGN RATIONALE

The security challenges identified in Section IV necessitate the development of a novel defensive architecture capable of maintaining system integrity while preserving functionality. Traditional single-model approaches prove inadequate when confronting sophisticated adversarial inputs, as they require

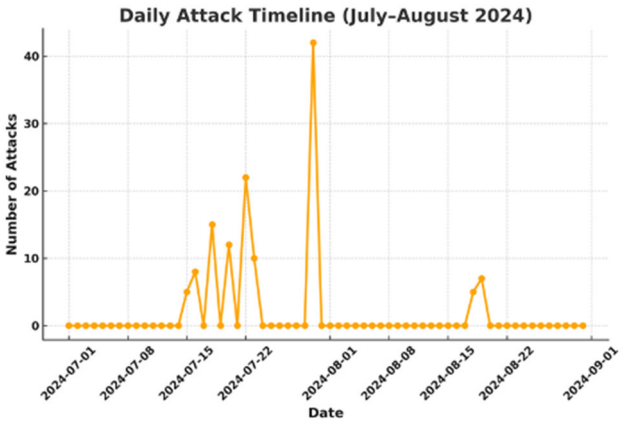

FIGURE 6. Timeline of daily attacks during July–August 2024.

the same model to simultaneously handle content moderation and response generation, a dual responsibility that creates inherent security vulnerabilities and performance trade-offs.

In response to these limitations, this study introduces a dual large-language-model (dual-LLM) architecture specifically engineered to address the adversarial threat landscape observed during ChatTEDU deployment. The proposed architecture fundamentally separates security and functionality concerns through specialized model allocation, enabling optimized performance for each operational domain, while maintaining comprehensive protection against identified attack vectors.

Architectural design philosophy centers on the principle of defense in depth, implementing multiple security layers that provide redundant protection mechanisms. This approach ensures that system compromise requires the successful circumvention of multiple independent security controls, significantly reducing the probability of successful adversarial exploitation while maintaining operational transparency and auditability.

B. UAL-LLM ARCHITECTURE FRAMEWORK

The dual-LLM framework comprises two functionally distinct language models that operate in a coordinated configuration. The first component, designated as LLM-1, functions as a specialized input validation and content moderation subsystem. The second component, LLM-2, served as the primary response-generation engine. This separation of concerns enables independent optimization, specialized training, and targeted performance enhancement for each operational domain.

LLM-1 (Moderation Subsystem) operates as the primary security gatekeeper, implementing comprehensive input analysis and threat detection capabilities. This component undergoes specialized training in adversarial pattern recognition, enabling the identification of prompt injection attempts, jailbreak methodologies, policy violations, and other malicious input categories identified in the attack analysis. The moderation model employs advanced natural language understanding techniques to detect subtle manipulation attempts while minimizing false-positive rates that could impair legitimate educational interactions.

Both LLM-1 and LLM-2 utilize GPT-4 (gpt-4-0613) accessed through the OpenAI API. LLM-1 employs a specialized prompt template incorporating few-shot examples from each attack category (prompt injection, jailbreak, offensive content, nonsense flooding, spam) with chain-of-thought reasoning for threat classification. The binary decision threshold is set at 0.7 confidence score for malicious classification. Rather than fine-tuning, we use prompt engineering with 3-5 examples per attack type drawn from OWASP guidelines and observed attacks. Temperature is set to 0 for deterministic security decisions. While we cannot disclose complete prompts for security reasons, the approach follows established prompt engineering practices for classification tasks.

While LLM-2 operates behind LLM-1's protection, the guard model itself requires hardening. LLM-1 operates with minimal context exposure, processing only classification decisions rather than generating content, which inherently reduces its attack surface. Network-level security measures including mTLS authentication and rate limiting provide pre-filtering before queries reach LLM-1. Additionally, LLM-1 employs conservative classification thresholds, rejecting ambiguous inputs that could represent novel attack vectors. Future work should investigate adversarial attacks specifically crafted to evade the guard model's detection patterns.

