Technology-Enhanced Learning for User Security Awareness Using AI-based Naive RAG: A Design and Prototype

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***Abstract*—The increasing use of Information Technology (IT) in all areas of life, followed by increasing cybersecurity threats on the user side, makes cybersecurity awareness among users an obligation that must be met. Several solutions currently available (guides, discussion forums, workshops) have not been able to provide good results and are lacking in terms of user engagement, adaptability, and optimizing available resources, so technology-based learning is needed, especially AI. This paper introduces the design and prototype of an AI-based learning system, especially with the Naive Retrieval-Augmented Generation (Naive RAG) method with three steps, including Retrieval, Augmented, and Generation. The system combines contextual user questions and answers with internal and domain knowledge systems to explain cybersecurity awareness to users dynamically and personally. The prototype that has been developed is then tested using the Black Box Testing method to evaluate functionality and usability. The test results show that the functionality of the system built has run well with a percentage of success of 100%, so it can be used as a technology-based learning medium for education and learning of user security awareness.**

Keywords— artificial intelligence (AI), embedding, naive RAG, technology-based learning, user security awareness

I. INTRODUCTION

The rapid development of information technology, on the other hand, increases the number of cyberattacks targeting users. Some types of these attacks are social engineering, phishing, man-in-the-middle attacks (MITM), advanced persistent threats (APT) [1]. This is triggered by the low understanding and awareness of cybersecurity among users. Users' ignorance of cyber security techniques, technical errors made by users, and lack of awareness of cyber security on the user side allow attackers to carry out these types of attacks. Thus, efforts to educate users and increase cybersecurity awareness need to be made.

Several solutions are available for this, including the provision of free cybersecurity guides on the Internet, discussion forums, workshops, and paid consulting services [2]. However, these solutions have not been able to reduce the number of cyberattacks targeting users. This is due to the lack of interactivity of these solutions with users and the failure to maintain users' attention to stay focused on learning. In addition, the abundant resources in the form of cybersecurity documents and guides are not balanced with the ability of users to understand. All users can download cybersecurity guide material documents for free on the internet, but not all users have the ability to understand the material. The role of IT is needed to create better cybersecurity learning methods by utilizing existing resources.

Artificial Intelligence (AI), as one of the IT fields that is growing rapidly and are used in some areas of life today, has the potential to be empowered in creating better cybersecurity learning models based on technology. Generative AI (GenAI) in the form of large language models (LLMs) are the most widely used AI methods in implementing AI-based solutions [3].

Several previous studies have attempted to design and develop prototypes of AI-based learning technology. The first study developed a prototype called APIHelper to help junior Android programmers learn API usage, where the prototype can track and manage API calls so that junior Android programmers can learn how to implement functions according to the API call sequence [4]. The second study developed an AI-based chatbot for educational environments at the University of Warwick along with its testing and evaluation [5]. The third study conducted a systematic review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework on some literature on the development of AI-based applications and tools and their use as virtual teaching aids that reduce educators' monotonous tasks and create a better learning environment tailored to students' needs [6]. The fourth study developed an AI-based application to support learning where the application was able to create quiz questions and answers based on documents uploaded by users as knowledge-based [7]. The fifth study conducted a systematic review of 53 studies on the use of chatbots in education to provide a comprehensive understanding of the use of chatbots in education, its benefits, and future challenges [8]. The sixth study conducted a literature review on the use of AI to support learning with a focus on three parts (administration, instruction, and learning) in the form of machine learning, learning analytics, data mining, and adaptive and intelligent web-based education systems (AIWBES) [9]. The seventh study examined the role of AI in natural language interfaces-based learning with the concept of Intelligent Personal Assistant (IPA) along with trends, critical areas, and challenges, using the Population, Intervention, Comparison, Outcome, Context (PICOC) method [10]. The eighth study developed an AI-based career counselling learning service to help individuals understand themselves and job trends and make the right decisions regarding careers and education [11]. The ninth study was about the development of an AI-based application called Python-Bot to help computer science students learn Python programming from the perspective of syntactic and semantic structures [12]. The tenth study was about bibliometric analysis of artificial intelligence in education (AIED) from 2.223 related papers [13]. The eleventh study developed an AI-based chatbot application to assist teachers in providing writing instruction to students in schools, where the chatbot helped students improve review feedback on their writing [14]. The twelfth study conducted a literature review on the use of AI for education and management studies in the market and managing online interactions with consumers [15]. The thirteenth study reviewed systematic literature on user interactions with AI through face-to-face chatbot applications for education in terms of user satisfaction, engagement, and trust, as well as future challenges faced [16]. The fourteenth study examined from a human-computer interaction perspective the use of AI in the learning process using a sample of 57,000 forms of user interactions with AI-based applications [17]. The fifteenth study developed an AI-based application that can utilize digital documents as training data and knowledge to be able to answer questions asked by users in a more user-friendly, interactive, and scalable manner [18]. The sixteenth study developed an AI-based system to integrate and predict the performance of AI used to assist the learning process to improve student understanding in schools in a case study of online learning [19]. The seventeenth study reviewed 143 kinds of literature to analyze the challenges related to Artificial Intelligence in Education (AIED), where China and the US are the two countries that have conducted the most research [20]. The eighteenth study examined the role of AI in education in the form of social co-regulation in learning (SSRL), which collaborates between humans (users) and AI to realize a better learning process, and proposed a hybrid human-AI co-regulation model in learning (HASRL) [21]. The nineteenth study conducted a systematic literature review of 94 papers from Web of Science, ERIC, and Google Scholar related to the use of AI in the form of large language models (LLMs) in the learning process, with the result that LLMs for education have great research potential in the future [22]. The twentieth study conducted a meta-systematic review of AI in higher education using secondary sources from Web of Science, Scopus, ERIC, EBSCOHost, IEEE Xplore, ScienceDirect, ACM Digital Library, OpenAlex, ResearchGate, and Google Scholar, where, for the period 2018 to 2023, 71.2% of the references were the result of research collaborations between researchers between countries, which shows the breadth of this research topic [23]. The last two studies examined the systematic literature review of the use of AI in education to support learning from the perspective of the relationship between education and AI, their interaction, AI's contribution to educational evolution, research challenges [24], and a study of the use of AI in education with a special focus on the type of generative AI in the form of the ChatGPT service along with its advantages and disadvantages [25].

