Using AI Assistants in the Creation of an Academic Program of Study (PoS) in CyberAI

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Abstract—Artificial Intelligence (AI) is playing an increasingly vital role in cybersecurity. As AI becomes more prevalent, cybersecurity professionals need AI skills, and academic institutions need to provide students with the opportunities to gain them. To meet this demand, the NSA National Centers of Academic Excellence in Cybersecurity (NCAE-C) program, in collaboration with the National Science Foundation (NSF), launched an initiative to outline the AI content cybersecurity academic programs need to teach their students. The initiative aims to build knowledge units (KUs) and recommend a Program of Study (PoS) in Cybersecurity and Artificial Intelligence (Cyber AI). This paper outlines the development of an AI assistant that was used to collaborate on the KU creation process for the CyberAI PoS. We will discuss the methodology behind the integration of the AI assistant, evaluate its contributions, and explore future directions for using AI assistants to develop curricular guidelines for academic programs.

Keywords—*CyberAI, AI Assistants, Curricular Guidelines, Cybersecurity, Artificial Intelligence*

I. INTRODUCTION

Within cybersecurity, Artificial Intelligence (AI) is increasingly taking on many critical roles necessary to secure modern computing systems. Cybersecurity professionals must learn to not only work with AI tools but also build and deploy secure AI systems. As AI becomes more prevalent, organizations are urging their current and future employees to acquire these new skills rapidly, prompting the academic community to adapt the topics they teach accordingly. The 2022 CHIPS and Science Act [17] has required the National Science Foundation (NSF) to determine the workforce needs of the US Government and determine the feasibility of a Scholarship Program for students in AI programs of study at community colleges and universities. This has led to a considerable debate on the AI topics that should be taught within cybersecurity programs and the role that accrediting bodies play in assisting educators in defining these topics.

In February 2024, the National Security Agency (NSA) National Centers of Academic Excellence in Cybersecurity (NCAE-C) program (with over 400 institutions), in collaboration with the National Science Foundation (NSF), launched an initiative to outline the AI content cybersecurity academic programs need to teach their students. The program of study (PoS) is referred to as CyberAI in the remainder of the paper. In line with other curriculum guideline efforts, the PoS development focuses on knowledge units (KUs). The KUs for a PoS are generally developed through a collaborative process with educators across the academic community, government partners, and industry representatives. This labor-intensive process can take several years, but with the rapid pace of AI, the development of the KUs for the CyberAI PoS necessitated a much faster pace. This presented several challenges for the educators and their collaborators tasked with creating these KUs, as they had to quickly adapt to the evolving needs of both the fields of AI and Cybersecurity while maintaining the quality and relevance of the developed KUs. In this work, we present the process of developing an AI assistant that was integrated as a collaborator in the development process of KUs for the CyberAI PoS using the NSA NCAE-C program as a model.

Specifically, we explored the following research questions:

RQ1: How can AI assist in the development of the guidelines for academic programs of study?

RQ2: What attributes of a knowledge unit and a program of study can an AI effectively contribute to?

This paper is organized as follows: Section II presents the background and related literature. Section III provides a detailed overview of the methodology used to integrate the AI assistant into the KU development process. Section IV discusses the usefulness of the various aspects of the AI-generated KUs in developing the KUs for the PoS. Section V discusses the insights gained and potential directions for future work.

II. BACKGROUND AND LITERATURE REVIEW

Using AI Assistants for time-consuming and/or knowledge-intensive tasks can improve output quality and increase job satisfaction for humans in almost every field [2]. Within software development, this can include writing code or documentation, leaving time for problem-solving and requirements gathering [3]. For education, AI can be used to diagnose the needs of the domain landscape, create learning outcomes, and select topics to teach within a lesson, allowing educators more time to work with students [4]. AI Assistants have also been explored within the medical field to assist physicians in drafting responses to patient queries, accelerating response times, and enhancing the quality of care [5]. However, there is a lack of methods and practical examples of using AI assistants as collaborators with humans within specific contexts [4] [5].

AI can augment human abilities and is a technology that can complement human knowledge and skills in collaborative settings [2]. AI can also be useful in high-velocity fields, like cybersecurity, where educators must stay updated with their domain's latest developments [9]. Large Language Models (LLMs) have the potential to be used by educators to assist with lesson planning, course design, assessment development, and creation of classroom activities [9]. Currently, there are few documented examples of systems that support curriculum design within computer and information technology programs [1]. Developing LLMs is a time-intensive task that demands significant computational power and substantial funding to support creation and operation, which is only possible by a few well-funded organizations [6]. As a result, many educators are dependent on LLMs that need more comprehensive information in specialized areas relevant to their needs (like cybersecurity and pedagogy), raising concerns about their applicability and effectiveness for certain tasks.

