An Intelligent Knowledge-based Chatbot for Customer Service

Abstract

This study proposes an intelligent knowledge-based conversational agent system architecture to support customer services in e-commerce sales and marketing. A pilot implementation of a chatbot for customer services is reported in a leading women's intimate apparel manufacturing firm. The proposed system incorporates various emerging technologies, including web crawling, natural language processing, knowledge bases, and artificial intelligence. In this study, a prototype system is built in a real-world setting. The results of the system prototype evaluation are satisfactory and support the contention that the system is effective. The study also discusses the challenges and lessons learned during system implementation and the theoretical and managerial implications of this study.

Keywords: Conversational agent; chatbot; knowledge-based system; system design; case analysis.

1. Introduction

Without a doubt, artificial intelligence (AI) is the emerging technology that has attracted the considerable attention of researchers and industry in the past decade. One of the applications of AI that is expected to have the most development in the near future is conversational agents (Carter 2018). Conversational agents, also known as chatbot, or chatterbot, is a machine conversation system that interacts with human users through natural conversational language (Hill et al. 2015). More and more companies and organizations are using chatbots to communicate with their customers. For example, Bank of America launched a chatbot named Erica as an AI-driven virtual financial assistant for their clients in 2018, and as of 2019, Erica has had 10 million users (Bank of America 2019). Chatbot applications can be found in banking (Bank of America 2019), education (Kerlyl et al. 2006), and healthcare (Oh et al. 2017). In addition, chatbots have become popular over the past years in social networking sites, such that a useful and helpful chatbot is positively associated with consumer attitudes toward the brand (Zarouali et al. 2018) and reduces the perceived intrusiveness of subsequent chatbot advertising (Van den Broeck et al. 2019). In e-commerce, chatbots can help answer customers' questions promptly without involving any human. This capability can help improve customer service quality and human resource allocation. However, customers are not always satisfied with the performance of chatbots. For example, chatbots may provide unsuitable responses to customers, leading to a gap between customer expectation and system performance, which might, in turn, trigger unwanted customer behaviors such as noncompliance (Adam et al. 2020). To improve their performance, chatbots are thus integrated with a knowledge base (KB) for a more dynamic and successful conversation. Chatbots can instantly search the KB and use the data it finds to present a personalized response. In this research, we first review the related academic literature on chatbot design and system architecture for customer services to identify the gap and problem in current studies. On the basis of our literature review in Section 2, we can see that the research on KB design for customer service chatbot application has been limited.

To bridge the gap, we investigate the design of a KB that can effectively support customer service chatbot application. Therefore, we propose a KB design framework that incorporates customer knowledge management (CKM) and present the system architecture of a chatbot that proactively improves itself continuously. A prototype system is then developed based on the proposed design and piloted and evaluated in a multinational intimate apparel company. The results of the system prototype evaluation are satisfactory, showing that the prototype can be effective in improving the efficiency of customer service support. The framework can be used by managers as an important system architecture and academicians for further research. Hopefully, these contributions can be used by more companies to herald an era of a wider range of intelligent knowledge-based conversational agents to support e-commerce customer sales and marketing service.

This paper is organized as follows. A review on previous related works on chatbot design for customer service support is given in Section 2. The design framework of a KB supporting customer service conversations is proposed in Section 3. The architecture of the conversational agent integrating the proposed KB design is described in Section 4. The case study covering the prototype system based on the proposed architecture and the evaluation of the prototype system is presented in Section 5. The benefits and challenges involved in the development and implementation of an intelligent knowledge-base-supported conversational agent is discussed in Section 6. The conclusion with future study directions for this research is provided in Section 7.

2. Literature Review

Chatbots that adopt a machine learning approach have been used in many different industries and applications, such as education (Kerlyl et al. 2006), medical (Laranjo et al. 2018), and government (Androutsopoulou et al. 2019). Chatbots are frequently used to facilitate customer service experience, including but not limited to selling, promotion and customer engagement. (Androutsopoulou et al. 2019; Cui et al. 2017). In the past decade, a number of prior studies have been conducted on the design of chatbots specific for customer services. Conducting a comprehensive literature review can give us a general overview of a body of research in chatbot design and give us new ideas which we can use in our own research. We performed a systematic literature review by searching databases, including Web of Science and Scopus, based on the descriptor, “chatbot(s),” “chatter bot(s),” “chatterbot(s),” “conversational agent(s),” and “conversational interface(s)”. The search result was further filtered by other keywords, including “design,” “framework,” and “architecture,” and the scope of this investigation was limited to the timeframe of 2011 - 2020. As a result of our search, 883 and 2,933 articles were collected from Web of Science and Scopus respectively. After a removing the duplicated records, the full text was reviewed and 21 articles pertaining to the design and architecture of chatbots for customer services were identified. To illustrate the discrepancies that exist across extant studies, a summary of selected studies on chatbot for customer services is provided in Table 1. Although this search was not exhaustive, we believe that it serves as a comprehensive base for an understanding of chatbot design for customer service support.

Study	Research question/gap/problem	Objectives	Methodology	Major findings	KB
Acharya et al. (2020)	No travel chatbots in place for the Indian Travel and Tourism Industry.	Present a research conducted on a travel chatbot, which helps users in bookings and recommendations.	System development, experiment	The proposed chatbot produces a performance accuracy of 98.67%.	✓
Bhawiyuga et al. (2017)	The research work on designing chatbots aimed at e-commerce is still very limited.	Propose the design and implementation of an e-commerce chatbot system that provides automatic responses to customers' questions.	System development, experiment	In the usability and performance testing, the proposed system can automatically deliver the answer in less than 5 seconds with relatively good matching accuracy.	
Catapang et al. (2020)	A need to supply a proper corpus builder or corpus engine specifically for Taglish.	Present a bilingual retail chatbot that could handle the two official languages of the Philippines	System development, experiment	The proposed chatbot is 94% reasonable according to the test users	
Cha et al. (2019)	Reduce the cost caused when a person switches among different chatbots for different services.	Propose the federated chat service framework.	System (prototype) development	The proposed framework can organize service requests with context information and responses to emulate the conversations between users and chat services and hopefully contribute to reducing the cost for a user to communicate with different chatbots.	✓
Chakrabarti and Luger (2012)	Existing approaches perform well in pairwise utterance exchanges but not so well in longer conversational contexts.	Propose more meaningful chatter bot conversations by using an architecture that can leverage content and context.	System development, experiment	The proposed chatter bots can • perform well in conversations where they are required to troubleshoot issues and • go beyond mere question–answer or utterance–response exchanges and hold a more meaningful conversation with a human.	
Chakrabarti and Luger (2014	Contemporary chatter bots do not perform well at tasks where a specific context has to be maintained across a several utterance exchanges pairs.	Demonstrate a modular, robust, and scalable architecture for chatter bots.	System development, experiment	The proposed system had a success rate of 87.5%.	
Chakrabarti and Luger (2015)	The existing approaches perform poorly in conversational situations requiring contextual continuity over a series of utterances.	Present an approach framework that combines pragmatics with content semantics to generate artificial conversations in the customer service domain and a specific set of criteria that	System development, experiment	• The artificial conversations satisfy the four conversation maxims proposed by Grice (1975). • For the task of online troubleshooting, the artificial conversations are virtually indistinguishable from natural conversations. • The Quantity Maxim was perceived to be less	