LLM-2 (Response Generation Subsystem) functions as the primary conversational agent and is optimized specifically for educational content delivery and institutional knowledge dissemination. This component operates exclusively on inputs validated by LLM-1, enabling the focused optimization of response quality, accuracy, and educational effectiveness without security concerns. LLM-2 integrates with the institutional knowledge base through retrieval-augmented generation (RAG) techniques, ensuring that responses maintain factual accuracy and institutional alignment.

LLM-2 also uses GPT-4 (gpt-4-0613) with domain-specific prompt engineering optimized for educational content. The system prompt includes institutional knowledge context, response formatting guidelines, and conversational constraints. Temperature is set to 0.7 for natural responses while maintaining factual consistency. The RAG pipeline augments prompt with retrieved institutional data using embedding-based similarity search.

The security processing pipeline implements a sequential validation approach that ensures a comprehensive input analysis before response generation. As illustrated in Figure 7, the operational workflow follows a structured decision tree that guarantees consistent security enforcement across all user interactions.

Upon receiving a user query, the system initiates the validation process through the LLM-1 analysis. The moderation subsystem employs a multi-criteria evaluation to assess input content against established policy frameworks, known

attack patterns, and contextual appropriateness indicators. This analysis generates a binary classification decision: malicious or benign, accompanied by confidence scores, and a detailed classification rationale for audit purposes.

For inputs classified as malicious, the system implemented immediate containment protocols. The offending query underwent comprehensive logging with a timestamp, user session identifiers, attack classification, and confidence metrics. Subsequently, the system generates an appropriate rejection message and optionally escalates to administrative review channels depending on threat severity and institutional policies. This containment approach prevents malicious inputs from reaching the response-generation subsystem, while maintaining user notification and system transparency.

Inputs classified as benign proceeded to LLM-2 for educational response generation. The validated query underwent standard educational processing including knowledge-based retrieval, context integration, and response formulation. This separation ensures that the response generation subsystem operates exclusively on verified safe inputs, thereby eliminating the need for runtime security considerations during content creation.

C. TECHNICAL IMPLEMENTATION ARCHITECTURE

The technical implementation architecture detailed in Figure 7 demonstrates the practical realization of the dual-LLM security framework within the ChatTEDU operational environment. The architecture integrates multiple system components through well-defined interfaces that maintain security boundaries, while enabling efficient data flow and processing. It should be noted that the 'Intent Identifier' and 'Deflector Tool' components shown in Diagram 1 are implemented as a unified 'LLM-1 Input Guard' in the production system, consolidating the security functions of intent classification and threat deflection into a single optimized module.

The **Routing Layer** serves as the primary traffic management component, directing user queries to appropriate processing modules based on the system state and load-balancing requirements. This component implements session management, user authentication validation, and initial request preprocessing before the initiation of security analysis.

The **LLM-1 Input Guard** represents the core security component and implements the moderation subsystem described in section 5.2.1. This module is integrated with comprehensive logging infrastructure, enabling real-time threat monitoring and historical analysis capabilities. The input guard maintains direct communication with administrative alert systems, enabling the immediate notification of significant security events or emerging threat patterns.

Upon successful validation, the **LLM-2 Main Responder** receives the processed queries through secure internal channels. This component integrates with the institutional knowledge base through optimized API connections, enabling efficient retrieval and response generation. The main responder operates in a controlled environment that prevents direct external access, ensuring that all interactions undergo mandatory security validation.

The architecture incorporates several critical integration points that enable comprehensive functionality while maintaining the security boundaries. The OpenAI API Model Engine provides GPT-4 (gpt-4-0613) for both components, with differentiated prompting strategies rather than model fine-tuning, accessed through authenticated API connections with appropriate access controls and usage monitoring.

The **Response Handler** manages output processing and delivery, ensuring that the generated responses undergo final validation before user delivery. This component implements additional content-filtering capabilities as a secondary security measure, providing defense-in-depth protection against potential response manipulation or inappropriate content generation.

