AI CHATBOT-BASED SMART KIOSK SYSTEM TO ENHANCE THE ACCESSIBILITY AND EFFICIENCY OF INFORMATION AT ACADEMIC INSTITUTIONS

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ABSTRACT

In the dynamic landscape of educational institutions, the demand for streamlined information dissemination and enhanced accessibility has never been more crucial. This work introduces an innovative solution: an "AI Chatbot-Based Smart Kiosk System" designed to augment accessibility and efficiency in educational environments. Leveraging Artificial Intelligence (AI) and conversational interfaces, this system aims to redefine the way information is accessed and delivered within educational institutions. The AI Chatbot, embedded within interactive Smart Kiosks strategically placed across campuses, serves as an intelligent intermediary between users and institutional information repositories. The system is meticulously crafted to facilitate seamless communication, providing instant and personalized responses to queries related to course schedules, campus maps, event details, and various other informational needs. The key features of the proposed system include natural language processing capabilities, adaptive learning from user interactions, and integration with institutional databases and online platforms. By harnessing the power of AI, the Chatbot adapts to user preferences and continually refines its responses, ensuring a tailored and efficient information retrieval experience. Furthermore, this research explores the potential impact of the AI Chatbot-Based Smart Kiosk System on accessibility for individuals with diverse needs, promoting inclusivity within the educational landscape. The study delves into the usability and user satisfaction aspects, measuring the effectiveness of the system in enhancing the overall experience for students, faculty, and visitors. Through rigorous evaluation and testing, this research aims to validate the effectiveness of the proposed system in improving information accessibility and efficiency within educational institutions. The outcomes of this study are anticipated to contribute valuable insights for the integration of AI-driven technologies in educational settings, paving the way for a more connected and responsive learning environment.

Keywords: AI Chatbot, Smart Kiosk System, Educational Technology, Efficiency, Conversational Interfaces, Artificial Intelligence, Natural Language Processing, User Interaction, Adaptive Learning, User Preferences, User Satisfaction, Connected Learning Environment

I. INTRODUCTION

1.1 Background

A chatbot, functioning as a software entity, is designed to replicate human-like conversational interactions, be it through typed messages, spoken dialogue, or non-verbal communication. Widely prevalent across diverse platforms, from archaic HTML pages to contemporary social networks, chatbots serve as engaging entities offering assistance. The development of a college inquiry Chatbots utilize machine learning principles to engage in conversations with users. The primary goal of this initiative is to create an intelligent chatbot system specifically tailored for addressing academic queries, covering aspects such as admission procedures, fee structures, scholarship details, departmental timetables, and document requirements. By employing this chatbot system, students can efficiently obtain quick and accurate responses to their queries, significantly reducing the time required for information retrieval. Typically featuring a text-based interface, chatbots empower users to input commands and receive textual responses to address their inquiries. Equipped with a comprehensive dataset containing relevant information, the chatbot employs machine learning algorithms to discern user queries and autonomously generate contextually appropriate responses. The program meticulously analyzes user inputs, enabling the bot to offer

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precise and timely information. This innovative approach enhances communication efficiency and facilitates seamless information dissemination within the academic realm. This work provides a thorough review of the existing literature pertaining to the research area. It encompasses a diverse range of research works documented in open literature, focusing on aspects such as chatbot design, architecture, and implementation. The evolution of chatbots is explored, accompanied by thedevelopment and implementation of an AI Chatbot-Based Smart Kiosk system. This enhances the accessibility and efficiency of information and services at our college. This innovative solution will empower students, faculty, parents, and stakeholder groups with instant access to essential information regarding admission inquiries, placement, academic departments, curriculum, syllabus, sports, and exams.

