Enabling Context-based AI in Chatbots for conveying Personalized Interdisciplinary Knowledge to Users

Asif Raza
Department of Computer Science and Information Technology, NED University of Engineering and Technology, Pakistan
asif.raza7589@gmail.com (corresponding author)

Mustafa Latif
Department of Software Engineering, NED University of Engineering and Technology, Pakistan
mustafalatif@neduet.edu.pk

Muhammad Umer Farooq
Department of Computer Science and Information Technology, NED University of Engineering and Technology, Pakistan
umer@neduet.edu.pk

Mirza Adnan Baig
Department of Computer Science, IQRA University, Pakistan
adnan.baig@iqra.edu.pk

Muhammad Ali Akhtar
Department of Computer Science and Information Technology, NED University of Engineering and Technology, Pakistan
aliakhtar@neduet.edu.pk

Waseemullah
Department of Computer Science and Information Technology, NED University of Engineering and Technology, Pakistan
waseemu@neduet.edu.pk

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ABSTRACT

Adaptable chatbots have revolutionized user interactions by dynamically tailoring responses to users' knowledge and explainability preferences in interdisciplinary domains, such as AI in education and medicine. While strides have been made in model explainability, little attention has been paid to making models contextually aware and responsive to users' background knowledge. This study investigated interdisciplinary knowledge learning principles in a different domain, where the chatbot's contextual understanding is enhanced through dynamic knowledge graphs that capture users' past interactions to deliver up-to-date and relevant responses. By incorporating explainability features, chatbot responses become enriched, enabling users to understand the reasoning behind answers. This study proposed a model that showed superior chatbot performance and accurately addressed most queries, outperforming competitor chatbots DBpedia, ODC, and ODA. A 0.7 F-measure showcased its excellence, attributed to dynamic knowledge graphs and explainability checks. This study envisions a new era of conversational AI that not only meets user needs but also fosters a deeper understanding of AI decision-making, making it indispensable in delivering personalized, informed, and contextually aware interactions.

Keywords-personalized chatbot; contextually aware interactions; dynamic knowledge graphs; explainability level check

I. INTRODUCTION

In the ever-evolving landscape where technology intertwines with various domains, the acquisition of interdisciplinary knowledge has emerged as a challenging endeavor, characterized by multiple variables and disjointed components that often operate independently. Learners face difficulties in assimilating and integrating diverse aspects cohesively, leading to barriers that impede effective knowledge acquisition. These barriers include limited access to resources, discrepancies in the pace of learning among students, and the time-consuming nature of mastering new topics. Moreover, as industries embrace rapid advancements through the adoption of Artificial Intelligence (AI), a new set of challenges arises, disrupting and revolutionizing existing workflows. In this context, chatbots have become indispensable tools for engaging with consumers and service users, offering seamless interactions and serving as efficient assistants to service providers. According to [1], a chatbot is not just an agent that interacts with the user. It rather functions as an autonomous partner and has a presence within the conversational setting. This study emphasized the importance of recognizing and generating engagement, as well as the importance of fostering long-term relationships between humans and chatbots.

The past few years have witnessed the proliferation of large chatbots and virtual assistants, exemplified by popular platforms such as Alexa and Siri. As the field of chatbot technology progresses, the focus shifts towards enhancing chatbots across various domains to adapt to diverse user needs and leverage context awareness. Many research efforts attempted to address the aspect of personalization. In [2], novel methods were presented to eliminate the need to learn prior representations, allowing them to effectively generalize to previously unseen knowledge graphs. The evaluation of these methods demonstrated their superior performance in both academic and internal datasets. In [3], the myPersonality dataset was used to identify a user's personality. However, it was restricted to a specific age group and did not address dynamic personality aspects. The objective is to provide more interpretable, explainable, and personalized responses, catering to individual user preferences and understanding. This study aimed to fill these gaps by constructing a Brain Objects knowledge graph and further interconnecting them with each other to enable personalization. It also used an explainability level check that further improved interdisciplinary knowledge and chatbot capabilities, aiming to offer interpretable personalized responses that surpassed competitor chatbots.