		are used to evaluate the quality of artificial conversations in the customer service domain.		important than the Quality, Relation, and Manner Maxims by the panel of judges. • Increasing the fraction of follow-up questions and the number of coherent turns in the artificial conversation is important for successful resolutions and is a key consideration for bot design. • The overall performance of the chatter bot is comparable to humans in the customer service domain.	
Cui et al. (2017)	There are significant issues in terms of data scale and privacy.	Present a customer service chatbot that leverages large-scale and publicly available commerce data.	System development	Improved the end-to-end user experience in terms of online shopping as it is more convenient for customer's information acquisition.	✓
Doherty and Curran (2019	There is a lack of technology in place to enhance the customer online banking experience.	Implement a web-based chatbot to assist with online banking.	System development, experiment	Enhance accessibility.	
Griol and Molina (2016)	Find ways to develop dialog management strategies that have a more robust behavior, better portability, are generalizable, and easier to adapt to different user profiles or tasks than the traditional hand-crafting dialog strategies.	Describe a dialog management technique adapted to multi-task conversational systems.	Experiments, survey	• The evaluation results show that the number of successful dialogs is increased in comparison with using a generic dialog model learned for the complete task. • The dialogs acquired using the specific dialog models are statistically shorter and present better quality in the selection of system responses.	✓
Gunawan et al. (2020	There is still an absence of chatbot for hotel industry in Indonesia.	Develop a chatbot for hotel industry in Indonesia	System development, experiment	85.7% of the respondents believe that using chatbot would enhance their job performance and 84.33% of the respondents believe that using the technology would be free of effort.	
Herrera et al. (2019)	Help people interact more easily	Present a live customer service using a chatbot along with several services.	System development	Customer support and experience are improved.	✓
Kurachi et al. (2018)	Improve efficiency of contact centers by utilizing AI.	Outline the contact point solution and describe the AI chatbot technology behind the solution.	Concept presentation only	It proposes the CHORDSHIP Digital Agent, which is equipped with an AI technology ideal for contact centers; it is a "conversation-machine learning hybrid AI".	✓
Kwizera et al. (2017	There are implementation challenges arising from the presence of multiple languages (code mixing), underdeveloped training corpora and non-uniform spelling.	Develop several components of a chatbot system intended to handle customer service queries in Kenya.	System development, experiment	• Customer inquiry tweets can be redirected to broad categories for processing with 50% accuracy. • The initial results show that both TF-IDF with N-Gram and word embeddings are applicable for QA systems it is important to note there are still a number of challenges and work that needs to be done.	
Nuruzzaman and Hussain (2020	Existing chatbots have several shortcomings, e.g. failing to provide a meaningful response to the user, offering semantically incorrect information etc.	Proposes a domain-specific chatbot, that uses multiple strategies to generate a response.	System development, experiment	The comparison results between it and 3 other chatbot demonstrate its superiority in providing the user with a complete answer and engaging the user in a dialogue.	✓
Paikens et al. (2020)	The technical aspects of building human-in-the-loop conversational agent systems have not been well described in existing literature. Most known applications of this approach are proprietary, and the inner workings of these systems are not published.	Present a prototype system for partial automation of customer service operations of a mobile telecommunications operator with a human-in-the loop conversational agent.	System development	The detected intent and the automatically chosen answer template were accurate approximately 92% of the time and only required operator intervention for the remaining 8% cases, thus saving time and effort.	
Pradana et al. (2017	Improve the interactivity and effectiveness of corporate website in providing information.	Introduce a prototype of conversational bot called SamBot	System development, experiment	The results reflect that SamBot is capable of handling common knowledge questions as well as highly capable of handling domain questions.	✓
Putri et al. (2019	There is only little research in developing chatbot-hotel in Indonesia.	Develop an interactive intelligent personalized chatbot-hotel by using AIML and Google Flutter.	System development	The proposed prototype chatbot-hotel Berscha in Indonesia was developed; however, no performance evaluation was reported.	
Subramaniam et al. (2018)	Research problem: automatically extracting	Describe a scalable conversational framework	System development,	More than 75% of the time, the proposed application was able to provide relevant solutions	

	domain knowledge and representing it in a suitable way to create conversational flows automatically.	that automates the process of guided troubleshooting.	experiments	for their queries.	
Wang et al. (2019)	• Current research on generative chatbots seldom takes the task-oriented requirement into consideration. • For the task-oriented conversational agents, the generated bland responses are more detrimental to user experience.	Propose frameworks to generate responses based on extra information in addition to the current user input, one encodes the entire dialog history while the other integrates external knowledge extracted from a search engine.	System development, experiment	• The proposed systems are promising in terms of generating more informative responses. • Case studies suggest that some particular features of the proposed systems and the datasets might restrict the systems from fully exploiting such extra information.	✓
Zhao et al. (2019)	• End-to-end trained systems perform poorly on dialogs that require specific domain knowledge. • The task focuses on identifying instructional answers that match the user's question and its context and hence cannot simply be gleaned from a text corpus. • Work combining question answering and dialog systems is still sparse.	Automatize the task of matching instructional answers from a QA-KB to user queries in online support chats.	System development, experiment	• For answer ranking, the proposed models clearly outperform the baseline models, achieving a 43% error reduction. • The end-to-end P@1(Precision at top 1) of the proposed system was 0.69 and the customers' satisfaction was 0.73.	✓

Table 1. Summary of selected studies on chatbot for customer services

All the studies aim at presenting the chatbot design or architecture that addresses the identified research problems, gaps, or questions. The chatbots serve customers in different industry sectors, including tourism (Acharya et al. 2020), e-commerce (Bhawiyuga et al. 2017), and telecommunication (Paikens et al. 2020). The motivations of the studies usually come from the limited research on the desired chatbots (Bhawiyuga et al. 2017; Luo et al. 2019; Paikens et al. 2020; Wang et al. 2019; Schanke et al. 2021) or the existing approaches that cannot do well at some specific situation or address some specific problems (Chakrabarti and Luger 2012; Chakrabarti and Luger 2015).

