EMITTER International Journal of Engineering Technology
Vol. 14, No. 1, June 2026, pp. 98~120
DOI : 10.24003/emitter.v14i1.1055

The Ontology Driven E-Commerce Chatbot for Fashion Industry

Maryam Mairaj[1,2], Shakil Ahmed[3], Kiran Hidayat[4], Aamir Zeb Shaikh[5], Shabbar Naqvi[6]

[1]Department of Computer Engineering, Sir Syed University of Engineering and Technology, Karachi. Pakistan.
[2]Marketing Executive, SUDO Consultants, Dubai, UAE
[3]Department of Computer Science, National University of Computer and Emerging Sciences, FAST, Karachi. Pakistan.
[4]Department of Software Engineering, Sir Syed University of Engineering and Technology, Karachi. Pakistan.
[5]Department of Telecommunications Engineering, NED University of Engineering and Technology, Karachi. Pakistan
[6]Teaching Fellow, University of Leeds, UK.
Corresponding Author: aamirzeb@neduet.edu.pk

Received January 5, 2026; Revised March 7, 2026; Accepted June 9, 2026

Abstract

Conventional chatbots in fashion e-commerce rely on keyword matching and lack the semantic structure needed to correctly handle multi-entity product queries. This leads to inaccurate, context-blind responses that frustrate users and reduce platform engagement. This paper proposes and evaluates an ontology-driven chatbot system for fashion e-commerce and compares it directly against a non-ontology baseline built on the same dataset. Both systems were developed using Google Dialogflow for natural language processing, with product data collected through Python web scraping from the Alkaram fashion website. The ontology knowledge base was engineered in OWL 2 using Protégé and queried via SPARQL, with a class hierarchy covering product categories, attributes, and brand entities. To evaluate both models, five analysts conducted structured 10-minute conversations using a fixed set of 50 product queries, scoring each response across seven criteria, including accuracy, context retention, and grammatical quality, on a 0 to 9 scale. The ontology-based system achieved 88% accuracy compared to 67% for the non-ontology model, a 21% improvement. It also outperformed across all other criteria, with inter-analyst agreement within 0.5 points confirming evaluation reliability. These results show that integrating an OWL/SPARQL ontology into a Dialogflow-based chatbot meaningfully improves product query handling in fashion e-commerce, and the approach is practical enough to scale to other retail domains.

Keywords: chatbot, Dialogflow, ontology, NLP, fashion-industry.

1. INTRODUCTION

Running a business online is no longer optional, and the COVID-19 period made that clearer than anything else. When physical stores shut down, brands that had already invested in digital channels stayed afloat. Fashion brands in particular felt this pressure, since their products depend heavily on browsing, discovery, and personalized advice that in-store staff would normally provide (1). A good e-commerce store lets customers find what they want without friction (2), but most websites still fall short because search results are generic and product filtering is not smart enough to match what people actually mean when they type a query (3). Chatbots came in as a practical fix for this, and they have grown quickly because they are cheaper than hiring support staff full-time, available around the clock, and can handle a large volume of routine questions so human agents can focus on complex ones (4).

A chatbot is an AI program. It can converse with a user in natural language via messaging services, websites, and mobile applications. A human and an automated conversing with each other it's challenging to use conversational agents. Chatbots, also known as" Artificial conversational agents," have made their way into a variety of fields because of the quick advancements in the pro- processing of natural language input and the development of advanced machine learning techniques. Typically, chatbots employ a knowledge base to deliver answers to frequently asked queries by users. As a result, human specialists are relieved of the burden of repeatedly providing the same answers to the same queries (5). Additionally, rather than managing the vendor's E-commerce website alone, the chatbot should be available 24/7 and behave like an assistant. As its primary goal is to assist sellers in enhancing their online fashion E-commerce businesses, the chatbot interface should be straight forward (6). Furthermore, we may say that there is a high probability of the chatbot technology's accept- ability, particularly by younger individuals by 2026 (5, 7, 8). In this paper, multiple fashion brands are examined that employ chatbots on their websites and their impact on communication quality and general consumer experience. The chatbot idea fits with fashion firms' beliefs, which emphasize providing outstanding customer service (9). By guaranteeing that personalized service is available to satisfy customer's demands whenever and wherever they may be, chatbots add a new layer of support to the concept of service quality (7). Future interactions between fashion brands and consumers are also a goal of the chatbot. For instance, Louis Vuitton, Sephora, H&M, etc. offer a chatbot service that delivers details about offline locations worldwide, access to personal service representatives for quality control and conversational interfaces that showcase the product's workmanship.

The most crucial stage for developing a chatbot is choosing the appropriate Natural Language Processing (NLP) engine (1). The lack of high-quality real-world datasets restricts research in this area(10, 11). The use of Artificial Intelligence (AI) technology, such as deep learning, NLP, and Machine Learning (ML) algorithms, has allowed chatbots to advance dramatically in recent years, chatbots have evolved significantly in recent years, and they now require a significant amount of data to produce correct results. The precision increases as you engage with the bot more (12). Thus, chatbots can be viewed as an important, relevant interface element for various fashion E- commerce jobs, such as providing Frequent Ask Questions (FAQ), customer service, product information, recommendations, product inquiries, and providing a personal assistant. With a focus on enhancing the interface between data and search requests to more closely match the result sets to user's research needs (13). An AI chatbot can help customers with general issues (such as product search, return, exchange, etc.) and give them the impression that they are interacting with a human retail assistant rather than having them send emails to merchants (14). Better customer service will be provided by combining E-commerce sites with chat- bots supported by AI to generate successful sales through tailored marketing (15). One last finding was that many articles just present the work completed without putting the chatbot to the test and accuracy, with few papers appearing to evaluate their chatbot at all. While the lack of review may be due to money or time restrictions, the absence of evaluation standards for chatbots may also be a factor (16). A uniform method of evaluating chatbot quality is necessary (3). Moreover, as accuracy improves, users can enjoy intelligent social dialogues with virtual agents (17). Thus, fashion brands such as Burberry, Louis Vuitton, Tommy Hilfiger, Levi's, H&M, and eBay are recognizing the bright promise and increasing popularity of e-service agents (7). Despite a growing body of work on chatbots in retail, research specifically focused on ontology-driven chatbots for fashion e-commerce remains limited (10).

This paper contributes to filling that gap by designing, building, and comparing two chatbot models on real product data from the Alkaram fashion website. The goal was straightforward: find out whether embedding an OWL/SPARQL ontology into the chatbot pipeline produces measurably better results than running without one. The answer, as this paper shows, is a clear yes. Both models were tested against each other on the same query set, and the results are presented in the Results section with full evaluation detail.

The rest of this paper is organized as follows. The Related Works section covers what others have done in the chatbot and fashion e-commerce space, both with and without ontology. After that, the Marketing Efforts section briefly looks at how fashion brands are currently using these tools. The Methodology section then explains how we built and connected both chatbot models. Under that, the System Architecture and Implementation sections walk through the actual design and setup. Finally, the Results section compares the two models, followed by a discussion of future directions and the conclusion.