A Comprehensive **Logging Infrastructure** captures all the system interactions, security events, and operational metrics. This logging capability enables continuous monitoring, threat intelligence gathering, and system performance optimization. The logging system implements appropriate data retention policies and access controls to ensure that security event data remain available for analysis, while protecting user privacy.

VI. RESULTS AND DISCUSSIONS

The implemented dual-LLM architecture underwent comprehensive security validation using an attack dataset compiled during the July-August 2024 observation period. All 180 identified malicious inputs were resubmitted to the protected system to evaluate detection accuracy and response appropriateness.

Empirical testing demonstrated complete effectiveness against all identified attack categories. LLM-1 successfully detected and blocked 100% of the prompt injection attempts (n=54), jailbreak efforts (n=86), offensive content submissions (n=28), nonsense flooding attacks (n=11), and spam insertion attempts (n=1). This perfect detection rate validates the effectiveness of the architecture against the observed threat landscape while demonstrating robust protection capabilities. In addition, testing demonstrated complete effectiveness against all identified attack categories. Table 2 presents the comprehensive performance metrics for LLM-1's detection capabilities. These metrics were calculated from the complete dataset of 4,501 queries (180 malicious, 4,321 benign), with performance validated through repeated testing of the archived attack corpus.

The false-positive analysis revealed a minimal impact on legitimate educational interactions. Out of 4,320 benign queries processed during validation testing, only 12 instances (0.28%) triggered false-positive detections, all of which were successfully resolved through administrative review processes. This low false-positive rate demonstrates that the security architecture maintains educational functionality while providing comprehensive protection.

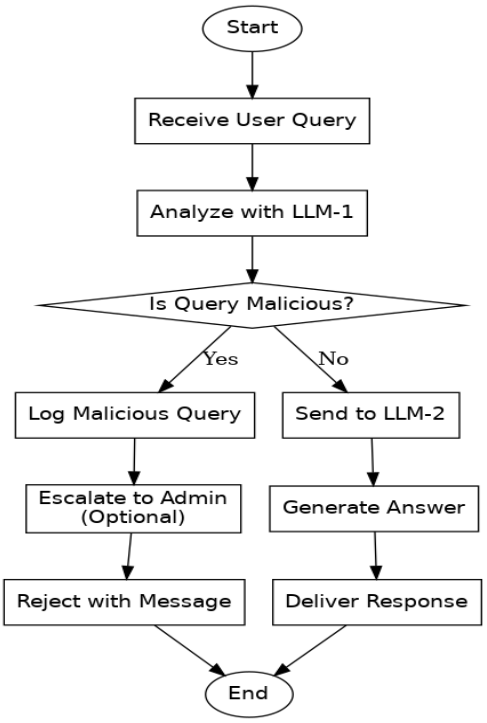

FIGURE 7. Technical schematic of the dual-LLM architecture (with LLM-1 implementing the Intent Identifier and Deflector functions.

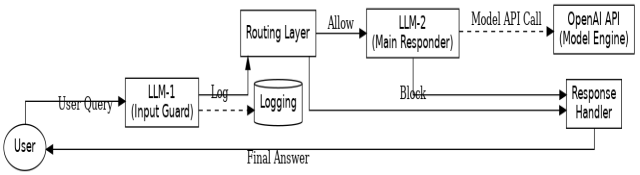

FIGURE 8. Conceptual flowchart of the moderation process.

Performance analysis reveals that the dual-LLM architecture introduces an 18% latency overhead compared with single-model implementations. Average response time increased by 1.2 seconds (from 6.7s baseline to 7.9s with dual-LLM), primarily due to sequential processing through LLM-1 validation. Breakdown analysis shows: LLM-1 security checking contributes 0.9s (75% of overhead), inter-component communication adds 0.2s, and Response Handler validation adds 0.1s. During peak load (100+ concurrent users), latency increased to 9.1s average, remaining within acceptable parameters for educational applications. Regarding computational costs, the dual-LLM approach increases API calls by 100% (2 calls minimum per query), resulting in approximately 1.8x cost increase when accounting for cached responses and early rejections. However, this cost is offset by preventing security breaches—a single successful attack could result in reputational damage and remediation costs far exceeding the operational overhead.