In most of the studies, system prototypes were developed (Acharya et al. 2020; Chakrabarti and Luger 2015; Paikens et al. 2020), some of which were evaluated through user survey, expert review, or experiments. Almost all the evaluation results for the system prototypes reported that the proposed chatbots performed well and effectively. They could improve the performance, accuracy, or efficiency of the operations. For example, the chatbots could improve the end-to-end user experience because it is more convenient for customers to acquire information during online shopping (Cui et al. 2017) , thereby helping save time and human effort (Paikens et al. 2020). Some studies present the conceptual design without developing a prototype or conducting any evaluation, such as (Kurachi et al. 2018).

A KB contains the required knowledge and information to support artificial conversation, such as product information, frequently asked questions (FAQs), dialog history, historical behaviors, and facts. The conversational agents will retrieve the required information or knowledge from the KB to understand customers' queries and construct answers to the questions. From the literature, a number of chatbots are supported by KB containing FAQs and data crawled from external sources, such as webpages (Herrera et al. 2019). There are also some chatbots that answer queries incorporating chat history (Griol and Molina 2016; Wang et al. 2019) or user profiles and behaviors (Cha et al. 2019). Researchers found that the chatbot with a KB and dialog history can generate more informative responses (Wang et al. 2019). As shown in Table 1, almost half of the studies in our dataset (10 out of 21) present the chatbot design incorporating a KB. However, all of them only discuss the KB briefly, without any deeper investigation into it. Moreover, the designs of the KBs in those studies are not underpinned by any theoretical basis. On the other hand, to maintain the quality of the information and knowledge supporting effective conversations between the conversational agent and customers, the KB must be updated. However, based on the literature of KB-supported chatbot, this issue was overlooked. To address the gaps in literature, we first suggest a KB design that supports customer service chatbot and then propose the architecture of a chatbot that proactively improves itself continuously. Afterward, the design is realized in a case study to illustrate its effectiveness.

3. Design Framework of an Intelligent Knowledge-based Conversational Agent to Support Customer Service

The system design and components for the intelligent KB conversation agent to support customer service is discussed in this section to answer the research questions. One of the purposes of using a chatbot is to improve customer experience and, subsequently, customer relationship management. To build and maintain good customer relationship, customer knowledge should be well managed (Wilde (2011). CKM is about gaining, sharing, and expanding the knowledge regarding customers in order to collaborate with them for joint value creation (Gibbert et al. 2002). In this study, customer-oriented knowledge is applied, shared, and transferred when chatbots communicate with customers to gain benefits for organizations and customers. Thus, the chatbot is clearly involved in the CKM process. Customer knowledge involved in the CKM should be a good basis to determine what components should be included in the KB to support chatbot conversations and gain benefits for organizations and customers. The design of the knowledge in this study is hence initiated by the concept of CKM. Customer knowledge can be categorized into three types (Wilde 2011): knowledge about the customer, knowledge from the customer, and knowledge for the customer. Knowledge about the customers consists of customer information such as age, gender, purchase history, payment behavior, motivation, and buying habits and demands. This type of customer knowledge is usually not acquired actively through interaction with the customer but is the result of analyses, interviews, and observations done for market research. Knowledge from the customer is mostly obtained by the company in a direct way, with customers informing the organization about their experiences with products, services, and processes or their expectations, objectives, and interests. This category of knowledge also includes the interpretation of market, customer's knowledge of the competitors, or technologies and proposals for solution. Knowledge for the customer is used to support the customer to close any knowledge gaps revealed by the company. Information regarding product quality, prices, features, and special offers are examples of this type of knowledge.

Hence, the KB should contain the abovementioned three types of knowledge to support chatbots' communication with customers in order to gain benefits for organizations and customers. Owing to the variation in data sources, the quality and nature of knowledge also vary. In the proposed system, each type of knowledge must be divided further into two types according to the quality and nature of the knowledge, namely, reference information and confirmed knowledge. This is necessary because without the review of human experts and the process of confirmation, the quality of data, especially of those collected from the Internet, cannot be assured. The data collected from the Internet can be written by anyone and may not be accurate or objective. Much of the information about the product and brand may also be the opinions or comments written in social media. The nature of this information cannot be considered as knowledge because it is biased and subjective. This kind of information can be used as reference. To avoid making the chatbot talk with the customer with inaccurate knowledge, the knowledge has to be confirmed by human experts as “confirmed knowledge” and those not qualified as knowledge should be saved as “reference information.” The chatbot will provide advice and suggestions to customers according to the confirmed knowledge but can also give supporting information based on the useful information. In addition, information that is dynamic or changes frequently, for example, price and stock, is considered “reference information” while confirmed knowledge is one that is relatively static, such as the maintenance procedure.

Therefore, in our proposed system, “confirmed knowledge” is the knowledge reviewed and confirmed by human experts, such as knowledge from experts, facts, and rules, while “reference information” is useful and relevant information that can be used as supportive information to improve customer experience, for example, comments and posts in social media about the products and the brands.

In the proposed system, knowledge needs to be produced through a defined process. The data are collected from different sources. The filtered, categorized, and structured data are transformed into information (Sain and Wilde 2014). Knowledge occurs when information is interpreted or put into context, that is, connected in relationships (Sain and Wilde 2014). Therefore, the system further analyzes the information to convert it to “pre-confirmed knowledge,” given that human expert review is required to review, process, and confirm the knowledge before storing it in the KB as “confirmed knowledge.” However, not all “pre-knowledge” is considered “knowledge”; some are only considered as reference information. Table 2 presents the customer knowledge proposed in the KB. The sources of the confirmed knowledge are mainly professional market reports, handbooks, or training manuals prepared by experts or professionals. These documents are considered as confirmed knowledge because when information is blended with context and expertise, we can consider it as knowledge (Campbell et al. 2020). On the other hand, reference information is the information based on the data collected from the Internet, such as social media and blogs or other internal systems. Each type of customer knowledge consists of confirmed knowledge and reference information. Table 2 shows the examples of data source and information for each type of knowledge. Hence, as shown in Figure 1, the KB for the proposed system should contain six components.

