AskAda: An AI-Anchored Conversational Agent for Scholarly Information Seeking in Educational Contexts to Improve Learning

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ABSTRACT

AskAda is a conversational agent designed to lower barriers to accessing AI-driven tools and support university students in accessing authoritative scholarly resources for their academic activities. It enables topic identification and definition retrieval of appropriate terms to help students locate trustworthy and current scholarly information that is inaccessible as a commodity through public search engines. Operating within the WhatsApp platform, AskAda reduces the learning burden of adopting a new system and GUI and allows students to use the AI tool directly from a smartphone. Unlike many AI tools, AskAda emphasizes accountability and transparency that instructors can rely on and trust by validating the audit trails generated by the students' search journey while completing their assignments. Two authors conducted an autobiographical study and evaluated the performance of AskAda based on two dimensions: efficiency and usability. The system facilitates topic identification and retrieval of scholarly resources from library databases while maintaining an auditable session history and fostering transparency in AI interaction in the educational context.

CCS CONCEPTS

• Human-centered computing → Human computer interaction (HCI); Information systems → Information retrieval

KEYWORDS

Artificial intelligence, conversational agent, pedagogy

1 Introduction

Investigation of learning tools that integrate Artificial Intelligence (AI) methods with the educational frameworks to improve pedagogical outcomes is an active research area [5, 6, 13]. Although such AI-driven learning approaches can enhance the originality and usefulness of student work, their overall impact remains modest, as students rely passively on AI-generated output instead of engaging creatively and accepting familiar solutions [5]. The problem is challenging due to the availability of multiple AI systems, such as Google AI and ChatGPT, and student preferences for certain tools while searching for specific information [6]. When using external AI systems, it is also difficult to decouple activities associated with scholarly enquiry from casual searching [13]. In addition, the lack of transparency of the datasets used to train these AI tools often leads to ambiguity about the type of authority of the resources retrieved by these systems [3], leading to a question about whether these resources are appropriate for students to conduct scholarly work.

1.1 Problem Statement

The recent advancement of large language models allows researchers to develop AI-anchored conversational agents, supporting pedagogy and learning [16, 20, 24]. However, these agents often operate under custom environments that university students are unfamiliar with, such as LibreChat [24] or custom web user interfaces [16], hampering students' search journey for completing an assignment and disrupting access to authoritative scholarly resources. Similarly, accessing authoritative scholarly resources using these platforms could be challenging, lowering the quality of students' assignments. In addition, these systems rarely capture or share audit trails for the instructors, raising

concerns about the ethical usage of AI tools in education. The objective of this demonstration paper (see figure 1) is to describe the first two challenges:

1. How could we lower the barriers to accessing AI-anchored education tools to improve learning?
2. How could we ensure that an AI-anchored conversational agent that focuses on education has the capabilities to access authoritative scholarly resources and allow students to access them?
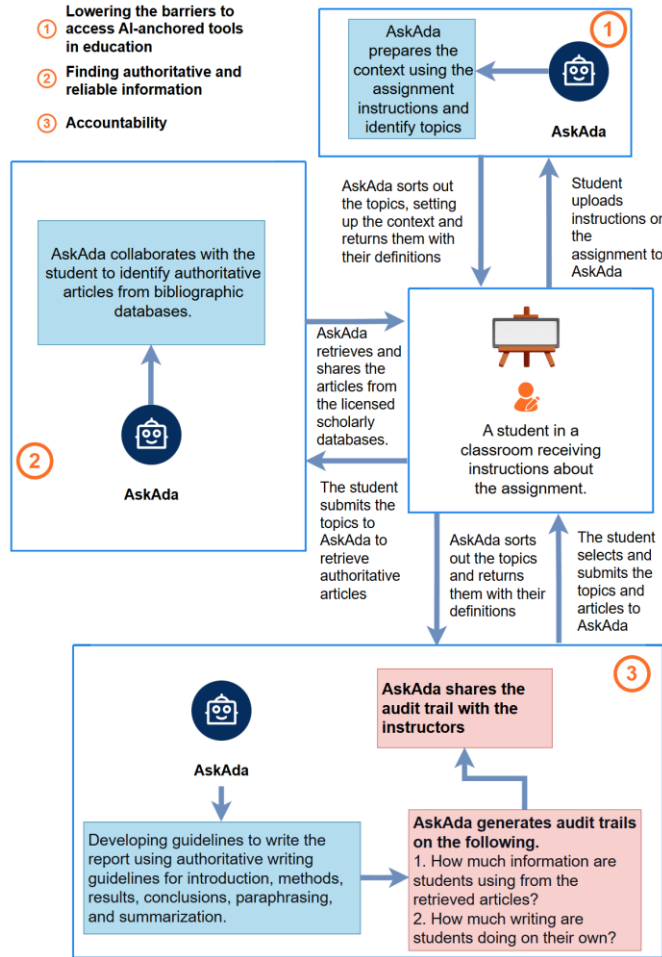
Figure 1: Student search journey workflow while completing an assignment using AskAda.