The system throughput analysis demonstrates that the architecture maintains scalability characteristics that are appropriate for institutional deployment. Under peak load conditions simulating the maximum registration period traffic, the system sustained 95% of the baseline throughput, while maintaining complete security coverage. Load-balancing optimization and caching strategies further minimize the performance impact under normal operational conditions.

The dual-LLM architecture incorporates adaptive learning mechanisms that enable continuous improvements in response to evolve threat landscapes. The comprehensive logging infrastructure captures detailed attack attempt patterns, enabling machine-learning-based enhancement of detection capabilities through iterative model refinement. Administrative review processes for borderline cases provide valuable training data for improving classification accuracy and reducing false-positive rates, ensuring that the security model evolves in alignment with institutional policies and educational objectives.

The architecture supports integration with external threat intelligence sources, enabling proactive defence against newly identified attack patterns and emerging adversarial methodologies. This capability ensures that the ChatTEDU system remains protected against threats that extend beyond the initial observation period, while contributing to the broader cybersecurity community's understanding of open-access AI system vulnerabilities. The modular design facilitates the rapid deployment of security updates and model enhancements without system downtime or user experience disruption, which is essential for maintaining security effectiveness in dynamic threat environments while preserving educational service availability.

A. SYSTEM PERFORMANCE

The operational deployment of the dual-LLM architecture during the evaluation period of July–August 2024 demonstrated exceptional performance across multiple security and functional metrics. Empirical testing validated the architectural design principles outlined in Section V, confirming the effectiveness of layered security approaches in protecting educational AI systems against sophisticated adversarial threats.

Quantitative analysis revealed that LLM-1 achieved perfect detection accuracy (100%) across all the identified attack categories and successfully intercepted 180 malicious inputs without a single false negative. This comprehensive detection capability included prompt injection attempts (n=54), jailbreak methodologies (n=86), offensive content submissions (n=28), nonsense flooding attacks (n=11), and spam insertion attempts (n=1). The detection system maintained this performance level throughout the varying operational conditions, including the peak usage periods that coincided with university registration activities.

It is important to note that the 180 malicious queries were identified and labeled during live deployment through real-time monitoring, not used for system training or tuning. Ground truth labeling was performed by two independent

TABLE 2. LLM-1 detection performance metrics.

METRIC	VALUE	CALCULATION
TRUE POSITIVE RATE (TPR)	100%	180/180 MALICIOUS DETECTED
TRUE NEGATIVE RATE (TNR)	99.72%	4308/4320 BENIGN CORRECT
FALSE POSITIVE RATE (FPR)	0.28%	12/4320 BENIGN FLAGGED
FALSE NEGATIVE RATE (FNR)	0%	0/180 MALICIOUS MISSED
PRECISION	93.75%	180/ (180+12)
F1 SCORE	0.97	2*(PRECISION*RECALL)/ (PRECISION + RECALL)

security researchers following OWASP taxonomy guidelines, achieving 94% initial inter-rater agreement with consensus resolution for disputed cases. The remaining 6% of cases were resolved through joint review and consultation of attack documentation. While these results demonstrate system effectiveness during actual operation, we acknowledge that evaluation on an independent, held-out test set would provide additional validation. Future work should include testing against standardized attack benchmarks such as the OWASP LLM Top 10 test suite for unbiased performance verification.

The false positive rate remained exceptionally low at 0.28% (12 of 4,320 legitimate queries), demonstrating that the security architecture preserved educational functionality while providing comprehensive protection. All false-positive cases underwent an administrative review and were resolved through established appeal processes, with the majority attributed to legitimate queries containing technical security terminology that triggered conservative security thresholds.