Retrieval Augmented Generation (RAG) addresses this issue by enhancing LLMs with additional context, such as user-uploaded files that are relevant to specific queries [12]. By employing RAG, users can integrate up-to-date information, reduce the risk of hallucinations, and improve the overall quality of the content generated by publicly available LLMs [13]. Implementing RAG generally requires technical proficiency, but several no-code or low-code approaches have been made available for models like OpenAIs GPT and Google's Gemini [2].

A. Implementing AI and AI Assistants

AI has become more accessible in part due to large companies providing easy to use interfaces like chatbots. These approaches provide opportunities for non-technical or even highly technical people looking to save time to build LLM-based solutions for everyday tasks [2]. This democratization allows people of all technical abilities to leverage AI for their unique tasks in ways that were previously not possible. Przegalińska describes four levels of competence in the development of AI, starting with the basic use of interfaces, escalating to using existing tools, then to developing scalable AI projects, and ending with the implementation of AI algorithms [2]. AI Assistants are software systems that use AI models to respond to human inquiries. An example of an AI assistant is ChatGPT, which uses a version of the GPT model from OpenAI to respond to human queries [6].

B. AI Assistants in Education

The ability of non-technical users to implement AI presents several opportunities within education to innovate teaching and learning [2]. There are three broad categories of AI applications in education including: learner-facing, teacher-facing, and system-facing [7]. Learner-facing systems, where students receive and understand new information, can respond to individual student needs, while teacher-facing systems are designed to help reduce workload, gain insights about students, and innovate within their classrooms. System-facing refers to AI applications that are used by administrators to make data-driven decisions within education [7].

Examples of teacher-facing systems include developing learning outcomes from course metadata and existing learning materials. Almatrafi [8] utilized a GPT-3.5 model and course metadata such as title, description, and course topics to generate course learning outcomes. 80% of the generated learning outcomes were found to be correct and helpful, while 20% were found to be incorrect or irrelevant [8]. Sridhar et el. [10] also utilized course and module metadata to generate learning objectives using a GPT-4 model. They found that this model was able to generate reasonable learning outcomes for a given course, targeted the correct level of Bloom's Taxonomy, and used a diverse set of verbs [10].

C. The NSA NCAE-C Program and the NSF CyberAI Project

Supported by the National Security Agency (NSA), the Center of Excellence (CAE) program designates academic institutions that meet rigorous criteria for cybersecurity education and research [14]. Currently, over 400 schools, including both two- and four-year institutions, hold one or more of the three designations - (cyber defense, cyber operations, or research). To attain any of these designations, academic institutions must first complete a validation of their Program of Study (PoS). A PoS is a series of courses and experiences that students can realistically complete while working towards a degree or certificate [14]. It is structured around knowledge units (KUs), which are thematic groupings of learning outcomes and topics. Academic institutions document their fulfillment of requirements for a PoS through the process of KU alignment, by demonstrating their course learning outcomes and materials meet the PoS requirements. To maintain a PoS an academic institution must commit to continued maintenance when KUs are adjusted [16].

In March 2024, the NSA and NSF began a collaboration to launch an initiative to outline the AI content cybersecurity academic programs. The initiative aimed to recommend a Program of Study in Cybersecurity and AI (CyberAI) for the CAE program, which focuses on both using AI for cybersecurity and the security of AI. In this study, we used the PoS and KU model in the NSA designations as the case to explore the applicability of AI assistants.