To address these challenges, we introduce AskAda, an AI-anchored conversational agent on a social platform that can interact with students without installing specific software or learning a complex user interface. AskAda is running on the WhatsApp Cloud Environment, allowing students to interact with the agent from a familiar environment, reducing the cognitive burden of learning new software and interface. In addition, AskAda enables students to identify the topics they are interested in, reuse them to retrieve authoritative information, and share the results. In this current version, AskAda also stores the audit log of

the current sessions and the conversation history, allowing students to share the search results via email.

2 Literature Review

2.1 Information Seeking Behavior

University students often struggle to define their research questions or search for authoritative resources effectively. More than three decades ago, Kuhlthau pointed out that searchers move through feelings of uncertainty before they reach understanding [9]. Marchionini described information seeking as a process with stages of problem definition, exploration, and interpretation [11]. In addition, Bates used the idea of "berry-picking" and explained the process of adjusting goals when users search and discover new information [1]. It is also known that many searches involve quick retrieval during the search, and users spend more time on limited results, preventing themselves from broader exploration [23]. We drew upon the latter information to develop and deploy the search interaction workflow in AskAda.

2.2 Refinement of Search Interaction

Studies have shown that users encounter incomplete search sessions when using traditional keyword-based search that do not provide enough context on the topics, particularly in exploratory search, except by providing a ranked list of the retrieved results when dealing with ill-defined problems [21]. However, systems that allow users to control and adjust their queries can improve the process significantly [7]. Recently, studies found that interactive search engines enable users to drag and drop search queries and save their results in a separate workspace, which helps users improve their planning and reviewing [17, 18]. The latter findings were crucial in shaping the search workflow we developed to support university students using AskAda.

2.3 AI-anchored Solutions to Improve Writing and Learning

With the rise of generative AI, many chatbots and virtual tutors now appear in education. Early systems like Jill Watson [4] acted as a teaching assistant that answered course questions. Newer tools such as Duolingo Max and ChatGPT have combined large language models with tutoring strategies, helping learners practice dialogue, solve problems, and review feedback in real time. The study has shown that AI in the educational context can process and generate information faster, but it lacks understanding of the needs of learners [2]. However, teachers also report that many online chatbots still give vague feedback and do not support deep conceptual learning for students [8] . These findings demonstrate a need for an AI-anchored conversational agent to serve as a supportive learning partner with the ability to keep a shareable audit trail of the students' work. In addition to that, certain studies focus on AI tools that help students in academic research and writing [10, 15, 22]. However, we found no current systems combining searching, learning, and writing guidelines within one

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environment. This gap points to the need for tools that combine these processes to better support academic tasks.