1.2 Primary Focus

The primary focus of this work revolves around AIML-based chatbots, specifically tailored to meet the requirements of small to medium-sized businesses. AIML, known for its popularity in implementing rule-based chatbots, is lauded for its flexibility and ease of configuration. Numerous variants of AIML-based chatbots have been documented in the open literature. A pivotal contribution discussed in the state-of-art works involves the implementation of a generic architecture aimed at creating chatbots with distinct personalities using AIML, as detailed in [1]. Existing research works signified intelligent chatbot systems, enabling the creation of diverse and cohesive personality models for integrating personalities into AIML chatbots. This solution will enhance the accessibility of information for prospective students and streamline administrative processes. This chatbot will serve as a virtual assistant to students, faculty, and visitors, providing real-time information and assistance to streamline various campus operations. These components collectively enable the description of attitudes, emotions, mood, physical states, and traits.

The extension of AIML known as Graphical Artificial Markup Language, introduced in [1], facilitates the merging of verbal and graphical interaction modalities. This language defines personalized interface patterns suitable for the exchanged data type during user-system conversations. The Graphbot system is designed to Provide easy access to crucial college-related information through an intuitive AI Chatbot interface accessible via smart kiosks.

II. LITERATURE REVIEW

Addressing chatbot enhancement approaches, [2] introduces intelligent machine learning mechanisms incorporating conviction data into conventional chatbots based on large language models (LLM) and intelligent intended solutions. This work utilizes LLM as natural language processing heuristic, considering intentionality in adjacent pairs in dialogue to facilitate consistent user interactions. The proposed approach involves redefining the AIML base by adding protocols based on language and heuristics. The study validates the AIML mechanism through two experiments conducted with real interlocutors and a chatbot expert. Furthermore, [3] proposes an adaptive chatbot employing a corpus-training approach to assist students in actively learning conversational skills. Extend the chatbot's capabilities to include personalized academic advice during admissions. The chatbot can analyze a student's academic history and preferences to recommend suitable courses and majors.

The integration of Artificial Intelligence (AI) into educational settings has led to innovative applications such as AI chatbot-based smart kiosk systems. These systems aim to improve the accessibility and efficiency of information dissemination within academic institutions. This literature review explores the existing research and developments in this area, focusing on the impact of AI chatbot-based smart kiosk systems on enhancing the educational experience.

AI chatbots have been extensively studied for their role in enhancing communication and support within educational environments. Research by [11] demonstrated the effectiveness of AI chatbots in answering student queries and providing real-time assistance, contributing to improved communication channels within academic institutions.

The implementation of smart kiosk systems in educational institutions has been explored for its potential to provide centralized information hubs. The authors [12] investigated the integration of smart kiosks on campuses, emphasizing their role in streamlining administrative processes and improving accessibility to essential services.

The role of AI chatbot-based smart kiosk systems in promoting accessibility and inclusivity in academic environments is a focus of research. Studies by [13] highlight how these systems cater to diverse learning needs, languages, and abilities, contributing to a more inclusive educational environment.

Efficiency gains and automation in academic processes through the use of AI chatbot-based smart kiosk systems have been investigated. The authors [14] explored the impact of automation on routine administrative tasks, demonstrating how these systems contribute to resource optimization and increased efficiency.

Research on user experience and satisfaction with AI chatbot-based smart kiosk systems is crucial for their successful implementation. The authors [16] conducted a user satisfaction study, highlighting the importance of user-centric design and continuous improvement to ensure positive experiences.

The literature indicates a growing body of research on the integration of AI chatbot-based smart kiosk systems in academic institutions. These studies collectively emphasize the potential of these systems to enhance accessibility, efficiency, and user satisfaction within educational settings. As this field evolves, further research is warranted to address challenges, refine functionalities, and explore new avenues for optimizing the educational experience.

III. RESEARCH QUESTIONS

This work delves into a comprehensive examination of the state-of-the-art literature within the realm of Human-Computer Interaction (HCI), with a specific emphasis on ubiquitous and interactive techniques geared towards advancing smart living.

The work endeavors to address specific Research Questions (RQ) by scrutinizing the current literature:

Research Question 1 (RQ1): How does human-attention sensing differ between physical and virtual setups?