Customer knowledge	**Category in the proposed system**	**Example of data source**	**Example of information**
Knowledge about customer	Confirmed knowledge	Market analysis report	Age group and gender of customers
	Reference Information	Social media, chat history	Posts in forum discussing color of the products
Knowledge from customer	Confirmed knowledge	Focus group research analysis report	Comments on the products by focus group members
	Reference Information	Social media, blog	Experience of using the products shared by a blogger
Knowledge for customer	Confirmed knowledge	Handbook, training manual	Procedure for the maintenance of products
	Reference Information	Other internal systems	Product stock and prices

Table 2. Customer knowledge in the proposed system

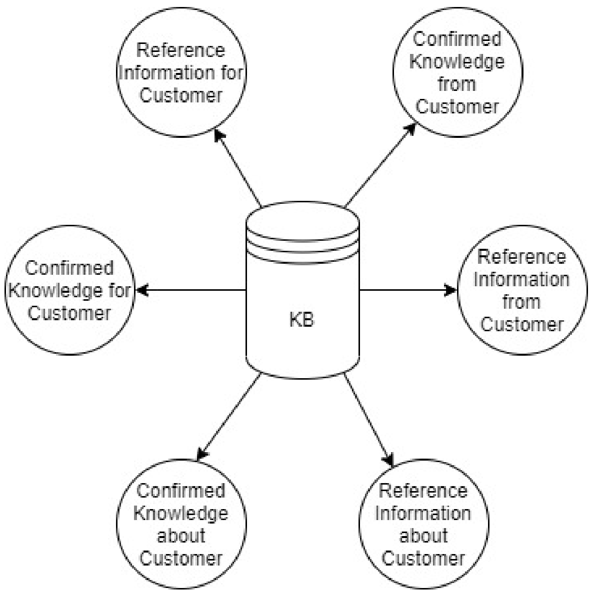

Figure 1. Design framework of knowledge supporting customer service conversation: the six KB components

Here are some examples to illustrate how the six components can be used in a KB supporting chatbot conversation. When a customer asks for recommendations after sharing their age group, the chatbot can suggest a product with the support of knowledge about popular products for different age groups based on the market analysis report and the discussion in the discussion forum. The chatbot can also share the experience of other customers according to the focus group research analysis report and the content written by bloggers in the Internet to support the recommendation. Another example is when the customer asks about how to clean or wash a product, the chatbot can provide the standard procedure based on confirmed knowledge, namely, the handbook. The chatbot can also provide the product stock and price for customers as reference when customers ask about this.

4. System Architecture

This study proposes the design of an intelligent knowledge-based conversational agent for customer service support. Figure 2 shows the overview of the system architecture, presenting the relationship among four main system modules: knowledge module, dialogue module, handover module, and adapter. Dialogue module works with knowledge module to generate artificial conversation to communicate with customers through the adapter, which interfaces with the user interface, such as different instant messengers and online store websites. Meanwhile, the handover module takes on the role of middleman by passing the queries that cannot be answered after querying the knowledge module to the human customer service and returning the answer of the customer service to customers through the adapter. The knowledge module cooperates with human experts to improve the KB proactively.

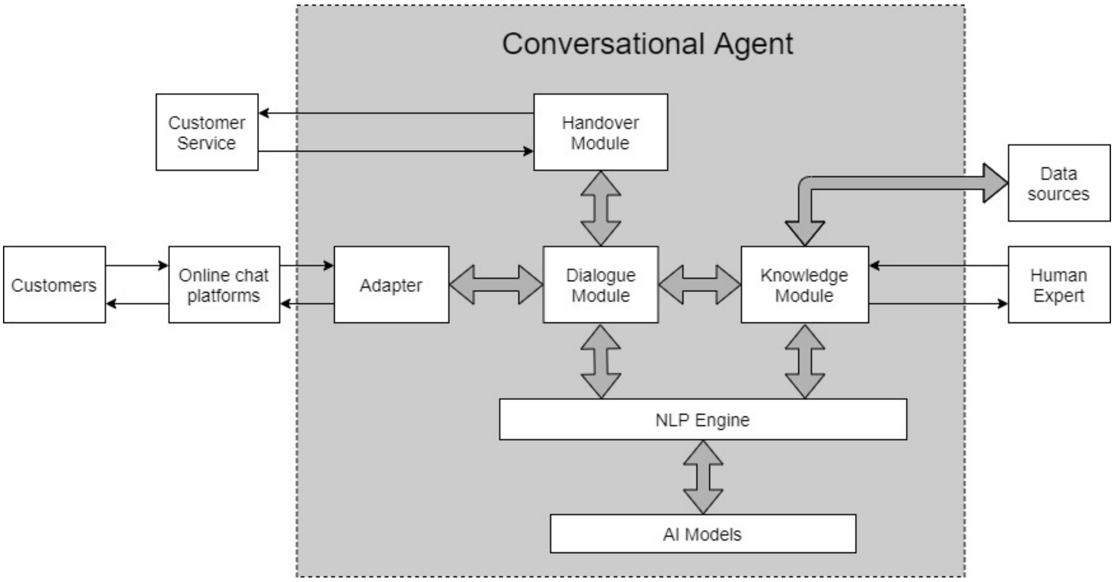

Figure 2. Overview of system architecture

4.1. Dialogue Module

Dialogue module is responsible for handling the conversation with the customer. To communicate with customers effectively, conversational agents should be able to understand human language and reply with this language. Language has three major dimensions, including content, form, and use (Lahey 1988). Language content is the meaning or semantics of language, and form is the shape of language (Lahey 1988). Language use or pragmatic is defined as the function of language and its relations to everyday context (Lahey 1988).

In the proposed system architecture, language content indicates the topics, keywords, and entities in the sentence while language use can be simply considered as the underlying intent of the sentence. Language form in a text message refers to the structure and syntax of the sentence, which is the arrangement of words according to the meaning relations among them (Lahey 1988). Supported by the natural language processing (NLP) engine, as shown in Figure 3, the query understanding unit can understand the three components of human language by recognizing named entities (language content), classifying intents (language use), and parsing (language form) of the pre-processed messages passed by the adapter.

Customer queries can be understood by combing the pragmatic (language use), semantic (language content), and syntactic (language form) analysis results. Afterward, based on the analysis result of the customer query, the knowledge retriever will query the knowledge module to obtain information and prepare for the reply to the customers. If the required information can be obtained from the KB, then the information will be passed to the reply generator. If the required information cannot be retrieved from the KB, then the knowledge retriever will notify the handover module to route the customer's query to the corresponding human customer service. After the human customer service answers the query, the answer will be passed to the reply generator. The reply generator will integrate the templates for replying to questions of various intents and the retrieved information to generate a reply and return the reply to the user through the adapter. At the end of the conversation between the customer and the agent, the customer can rate the satisfaction level of the response from the agent. The feedback of the customers will be returned to the dialogue module from the adapter.