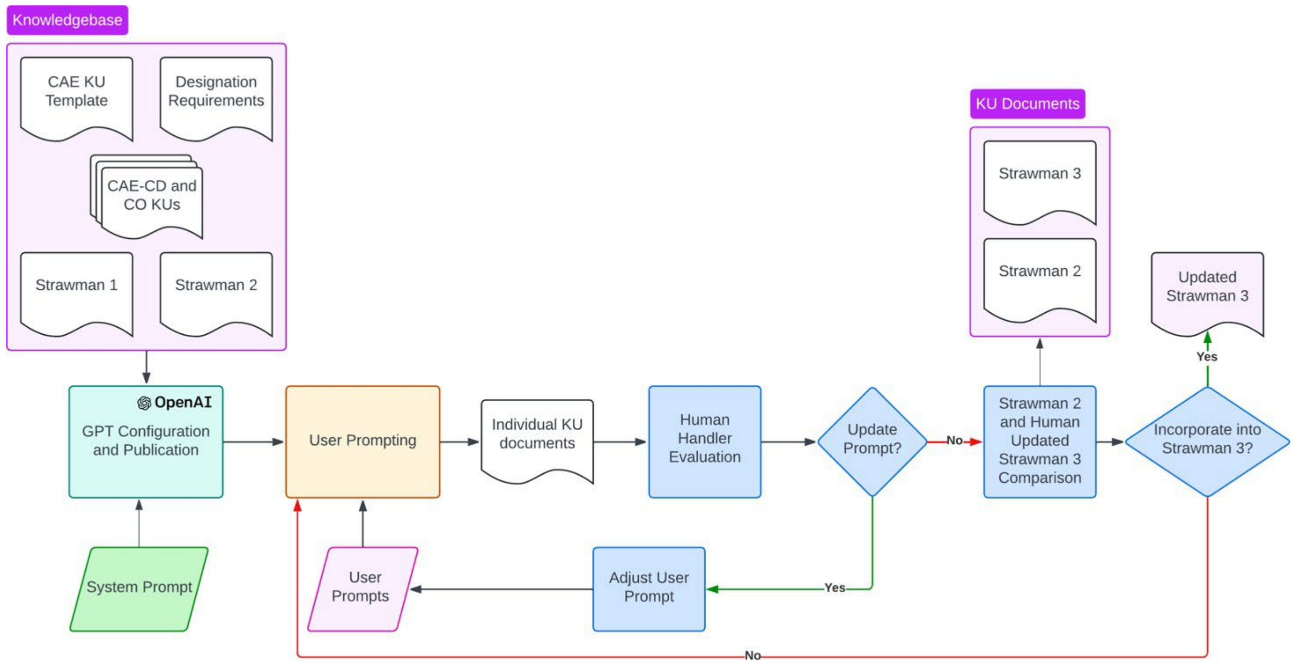

Fig. 1. AI Assistant creation process

III. METHODOLOGY AND SYSTEM DESIGN

Over a six-month period, which included in-person and virtual workshops and asynchronous feedback mechanisms, 235 educators, government partners, and industry members contributed to the creation of the CyberAI KUs. This process was done iteratively through a series of documents nicknamed "Strawman" with the final iteration being called "Stoneman". All versions of the documents and their publication dates can be found in Table I. The leadership team used AI Assistants in several iterations of the documents to guide the development of individual KUs. The system design and the process of creating the Assistant and integrating its output can be found in Figure 1

TABLE I. Program of study iterations

Iteration	Publication Date	AI Assistant Used
Strawman 1	May 14, 2024	None (human creation only)
Strawman 2	July 11, 2024	Custom GPT
Strawman 3	July 19, 2024	Custom GPT
Strawman 4	July 22, 2024	None
Strawman 5	July 23, 2024	None
Strawman 6	July 23, 2024	None
Stoneman	August 29, 2024	Custom GPT

A. *Human KU Creation Process*

Human authors worked collaboratively to incorporate feedback from various sources to iterate on drafts of the KUs. The lead human authors of the KUs were from nine different schools that all hold the CAE-CD, CAE-CO, CAE-R, or a combination of these designations. At least six of the leads have been involved with the creation and/or updating of KUs for other PoS's in the past. The structure of a KU is consistent for all programs of study within the NCAE-C program and contains a title, description, learning outcomes, topics, and notes. Learning outcomes are constructed using verbs that align with one of the taxon's within Bloom's Taxonomy [15] and define the knowledge and ability of the student upon completion of a course aligned to that KU [16]. Topics are areas that the learning outcomes will cover and are often broad to allow for unique programs across the NCAE-C program. Notes are used to define any other information necessary for successful alignment which vary based on the KU.

B. *GPT Configuration*

GPTs are tailored versions of ChatGPT that do not require in-depth machine learning or programming skills to finetune for a specific task [11]. A GPT can be given abilities to search the web, generate images, or generate text using a specific GPT model and the provided knowledgebase. The knowledgebase stores files that can be referenced in prompts to the GPT and is one of the methods of providing documents for RAG. The use of GPTs requires a subscription to ChatGPT which is $20 per month per user at the time of publication.