Research Question 2 (RQ2): What modalities are considered feasible for online attention estimation?

Research Question 3 (RQ3): Which forms of attention have been the focus of system development efforts?

Research Question 4 (RQ4): Is touch-free interactivity a necessary component for innovative HCI?

Research Question 5 (RQ5): Can the promotion of such interactivity be realized on a global scale?

In this manner, the work not only provides a panoramic view of the academic information dissemination to follow but also strives to answer these pivotal research questions through a comprehensive review of the current literature in HCI.

IV. METHODOLOGY

Exploring user queries meaningfully with intent empowers the chatbot to efficiently uncover additional insights. The design of a preliminary intentiveness chatbot level was detailed and capable of identifying a single missing piece of information. However, scenarios may arise where generating a response requires multiple pieces of information, all of which might be updated with language understanding and logic. This implementation also provides the development of a multilevel intention chatbot adept at managing numerous missing details through strategic user probing. The proposed design advocates for an ontology-based approach to facilitate multilevel intentiveness.

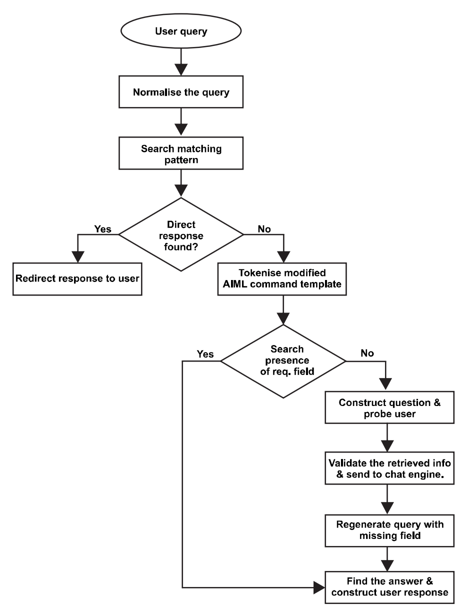

Figure 1: Flow chart for the Query Processing

In a general context, the term "ontology" refers to an artifact specifically crafted to facilitate the modeling of knowledge within distinct domains. These artifacts serve to establish a structured knowledge base for a given domain, allowing machines to interpret it both syntactically and semantically. Reduce administrative workload and response times by automating routine inquiries and requests. A complete knowledge base is created by combining an ontology with a set of distinct instances of classes.

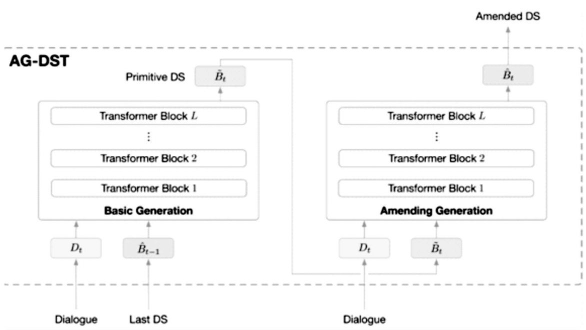

Figure 2: AG-DST Architecutre

Classes take center stage in ontologies, serving as the primary entities that describe concepts within a given domain. Subclasses, representing concepts more specific than their parent classes, are utilized to further refine the conceptual framework. The practical development of an ontology involves a smart kiosk that would provide information about academic programs, courses, and schedules. By defining individual instances within the defined classes, this process culminates in the creation of a knowledge base.

V. WORKFLOW-INTENSIVE CHATBOTS AND PHASES

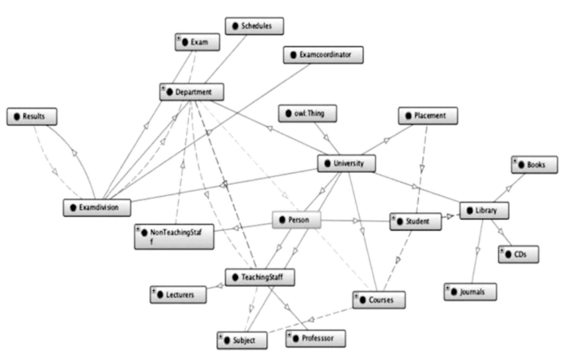

Figure 3: Workflow-Intensive Chatbot

Phase 1: Chat bot Input resources

Define the scope, objectives, and anticipated outcomes. Establish precise goals for the implementation of the Chabot-based kiosk system.