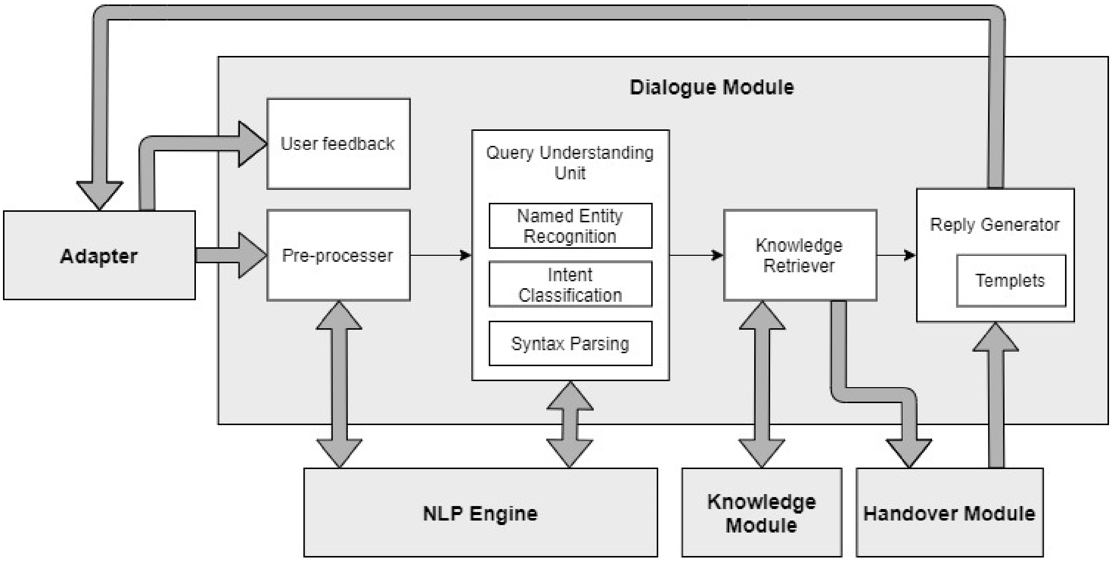

Figure 3. Dialogue module: queries from customers are understood and replies to customers are generated after querying the KB or human customer services

4.2. Knowledge Module

The knowledge module contains a KB and the components supporting proactive knowledge improvement. The KB stores the knowledge and information in the form of question and answer (Q&A) pairs. To ensure that the KB is updated, a web crawler will retrieve data continuously from the Internet. Controlled by the scheduler and admin interface server, the web crawler virtual personal computer (PC) farm crawls data from different webpages regularly. The web browsers opened in the virtual PC crawl data through the proxy server. The latest crawled data are stored in the database server and pre-processed, such as stemming and stop word removal, and converted into the form of Q&A pairs. The latest Q&A pairs are then classified and organized.

After the latest Q&A pairs are compared with the existing Q&A pairs in the KB, the new Q&A pairs or new answer for the existing questions can be identified. Both Q&A classification and comparison are enabled by the NLP engine. Details of the NLP tasks in the NLP engine will be described in detail in Section 4.5. The system will notify human experts to review the new information to decide whether it should be stored in the KB. The usage reviewer in the knowledge module will also regularly check the usage of the KB and report to human experts for improvement. Figure 4 describes the components of the knowledge module and how they work together to realize proactive knowledge improvement.

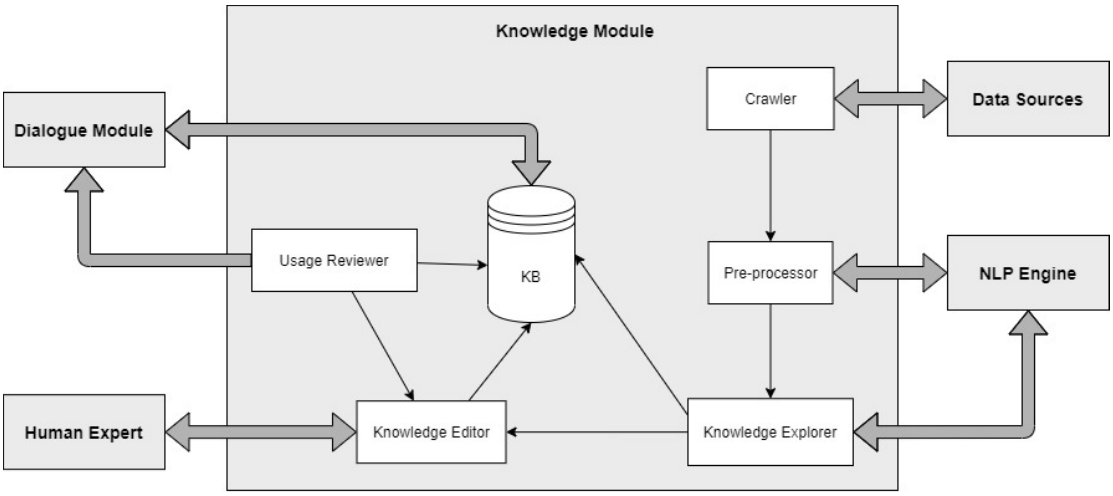

Figure 4. Knowledge module: the components of the knowledge module work together to realize proactive knowledge improvement

4.3. Handover Module

Human-in-the-loop pattern is strategically important to ensure that the performance of the algorithm meets the requirements of the organization and the changes in the environment (Grønsund and Aanestad 2020). Instead of merely replacing humans, machines allow firms to achieve the most significant performance improvements when they work together with humans to augment employees (Henkel et al. 2020; Wilson and Daugherty 2018). Therefore, human involvement is important and significant for user–machine communication if companies want to optimize the benefits of chatbots to the adopters. Therefore, in the proposed system architecture, the handover module is included to allow human involvement in the operation flow.

As shown in Figure 5, the handover module is responsible for switching between human customer service and conversational agent when it finds it cannot answer the query from customers. If the knowledge retriever in the dialogue module cannot retrieve the required information from the KB, it will trigger the handover module to route the queries to the corresponding customer service. The human customer service will read the chat history between the machine and customers and input the reply through the messenger. The reply by human customer service will be forwarded to the dialogue module by the messenger.