Despite all this growth, most chatbots deployed in fashion e-commerce still work on simple keyword matching. They do not understand how product categories connect to attributes like color, fabric, or price range, which means when a customer asks a multi-part question, the system often gives back a wrong or unrelated answer. Researchers have pointed to this as a consistent weak point across rule-based and pattern-based systems (3, 16). Ontology-based approaches have been tried in general e-commerce to solve exactly this problem (18, 19), but very few papers test them specifically in fashion retail, on real product data, with a direct side-by-side comparison against a non-ontology version of the same system. That is the gap this paper fills. We built both models on the same dataset from a real fashion brand and measured which one actually works better.

2. RELATED WORKS

This section presents a brief summary of work that summarizes the impact of AI driven chatbots on fashion ecommerce industry.In this context (20) Presents a comprehensive discussion on the use of Chatbots and AI in the field of fashion industry. Additionally, combination of deep learning algorithms such as RNN, Seq2Seq, LSTM, BERT, and GPT with the make the use of AI in chatbots more effective. The major aim is to assist the end clients appearing on the online web store in such a way so that they can be offered best possible options and choice available to the store hence, the user will be happier to select as many choices of his own in a timely manner by purchasing more in lesser time.

In addition to appreciating the store by visiting more and often in future as well. In (21) , authors explore the role and impact of machine learning algorithms in motivating the purchase of different entities from fashion industry. Additionally, authors explore the key parameters of chatbot that push a online purchaser to select the required products from the online store. For this extensive task, a comprehensive study of 384 participants was employed who had prior experience of online shopping. Some of the parameters that were considered are perceived usefulness, system quality, and ease of use, information quality, with computation of consumer purchase intention as the key variable. Authors foresee to use augmented reality in this domain to pursue reasonable results for future research in this domain. Similar to this research work, In (22) authors investigate the effect of Artificial Intelligence chatbots with visual search capabilities on the purchasers behavior especially for the fashion sector. The results show that the proposed setup driven fashion sites can generate better sales opportunities in comparison to the ecommerce websites which don’t use those. The issue addressed by the publication is that fashion industries don’t always respond to customer queries posted on social media in a timely manner (23). Customers can communicate with the chatbot system to identify the precise queries they are having. The chatbot system will also attempt to provide specific problems with solutions (24). This study demonstrates the layout and implementation of a few E-commerce chatbots as well as the various methods that can be used to create them. A chatbot is an AI Programme that is automatically run and allows for human- bot conversation. Chatbots have many names, including chatterbots, Chat Robots, talk bots, IM bots, and virtual assistants (3). One approach to artificial intelligence that is frequently utilized in chatbot design is pattern matching. The method involves comparing the user's input to the database and receiving a response from that comparison (25). Different studies incorporate chatbots that perform many kinds of analyses and services. Many researchers have worked to develop a chat- bot for the E-commerce domain. The studies pertaining to the use of chatbots in E-commerce contexts are analyzed in the following sections to identify a flaw in the existing research in this area. Chatbots were initially designed as chitchat systems. to speak as a non-directive psychotherapist would in a conversation, Utilizing straightforward pattern matching and a response tem plate, the chatbot ELIZA (26)was developed. The chatbot PARRY was created to have a paranoid persona (27). Artificial Linguistic Internet Computer Entity, or ALICE, converses with users by utilizing adaptable pattern-matching methods (27, 28). The chatbot Jabberwacky was distinctive during its reign because it could learn from previous interactions and generate new responses for its users (17, 28). In 2011, Apple launched Siri, its intelligent personal assistant, Cortana by Microsoft, and more recently social chatbots such as Microsoft's Xiaoice in the current social media age, the scope of chatbots as conversational systems has expanded to cover a wide range of domains including E-commerce (25).

For a pattern-based chatbot to respond accurately to diverse user inputs, millions of training instances must be provided. The authors Kandale & Atkar of this research presented a system that details a chatbot-based online application. The chatbot is connected to an online store. The chatbot uses natural language to communicate with users. For the project's demonstration. A website for online shopping was made. The website has a catalogue of numerous products. The bot makes product recommendations depending on the user's preferences. The project was carried out using content-based filtering, chatbots, and classification machine learning techniques. A web server with Internet access, PHP 5+, MySQL, XAMPP, Composer, and APIs were utilized for implementation. A collectionof pre-programmed instructions is present in the chatbot. This system did not analyze the rate of accuracy. In (29), authors suggested solution included a chatbot for an E-commerce website. A website for online shopping was developed to show how a chatbot could be used. A product catalogue is available on the website for browsing. The chatbot and the established website can work together without any issues. This chatbot is connected to an online store. This website offers a wide range of products. Essentially, the chatbot functions as a digital assistant. The chatbot assists people in choosing the best product for their needs. It performs much the same tasks as an online auto- mated assistant. This system also did not analyze the rate of accuracy.

The authors in (3) of this article put forth a revolutionary strategy for woo-commerce companies. A chatbot system for an E-commerce website that sells both physical and digital goods and services is introduced by the proposed system. It was created and implemented on Telegram because it is a popular messaging platform. By making a few adjustments, it may be quickly implemented using any messaging platform. To help the users, a straightforward order-taking bot has been created. The WooCommerce system's existing data is used by the recommendation engine. This also contains product classifications, overall sales, prices, and product reviews. This system did not analyze the rate of accuracy of their chatbot and only limited for WooCommerce shopping website.

In this study (30), the author proposed the development of an e-commerce sales chatbot in order to provide customer support and increase sales because consumers have a lot of queries regarding products like product quality, the return policy of the product, etc. the system used Machine learning algorithm for Natural Language Understanding (NLU). Using administratively provided classified training data, the NLU engine trains its classifier. It also uses the Support Vector Machine (SVM) technique as a basis. But they might improve their research by utilizing artificial neural networks, in this way the NLU Engine's accuracy can be improved. It is also possible to increase the dataset by using a semi-supervised learning system. Customer service may also get better as a result. In this proposed research (20) Free software repository Deep- Pavlov was created primarily for the development of conversational bots. The library focuses effectiveness, flexibility, and extensibility to make it easier to construct dialogue systems from scratch and with limited data available. It supports both end-to-end and modular implementation options for conversational agents. Each component of a conversational agent can be dissected into its component elements. Typically, components which are frequently models are utilized to address common NLP issues like intent classification, named entity recognition, or pre-trained word vectors. The components provided in the collection can be used to create conversational, question-and-answer, or task-oriented skills. Implementing models for the Skill Manager is one of the top objectives since it will enable developers to create dialogue agents that are fully functioning and can switch between different Skills. The library is currently undergoing additional upgrades to increase use. SuperAgent (31) Chabot is a chatbot with capabilities that allow it to read data from web sites (about products) and can respond to user questions based on information accessible on these web pages. In addition to these functionalities, the chatbot can converse with users on a regular basis (chit- chat), and the developer can also add to the chatbot's knowledge base. This chatbot was created utilizing NLP, machine learning techniques, and the Deep Structured Semantic Model (DSSM) model for attribute matching. The first candidate will be selected as a result of the chatbot's response. This chatbot is a web extension that may be utilized on any website. SuperAgent chatbot is only based on FAQs but however, they can explore more far into multi-turn questions, where context modelling will be researched further.