Phase 2: Stakeholder Identification

Identify key stakeholders, encompassing administrators, faculty, students, parents, and other pertinent parties. Comprehend their requirements and expectations.

Phase 3: Market Research

Conduct an exhaustive examination of available Chabot technologies, kiosk hardware, and analogous implementations in educational institutions. Identify optimal practices and potential challenges.

Needs Analysis:

Execute surveys, interviews, or focus groups with stakeholders to amass specific requirements and preferences for the chatbot-based kiosk.

Technology Selection:

Opt for the appropriate AI chatbot platform and kiosk hardware that align with the institution's requirements and budget constraints.

Integration Strategy:

Devise a strategy for integrating the chatbot with existing college databases, systems, and information sources to furnish real-time and precise data.

Phase 4: Development and Implementation

Chatbot Development:

Develop the AI chatbot utilizing natural language processing (NLP) and machine learning algorithms. Train the chatbot with comprehensive data related to college information and services.

Kiosk Setup:

Deploy smart kiosks equipped with touch screens, cameras, microphones, and other necessary hardware components strategically across the college campus.

Voice Recognition Integration:

Implement voice recognition technology for multimodal interaction, enabling users to engage with the chatbot through spoken language.

User Interface Design:

Design an intuitive and user-friendly interface for smart kiosk touch screens, ensuring ease of navigation and accessibility.

Content Creation:

Generate content for the chatbot, including responses to common queries, virtual tour scripts, academic advising materials, and emergency information.

Testing and Quality Assurance:

Conduct thorough testing of both the chatbot and kiosk hardware to ensure functionality, accuracy, and security. Address any identified bugs or issues.

Phase 5: Deployment

Prototype Deployment:

Deploy the chatbot-based kiosk system in a limited capacity in a specific area of the campus or a particular department. Collect feedback for necessary improvements.

Full Deployment:

Roll out the system campus-wide upon successful completion of the pilot phase and resolution of any identified issues.

Phase 6: Training and Support

User Training:

Conduct training sessions for users, including staff and faculty interacting with the kiosk system, to ensure effective utilization of features.

Technical Support:

Establish a technical support team to address technical issues and user inquiries. Implement a ticketing system for problem tracking and resolution.

Phase 7: Monitoring and Accuracy Checking

Data Collection and Analysis:

Collect data on user interactions and feedback. Analyze the data to identify areas for improvement and optimization.

Continuous Improvement:

Regularly update and enhance the chatbot's responses, services, and features based on user feedback and evolving needs.

Security and Privacy:

Continuously monitor and enhance security measures to protect user data and system integrity.

Phase 8: Evaluation and Reporting

Performance Evaluation:

Assess the impact of the chatbot-based kiosk system on administrative processes, user satisfaction, and efficiency. Compare outcomes against project objectives.

Reporting and Documentation:

Prepare a comprehensive report summarizing project achievements, challenges, lessons learned, and future recommendations.

Phase 9: Scaling and Maintenance

Scaling Up:

If successful, consider expanding the use of chatbot-based kiosks to additional locations or implementing more advanced features.

Academic Institutions Community Engagement:

Involve students, faculty, and stakeholders of educational institutions in the ongoing development and enhancement of the system to ensure its continued relevance.

Stanford CoreNLP stands as an integrated Natural Language Processing (NLP) toolkit, encompassing a suite of tools for natural language analysis. This Java-based annotation pipeline framework is equipped with a wide array of common NLP techniques, ranging from tokenization to co-reference resolution. Its language support extends beyond English to include major languages like German, French, and Chinese. Stanford CoreNLP consolidates several NLP tools, such as Part-of-Speech (POS) tagger, Named Entity Recognition (NER), parser, co-reference resolution, sentiment analysis, bootstrapped pattern learning, and open information extraction tools. This versatile framework finds applications in academia and industry, accommodating rule-based, probabilistic machine learning, and deep learning techniques.