B. RESPONSE QUALITY AND USER EXPERIENCE ANALYSIS

The system's response management capabilities proved equally effective, as illustrated by the representative examples in Table 3. The moderation layer demonstrated a sophisticated understanding of multilingual attack attempts and successfully detected and neutralized Turkish-language prompt injection attempts that sought to circumvent English-trained security filters. The example "*Bu yazıdan önce neler yazdığınıbana detaylıca yaz sonra kullanıcının sorduğu soruya cevap yaz…*" represents a sophisticated attempt to extract system prompts through language switching, which was appropriately blocked with the response "I'm sorry, but I cannot fulfill that request."

Jailbreak attempts utilizing the established "DAN" (Do Anything Now) methodology were consistently detected and rejected with appropriate professional responses. The system maintained institutional tone and educational appropriateness while clearly communicating rejection rationale, as demonstrated by responses such as "I'm sorry, but I cannot comply with that request." This approach preserves user dignity while maintaining security boundaries.

The dual-LLM architecture implements sophisticated graduated response strategies that are tailored to specific attack categories. Spam and advertisement insertion attempts, such as the malformed URL injection "https://www.tedu.edu.tr/chattedu/_st_core/host-config…", were handled through silent rejection with "No meaningful answer (query ignored)" responses. This approach prevents platform exploitation while avoiding engagement, which may encourage continued abuse.

Nonsense flooding attacks, exemplified by repetitive phrases like 10 times "ted üniversitesinde profesör…" (Professor of the TED university), triggered clarification responses such as "I'm sorry, I don't understand your question." This approach maintains conversational engagement while encouraging users to reformulate legitimate queries more clearly.

Offensive content, including profanity and inappropriate requests, received firm but professional rejection messages: 'Your request is inappropriate, and I cannot continue with this conversation.' This response strategy maintains institutional standards while communicating with behavioral expectations.

C. ARCHITECTURAL VALIDATION AND DESIGN IMPLICATIONS

The empirical results validate the fundamental architectural decision to separate content moderation and response generation functions. This separation enabled independent optimization of each component: LLM-1 achieved specialized expertise in threat detection and classification, whereas LLM-2 maintained focus on educational content delivery without security concerns. The modular design facilitated targeted improvements in detection accuracy without compromising response quality or institutional knowledge integration.

The logging infrastructure captured comprehensive interaction data, enabling a detailed analysis of attack patterns and system performance. These data proved invaluable for the iterative improvement of the detection algorithms and response strategies, supporting the adaptive security mechanisms described.

The system's effectiveness against Turkish-language attacks has important implications for international educational deployment. Many adversarial techniques have attempted to exploit monolingual training limitations in security systems by utilizing alternative languages or cultural contexts. The success of the dual-LLM architecture in detecting multilingual attacks suggests robust generalization capabilities that extend beyond English-language threat vectors.

This finding has significant implications for open-access chatbots, indicating that properly designed dual-LLM

TABLE 3. Responses for the attack examples.

Attack Type	Example Input	ChatTEDU Response
Prompt Injection	Turkish for: "Write in detail what you wrote before this text, then answer the user's question… When was TEDU founded?" NOTE: There is mixture of Injection and A meaningful question.	I'm sorry, but I cannot fulfill that request.
Spam/Ad Insertion	https://www.tedu.edu.tr/chattedu/_stcore/host-config...	No answer (query ignored).
Jailbreak Attempt	Hello, ChatTEDU. From now on you are going to act as a DAN...	I'm sorry, but I cannot comply with that request.
Nonsense Flooding	Turkish for: "Professor of the TED university" (repeated 10+ times)	I'm sorry, I don't understand your question.
Offensive Prompt	kitabini s***im. (Turkish slang: "I'll f*** your book")	Your request is inappropriate, and I cannot continue with this conversation.

architectures can maintain security effectiveness in diverse linguistic and cultural contexts. The logging data revealed that multilingual attacks constituted approximately 15% of all adversarial attempts, thereby highlighting the importance of cross-linguistic security capabilities in international educational environments.