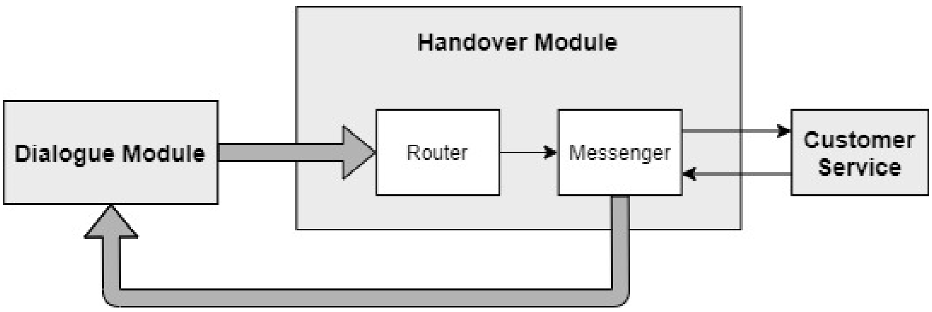

Figure 5. Handover module: route the queries to the corresponding customer services

4.4. Adapter

The adapter (Figure 6) enables the conversational agent to connect with different platforms that can support online chatting, for example, Skype, Instagram, and Facebook. It receives incoming messages from the customer, and after a reply is returned from the dialogue module, it delivers the reply to the online chat platform.

Figure 6. Adapter: connect the conversational agent with the online chatting platform

4.5. NLP Engine

As shown in Figure 2, the NLP engine supports the intelligence functions in the dialogue module and knowledge module. The NLP engine, which allows machines to understand and interpret human language, enables the NLP pre-process tasks, such as tokenization, sentence breaking, chunking, stemming, and NLP tasks and applications, including part-of-speech tagging, named entity recognition, sentiment analysis, relation extraction, and semantic textual similarity. Different AI-based methods are used for different NLP tasks and applications, and the below table summarizes the techniques used to implement the NLP engine in this study.

Module	Function	NLP Tasks	Description	Technique
Dialogue Module	Query understanding	Named entity recognition	Locate and classify entities into predefined categories such as organizations, locations, person names, date time, quantities, monetary values, percentages, etc.	AI-based method: BILOU (Beginning, Inside, Last, Outside, and Unit-length) Entity Tagging, the tagging schema used by the machine learning model when processing entities.
		Intent classification	Analyze texts and categorize them into intents, for example, purchase, request information, complaint, etc.	AI-based method: DIET (Dual Intent and Entity Transformer), a multi-task transformer architecture that handles both intent classification and entity recognition together.
		Syntax parsing	Identify the grammatical arrangement of words in a sentence and their relationship with one another.	AI-based method: spaCy syntactic dependency parser which powers the sentence boundary detection and allows it to iterate over base noun phrases or "chunks."
Knowledge Module	Knowledge classification	Text classification	Assign a piece of text or document to one or more categories.	AI-based method: FastText, which is an efficient tool for generating word representations and sentence classification (Bojanowski et al. 2017).
	Knowledge comparison	Semantic textual similarity	Determine how similar two pieces of texts are.	AI-based method: FAISS (Facebook AI Similarity Search), which is a library for efficient similarity search and clustering of dense vectors (Johnson et al. 2019).

Table 3. AI-based methods implemented in the NLP engine for different NLP tasks

5. Case Study: Applications and Evaluation

Company A is a leading global women's intimate apparel manufacturer that provides and distributes its products under several brands. The company intends to continuously improve its marketing strategies to increase sales and support e-commerce marketing. A prototype system of an intelligent knowledge-based conversational agent was developed and tested to evaluate the effectiveness of the design. The company handles hundreds of direction messages per month in a popular social media platform but lacks personnel dedicated to the task. Therefore, the company cannot reply promptly to customers and replies only when convenient. Occasionally, the company may miss customers' messages. The research team analyzed 5,634 conversations between customers and the customer service staff for the social media platform. After analyzing the messages, the research team observed that 67% were queries, and 33% were nonquery messages, including greetings, praise, and appreciation. Regarding the queries, the chart in Figure 7 shows the distribution of the messages by query type. Most of the queries were regarding online shops (16%), prices (15%), store locations (15%), collaboration invitations (15%), complaints (13%), and order placements (12%). Some customers requested for information on products (7%) and sizes (5%) and asked if they can speak languages other than English.

Moreover, 3,705 conversations (66%) involved a customer service staff, and nearly all the conversations contained fewer than five message exchanges. Therefore, 34% of the messages received no response from the customer service staff. Regarding the response time for the messages with a staff response, in 21% of the conversations, the first message was handled within one hour, whereas in 88% of the conversations, a reply was sent within a day. Moreover, the staff admitted to receiving complaints about slow response and no replies. The abovementioned problems lead to unsatisfactory customer service and unpleasant experiences. Despite the importance of handling customer queries properly, the company lacks a well-grounded process for such matters. Therefore, a solution to help the company handle customer queries effectively to resolve the abovementioned problems and improve customer satisfaction and experience is necessary.

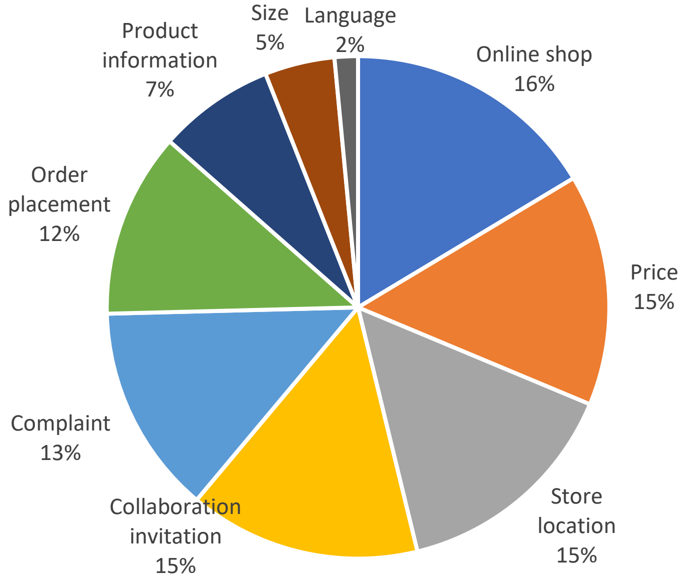

Figure 7. Distribution of messages according to query type

From the data analysis, the research team found that most of the customer queries were regarding prices and stocks, which required relatively dynamic information. Thus, a chatbot cannot be implemented using only static questions and answers. Moreover, complicated queries were also received, such as complaints, which should be handled appropriately by human agents. In addition, the management was concerned that the improper handling of complicated queries by a chatbot may have adverse effects and worsen customer experience. Hence, a need for customer service chatbots supported by an intelligent KB with a human involvement mechanism and its empirical evaluation to address the deficiency and support customer relationship management emerged. According to the needs of the company, the research team built a prototype system based on the proposed architectural design.