Chatbots are increasingly finding use in domains such as education [4], healthcare [5], and businesses, acting as online assistants and replacing the services provided by humans in call centers. Another additional benefit is their deployment on widely used messaging apps such as Facebook Messenger, WhatsApp, and Twitter, allowing extensive user interaction. This aligns with the focus on improving the accuracy of sentiment analysis on these platforms [6]. The most popular method for developing dialogue systems is to mimic human conversational behavior, with the aim of the system to resemble a human interlocutor by converting user queries from NLP to SQL and SPARQL [7].

A very convenient means of designing chatbots is the use of Artificial Intelligence Markup Language (AIML), which is an XML-based scripting language for specifying conversations with chatbots. The creation of a chatbot in AIML involves creating a large number of categories that, at the basic level, consist of a pattern that is matched with the user's input and a template that specifies the chatbot's response [8]. If the user input matches the text in the pattern, the contents stated in the templates are retrieved. The graph is traversed until a pattern is found that matches the input. Explainable machine learning models are imperative for greater transparency which in most cases is a necessity. Recent studies investigated more visual and interactive approaches to make machine learning models explainable. For this purpose, an XAI pipeline was proposed that can be utilized to streamline different elements together to provide explainability [9]. Similarly to this design of introducing explainability levels, with each level defining a particular expertise level or understanding of a user about a domain and machine learning knowledge, the XAI pipeline approach also deals with three main groups: Model users, model developers, and model novices. As multiple knowledge graph-based chatbots are available [3, 10-12], but none of them creates a user's dynamic personality, this design focuses heavily on generating user-specific dynamic knowledge graphs with domain-specific data organized in a visually interactive manner to assist the chatbot in generating responses. Visual analytics and interactive machine learning can play a significant role in making machine learning models explainable. The XAI pipeline incorporates both VA and IML to make it easier to develop visual interfaces.

Authors in [13] initially focused on chatbots in education, examining their role with students, their specific educational applications, and the impact of chatbot implementation on learning. This framework emphasizes personalization and transparency to address individual learning gaps, using previous interactions to adapt its knowledge base, but does not assess users' knowledge levels. In [14], the B-point tree method improved efficiency by incorporating an additional data structure into the binary search tree structure. This algorithm aimed to reduce the depth of the search, which ultimately reduced the number of memory accesses. A sorted array of pointers of the most used points was maintained and updated after each query, each element in the array also acted as a shortcut, but there was no personalization. Early chatbot technology used simple keyword matching and had minimum context awareness to generate responses. Language processing, detailed ontologies, and continuously updated personalization have made significant improvements to the user experience [15].

Task-oriented chatbots use feature ontologies and user personality to establish context-aware responses and questions to drive a more explainable and personalized setup. This study aimed to bridge these gaps by investigating strategies to enhance chatbot capabilities, ensuring more interpretable, explainable, and personalized responses that align with individual user preferences. By addressing these challenges, this study aimed to achieve substantial advancements in chatbot performance, surpassing the achievements of previous chatbots.

II. PROPOSED ARCHITECTURE

This study presents a novel framework designed to empower chatbots with explainable and context-based AI capabilities, enabling them to impart personalized interdisciplinary knowledge to users. The proposed architecture amalgamates cutting-edge NLP techniques that help create Brain Objects, a context awareness engine, a dynamic Knowledge Graph, and an Explainability Module. By leveraging user interactions and context, the chatbot dynamically constructs a comprehensive knowledge graph and customizes responses based on user-specific explainability levels. This approach guarantees a more impactful and personalized conversational encounter that transcends various domains. The proposed bot was named Cronus-bot and effectively addresses the demand for chatbots that are both interpretable and contextually aware, thereby fostering profound interdisciplinary knowledge sharing with users. This chatbot architecture encompasses six key components, as shown in Figure 1.