2.1. Rule-Based and Non-Ontology Chatbot Approaches

A number of researchers have explored rule-based and keyword-driven chatbot approaches, particularly in the e-commerce space. Among early fashion-related ontology work that informed these rule-based designs, Bollacker et al. built a fashion ontology grounded in human attributes, clothing categories, and manufacturing concepts(20) Similar to this, Vogiatzis et al. suggested a method that suggests clothing by taking into account knowledge of all characteristic of fashion, such as material, colors, body, and face traits (39) . OWL was employed by the authors in their study (20) . Paper (32) worked out an e-commerce ontology-based chatbot that responds to user inquiries for an e-commerce website. This system will facilitate users in obtaining information from the eBay website. The suggested system retrieves data and maps relationships successfully. They developed the chatbot using the results to assist users in understanding product details with-out having to log into the website. After receiving the necessary details, the user can log in and purchase any product. To diversify the solutions for the future, the proposed system can be improved by enhancing entity recognition with the use of effective algorithms (such as KNN, and Similarity). This paper does not clarify the accuracy rate of chatbots.

(22) Proposed a clothing brand ontology from a custom-made dataset of 5000 question-answer pairs and connected it with a conversation agent to assist online consumers, the suggested method solves the issue for the Pakistani fashion market. Based on data obtained from Facebook pages and official websites, they focus on providing general information on brand facilities, services, products, and accessories. The system performs better when measured against the standards of accuracy, non-sequitur, and structured replies. The experts gave an average score of 0.70, 0.60, and 0.73 percent. How- ever, the system performs poorly on the follow-up questions, fails to (behave dynamically), and generates inconsistent responses in a greater number of rounds. It could be because there isn't any inbuilt natural language generation.

2.2. Chatbots with Ontology

Various authors have developed ontologies for the fashion industry. For example, Bollacker et al. developed a fashion ontology that provides (fashion) guidance based on concepts from human attributes, clothing, and manufacturing (10) Similar to this, Vogiatzis et al. suggested a method that suggests clothing by taking into account knowledge of all characteristic of fashion, such as material, colors, body, and face traits (22) . OWL was employed by the authors in their study (10),(27) Worked out an e-commerce ontology-based chatbot that responds to user inquiries for an e-commerce website. This system will facilitate users in obtaining information from the eBay website. The suggested system retrieves data and maps relationships successfully. They developed the chatbot using the results to assist users in understanding product details with- out having to log into the website. After receiving the necessary details, the user can log in and purchase any product. To diversify the solutions for the future, the proposed system can be improved by enhancing entity recognition with the use of effective algorithms (such as KNN, and Similarity). This paper does not clarify the accuracy rate of chatbots, (19) proposed a clothing brand ontology from a custom-made dataset of 5000 question-answer pairs and connected it with a conversation agent to assist online consumers, the suggested method solves the issue for the Pakistani fashion market. Based on data obtained from Facebook pages and official websites, they focus on providing general information on brand facilities, services, products, and accessories. The system performs better when measured against the standards of accuracy, non-sequitur, and structured replies. The experts gave an average score of 0.70, 0.60, and 0.73 percent. However, the system performs poorly on the follow-up questions, fails to (behave dynamically), and generates inconsistent responses in a greater number of rounds. It could be because there isn't any inbuilt natural language generation.

2.3. Marketing Efforts of Fashion E-Commerce Brands

E-commerce fashion agents can offer crucial marketing initiatives that affect decision-making processes. Salespeople build consumer trust in encounters with customers by demonstrating empathy and paying attention to their needs. Such marketing initiatives are crucial for fashion firms since they must resolve user queries regarding product information or specialized services (Hasanova). By providing customers with simple access to product information, fashion brands can decrease the distance between fashion brands and their customers both physically and temporally. However, research on fashion e-commerce chatbot is lacking, particularly when it comes to online brand communication. To close this gap, we look at interactivity, problem-solving as marketing strategies in the context of fashion brands.

Using these concerning statistics, it is necessary to improve the conversational quality of chatbots, particularly by enhancing their machine learning capabilities and putting them to use with all-in-one technologies like natural language processing, ontology, intent, entity, datasets Dialogflow etc.

Most prior work either lacks ontology integration, does not evaluate accuracy explicitly, or is limited to non-fashion domains. Studies that do employ ontology, such as Nazir et al. (19) operate on custom question-answer datasets without real-world website data and do not provide head-to-head comparisons with a non-ontology baseline on the same dataset. The system proposed by Vegesna et al. (18) addresses e-commerce chatbots using ontology but targets the eBay platform and omits accuracy reporting. In contrast, this work contributes: (i) a real-world fashion dataset collected via web scraping from the Alkaram e-commerce platform, (ii) a parallel implementation of both ontology-based and non-ontology-based chatbots using the same dataset and framework, (iii) an OWL/SPARQL ontology knowledge base engineered with Protégé specifically for fashion product entities, and (iv) a structured analyst evaluation with quantified accuracy metrics, enabling direct performance comparison. These contributions collectively address the gaps left by existing studies in this domain.

3. ORIGINALITY

The proposed system was designed to overcome the limitations of conventional keyword-based chatbots by integrating an ontology knowledge base that enables semantic relationship mapping between user queries and product entities. The approach is original in that it applies ontology engineering to a real-world fashion e-commerce platform (Alkaram), constructs the ontology from scraped data, and validates it against a chatbot built on the same dataset without ontology. This comparative setup directly supports the claim that ontology integration drives measurable accuracy improvements.

4. SYSTEM DESIGN

This section describes the methods and workflow used to design, develop, and evaluate the ontology-based and non-ontology-based chatbot systems on the same dataset. The overall research workflow follows five sequential stages:
(1) Dataset Collection, where product data was gathered from the Alkaram e-commerce website using Python web scraping and stored in Google Sheet DB format;
(2) Ontology Engineering, where the scraped data was converted into an OWL-based ontology knowledge base using Protégé, with classes, object properties, and SPARQL query templates defined for the fashion product domain;
(3) Chatbot Development, where both the non-ontology chatbot (Model 1) and the ontology-based chatbot (Model 2) were implemented using Google Dialogflow, with the ontology model incorporating an additional validation layer via the ontology KB;
(4) System Integration, where webhooks connected Dialogflow to the Google Sheet DB and, in Model 2, to the ontology KB for semantic response generation;
and (5) Evaluation, where both models were tested on the same 50-query set by five independent analysts using defined scoring criteria. In order to acquire domain expertise for this design, we reviewed over 60 research articles across the fields of ontology-based chatbots, rule-based chatbots, natural language processing, and semantic web technologies.