Related to the case study raised and the absence of previous research that raises the case study and its solution, this study proposes to design and develop a prototype of an AI-based application to help educate users about cybersecurity awareness. This paper focuses on the design and development of a prototype of a technology-based learning system using AI with the Naive RAG method to foster user security awareness, where the system utilizes and optimizes the resources of cybersecurity documents and guides owned by users as an internal knowledge base.

II. Material and Method

A. Literature Review

We use the method of collecting secondary data in the form of a literature review as a method of collecting data in research that involves a series of activities related to collecting library data, reading and recording, and managing research materials from various valid reference sources [26]. In this study, the literature review was conducted by collecting and reading various literature on the application of AI in the fields of education and teaching, which came from several papers in scientific journals and conference proceedings.

B. Tool and Materials

Tools and materials that support this research including hardware and software. The hardware used is a notebook with Intel(R) Core(TM) i7-10750H CPU @2.60GHz 2.59 GHz processor specifications, 16 GB memory (RAM), and 512 GB SSD. Hardware for servers and computing in the form of several AMD EPYC server nodes and L4 GPUs in the data center remotely. We also using switch and router. The softwares used for prototype design and development are Linux Ubuntu 64 bit, Postgre SQL pg-vector for vector database library (embedded in Yuga Byte), Pinecone HNSW indexing tool, Python, C++, Node JS, Message Query Redis pub/sub, Dia Diagrams, and Canva. The softwares used for data processing, data analysis, and documentation are Google Forms, Google Office, Libre Office, Zotero, Mendeley, and GNU PSPP.

C. Large Language Model (LLM)

Large Language Models (LLMs) is a further development of AI, especially natural language processing (NLP), which apply deep learning (DL) techniques to computers using transformation architectures to learn and understand complex and structured patterns of a language and large amounts of data and semantic relationships between words and phrases [27]. LLM is widely applied today along with the rapid development of AI and the use of AI in all areas of human life. One example is the ChatGPT service from OpenAI.

D. Retrieval Augmented Generation (RAG)

RAG is a method in LLMs that uses datasets to generate text by combining information retrieval capabilities or retrieval and text generation or generation [28]. RAG consists of three steps, namely retrieval, augmentation, and generation, which are related to retrieving information from user input, searching for contextual matches, adding text, and compiling answers or system responses to users based on generative AI 29]. RAG also widely applied to several AI-based services, one of them is in health services [30].

E. Naive RAG

The development using Naive RAG as a basic type of RAG consisting of three steps, namely: retrieval, augmentation, and generation. Naive RAG involving embedding and cosine similarity techniques for similarity between the context of questions asked by the user and the response from the RAG system [31]. This research uses Naive RAG as a method in the prototype of an AI-based application developed for learning cybersecurity awareness on the user side, considering that

Naive RAG with its three steps is able to optimize the use of local user documents as a knowledge base for learning. Naive RAG theoretically offers the simplest approach, ideal for direct question-and-answer systems and basic document searches, using simple vector retrieval and direct response. The diagram shown in Fig. 1.