1) System Prompt

To provide the GPT with the necessary context a system prompt was used. The prompt (Figure 2) is created by the author of the GPT and is provided to the model each time a user prompt is sent through the custom GPT. Users of the GPT do not have the ability to view or adjust the system prompt. The system prompt was developed iteratively and based off the language used in various documents and presentations used to guide the human participants in developing the KUs.

> You are a helpful assistant to professors in the NCAE-C Community that are building knowledge units for a new program of study (PoS) in AI for Cybersecurity and Security of AI. Keep all conversations on the topic of creating knowledge units, gaining understanding on certain topics related to either AI for Cybersecurity or Security of AI. Use the definitions of Knowledge Unit, Knowledge Area, Program of Study, Learning Outcomes, and Topics defined in the documents provided to you in your Knowledge. When asked to generate a KU or Knowledge Unit please follow the headings in the Knowledge Unit Template provided in the documents. A single knowledge unit should not be larger or more complicated than what could reasonably be taught during a 15 week college semester. The Strawman 2 document provided in your knowledge is what human participants have generated for a list of Knowledge units for a program of study in AI for Cybersecurity and Security of AI. Strawman 1 is a previous version of this document and provided to you as a reference. If asked to provide input on the KUs in that document, always indicate the changes or suggestions you are making in your response.

Fig. 2. System Prompt to custom GPT serving as AI-Assistant

2) AI Assistant Knowledgebase Creation

Documents selected for inclusion in the knowledgebase were selected based on the resources provided to the human authors of the KUs. The goal of the knowledgebase was to provide the AI Assistant with content that would also be available to the human authors, either through their experience or from documents publicly available online. The links to the documents included in the knowledgebase for this study are described below and can be found in the following GitHub repo:

https://github.com/pzalep1/cyberAI-documents.

The existing KUs for the NSA CAE PoS in Cyber Defense (CD) and Cyber Operations (CO) were provided to the GPT as examples of KUs. The requirements for designation were provided to provide the GPT with definitions of terms that were referenced in the system and user queries. The template of a KU was provided for a similar reason. Strawman 1 and Strawman 2 were provided to allow for a more concise user query that did not require additional file uploads at the time of prompting.

C. User Prompt

The user prompt to make edits to specific KUs was developed iteratively, where the prompt was used for a single KU and then the output was evaluated for structure. If the structure of the output was not in the desired format the prompt was adjusted. Once the desired structure was achieved, the prompt (Figure 3) was used to generate an updated version of each KU in the Strawman 2 document and then evaluated for inclusion in the Strawman 3 document. A similar process was adhered to for the final Stoneman document, but several authors had access to the GPT and used their own prompting techniques that were not documented.

> For the {{ name }} KU in the Strawman 2 document make adjustments to the outcomes and topics list in order to make it easier for a professor trying to align the content taught in their courses to the knowledge unit. Adjustments can include additions or subtractions to either list, reordering learning outcomes to be in an order that reflects verbs in Blooms taxonomy taxons, combining topics into a single topic, breaking out topics into multiple topics, or adjusting words to better articulate the outcome or topic.

Fig. 3. User Prompt

D. Assistant Output

For each KU in the Strawman 2 document, the AI Assistant produced a fully developed KU that included the title, description, learning outcomes, topics, and notes. Although not explicitly requested in the user prompt, the learning outcomes were grouped within the 6 taxon's of Bloom's taxonomy in addition to be ordered by their verbs. The consistency in the formatting of the output allowed for a systematic approach to incorporation in the Strawman 3 document by human evaluators.

E. Human Evaluation

The output of the AI Assistants was evaluated by a lead author that acted as the human evaluator to determine the contents incorporation into the various Strawman versions. The other human authors reviewed the AI-generated suggestions curated by the evaluator and determined their inclusion in the final document. Meanwhile, the evaluator assessed the suggestions for clarity and usefulness while also checking for potential AI hallucinations. For learning outcomes, the human evaluator reviewed the suggested outcomes to see if they were newly created or revised versions of the existing ones and made suggestions in the documents. For the topics, the human evaluator compared the list the assistant suggested and the one the human authors edited. Since most of the KUs in the Strawman 3 document lacked a description, many suggestions made by AI were incorporated into Strawman 3 for this attribute of a KU. Similarly, many of the KUs did not contain notes, but the notes generated by AI were generally not incorporated as they were repetitive and did not provide useful information. One area largely ignored by the AI Assistant was the titles of KUs, and no changes were added to the Strawman 3 document for this attribute. Human contributors were made aware of the AI's specific contributions through document change tracking and comments provided by the evaluator of the AI contributions.