With the information acquired, we developed a concept for the study based on the use of semantic NLP for the experiment utilizing the Google Dialog flow framework. ”Applying chatbots to fashion e-commerce specific needs such as providing Frequent Ask Questions (FAQ), customer sup- port, product information, exploring enormous collections, product queries, context-based queries, product price range, and providing a personal assistant, Using this technique, chatbots for e-commerce websites could offer responses at a lower computing cost and with a more intelligent strategy”.

We used an innovative incremental strategy for websites that deal in fashion. In this respect, a variety of development tools, frameworks and libraries have been used. We have designed two workable models on same dataset; one is ontology based chatbot and the other one is non-ontology based chatbot for fashion ecommerce brand. In ontology based chatbot we used Protégé
(33) tool for the ”E-commerce brands” domain’s ontology engineering. It is one of the best ontology engineering tools available, Pro- tégée also allows us to export ontologies in a variety of additional language formats, including Resource Description Framework (RDF) schema (34) and VOWL (35). Similarly, for the display of taxonomy, we employed Web Ontology Language (OWL) and OntoGraf (18) plugins, while SPARQL was used for data retrieval and querying systems. (19, 36) similarly Dialog Flow will be used to handle the NLP, intent classification, training, context, and entities . Due to Lack of high-quality real-world datasets in the e-commerce industry (11) we used web scraping to collect datasets [20] from E-commerce “Alkaram” websites using python. A workable model of an E-comm bot (ontology and non-ontology-based chatbot) that responds to user inquiries for an e-commerce website is kept forward. The shortcomings of typical chatbots are overcome by this chatbot by mapping relationships between the many entities the user requests, delivering detailed and precise information.

4.1. System Architecture and Modular Description

This section provides a thorough examination of both chatbot models with their components and demonstrates how the conversations between chatbots that use semantic natural language processing are connected by examining with E-commerce bot for both models.

a. Architecture

We have designed two E-comm bot architecture model (ontology and non- ontology based) which will defined in detailed and then compare their results. Figure 1 and 2 illustrates the architecture of our chatbot, which is built upon the Google Dialog flow framework.

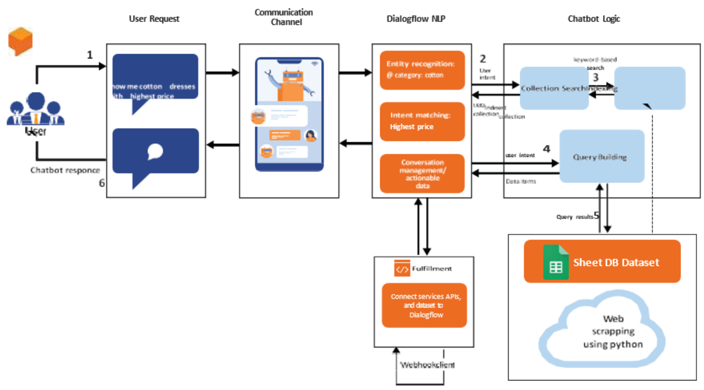

Figure 1. E-comm bot architecture model without ontology model

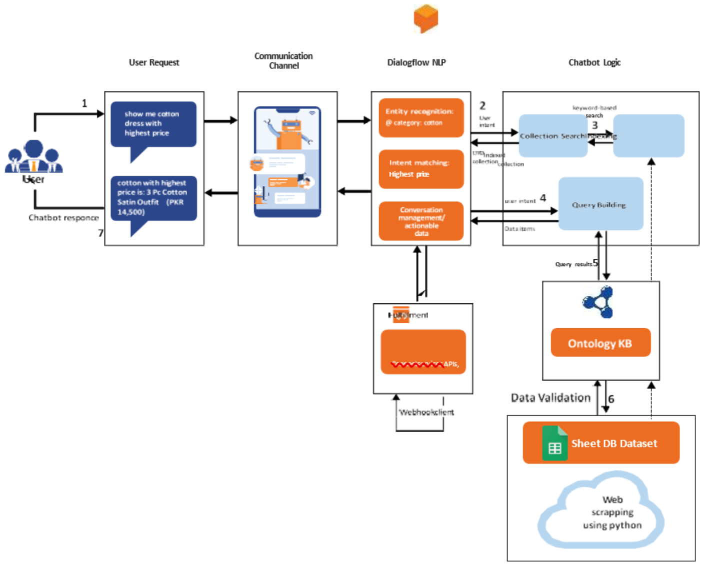

Figure 2. E-comm bot architecture model with ontology model

Conversational systems can be quickly and easily implemented using the Google Dialogflow framework. It enables i) communication with a chatbot through a variety of guaranteed instant messaging and social networking services (such as Skype, Facebook Messenger, WhatsApp, Google Assistant, and Messenger for Facebook), ii) processing of user requests in natural language and management of user-chatbot conversations, and iii) connection to external services and data sources. The NLP modules use cutting-edge machine learning methods for two key functions: entity recognition and intent matching (20, 22). As a result, using Dialogflow, providing chatbots with their concepts and intents constitutes a significant portion of the implementation process. The framework builds its machine learning models automatically using these corpora texts. Our chatbot has several distinct intents that we have established.

Figures 1 and Figure 2 depict the chatbot's parts and modules, as well as how they link and handle data. The user uses chats on an instant messaging service to access and communicate with the chatbot (stage 1 in the Figure 1 and 2). A manually typed text request from a user is given to Dialog flow's NLP component. The input is then sent from that application or device to Dialogflow which separates out entities and determines the expected outcomes. The official customer support for an e-commerce brand is provided by E-comm Bot's interface. The customer can utilize this platform to ask the bot questions about products, product specifications, FAQs, and other topics while also perusing massive collections.

If the intent is searching for a collection (stage 2 in Figure 1 and 2), the chatbot asks the user for terms that may be associated to relevant collections, every action has a related intent (defined in Fulfillment webhook). The webhook searches for an appropriate response using external APIs after

Dialogflow identifies an intent. API synchronizes the fulfilment webhook with information. The webhook then provides a formatted reply to match the query's intent. Which tends to result in actionable data. The Programme transforms the actionable data into human language at the output stage before sending it. In a non-ontology-based chatbot, the phrases are used to start a keyword- based search over a database in Google Sheet DB. (Stage 3 in Figure 1), and in ontology base chatbot uses the provided terms to validate data over Google sheet and ontology kb (stage 3 Figure 2). Following the procedure, the user is shown a list of collections that have indexed the input keywords (stage 6, Figure 1) and (stage 7, Figure 2). The intent is transmitted to a query constructing module, however, if it has to do with dataset instance. (Stage 4, Figure 1 and Figure 2). A conversation is then maintained with the user. Once the query is created, it is launched to the database (stage 5), retrieving the data items of interest. However we analyzed that most of the query are not matched to the database and there is a lacking answer to match their entity, maps relationship and retrieving data in non-ontology base chatbot.