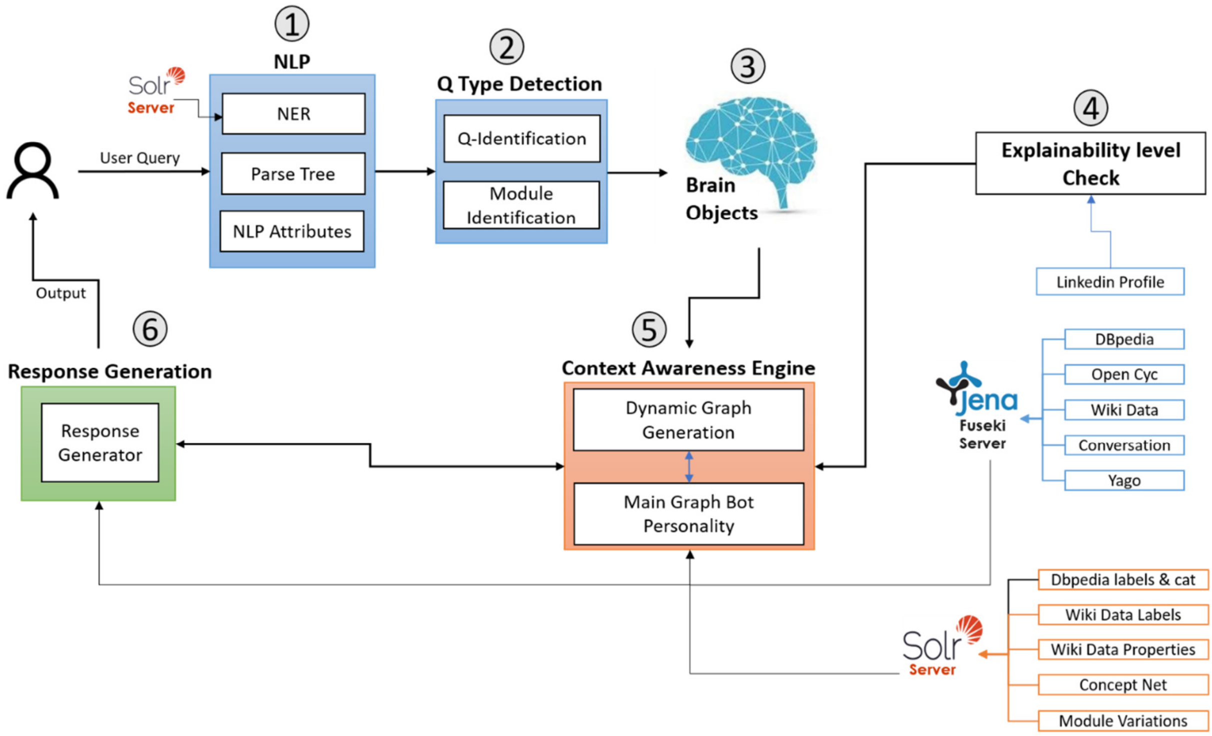

Fig. 1. Cronus-bot architecture diagram.

A. NLP

This study focused on developing user and bot personalities, which necessitates obtaining user queries in a triple format, consisting of Subject, Predicate, and Object. In this format, both Subject and Object are represented as Noun Phrases (NPs), while the Predicate can take the form of a Verb Phrase (VP). Natural Language Processing (NLP) libraries can be used to discern NPs and VPs within user queries, such as Sandford NLP. The semantic match between the user query and the desired response is crucial to enhancing the overall user experience. Therefore, it is essential to extract additional Part-Of-Speech (POS) attributes from the user queries to further refine the identification process. The extraction of POS attributes includes:

- Subject and Subject Adj: Identify the main query topic and associated adjectives.
- Object and Object Adj: Determine the query object and relevant adjectives.
- Predicate: Understand the action/relationship of the query to fit responses.

This integration of POS attributes improves understanding, resulting in an improved user experience and improved human-computer interaction.

B. Query Type Identification

This step involves the extraction of two key attributes:

- Query Identification (QI) categorizes user queries (e.g. "reason-based," "confirmation," etc.) for tailored responses.
- Module Identification (MI) identifies relevant modules (e.g. News, Education) for accurate responses.

C. Brain Objects

The concept of a Brain Object emerges as a fundamental building block in a chatbot's cognitive architecture, representing interconnected information derived from user queries. Each user query is treated as a brain object, which contains POS attributes extracted using NLP, and some virtual attributes, which identify the QI, MI, and explainability level. As shown in Figure 2, these objects are semantically connected to form a dynamic graph known as the Semantic Dynamic Graph. This graph serves as a powerful tool for context identification in conversations, allowing the chatbot to comprehend the flow of the discourse and deliver more contextually appropriate responses.