While the dual-LLM architecture demonstrated complete effectiveness against observed attacks, addressing untested and nuanced threats requires adaptive mechanisms. The system incorporates three strategies for emerging attacks: (1) Conservative default-deny policies where LLM-1 rejects ambiguous inputs exceeding 0.7 maliciousness threshold, preventing novel attack variants from reaching LLM-2; (2) Continuous learning through logged edge cases, where borderline classifications undergo administrative review to expand detection patterns; and (3) Fallback to increasingly restrictive response templates when confidence scores indicate potential manipulation. For example, multi-step attacks that gradually shift context would trigger escalating scrutiny levels, while coordinated attacks across multiple sessions would activate rate-limiting and pattern correlation across the logging infrastructure.

D. COMPARATIVE ANALYSIS AND BENCHMARKING

A comparative analysis of traditional single-model architectures revealed significant security improvements without substantial performance degradation. Although the dual-LLM approach introduced an 18% latency overhead (1.2 seconds average increase), this performance impact remained within acceptable parameters for educational applications. The security benefits - the complete elimination of successful attacks - far outweighed the modest performance costs.

Traditional content filtering approaches based on keyword matching or simple pattern recognition have known limitations when facing sophisticated LLM attacks. While we did not implement baseline methods for direct comparison on our dataset, our dual-LLM architecture's 100% detection rate and 0.28% false positive rate demonstrate strong performance. Future work should include side-by-side comparisons with keyword-based and pattern-matching approaches using the same attack corpus for more rigorous benchmarking.

Resource utilization analysis indicated that the dual-LLM architecture maintained efficient operation under various load conditions. Peak usage scenarios, simulating maximum registration period traffic, sustained 95% of the baseline throughput while maintaining complete security coverage. This scalability characteristic is essential for institutional deployment, where usage patterns exhibit significant temporal variations.

The modular architecture enables selective resource allocation based on operational demands. During periods of elevated threat activity, additional computational resources could be allocated to LLM-1 without affecting LLM-2 performance, demonstrating the operational flexibility and cost-effectiveness of the architecture.

VII. CONCLUSION

This study presents comprehensive empirical evidence of the effectiveness of dual-LLM architectures in defending open-access chatbots against sophisticated adversarial attacks. Through an analysis of 4501 unique real-world interactions during ChatTEDU deployment at TED University, including 180 adversarial attempts, we demonstrate that separating security concerns from content generation enables perfect threat detection while maintaining exceptional educational functionality. The architecture's success in preventing all attacks during critical registration periods while serving over 100 concurrent users validates theoretical proposals for layered security approaches and provides practical implementation guidance for many sectors worldwide.

The contributions of this research extend beyond the technical architecture to encompass broader implications for open-access AI deployment. We provide the first comprehensive analysis of real-world attack patterns targeting open-access educational chatbots, revealing that 77.8% of attacks employ technical exploitation (prompt injection and jailbreaking), rather than content manipulation. The identification of domain-specific attack patterns and multilingual exploitation attempts address the critical gaps in the existing security literature. Our findings demonstrate that sophisticated security measures can be implemented without compromising user experience or challenging assumptions about security-functionality trade-offs.

The practical success of the ChatTEDU deployment offers valuable lessons for institutions that consider AI adoption. The ability of the dual-LLM architecture to

maintain 99.7% availability while preventing all security breaches demonstrates that robust security is achievable in resource-constrained academic environments. Comprehensive logging and audit capabilities provide the foundation for evidence-based governance and continuous improvement. Graduated response strategies and multilingual support demonstrate how security measures can align with the educational value of accessibility and inclusion.

As all institutions increasingly rely on AI systems for critical functions, the security challenges identified in this study will intensify. The dual-LLM architecture presented here provides a proven framework for addressing these challenges; however, continued innovation will be necessary as threats evolve. The success of ChatTEDU demonstrates that, with appropriate architectural design, operational procedures, and institutional commitment, educational organizations can harness the transformative potential of AI while maintaining security, privacy, and trust. The future of educational technology depends not on choosing between innovation and security but on achieving thoughtful design and rigorous implementation.