5.1. Prototype Implementation

First, the knowledge module and KB, which contained the knowledge and information required to support chatbot implementation, were built. As described in Table 2, the KB contained six components of customer knowledge extracted from external data sources by a web crawler, such as posts about the brands and products on social media platforms and information in knowledge-sharing websites, as well as from internal data sources, such as the chat history of conversations between customers and staff and price lists. Second, the dialogue module was developed, in which AI models addressing issues based on the chat history were trained for the questionnaire understanding module to customize the chatbot for the company. Finally, the handover module was constructed by integrating it with the messenger system currently used by the company.

The following examples show how the system prototype can support the company in automatically answering customer queries after retrieving customer information from the KB and involve human personnel in the loop. In the first example illustrated in Figure 8, when a customer asks about the prices of products with images, the chatbot will immediately greet the customer and ask his/her location. After obtaining information on the customer's location, the chatbot will check it against the KB to retrieve the product prices in the specified location (information for customers). Then, an answer is given to the customer. Figure 9 presents another example, which is a customer complaint about the website. If the chatbot is unable to handle this type of problem, then it will be handed over to a human staff. Based on the location reported by the customer, the regional staff will receive a notification in their instant messenger system from the chatbot. The human staff can then directly provide an answer to the customer. An example of a product recommendation for a customer is shown in Figure 10. The conversational agent asks the customer follow-up questions and suggests a product with reference information. The conversational agent uses knowledge about customers (age group of customers for each product) and information from customers (review comments) to answer queries.

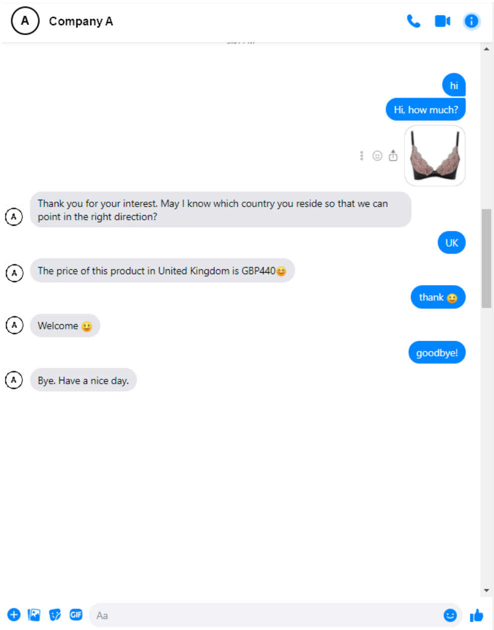

Figure 8. An example of returning price of products with a photo to customer

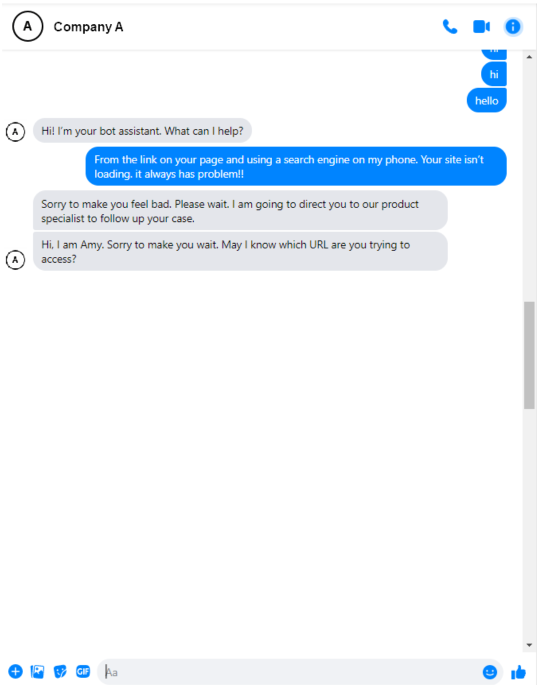

Figure 9. An example of handing over a customer complaint to human staff

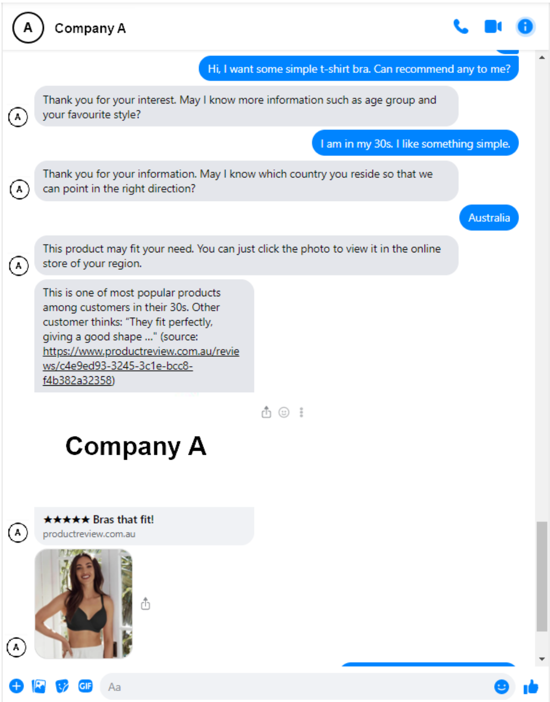

Figure 10. An example of recommending products to a customer

5.2. Evaluation

The prototype system was evaluated as follows:

1) Potential users' evaluation

The prototype system was evaluated by using the metric based on the principles and maxims that characterize meaningful conversations proposed by Grice (1975). The Cooperative Principle introduced by Grice (1957) states "Make your contribution such as it is required, at the stage at which it occurs, by the accepted purpose or direction of the talk exchange in which you are engaged". The Cooperative Principle consists of four sub-principles, which are usually referred to as the conversational maxims: quality, quantity, relation and manner (Grice 1975).

- Quality: do not say what you believe to be false or that for which you lack adequate evidence
- Quantity: make the contribution as informative as is required but not more informative than is required
- Relation: be relevant
- Manner: be perspicuous; avoid obscurity of expression or ambiguity; be brief and orderly.

The Grice' maxims have been demonstrated to evaluate chatbots using effectively in the literature (Chakrabarti and Luger 2015; Saygin and Cicekli 2002). We evaluate the proposed conversational agent from the four aspects through looking up the response from the domain knowledge and subjective evaluations. Users in the case study tested the prototype by chatting with the agent such as asking product information and price. Ten users (part-time MBA students at The Hong Kong Polytechnic University) participated in the trial of the prototype. These users are fashion industry practitioners with an average of 3 years of experience in using customer service chatbot. Users greeted the chatbot, praised the products, expressed appreciation and asked different real-life queries. In total, there are 500 complete conversations in the evaluation test, involving 1,500 messages, in which 194 times of handover occurred. After the trial, the users filled in a questionnaire, based on the Grice's maxims, about the performance of the agent. Questions are designed based on the Grice's maxim and users evaluate the agent on a numerical scale in the four aspects. Table 4 shows the results of analysis of the questionnaire.