However, in ontology-based chatbots, data is obtained from an API (a sheet Database), and it is validated against the ontology response because the ontology generates the appropriate response with entities and converts it from the ontology template to Dialogflow format. Finally, the user is shown these items in a format that is appropriate. (Stage 7, Figure 2).

5. EXPERIMENT AND ANALYSIS

This section provides the each steps of our models.

5.1. Web Scraping using Python

Due to the lack of high-quality real-world datasets in the fashion e-commerce industry (11), we used web scraping to collect datasets (37) from e-commerce "Alkaram" websites using python. In this paper, we concentrate on Web scrapers, which take textual data from Web pages. Information can be gathered from the Web using a variety of techniques (4). A computer software technique called web scraping (web data extraction) is used to gather data from websites. It is a word that refers to the process of using an algorithm or computer to extract and process significant amounts of data from the internet. A request library using the most common HTTP methods is made to the URL that we have specified when the web scraping code is performed(38). The server responds to the request by sending the information and allowing users to view the XML or HTML page. Moreover, we used Beautiful Soup library (39) which is a package for parsing HTML and XML documents. It creates parse trees that are helpful to extract the data easily.

Extracting data from ALKARAM website

After employing a variety of techniques to scrape the data. The data will subsequently be transformed into structured tables. The resulting file can be exported as an Excel sheet, Google sheet db or possibly a .csv file, and it contains all the scraped data for later usage.

5.2. Ontology

After extracting the data from the website in Google Sheet DB format, the data was converted into an ontology knowledge base for improved semantic retrieval. The ontology was developed using the Protégé 5.5 editor and serialized in OWL 2 (Web Ontology Language). Figure 3 describes the key components of the ontology schema design (22). Utilizing a domain ontology has many benefits, one of which is its capacity to define a semantic model of the data along with the associated domain knowledge. Ontologies can be used to specify connections between several domains of semantic knowledge. Ontologies can therefore be utilized to create multiple data searching strategies.

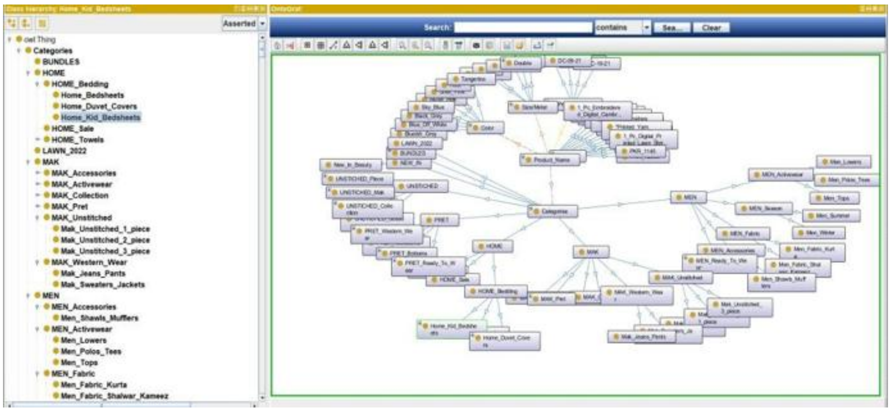

Figure 3. E-comm bot ontograph

The ontology schema is structured around a top-level class hierarchy with four primary classes: Product, Category, Attribute, and Brand. The Product class serves as the central node and contains data properties including productName (xsd:string), productPrice (xsd:float), productURL (xsd:anyURI), and productAvailability (xsd:boolean). The Category class encompasses subclasses such as ReadyToWear, Unstitched, Accessories, Footwear, and HomeItems, reflecting the product taxonomy of the Alkaram e-commerce platform. The Attribute class holds object properties including hasColor, hasFabric, and hasSize, each linking a Product instance to a corresponding literal value. The Brand class connects products to their brand entity through the hasBrand object property. Object properties are defined with explicit domain and range restrictions to enforce semantic consistency: for example, hasColor has domain Product and range Color (a named individual class), while belongsToCategory has domain Product and range Category. SPARQL queries are used for data retrieval; for instance, a query to retrieve all cotton dresses above a specified price threshold filters by hasColor value and productPrice datatype property. The ontograph visualization in Figure 3 shows the class hierarchy and relationship graph as rendered by the OntoGraf plugin in Protégé. This structured ontology schema enables the chatbot to map user intent precisely to product entities, which is the core reason for the observed accuracy gain over the non-ontology model.

5.3. Dialogflow

A Google Cloud chatbot platform called Dialogflow was selected for the creation of this project after a comparative analysis. One of Dialog flow's key features is that it makes it possible for the user's inquiry to line up with the best effort by using the data in the user input. Its ability to permit integration with a variety of messaging and social network applications is another crucial feature. After comparing the major chatbot platforms (19), it is determined that Dialogflow is the most comprehensive framework for highlighting the characteristics of the attempt and the identification of the entity.

Google Dialogflow Components

The following Dialogflow building components can be used to develop a chat- bot: Agent, Intent, Entities, Contexts, Fulfillment, Integration, and Smalltalk. E-comm Bot was constructed using each of these components.

Agent: The agent is the one who engages the user in conversation using building components. Here agent is E-comm bot.

Intent: It specifies the course of action to be taken in response to a user's request or search. You might need to come up with a set of intentions for the conversation. With the aid of taught words, the agent determines the user's intent during a search and routes the request to the intent that is most closely matched. Purpose of the E-comm bot is to inform users about e-commerce fashion products.

Contexts: Most researchers have discovered that flow of chat conversion to understand what "they" are pointing to is crucial for NLP applications, its influence seems to be quite limited. Mostly researchers use the term of anaphora resolution to understand the term of he or she etc(33). The ability to understand questions based on previously asked and answered questions is a requirement for a chatbot. By using Dialogflow "Context" we can control Natural language conversation. Context must be given to Dialog flow for it to properly match an intent when handling an end-user phrase like that. By manipulating context, we may control the course of a dialogue. Figure 4 shows an example that uses context for an e-comm bot agent, where we don't need to write and repeat the same product name for their details.

Figure 4. E-Comm bot chat flow context

Entity: In Dialog flow, entities are a mechanism for locating and retrieving valuable data from natural-language inputs. E-comm has entity name product for extracting product related data for user.

Fulfillment: E-comm bot employs fulfilment to obtain answers from ontology KB that are stored in accordance with user requirements. Use of the inline editor in fulfilment is used to implement the code for connecting to the Google sheet db and ontology kb and retrieving related data from it. Product information is validated for semantic replies using Google Sheets' database and the Ontology Knowledge Base (34).