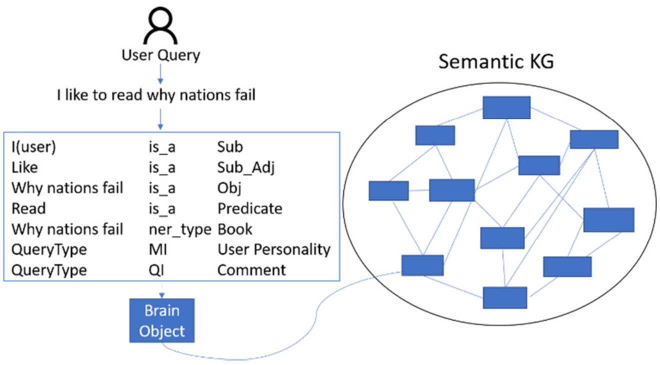

Fig. 2. Brain objects workflow.

D. Context Awareness Engine

The Context Awareness Engine is a pivotal component that enables sophisticated personalized interactions, integrating upper-level ontologies and semantic enrichment for a dynamic semantic graph and reflecting users' personalities through brain objects. This empowers the chatbot with a wealth of contextual information to craft responses. The proposed system employed the Fuseki server, a robust SPARQL server that manages RDF data and queries. Upper-level ontologies (DBpedia, Open Cyc, Wiki data, and Yago) enrich the data. The dynamic Bot's Personality graph, created via Fuseki, forges links with ontologies during user interactions. This dynamic graph captures upper-level ontology data, anchoring the chatbot's responses. An on-the-fly method forges the user's personality using brain objects, dynamically linking data per query. This agility facilitates personalized and contextually relevant conversations.

E. Explainability Level Check

This module was introduced to assess the user's explainability levels, which dictates the complexity and depth of the chatbot's responses. As shown in Figure 3, the explainability level ranges from 1 to 5, with 1 representing the simplest level and 5 denoting the most advanced level. Each explainability level governs the types of cognitive services from which the knowledge should be drawn and the level of abstraction that the knowledge graph should adopt. The dynamic response generation process utilizes the knowledge graph formed by factoring in the user's profile, personality, general, and domain-specific ontologies. Intent identification is employed based on the user's input, and the dynamic knowledge graph helps extract information for the chatbot's response.

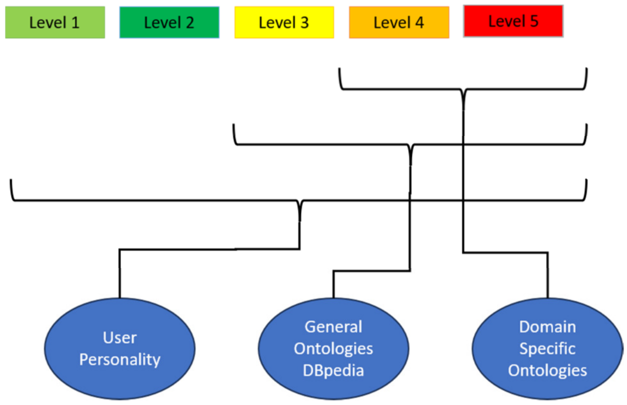

Fig. 3. Explainability level ranges.

To maintain context awareness, the chatbot tracks user queries, identifying common questions and issues. It provides relevant information based on this context, offering varying levels of explainability. For physicians, it offers a deeper level of detail, while for patients with a basic understanding, it adjusts explanations accordingly. This adaptability enhances user experience and comprehension. Figure 4 illustrates the process.

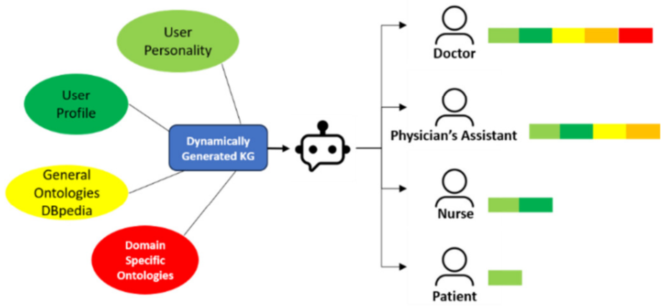

Fig. 4. User's profile vs explainability levels.