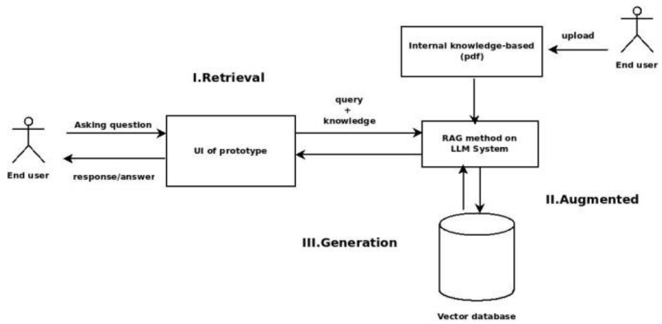

Fig. 1. A The diagram of Naive RAG.

Based on Fig. 1, Naive RAG simply consists of three steps (retrieval, augmentation, and generation), users who input questions and upload documents for the internal knowledge base, and a vector database. A vector database is a database dedicated to storing digital data in the form of vectors that represent mathematics to facilitate machine learning models in AI to support search, recommendation, and text generation [32]. Data matches in the vector database are identified based on similarity metrics, allowing AI-based computer models to understand data contextually. The retrieval process functions to obtain information and knowledge from questions asked by users (in this case, the context of the question). Augmented functions to help obtain a match between the user's query (context) and the availability of knowledge in the vector database taken from the knowledge in the uploaded document (internal knowledge base). Generation functions to compile responses or answers from the system to be displayed on the application interface to answer questions submitted by users.

F. *The Flowchart*

A flowchart is a process flow diagram that outlines the steps and procedures involved in the research, development, and testing of software and systems [33]. We created a research flowchart to clarify each stage that we do in this research, shown in Fig 2.

Based on Fig. 2, the flowchart consists of five stages, namely: the introduction stage, the design and implementation stage, the testing stage, the analysis and conclusion stage, and the final stage. Each stage has a sequence of steps starting from case study research, problem identification, state of the art, proposed solution, design of prototyping, prototyping, black box testing, analysis and conclusion, and paper publication.

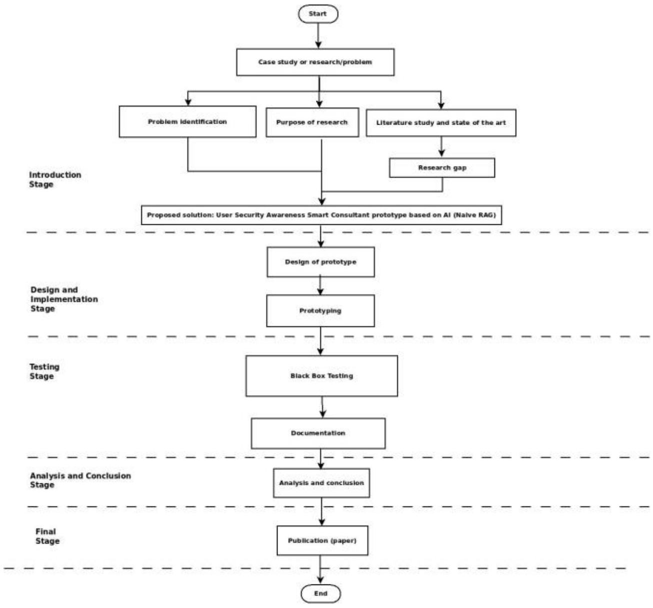

Fig. 2. The flowchart.

G. *The Specification*

We developed our prototype according to the design and specifications of the needs and named it User Security Awareness Smart Consultant. The specifications of the system are based on the needs and case studies of the problem. With the need to increase user security awareness and optimize reference documents owned by users, the AI-based prototype using the Naive RAG method needs to meet the following specifications: web-based and online systems, multi-platform, easily accessible to users, synchronous processes with event-driven architecture support, the system provides a menu for user login, the system provides a menu for uploading documents where the uploaded documents will become internal knowledge-based which is the basis for references and knowledge for the system when compiling responses to questions from users, the system can perform text processing to convert text documents into vectors and save them in a vector database, the system can provide responses or answers according to context by utilizing internal documents as internal knowledge-based, the system can apply the three steps in Naive RAG (retrieval, augmentation, and generation).