Within the CoreNLP framework, the Stanford NER tool serves as an information extraction tool, specializing in the detection of named entities within text. For English, the

Stanford NER annotator inherently recognizes named entities like persons, locations, numerical values (e.g., money, numbers, ordinal), and temporal entities (e.g., date and time). Additional entity classes, such as email, city, country, and URL, can be incorporated through the addition of a regular expression annotator.

Stanford NER employs a linear chain-based Conditional Random Field (CRF) sequence model for named entity recognition. It combines three CRF sequence taggers trained on diverse corpora, including CoNLL 2003, MUC 6, and MUC 7, to recognize named entities. Numerical entities are identified through a rule-based system.

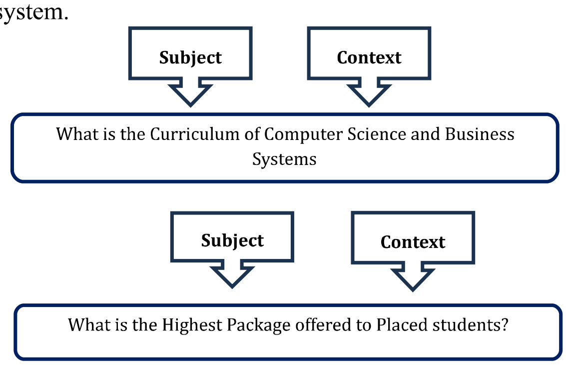

Figure 4: Rule-Based System

Table 1: Responses Quality and Participant Engagement

	Chatbot		Qualtrics		F score	p	η2p
Responses Quality							
Informativeness (bits)	283.33	152.90	203.53	184.19	F(1,576)=38.55	<0.01	0.06
Relevance	15.72	4.16	14.05	5.55	F(1, 576)=17.63	<0.01**	0.03
Response Quality Index	27.28	10.20	21.70	10.31	F(1, 576)=48.72	<0.01**	0.08
Participant Engagement							
Engagement Duration (mins)	24.38	13.42	17.90	17.20	F(1, 576)=24.60	<0.01**	0.03
Response Length (words)	90.11	46.23	63.98	54.17	F(1, 576)=57.92	<0.01**	0.09
Self-Disclosure	5.16	2.26	3.57	2.45	F(1, 576)=34.82	<0.01**	0.06

In terms of informativeness, we calculated the informativeness score for each completed survey using Formula 1, which is based on participant responses. The results revealed that, on average, the chatbot surveys collected 39% more information compared to the Qualtrics surveys. The survey method was the independent variable in an ANCOVA analysis that also looked at demographics like gender, age, and level of education, as well as weekly game play time and engagement duration. The results showed that the chatbot surveys got a lot more detailed information than the Qualtrics surveys (Table 1). The survey method emerged as a significant factor contributing to these differences.

Among the control variables, only the level of education exhibited significance. Participants with at least a college degree (M = 259.93 bits, SD = 166.14 bits) provided more substantial responses compared to those without a college degree (M = 224.46 bits, SD = 180.53 bits): $F(1, 576) = 6.81$, $p < 0.01$**, $\eta 2p = 0.01$. No interaction effect between the survey method and educational level was observed. There was no indication of the impact of age, gender, engagement duration, or game-playing time.

Moving on to relevance, we conducted an analysis of the relevance of the collected responses. As detailed in Section 3.5, we manually evaluated the relevance of participants' free-text responses to a specific set of nine open-ended questions. For each completed survey, we generated a relevance index by summing up the relevance scores of all its responses. The findings indicated that, on average, the chatbot surveys obtained 12% more relevant responses compared to the Qualtrics surveys.