TABLE I. NOTATIONS USED IN ALGORITHMS

EL	Explainability Level
SD	Sub Domain
SG	Sub Graph
SQ	SPARQL Query
UP	User Profile

Algorithm I introduces an approach to enhance user interaction with chatbots. It adapts the complexity and depth of chatbot responses based on the user's profile, domain knowledge, and evolving understanding. The algorithm begins by extracting user input and assessing the existence of relevant subgraphs. If found, personalized explainability levels are established for different subdomains. If not, the algorithm evaluates the familiarity of the user using semantic-based text matching to the topic, adjusting the explainability accordingly

[16]. Table I provides a comprehensive guide to the notation used in Algorithm I.

Algorithm I: Explainability Level Check

```
    Inputs: Brain Object of User Query (B)
    Output: Explainability level (EL)
1   # Variables:
    EL ← 0
    SD ← Extract_SD(B)
    SG ← SG_By_SD(SubDomain)
2   # Assess Explainability Level:
    UEL_user ← AssessExplainability(user_profile)
3   # Extract SubDomain from Brain Object:
    SD ← Extract_SD(B)
4   # Extract subgraph from user personality graph
    # using SPARQL by SD:
    SQ ← "SELECT ?subject ?predicate ?object WHERE
    { ?subject ?predicate
    ?object.FILTER(CONTAINS(?subject, '" +
    SubDomain + "')) }"
    SG ← Execute_Query(SQ)
5   # If SG not Found:
    if SG is Null then
        UP ← Get_UP()
        Enriched_SD ← Enrich_Text(SD,
        UP.Job_Role)
        Similarity_Score ←
        Cosine_Similarity(Enriched_SubDomain,
        Enriched_Job_Role)
        if Similarity_Score < 5.0 then
                EL ← 0
            else if Similarity_Score ≤ 7.0 then
                EL ← 1
            else if Similarity_Score ≥ 8.0 then
                EL ← 2
6   # If Sub Graph Found:
    Else
        EL ← Initial_EL
          for each Brain_Object in SG do
            List_Of_SubDomains ←
            Get_SD(Brain_Object)
          for each SD in List_Of_SubDomains do
            EL← Update_Explainability_Level(SD,
            User_Understanding)
7   # Return Current Explainability Level:
    Return EL
```

F. Response Generation

The response generator offers a powerful and adaptive mechanism to generate responses that are tailored to individual users, considering their past interactions, explainability level, and the wealth of knowledge stored in both the dynamic and the bot's knowledge graphs. This holistic approach enhances the chatbot's ability to provide personalized and contextually appropriate responses to user queries.

III. EXPERIMENTS

To facilitate an all-encompassing comparison, the performance of the proposed Cronus-bot was compared to other cutting-edge chatbots that also utilize linked data, including the DBpedia Chatbot, Open Data Chatbot, and Open Data Assistant. Table II shows the specific knowledge base used by each chatbot to provide answers. Table III presents a comprehensive analysis and comparison of the bots.

TABLE II. CHATBOT KNOWLEDGE BASES

Chatbot	Knowledge Base
DBpedia [17]	DBpedia
ODC [18]	DBpedia
ODA [19]	DBpedia
Cronus-bot	DBpedia, Wikidata, Dynamic User personality KG, Explainability level check

Three essential evaluation metrics were used to assess and compare the performance and effectiveness of the Cronus-bot when responding to user queries: precision, recall, and F-measure. Precision is a crucial measure for assessing the performance of a classification model, such as a chatbot. It gauges the ratio of accurately predicted positive instances to all instances the model labeled as positive. Recall evaluates the model's aptitude to identify all pertinent instances within the true positive cases. The F-measure amalgamates precision and recall, offering a well-rounded evaluation of model performance, particularly when both false positives and false negatives demand concurrent consideration. The F-measure guarantees that a model striking a commendable equilibrium between precision and recall attains a superior score.