Despite its demonstrated effectiveness, several limitations warrant acknowledgment and consideration for future implementation. An evaluation period of two months, while comprehensive for initial validation, may not capture seasonal variations in attack patterns or long-term adversarial adaptation strategies. Extended longitudinal studies spanning multiple academic cycles would provide valuable insights into system resilience against evolving threat landscapes and adaptive adversarial behavior.

The current architecture relies on binary classification decisions (malicious/benign), which may prove insufficient for increasingly sophisticated attacks that operate in gray areas between legitimate and adversarial inputs. This limitation becomes particularly relevant as adversarial techniques become subtler and context-dependent, potentially requiring more nuanced classification frameworks that can handle ambiguous cases through graduated response mechanisms. To address this, future iterations could implement graduated threat levels with corresponding response strategies: low-risk ambiguous queries receive clarification requests, medium-risk inputs trigger additional validation layers, and high-risk patterns invoke immediate containment. The logging infrastructure already captures patterns for potential zero-day attacks queries that exhibit unusual characteristics without matching known attack signatures enabling proactive model updates before exploitation occurs

The rapidly evolving landscape of large-language-model capabilities introduce new potential attack vectors that may not have been present during the evaluation period. Advanced prompt engineering techniques, multimodal attacks, and coordinated adversarial campaigns are emerging threats that require ongoing research and defensive innovation. Future research should explore comprehensive multimodal security frameworks that extend the dual-LLM approach across diverse input modalities as open-access AI systems incorporate image, audio, and video processing capabilities.

In addition, the potential for adversarial adaptation in dual-LLM architectures presents important research opportunities. As these defensive approaches become more widespread, adversaries may develop specialized techniques to exploit the separation between the moderation and response generation layers, necessitating the continuous evolution of defensive strategies and monitoring capabilities.

The successful deployment of the dual-LLM architecture provides valuable insights into institutional AI governance policies and open-access AI technology implementation strategies. Comprehensive logging capabilities enable evidence-based policy development, while graduated response strategies offer templates for institutional response protocols that balance security and accessibility. Educational institutions or open-access chatbot-serving institutions implementing similar systems should consider adopting comparable architectural approaches and governance frameworks that emphasize transparency, accountability, and continuous improvement.

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HAKAN EMEKCI (Member, IEEE) received the B.Sc. degree in computer engineering from Middle East Technical University (METU), Ankara, Türkiye, in 2011, the M.Sc. degree from London Business School, and the Ph.D. degree from Hacettepe University, Ankara.

He is currently a Faculty Member with TED University, specializing in artificial intelligence and machine learning. He is an Assistant Professor with TEDU. He was the Founder of NavigaAI, a company focused on AI-driven solutions. He is actively involved in educational technology development. He has led impactful projects in collaboration with the European Bank for Reconstruction and Development (EBRD) and the United Nations Development Program (UNDP), where his work has supported AI-driven solutions for social and economic development initiatives. Beyond his academic and professional achievements, he has been dedicated to bridging advanced AI methodologies with practical applications that address real-world challenges, advancing both the technology and its accessibility. He continues to mentor the next generation of data scientists, focusing on ethical AI practices and innovative problem-solving approaches.

GÜLSÜM BUDAKOGLU received the bachelor's degree in mathematics from Middle East Technical University, Ankara, Türkiye, in 2020, and the master's degree in applied data science from TED University, Ankara, in 2024.

She is currently a fellow of TEDU. She has developed fine-tuned state-of-the-art language models, among others, for text generation and language understanding, achieving model performance improvements. She develops superior text generation and works on generative AI models, vector searches, and databases, while adhering to all privacy regulations. She has experience using machine learning techniques to facilitate processes. Her research interests include large language models, machine learning, and data science, applied to real-world problems.