H. *The Prototype Design*

The prototype design of the User Security Awareness Smart Consultant that was built focused on the stages of uploading documents by users as internal knowledge-based data processing, converting documents to vectors, and data stored at a vector database. The prototype design is shown in Fig. 3.

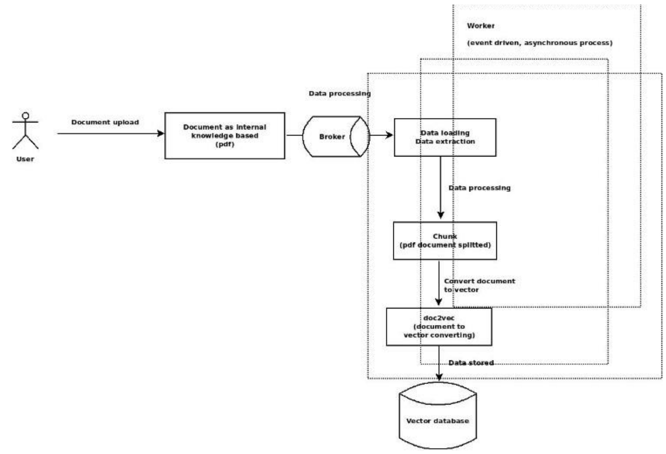

Fig. 3. The prototype design.

Based on Fig. 3., the user uploads a document (pdf) that functions as an internal knowledge base. This document is a reference for the prototype to obtain knowledge to compile answers or system responses to questions from users through the augmented and generation stages in Naive RAG. Documents that have been uploaded to the system then undergo processing (data processing) with the help of a broker. Furthermore, with the help of workers in an event-driven and asynchronous process-based architecture, data loading, data extraction, document separation (chunk), document conversion into vectors, and data storage into a vector database.

I. Black Box Testing

Black Box Testing is a test on software or a prototype to find out the details of the application and its functionality according to the design and specifications, without the need to check the source code [34]. Black box testing is done by involving a test scenario that contains a sequence of test steps or test cases. Black box testing can be divided into three types, namely: functional testing to test the functionality of software or prototypes, non-functional testing to test additional non-functional aspects of software or prototypes, and regression testing to test software or prototype regression after repair or renewal. In this study, the type of Black Box Testing used is functional testing.

III. TESTING AND RESULT

A. Black Box Testing Scenario

We conducted black box testing to test the functionality of the prototype that we have developed. To be able to conduct testing, we compiled a test scenario consisting of seven step sequences, shown in Table I.

Based on Table I, there are seven sequential steps in the test scenario: logging in to the system and entering the admin menu, entering the dataset menu, uploading reference documents as internal knowledge-based reference documents, text processing, typing the question, obtain the answer/response from system, and matching the system's answer/response with the explanation in the reference document. Each step is tested, observed, and documented.

TABLE I. BLACK BOX TESTING SCENARIO

No	Sequence of Steps
1	Log in to the system
2	Enter the admin menu
3	Choose the dataset menu and upload reference documents as internal knowledge-based reference documents in pdf format obtained from the BSSN website [35]
4	Text processing (documents are converted into vector form, broken down into several paragraphs, and saved into a vector database)
5	Switch to the user page and type the question: what is ransomware?
6	Obtain an answer (response) from the system.
7	Match the system's answer/response with the explanation in the reference document.

Each step is carried out, the results are observed and documented.

B. Black Box Testing Result

Based on the test scenario with seven sequential steps in it, we then test each step carefully. The test results documented in the form of screenshots and tables. For each step of the test results that are in accordance with the specification and designs, we give a value of "appropriate," while if they are not in accordance, we give a value of "not appropriate" The results of Black Box Testing are shown in Table II.

TABLE II. BLACK BOX TESTING RESULT

No	Sequence of Steps	Result
1	Log in to the system	Appropriate
2	Enter the admin menu	Appropriate
3	Choose the dataset menu and upload reference documents as internal knowledge-based reference documents in pdf format obtained from the BSSN website [34]	Appropriate
4	Text processing (documents are converted into vector form, broken down into several paragraphs, and saved into a vector database)	Appropriate
5	Switch to the user page and type the question: what is ransomware?	Appropriate
6	Obtain an answer (response) from the system.	Appropriate
7	Match the system's answer/response with the explanation in the reference document.	Appropriate

Each step is carried out, the results are observed and documented.