TABLE III. COMPARATIVE PERFORMANCE ANALYSIS

Chatbot	Total	Right	Wrong	P	R	F-measure
DBpedia	50	8	6	0.5	0.3	0.4
ODC	50	6	4	0.6	0.25	0.35
ODA	50	5	2	0.7	0.17	0.2
Cronus-bot	50	26	4	0.76	0.6	0.7

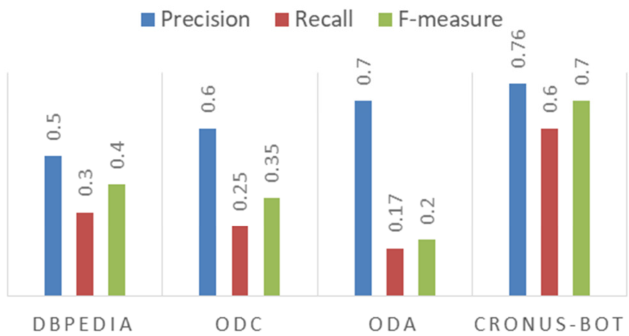

Fig. 5. Comparison of results.

The first column of Table III provides the name of the chatbot system, while Total indicates the total number of queries evaluated. Right represents the number of queries correctly answered by the system, and Wrong indicates the number of queries for which the system provided incorrect answers. For instance, out of 50 queries, Cronus-bot provided 26 correct answers, whereas the other state-of-the-art chatbots produced less than 10 correct answers. The correctness of the answers was determined manually with the previous context in mind. Figure 5 shows that the Cronus-bot achieved a recall rate of 0.6, and an F-measure of 0.7, outperforming the other systems. These results demonstrate that the Cronus-bot outperformed the other chatbots in precision, recall, and F-measure, as dynamic knowledge graphs and explainability checks boosted its performance.

IV. CONCLUSION

This study introduced a dynamic knowledge graph, containing brain objects interlinking the user's previous queries, and explainability levels to facilitate a personalized conversational experience. By connecting the response generator with the bot's knowledge graph, the proposed Cronus-bot gains access to a wealth of structured information, enabling it to deliver more informed and accurate answers. Moreover, as shown in the comparison of the results, the proposed Cronus-bot improved the end-to-end user experience in terms of interactive question answering and context awareness compared to other competitors. The proposed architecture propels human-centric AI-driven interactions, contributing to user-friendly, trustworthy AI and empowering confident interdisciplinary knowledge sharing.

REFERENCES

[1] G. Wilcock and K. Jokinen, "Conversational AI and Knowledge Graphs for Social Robot Interaction," in *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, Sapporo, Japan, Mar. 2022, pp. 1090–1094, https://doi.org/10.1109/HRI53351.2022.9889583.

[2] A. Ait-Mlouk and L. Jiang, "KBot: A Knowledge Graph Based ChatBot for Natural Language Understanding Over Linked Data," *IEEE Access*, vol. 8, pp. 149220–149230, 2020, https://doi.org/10.1109/ACCESS.2020.3016142.

[3] R. Dutt, K. Bhattacharjee, R. Gangadharaiah, D. Roth, and C. Rose, "PerKGQA: Question Answering over Personalized Knowledge Graphs," in *Findings of the Association for Computational Linguistics: NAACL 2022*, Seattle, United States, Apr. 2022, pp. 253–268, https://doi.org/10.18653/v1/2022.findings-naacl.19.

[4] B. Nethravathi, G. Amitha, A. Saruka, T. P. Bharath, and S. Suyagya, "Structuring Natural Language to Query Language: A Review," *Engineering, Technology & Applied Science Research*, vol. 10, no. 6, pp. 6521–6525, Dec. 2020, https://doi.org/10.48084/etasr.3873.

[5] the Department of Computing, Faculty of Arts, Computing and Creative Industry, Universiti Pendidikan Sultan Idris, Malaysia *et al.*, "Exploring the Trend and Potential Distribution of Chatbot in Education: A Systematic Review," *International Journal of Information and Education Technology*, vol. 13, no. 3, pp. 516–525, 2023, https://doi.org/10.18178/ijiet.2023.13.3.1834.