5.4. User Interface

The display interface of a chatbot, which enables communication between users and chatbots, is referred to as its user interface. Users must have the best possible experience when interacting with the user interface. Without it, chatbots are useless since they are challenging to use. Using natural language Processing, users (customers) can completely interact with the E-comm bot (chatbot) at this presentation layer and receive accurate and current responses.

5.5. Result and Evaluation

The result of this research work is E-commerce Alkaram website with multiple categories of products such as home items, Accessories, ready to wear clothes, unstitched clothes, makeup, footwear, and sunglasses etc. In the area of natural language processing automatic evaluation is advantageous since it enables speedy review without the costly physical labor of human judges (28). There are numerous methods for assessing performance of the system, including the Bilingual Evaluation Understudy (BLEU)(35) , METEOR (2) , and Recall-Oriented Understudy for Gisting Evaluation (ROUGE) (25); However, because there might be many different replies to each given turn, these measures are frequently regarded as being either weak or falling short of the mark when contrasted with human judgment (18, 34)

Figure 5. Non-ontology E-comm bot

Figure 6. Ontology E-comm bot

Figure 5 and 6 provides a glimpse into the conversation between the chatbot for both models. However, the Turing Loebner (16) method is used to thoroughly examine our chatbot. Using this method, we evaluate the chatbot by having a 10-minutes conversation with it for both models with and without ontology. Based on how accurate, intimacy, sustainable, non-sequitur, simplified, context-oriented and follow up responses were retrieved by the bot, we graded performance in form of graphs. The judgment scale ranges from 0 to 9.

For the experiment, we developed the following standards for assessing chatbots built using the suggested methodology:

Accuracy: The proportion of chatbot responses that correctly match the user's intended query. Formally, Accuracy = (Number of Correct Responses) / (Total Responses Evaluated). A response is considered correct if it directly addresses the query with factually valid product information. Analysts assigned a score from 0 to 9, where 0 indicates no correct responses and 9 indicates all responses fully correct.

Intimacy: The degree to which the chatbot response is semantically relevant and topically aligned with the user's question. It is scored on a 0–9 scale where 9 means the response is fully on-topic with no irrelevant content, and 0 means the response has no semantic overlap with the query. Formally, Intimacy Score = (Semantically Relevant Responses) / (Total Responses) x 9.

Sustainable: Measures the consistency and variability of responses when the same query is repeated multiple times. A score of 9 indicates the chatbot generates appropriately varied yet accurate responses across repeated inputs, while a score of 0 indicates it either produces identical repetitive responses or entirely inconsistent ones. Formally, Sustainability Score = (Varied Correct Responses to Repeated Queries) / (Total Repeated Query Instances) x 9.

Non-Sequitur: Measures how logically coherent the chatbot response is relative to the conversation thread. A response scores 9 when it follows naturally from the query and prior context, and
0 when it is completely unrelated or contradicts a previous answer. Formally, Non-Sequitur Score = (Logically Coherent Responses) / (Total Responses) x 9. Lower Non-Sequitur scores in the non-ontology model reflected its inability to track context across follow-up questions.

Simplified: Evaluates whether the chatbot response is grammatically well-formed, clear, and readable. Analysts scored responses from 0 to 9 based on grammatical correctness, sentence completeness, and absence of redundant or fragmented phrasing. A score of 9 indicates fully grammatical and clearly structured output; a score of 0 indicates incoherent or malformed responses. Formally, Simplified Score = (Well-Formed Responses) / (Total Responses) x 9.

Context-Oriented: Evaluates how well the chatbot uses prior conversation turns to inform its current response. A score of 9 means the bot correctly references earlier entities and builds on them. A score of 0 means every response is treated as a fresh query with no memory of prior turns. Formally, Context-Oriented Score = (Responses Using Prior Context Correctly) / (Total Responses Where Context Was Applicable) x 9.

Follow-up: Assesses whether the chatbot proactively requests clarification when a user query is ambiguous or incomplete. A score of 9 means the system always prompts for missing information rather than returning a wrong or empty answer. A score of 0 means it never asks and instead either fails silently or returns an irrelevant result. Formally, Follow-up Score = (Appropriate Clarification Requests on Ambiguous Queries) / (Total Ambiguous Queries) x 9.

Figure 7. Graphs of ontology E-comm bot's Evaluation Result

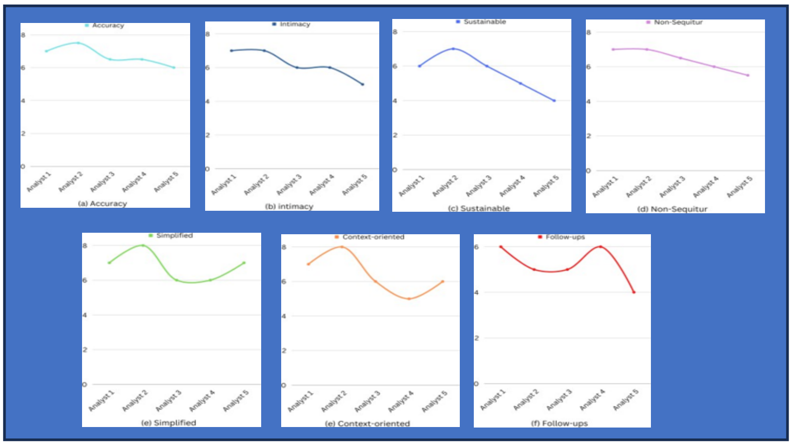

Figure 8. Graphs of non-ontology E-comm bot's Evaluation Result

Five independent analysts evaluated both chatbot systems using the criteria defined above. The evaluation protocol involved conducting 10-minute structured conversations with each chatbot model using a fixed set of 50 test queries drawn from the Alkaram product catalogue, covering product search, FAQs, price queries, and context-based follow-up questions. Each analyst independently scored every response on a 0-to-9 scale across all seven evaluation criteria. Final scores were computed as the mean of all five analysts' ratings per criterion, and results are reported as normalized percentages (score /9x100). Inter-analyst agreement was confirmed by computing mean pairwise score differences across criteria, which remained within 0.5 points on the 9-point scale, indicating consistent judgement across evaluators. The quantified data are combined to produce average and percentage-based evaluations. To compare the effectiveness of the two chatbot models, we analyzed each model on the same 50-query test set under identical conditions. The comparison of each independent analysis of Ontology E-comm bot and non-ontology E-comm bot are depicted in Figure 7 and 8.

The effectiveness of the system graphs in non-ontology E-comm bot according to the criteria of accuracy, non-sequitur, simplified, and context-oriented answers show the better results by yielding 0.67, and 0.64, 0.68 and 0.64 percentage marks on average by the analyst. The intimacy, sustainable and follow-up of the responses are a slightly above average. In ontology E-comm bot the system performed better than expected when measured by the experts' analyst average scores of 0.88, 0.86, 0.82, 0.84, 0.82, and 0.86 percentage, which were estimated from our log records using the accuracy, intimacy, sustainable, non-sequitur, and simplified and context-oriented answer criteria. The response is a little bit above average in terms of follow-up. Even so, there is still tremendous room for improvement. Figure 7 and 8 displays the full set of findings in forms of graphs. Using ontology in our model, we were able to attain an accuracy rate of 88%. Because Ontology upholds the connections between entities and intents. How- ever, with the non-ontology-based chatbot, we received 67% of the findings. We improved accuracy rate by 21% using ontologies. The accuracy remained the same as the number of questions increase. It is observed that we can even increase accuracy if we grow the dataset again by adding more queries.