Based on Table II., the seven steps in the Black Box Testing test scenario have been run in the testing process, where each step gets an appropriate score. This shows that overall, the User Security Awareness Smart Consultant prototype that was built is by the specifications and design. Screenshots during reference document upload and preview tests are shown in Fig. 4.; screenshots during text processing and cleaning are shown in Fig. 5.; questions asked by the user and the system's response/answer (in Bahasa Indonesian and English) are shown in Fig. 6; and the matching between the system's answer and the knowledge in the reference document used is shown in Fig. 7.

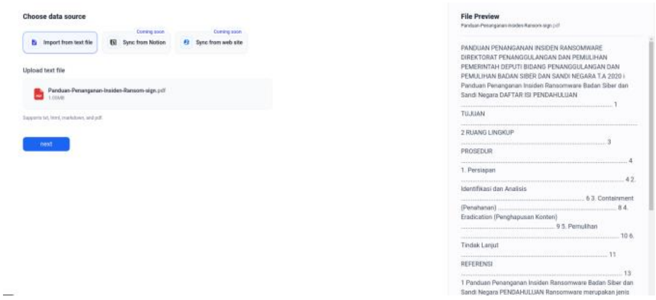

Fig. 4. Document upload dan preview.

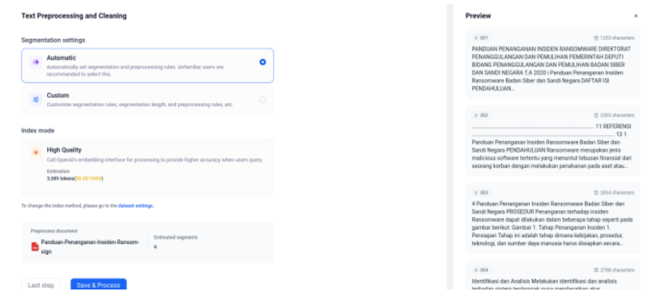

Fig. 5. Text processing and cleaning.

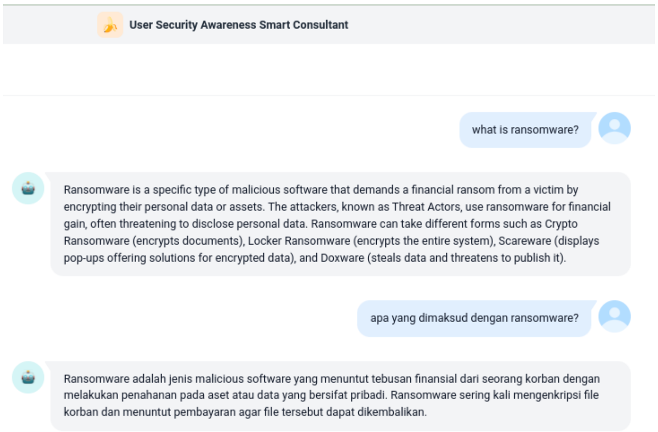

Fig. 6. Questions asked by the user and the system's response/answer (Bahasa Indonesia and English).

Fig. 7. Matching between the system's answer and the knowledge in the reference document used (Bahasa Indonesia).

Next, we calculate the percentage of success from the Black Box Testing test results to determine the extent to which the system functions as desired. The calculation of the percentage of success of the Black Box Testing test results is done by calculating the number of test cases in the successful scenario compared to the total number of test cases in the test scenario. The formulation is:

Percentage of success = (Number of successful test cases/total test cases) × 100%

Percentage of success = (6/6) × 100%

Percentage of success = 100%

From these results, the percentage of success is 100%. This shows that all the functionality of the developed User Security Awareness Smart Consultant prototype has run well without any errors and in accordance with what was desired during the design process.

IV. Discussion

The User Security Awareness Smart Consultant prototype was successfully developed according to the specifications and designs based on the requirement and case studies regarding the importance of increasing user security awareness through the provision of better cybersecurity education and learning services using technology, especially AI with the Naive RAG method. The results of the Black Box Testing of the prototype based on a number of sequences of steps in the test scenario showed that all steps went well according to the specifications and designs. This is evidenced by the appropriate values and descriptions for all test steps and a value of 100% based on the calculation of the percentage of success for the Black Box Testing test.

V. Conclusion and Future Research

Based on Black Box Testing and test results, the overall functionality of the cybersecurity learning prototype developed based on AI with the Naive RAG method to increase cybersecurity awareness in users, has run well and by the design and specifications of the needs. The system can make internal user documents as an internal knowledge base and optimize them to provide responses related to questions asked by users during the online cybersecurity learning process. In the future, this research will be continued by making reranking and other improvisation to produce a better system response to improve user security awareness and understanding related to cybersecurity learning.

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