Using the survey method as the independent variable and adjusting for demographics, game-playing time, and engagement duration, an ANCOVA analysis (see Table 1) showed that the survey method had a big effect on the differences in how relevant the responses were. Specifically, participants who completed a chatbot survey provided responses that were more relevant than those who completed a Qualtrics survey. Additionally, the results indicated that individuals who engaged in a higher number of weekly gaming sessions tended to produce more relevant survey responses ($\beta = 0.04$, $p < 0.05$*). This suggests that avid gamers may be more receptive to chatbots and more inclined to offer quality information during interactions with them. No interaction effects were observed.

To delve deeper into understanding the variations in response relevance, we focused on surveys with a relevance index value of zero (0), indicating that none of their responses were relevant. Among the 300 completed Qualtrics surveys, 27 (9.00%) contained entirely nonsensical content (e.g., "fdlfdbdffdh" or its variants) or fabricated statements (e.g., "Funding from a state Itsdhzxoy" given as a self-introduction). In contrast, among the 282 completed chatbot surveys, only 7 (2.48%) contained entirely irrelevant responses. A two-proportion Z-test revealed a significant difference in the proportion of nonsensical responses between the two conditions ($z = 3.35$, $p < 0.01$). This suggests that participants were less likely to engage in deceptive or irrelevant responses when interacting with a chatbot during a survey.

However, due to limited data collected (refer to "Study Limitations" in Section 5), it remains unclear which specific chatbot behaviors contributed to this result (e.g., probing, prompting, and social commenting). It could be attributed to a combination of the perceived anthropomorphic characteristics of the chatbot and the novelty factor. Participants' comments at the end of a chatbot survey indicated that many were unfamiliar with chatbot-driven conversational surveys, highlighting the novelty of the experience.

Response Quality Index (RQI): For each relevant response, we further assessed its quality using two metrics: specificity and clarity. To accomplish this, we formulated an overall Response Quality Index (RQI) by aggregating the three-quality metrics.

$$RQI = \sum_{n=1}^{N} relevance[i] \times clarity[i] \times specificity[i]$$

(N is the number of responses in a completed survey)

VI. WORKFLOW-INTENSIVE CHATBOTS AND PHASES:

The proposed Intentive chatbot introduces an additional Knowledge Base (KB) engine, enhancing its interactive communication capabilities with users. This chatbot excels at identifying missing information within a query, leveraging its intentional nature to actively gather the necessary data for addressing the user's inquiry. Through interactive information gathering, users perceive a more human-like interaction, leading to heightened satisfaction. To further augment the intention chatbot's performance, Named Entity Recognition (NER) was implemented to identify the intents of academic resources. The effectiveness of the intention chatbot was evaluated through a case study employing a combination of diverse metrics.

This work provides an extensive review of relevant literature available in the open domain pertaining to the subject addressed. It encompasses a thorough exploration of chatbots and their diverse applications across various domains. Implementation of a monitoring system to track user interactions and gather data for further improvements. The system provided regular maintenance to keep the kiosks and chatbots updated. Additionally, the work delivers a comprehensive examination of different Named Entity Recognition (NER) technologies, accompanied by an in-depth study of the Stanford NER tool.

V. CONCLUSION

The proposed Intentive chatbot demonstrates significant advancements in enhancing interactive communication with users by incorporating an additional Knowledge Base (KB) engine. By actively identifying and gathering missing information through its intentional nature, the chatbot provides a more human-like interaction, resulting in higher user satisfaction. The integration of Named Entity Recognition (NER) further improves the chatbot’s ability to identify academic intents, boosting its overall effectiveness. The case study used to evaluate its performance, coupled with the implementation of a monitoring system for continuous improvement, underscores the chatbot's potential. This work also offers a detailed review of relevant literature, a comprehensive exploration of various chatbot applications, and a thorough examination of NER technologies, especially the Stanford NER tool. Overall, this research contributes valuable insights into the development and optimization of workflow-intensive chatbots across different domains.

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