5.6. Future Direction

There is clearly room to push this further. The current system works well for the Alkaram product catalogue, but the ontology would need to grow alongside the dataset if more product categories are added. One direction worth exploring is combining the ontology layer with a large language model so the chatbot can handle open-ended questions it was not specifically trained on. Deep learning and transformer-based NLP would likely improve how the system handles follow-up questions and conversation context, which is still a weak spot in the current setup. It would also be worth running a larger user study, ideally with real customers rather than analyst evaluation, to see how the accuracy gains translate to actual satisfaction. Fashion brands looking to deploy something like this should also think about personalization, since the same query from different shoppers may call for different responses based on their purchase history or preferences. A particularly promising direction is the hybrid ontology-LLM architecture, where the OWL knowledge base serves as a structured semantic backbone while a generative model such as GPT or LLaMA handles the conversational layer. Recent work has shown that using LLMs to automatically generate SPARQL queries against an ontology, rather than relying on hand-crafted query templates, significantly reduces the manual engineering overhead while preserving the knowledge precision that pure LLM systems lack (31). This approach directly addresses the main limitation of the current system, which is the effort required to maintain and extend the ontology as the product catalogue grows. Rather than treating ontology and LLMs as competing approaches, the field is moving toward systems where the ontology guarantees factual accuracy and traceability while the LLM provides language flexibility and context awareness. For fashion e-commerce in particular, where product details must be precise but customer conversations are naturally open-ended, this combination represents the most practical path forward.

6. CONCLUSION

What this study shows is fairly straightforward: when you give a chatbot a structured semantic layer, it gets better at understanding what customers actually want. People tend to trust and use chatbots more when the answers make sense, and that comes down to how well the system maps intent to the right product information. For fashion e-commerce brands, chatbots that can handle product search, FAQs, price queries, and context-based follow-ups without breaking down are genuinely useful tools, not just add-ons. The cost savings in customer support alone make a strong case for investing in them. What we built here with the Alkaram dataset shows that the ontology-based model, with its 88% accuracy versus 67% for the plain version, does a meaningfully better job. The 21% gap is not a marginal difference. It comes from the ontology's ability to hold product relationships in a way that keyword search simply cannot replicate. The Dialogflow framework handled the NLP side well, but without the ontology KB behind it, it kept returning incomplete or off-target answers. With both working together, the system behaved like something a real customer could rely on. Future work can take this further by scaling the ontology, testing with more users, and exploring how newer AI models fit into this kind of architecture.

Acknowledgement

The author thanks the Administration of NED University of Engineering and Technology, Karachi, Pakistan, for providing resources to complete this research.

REFERENCES

[1] Abdulla H, Eltahir AM, Alwahaishi S, Saghair K, Platos J, Snasel V, **Chatbots development using natural language processing: a review**. *2022 26th International conference on circuits, systems, communications and computers (CSCC)*; 2022: IEEE. https://doi.org/10.23919/CSCC55931.2022.9860905

[2] Agarwal R, Wadhwa M. **Review of state-of-the-art design techniques for chatbots.** *SN Computer Science*, Vol. 1, No.2, pp. 246, 2020. https://doi.org/10.1007/s42979-020-00255-3

[3] Almansor EH, Hussain FK, **Survey on intelligent chatbots: State-of-the-art and future research directions.** *Conference on Complex, Intelligent, and Software Intensive Systems*; 2019, *Springer*. https://doi.org/10.1007/978-3-030-22354-0_47
[4] El Asikri M, Knit S, Chaib H. **Using web scraping in a knowledge environment to build ontologies using python and scrapy**. *European Journal of Molecular & Clinical Medicine*. Vol. 7, No. 03, 2020.
[5] Vebrianti R, Aras M, Putri MSS, Swandewi IA. **AI chatbots in e-commerce: Enhancing customer engagement, satisfaction and loyalty.** *PaperASIA.* Vol 41, No.2b, pp. 248-260, 2025. https://doi.org/10.62090/paperasia.v41i2b.254
[6] Skrebeca J, Kalniete P, Goldbergs J, Pitkevica L, Tihomirova D, Romanovs A. **Modern development trends of chatbots using artificial intelligence (AI).** *2021 62nd International Scientific Conference on Information Technology and Management Science of Riga Technical University (ITMS)*; 2021: IEEE.
[7] Chung M, Ko E, Joung H, Kim SJ. C**hatbot e-service and customer satisfaction regarding luxury brands**. *Journal of business research*. Vol 117, pp. 587-595, 2020. https://doi.org/10.1016/j.jbusres.2018.10.004
[8] Cheng X, Cohen J, Mou J. **AI-enabled technology innovation in e-commerce.** *Journal of Electronic Commerce Research*. Vol. 24, No.1, pp. 1-6, 2023. https://doi.org/10.1108/JEC-2023-0001
[9] Gautam V, Sharma V. **The Mediating Role of Customer Relationship on the Social Media Marketing and Purchase Intention Relationship with Special Reference to Luxury Fashion Brands**. *Journal of Promotion Management* https://doi.org/10.1080/10496491.2017.1323262
[10] Landim A, Pereira A, Vieira T, de B. Costa E, Moura J, Wanick V, et al. **Chatbot design approaches for fashion E-commerce: an interdisciplinary review**. *International Journal of Fashion Design, Technology and Education.* Vol. 15, No.2, pp. 200-210, 2022. https://doi.org/10.1080/17543266.2021.1990417
[11] Necula S-C, Păvăloaia V-D. **AI-driven recommendations: A systematic review of the state of the art in e-commerce**. *Applied Sciences*. Vol. 13, No. 9, pp. 5531, 2023. https://doi.org/10.3390/app13095531
[12] Ayanouz S, Abdelhakim BA, Benhmed M. **A smart chatbot architecture based NLP and machine learning for health care assistance**. *Proceedings of the 3rd international conference on networking, information systems & security;* 2020. https://doi.org/10.1145/3386723.3387897
[13] Antoniou C, Kravari K, Bassiliades N. **Semantic requirements construction using ontologies and boilerplates**. *Data & Knowledge Engineering.* Vol.152, 102323, 2024. https://doi.org/10.1016/j.datak.2024.102323

[14] Zhou Q, Sacramento C, Martinaityte I. **Work meaningfulness and performance among healthcare professionals: The role of professional respect and participative management**. *Journal of Business Research.* Vol. 163, 113908, 2023. https://doi.org/10.1016/j.jbusres.2023.113908

[15] Shafi PM, Jawalkar GS, Kadam MA, Ambawale RR, Bankar SV. **AI—assisted chatbot for e-commerce to address selection of products from multiple products.** *Internet of Things, Smart Computing and Technology: A Roadmap Ahead: Springer*; 2020. p. 57-80. https://doi.org/10.1007/978-3-030-39047-1_3

[16] Casas J, Tricot M-O, Abou Khaled O, Mugellini E, Cudré-Mauroux P. **Trends & methods in chatbot evaluation**. *Companion Publication of the 2020 International Conference on Multimodal Interaction*; 2020.