3 AskAda

We introduce AskAda, an AI-anchored integrated learning support conversational agent to assist university students in guiding their assignments from the initial step: identifying topics, accessing authoritative resources, and developing writing guidelines using the retrieved authoritative resources. In this version, AskAda can assist students in determining the topics, enhancing them, and allowing students to access resources related to their assignments using scholarly databases. In addition, AskAda can generate an audit trail on the identified topics and the corresponding definitions, topics that have been used to search academic databases, and the types of retrieved resources. The current version of AskAda can also retrieve the search results and email them to the university students for future planning. We developed AskAda on top of WhatsApp, keeping students in a familiar environment and avoiding learning new search systems and user interface. AskAda utilizes explanatory menu-based dialogue and Minimum Dictionary Language (MDL) [12] to identify topics, access authoritative resources, and share audit trails. Detailed guidance on how to use AskAda through the WhatsApp interface is available to users at the following web address: https://askada.lairhub.com/.
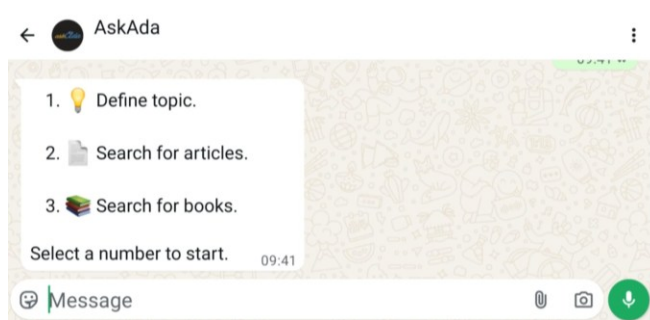

Figure 2: AskAda: menu selection

Figure 3: AskAda: definitions of topics

3.1 Identifying Topic

When a university student interacts with the interface of AskAda for the first time, AskAda provides a self-explanatory message to the user on how to start their journey, avoiding the need to refer to any documentation to understand the conversational agent. When the student starts communication with AskAda, it provides a menu from which the student knows how to identify a topic. AskAda uses the "define <topic>" command to identify topics (see figure 2). When AskAda receives the commands, it connects with Llama 4 [25] in identifying topics with a custom prompt, retrieves the given topics and four more associated topics and their definitions, and presents them to the student (see figure 3). Later, the student can retrieve the authoritative resources using the selected topic described in section 3.2.
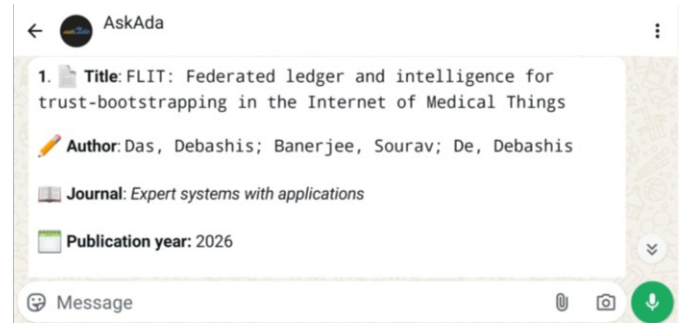

Figure 4: AskAda: article result set

3.2 Accessing Authoritative Resources

When AskAda generates the results of defined topics, it puts an index number with each topic (see figure 3). When students use the command "search article 1", AskAda will collect the topic associated with the index number and use the topic to retrieve articles from bibliographic databases (see figure 4). The current version of AskAda uses the Web of Science Starter API and Google Book API to retrieve metadata (title, author, published year, journal title) and present them to the users. Students can also use the "search book" command with the topic index number to retrieve metadata about the books. The current results include ten journal articles and ten books that best matched on the backend databases connected via APIs. We curated API endpoints in a PostgreSQL database to reduce the complexity of managing APIs. It also ensures smoother transactions between AskAda's backend, which we developed using Python FLASK, and allows us to scale the system easily.

3.3 Audit Trail

AskAda allows students to share the retrieved topic definitions and search results for articles and books for a specific session via email, enabling students to create an audit trail. To send an email to a specific address, users can use the command "email <email address>". Upon executing this particular command, AskAda retrieves the data from the user session and formats it based on which topics have been used to search articles and books by the

students, as well as the retrieved metadata from the Web of Science and Google Book API. This particular feature is the first stage in developing detailed audit trails to capture students' activity comprehensively and make it shareable with the instructor.