IV. DISCUSSION

The integration of an AI assistant into this process was seen as a benefit by the human authors. One significant contribution was improving the accuracy and diversity of the Bloom's taxonomy verbs used in the learning outcomes. For example, 'define' and 'understand' were often overused by humans creating learning outcomes, even when instructed to build outcomes for higher-level learning. The AI added verbs such as 'analyze,' 'evaluate,' and 'assess.' In addition to suggesting a wider variety of learning outcomes, it also prompted the human participants to review the human-produced learning outcomes for improvements to the verbs, specifically the taxonomy level at which learning is achieved. The AI assistant also aided the human authors with the KU descriptions. Descriptions for KUs produced by previous groups of human authors varied widely in structure. The assistant was able to take these varying compositions of the descriptions and produce uniform and succinct versions.

However, while the AI assistants helped with synthesizing a long list of topics, they were less successful at expanding or adding topics to KUs. The AI assistant was also unable to suggest significant changes to the notes for KUs. This was unsurprising because the example notes provided in the knowledgebase from other sets of KUs were sparse and often just listed the types of activities needed to achieve the learning outcomes. This demonstrates that AI assistants have certain contextual limitations and require proper examples to generate meaningful outputs. Finding or developing examples of notes and creating user prompts that specifically target the task of creating notes is an area that can be investigated in the future.

An interesting observation from providing the updates from the AI-synthesized KUs is that the academic participants reviewed the contributions similarly to how they would review other human contributions, if not with slightly more scrutiny. The human collaborators edited all KU descriptions (mostly AI-generated) in the subsequent Strawman versions. This was generally like a human making contributions to a shared artifact and other humans adjusting their input, implying that the humans treated the AI as an equal collaborator. However, an area for future research would be to determine which parts of the AI assistant's output prompted the suggested updates by the humans and which suggestions survive to the final document.

The increasing role of AI in educational content generation raises important questions about its influence on educational standards and the ethical considerations of its use. AI-driven tools, like AI Assistants, can help ensure consistency and provide valuable contributions, but they can also introduce potential biases based on the data it was trained on, the prompts used, and the additional information provided by users. Transparency in how AI-generated content is created, evaluated, and used in educational settings is essential to maintain trust. These considerations highlight the need for AI to serve as a complement to human expertise to ensure educational standards remain pedagogically sound.

V. CONCLUSION AND FUTURE WORK

As AI continues to transform cybersecurity, it is essential for academic institutions to adapt their curricula to ensure that students are gaining the necessary knowledge and skills to secure AI systems and use AI for cybersecurity measures. The collaborative effort by NSF and the NSA CAE program to define a PoS in CyberAI demonstrates a critical step towards meeting this need. The integration of an AI Assistant as a collaborator proved beneficial and assisted human contributors in developing learning outcomes and descriptions of the currently proposed KUs for the PoS in CyberAI. In future work, the final version of the KUs will be analyzed to evaluate what suggestions made by the Assistant persisted to the final version of the KUs.

Future research in this area could explore optimizing AI Assistants' roles and enhancing prompt design to improve curriculum development for teaching the topics outlined in the KUs. Additionally, it could explore refining the KUs themselves using AI Assistants and various prompting techniques to ensure greater clarity and effectiveness. The presence of AI hallucinations was not tracked in this study but could be an area of future work as the KUs continue to evolve with the assistance of AI. A comparison of the quality of the KUs generated with the assistance of AI and those generated by humans is also an area of future investigation. Additionally, investigating how the inclusion of AI-generated content influences the decision-making of educators in developing KUs could offer valuable insights into the process of creating and updating KUs.

VI. ACKNOWLEDGEMENT

This paper does not report on the actual program of study generated as a result of the CyberAI project. However, we would like to acknowledge the work of the lead authors the NSA CyberAI program of study document – Shankar Banik, Eman El-Sheikh, Paige Flores, Seth Hamman, Siddharth Kaza, Yair Levy, Vincent Nestler, Md Sajid, Sagar Samtani, Patrick Tague, Blair Taylor, and Paul Wagner. The AI assistant collaborated with the document as it evolved. We also acknowledge the human lead authors, who allowed us to observe their interaction with the suggestions of the AI assistant. The final version of the KUs can be found here: https://towson.edu/cyberai.

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