[17] Chen Q, Lu Y, Gong Y, Xiong J. **Can AI chatbots help retain customers? Impact of AI service quality on customer loyalty**. *Internet Research.* Vol. 33, No. 6, pp. 2205-2243, 2023. https://doi.org/10.1108/INTR-09-2021-0686

[18] Ben Mahria B, Chaker I, Zahi A. **A novel approach for learning ontology from relational database: from the construction to the evaluation**. *Journal of Big Data*. Vol. 8, No. 1, pp.25, 2021. https://doi.org/10.1186/s40537-021-00412-2.

[19] Khan MY. **A novel approach for ontology-driven information retrieving chatbot for fashion brands**. *International Journal of Advanced Computer Science and Applications (IJACSA)*. 2019. https://doi.org/ 10.14569/IJACSA.2019.0100972.

[20] Mishra MK, Pal R, Nayak R. **Chatbots and AI in fashion industry. use of digital and advanced technologies in the fashion supply chain**: *Springer*; 2025. p. 41-66. https://doi.org/10.1007/978-981-97-4910-0_3-

[21] Chen ER. **Not Just a Chat: Transforming the Luxury Fashion Shopping Experience through AI Chatbots**. 2025. *unpublished manuscript*, 2025.

[22] Qi L, Ko E, Cho M. **AI chatbots with visual search: Impact on luxury fashion shopping behavior**. *Journal of Global Scholars of Marketing Science.* Vol. 35, No. 2, pp. 99-117, 2025. https://doi.org/10.1080/21639159.2024.2367802-4017

[23] Kanthed S. **The Role of Chatbots in Reducing Customer Support Response Time in E-Commerce**. *International Journal of Scientific Research in Engineering and Management*. Vol. 7, No. 12, pp. 1-7, 2023. https://doi.org/10.55041/IJSREM26047-

[24] Nagarhalli TP, Vaze V, Rana N. **A review of current trends in the development of chatbot systems**. *2020 6th International conference on advanced computing and communication systems (ICACCS)*; 2020: IEEE. https://doi.org/10.1109/ICACCS48705.2020.9074420.

[25] Ngai EW, Lee MC, Luo M, Chan PS, Liang T. **An intelligent knowledge-based chatbot for customer service.** *Electronic Commerce Research and Applications.* Vol. 50, 101098, 2021. https://doi.org/10.1016/j.elerap.2021.101098

[26] Shum H-Y, He X-d, Li D. **From Eliza to XiaoIce: challenges and opportunities with social chatbots**. *Frontiers of Information Technology & Electronic Engineering*. Vol. 19, No.1, pp. 10-26, 2018. https://doi.org/10.1631/FITEE.1700826

[27] Ramki R, Gopi V, Markan R, Natarajan S, Rajalakshmi M. **AI-powered chatbots in customer service: Impact on brand loyalty and conversion rates.** *Economic Sciences*. Vol. 20, No.2, pp. 190-203, 2024. https://doi.org/10.14505/es.v20.1(37).

[28] Oguntosin V, Olomo A. **Development of an E-Commerce Chatbot for a University Shopping Mall**. *Applied Computational Intelligence and Soft Computing.* 2021;2021(1):6630326. . https://doi.org/10.1155/2021/6630326

[29] Cheng X, Bao Y, Zarifis A, Gong W, Mou J. **Exploring consumers' response to text-based chatbots in e-commerce: the moderating role of task complexity and chatbot disclosure**. *Internet Research*. Vol. 32, No. 2, pp. 496-517, 2022. https://doi.org/10.1108/INTR-08-2020-0460

[30] Chen S, Wu Y, Deng F, Zhi K. **How does ad relevance affect consumers' attitudes toward personalized advertisements and social media platforms? The role of information co-ownership, vulnerability, and privacy cynicism.** *Journal of Retailing and Consumer Services*. Vol. 73,103336, 2023. https://doi.org/10.1016/j.jretconser.2023.103336

[31] Reif J, Jeleniewski T, Gill MS, Gehlhoff F, Fay A. **Chatbot-based ontology interaction using large language models and domain-specific standards**. *2024 IEEE 29th International Conference on Emerging Technologies and Factory Automation (ETFA)*; 2024: IEEE. https://doi.org/10.48550/arXiv.2408.00800

[32] Ramki DR. **AI-Powered Chatbots in Customer Service: Impact on Brand Loyalty and Conversion Rates**, *Economic Sciences.* 2024. https://doi.org/10.69889/vs5gtv52

[33] Baci A, Friedrichs L, Demir C, Ngomo A-CN. **OWLAPY: A Pythonic Framework for OWL Ontology Engineering**. *arXiv preprint arXiv:*251108232. 2025. https://doi.org/10.48550/arXiv.2511.08232

[34] Lata K, Singh P, Dutta K. **A comprehensive review on feature set used for anaphora resolution.** *Artificial Intelligence Review.* Vol 54, No. 4, pp. 2917-3006, 2021. https://doi.org/10.1007/s10462-020-09917-3

[35] Kakad S, Dhage S. **Semantic web: Knowledge graph of digital minimalism ontology.** *2022 3rd International Conference for Emerging Technology (INCET)*; 2022: IEEE. https://doi.org/10.1109/INCET54531.2022.9824657

[36] Alhindi A, Alsaidi A, Munshi **A. Vehicle Routing Optimization for Non-Profit Organization Systems**. *Information.* Vol. 13, No.8, pp.374, 2022. https://doi.org/10.3390/info13080374
[37] Alhafiz V, Adiguna MA. **Pengembangan Aplikasi Web Scraping Untuk Pengumpulan Data Harga Produk E-Commerce Menggunakan Python (Studi Kasus: Tokopedia)**. J*UPIK: Jurnal Penelitian Ilmu komputer*. Vol. 2, No. 2, pp. 1-13, 2024.
[38] Sharma GD, Yadav A, Chopra R. **Artificial intelligence and effective governance: A review, critique and research agenda.** S*ustainable Futures*. Vol. 2, 100004., 2020. https://doi.org/10.1016/j.sftr.2019.100004
[39] Patel N, Trivedi S. **Leveraging predictive modeling, machine learning personalization, NLP customer support, and AI chatbots to increase customer loyalty.** *Empirical Quests for Management Essences*. Vol. 3, No.3, pp. 1-24, 2020.