4 Evaluation Method

Authors 1 and 3 employed an autobiographical case study [14] as an end-user to evaluate the AskAda in specific information-seeking tasks, following two user-personas: novice and experienced.

Novice User Persona: Person A completed a master's degree in information science and is familiar with research concepts. However, they struggle to identify familiar research concepts and have limited ideas on where to find relevant authoritative resources, including limited experience in using an AI system.

Experience User Persona: Person B is a third-year doctoral student in information science, an advanced user of an AI-driven learning tool, with sufficient knowledge to ensure the authenticity of relevant articles. In addition, Person B values tools that can enhance the efficient retrieval of academic resources and maintain transparency.

Task Complexity: We divided the task complexities into three categories: known or straightforward item search, moderately complex known item search, and conceptual subject search. Firstly, the simple task involved retrieving specific and factual information. Secondly, the moderately complex task involved contextual understanding. The third task involved an open-ended exploration or synthesis of contextual knowledge.

Task Design: We designed six tasks for each complexity level to evaluate AskAda. Task 1 aimed to assess the intuitiveness of AskAda. The expected output was to evaluate whether AskAda can identify the topic. Task 2 involved evaluating the definition clarity and response structure, with an expectation that produces concise and accurate topics and their definitions. Task 3 examined AskAda's capability to transition smoothly between different states, from identifying topics to using it for searching authoritative databases. Task 4 assessed the command structure and result readability for book search using the topic. Task 5 aimed to understand the text flexibility in narrowing down the topic. Task 6 examined how AskAda can recover from incomplete or erroneous commands. Hence, altogether, there were 18 tasks covering the three complexity levels.

The evaluation focused on two dimensions: efficiency and usability. We measured the efficiency using two indicators for each task: time taken to complete each step and the number of steps taken to complete each task. To assess usability, we followed Schneiderman's Eight Golden Rules [19].

5 Results

Efficiency evaluation: Authors 1 and 3 completed all 18 tasks. The set of six tasks for each complexity level took approximately 1.5 minutes to complete. The average response time per command was 7-10 seconds. For author 1, the command response was smooth and without repeated inputs. For author 3, task completion

times were almost identical. The users reported no significant delay for complex queries such as "The contributions of 20th-century economists". Steps are closely matched for both users.

Usability evaluation: Author 1 found that the workflow of AskAda was immediately accessible, with clear command prompts and closure messages like "to exit, type exit". The predictable conversational structure aided early interactions when users relied on syntax guidance. The system was also responsive - commands could be re-tried or refined without losing the session.

Author 1 also noted limitations during longer sessions. The system accepted fixed commands (e.g., define <topic>) and rejected variations like "defines" or "def". When given complex inputs such as "Define the contributions of 20th-century economists to microeconomic theory," AskAda reduced them to one-word topics like "Economics," resulting in less meaningful outputs.

Author 3, a more experienced user, reaffirmed AskAda's strengths in response consistency, speed, and predictability. The chatbot handled errors gracefully with polite recovery prompts, reducing frustration and supporting user control and feedback principles [19]. However, its fixed command structure made interactions feel rigid and repetitive, and memory handling was inconsistent—sometimes failing to recall previous queries or summarize completed tasks.

Both authors agreed that AskAda's strengths are its reliability, clarity, and speed, enabling users with limited AI experience to engage confidently with academic content. However, they also identified needs for greater language flexibility, richer topic context, and more adaptive user support.

6 Future Work

Future work will focus on developing the report planning assistant to help students structure assignments through outline generation and citation support. Enhancements will also target integrating more authoritative databases and adaptive feedback to interpret complex topics better.

7 Conclusion

This study introduced and evaluated AskAda, an AI-anchored conversational agent facilitating topic identification and scholarly resource retrieval. Using autobiographical evaluation, two authors assessed the system's efficiency and usability across tasks of varying complexity. The results demonstrate that the system delivers consistent performance and a clear interaction structure and supports novice users in structured academic exploration. Overall, AskAda represents a promising step toward more intelligent, transparent, and educationally grounded AI systems that enhance university students' research and learning processes.

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