[6] Y. Chen *et al.*, "Prostate cancer management with lifestyle intervention: From knowledge graph to Chatbot," *Clinical and Translational Discovery*, vol. 2, no. 1, Art. no. e29, 2022, https://doi.org/10.1002/ctd2.29.

[7] M. Madhukar and S. Verma, "Hybrid Semantic Analysis of Tweets: A Case Study of Tweets on Girl-Child in India," *Engineering, Technology & Applied Science Research*, vol. 7, no. 5, pp. 2014–2016, Oct. 2017, https://doi.org/10.48084/etasr.1246.

[8] V. K. Shukla and A. Verma, "Enhancing LMS Experience through AIML Base and Retrieval Base Chatbot using R Language," in *2019 International Conference on Automation, Computational and Technology Management (ICACTM)*, London, UK, Apr. 2019, pp. 561–567, https://doi.org/10.1109/ICACTM.2019.8776684.

[9] T. Spinner, U. Schlegel, H. Schäfer, and M. El-Assady, "explAIner: A Visual Analytics Framework for Interactive and Explainable Machine Learning," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 1064–1074, Jan. 2020, https://doi.org/10.1109/TVCG.2019.2934629.

[10] A. Saxena, S. Chakrabarti, and P. Talukdar, "Question Answering Over Temporal Knowledge Graphs." arXiv, Jun. 02, 2021, https://doi.org/10.48550/arXiv.2106.01515.

[11] E. Kacupaj, J. Plepi, K. Singh, H. Thakkar, J. Lehmann, and M. Maleshkova, "Conversational Question Answering over Knowledge Graphs with Transformer and Graph Attention Networks." arXiv, Jun. 24, 2021, https://doi.org/10.48550/arXiv.2104.01569.

[12] A. Saxena, A. Tripathi, and P. Talukdar, "Improving Multi-hop Question Answering over Knowledge Graphs using Knowledge Base Embeddings," in *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, Apr. 2020, pp. 4498–4507, https://doi.org/10.18653/v1/2020.acl-main.412.

[13] T. Wambsganss, R. Winkler, P. Schmid, and M. Söllner, "Unleashing the Potential of Conversational Agents for Course Evaluations: Empirical Insights from a Comparison with Web Surveys," *ECIS 2020 Proceedings*, 2020, Art. no. 50, https://doi.org/10.17170/kobra-202104153670.

[14] A. Atiyah, S. Jusoh, and S. Almajali, "An Efficient Search for Context-Based Chatbots," in *2018 8th International Conference on Computer Science and Information Technology (CSIT)*, Amman, Jordan, Jul. 2018, pp. 125–130, https://doi.org/10.1109/CSIT.2018.8486187.

[15] S. Hussain, O. Ameri Sianaki, and N. Ababneh, "A Survey on Conversational Agents/Chatbots Classification and Design Techniques," in *Web, Artificial Intelligence and Network Applications*, 2019, pp. 946–956, https://doi.org/10.1007/978-3-030-15035-8_93.

[16] A. Alqahtani, H. Alhakami, T. Alsubait, and A. Baz, "A Survey of Text Matching Techniques," *Engineering, Technology & Applied Science Research*, vol. 11, no. 1, pp. 6656–6661, Feb. 2021, https://doi.org/10.48084/etasr.3968.

[17] R. G. Athreya, A.-C. Ngonga Ngomo, and R. Usbeck, "Enhancing Community Interactions with Data-Driven Chatbots--The DBpedia Chatbot," in *Companion Proceedings of the The Web Conference 2018*, Lyon, France, Dec. 2018, pp. 143–146, https://doi.org/10.1145/3184558.3186964.

[18] S. Keyner, V. Savenkov, and S. Vakulenko, "Open Data Chatbot," in *The Semantic Web: ESWC 2019 Satellite Events*, Portorož, Slovenia, 2019, pp. 111–115, https://doi.org/10.1007/978-3-030-32327-1_22.

[19] S. Neumaier, V. Savenkov, and S. Vakulenko, "Talking Open Data," in *The Semantic Web: ESWC 2017 Satellite Events*, Portorož, Slovenia, 2017, pp. 132–136, https://doi.org/10.1007/978-3-319-70407-4_25.