Grice's maxim	Question	Average rate (SD) (1 - 5 scale*)
Quality	Do you agree that the responses provided by the agent were correct?	4.3 (0.46)
Quantity	Do you agree that the agent provided information which was not less or more than required?	3.9 (0.64)
Relation	Do you agree that the agent provided helpful and relevant response?	4.0 (0.53)
Manner	Do you agree that responses from the agent were clear?	4.3 (0.89)
	Do you agree that the agent were friendly?	4.3 (0.46)
	Do you agree that the agent used proper language?	4.0 (0.76)

*Scale: 1 = totally disagree; 3 = undecided; 5 = strongly agree.

Table 4. Evaluation results for the chatbot by questionnaires.

The users rated the system highly on the above four aspects with a mean of at least 3.9 on a five-point scales, with ratings of 5 being "strongly agree", 3 being "undecided", and 1 being "strongly disagree". Based on the results of the evaluation, the prototype system is seen to be a promising conversational agent to support customer service by using the conversational maxims (Grice, 1975).

2) System and Domain Experts' Evaluation

In terms of the system architecture described above, first, the research team evaluated the individual components separately then assessed the system with the integrated knowledge module, natural language processing engine, handover module, and adaptor as a whole. A domain expert, who is the marketing research manager of Company A, help to determine the accuracy of the embedded knowledge, constancy, and completeness of the responses. The domain expert conducted a usability evaluation study on the prototype system implemented in the corporation. The evaluation test included a total of 500 complete conversations comprising approximately 1,500 messages in which 194 handovers occurred. A computer systems analyst, who has expertise in chatbot development, evaluated the system technically by calculating the parameters based on the test data with the chatbot and comparing them with the chat history (reference value). The response time is the time interval between the first message from a customer and response from the customer service staff. The reference value was calculated based on the timestamps of the 3,705 conversations containing staff responses in the chat history. Accuracy represents the correctness and relevance of the answers, which was calculated based on the results of the test conducted by the users. The reference value was 100%, as the human staff's reply was assumed to be the standard reply.

6. Benefits and Challenges: Lessons from the Case Study

Although commercial conversational agents have been available for several years, challenging research problem remain. This section outlines some of the benefits and challenges involving in the development and implementation of an intelligent knowledge-based conversational agent.

6.1 Benefits

The benefits of implementing an intelligent knowledge-based supported conversational agent are examined from technological, processual, and managerial perspectives.

Technological perspective

(1) *Experience in AI* – The company is a traditional manufacturer without much experience in AI technology adoption. This project provided the company firsthand experience in AI implementation and raised awareness of the use of this emerging technology in the company. Moreover, the internal project team gained knowledge on the implementation process, data selection, and limitations of the technology. The management and internal project team can also apply the knowledge they gained from this project to future AI implementation projects.

(2) *Proactive and continuous system improvement* - As the system adopts the web crawler technology to retrieve updated and the most relevant information on the Internet, the KB can be improved continuously with new data. The updated information is processed and compared with the existing KB automatically without any human instruction. The system learns proactively from the new data to enrich the KB and support the conversational agent with the improved KB.

Process perspective

Improvement of customer query handling process and efficiency - Initially, the company lacked a defined process for handling customer queries on social media platforms and response guidelines or standards for customer queries. During the conversational agent implementation, the research team met with the company to understand their situation and needs. Meanwhile, standards for responses and a process for handling customer queries were clearly defined. The conversational agent follows the developed standards and process to handle queries and increase process efficiency.

Managerial perspective

(1) *Savings in human resources* - From the evaluation results, we observed that most of the queries on social media were handled by a machine without human involvement. Only 13% of the conversations required human intervention. Therefore, minimal human resources are required to read the messages and answer the customer queries. The human staff can be mainly responsible for answering complex queries that cannot be handled by the machine, such as complaints.

(2) *Improvement in customer service efficiency and satisfaction* - As the conversational agent can respond instantaneously (2~5 seconds) to customers on social media, customer service efficiency can be improved significantly. As their responsiveness increases, the company can build and maintain a positive relationship with customers, thereby reducing complaints and increasing customer satisfaction with the company's customer service.

(3) *Increase in productivity* – As the staff will not need to check social media frequently and answer customer queries repetitively, they will have time to perform certain creative and complex high-level tasks. Therefore, the human staff can concentrate on value-added tasks. As a result, productivity can increase in a highly engaging work environment.

(4) *Positive corporate image* – Recently, AI topped the list of emerging technologies set to impact businesses (Computing Technology Industry Association 2020). A general perception exists that AI technology is novel and experiences relatively fast growth but has numerous uncertainties. People consider companies adopting AI as innovative, open, and

creative. In addition, the company can improve its customer care as it adopts new technologies to optimize customer service efficiency and strengthen customer relationships.

(5) *Organizational knowledge management* – In the process of building the KB, the research team and company identified and collected various customer information that should be included in the KB and is useful for machine conversation. Through the system, the KB can organize and manage the company's organizational knowledge. Moreover, the use of organizational knowledge can benefit the company and create business value.

6. 2 Challenges

The challenges of implementing an intelligent knowledge-based supported conversational agent from technological, processual, and managerial perspectives are discussed below.

Technological perspective

(1) *Defining external data sources to collect high-quality data* – Various websites and social media platforms contain data and information on different types of underwear and brands. However, not all are high quality and reliable. When searching online, a search result with a huge number of websites is returned, but many of the websites contain irrelevant and incorrect data. For example, several knowledge-sharing sites contain misinformation or too many advertisements, which should be ignored. Therefore, the project team should identify reliable data sources that can provide useful, accurate, and relevant information.

(2) *Crawling data online* – With the web crawler technology, the system crawls data from different webpages regularly by opening web browsers in a virtual PC via a proxy server. However, the web crawler may be blocked if it accesses certain web servers frequently, leading to failure to collect the necessary data. Hence, the technical team should review and update the crawler regularly to ensure that it is working properly and not blocked.

Managerial perspective

(1) *Resistance to technological change* – Although the intelligent knowledge-based supported conversational agent can help in handling customer queries on social media platforms, some staff are resistant to the technological change. The staff are worried that the conversational agent will not function efficiently, thereby causing additional problems. Moreover, the staff are uncertain about the technology and perceive it to be unstable.

(2) *Inadequate strong expertise in AI technology* – The company lacks sufficient experience or expertise in KB and AI technology implementation. Specifically, the staff lack knowledge and expertise in machine learning, AI models and algorithms, training data, and KBs. This lack of skilled staff and knowledge in digital technologies is the main challenge in AI implementation in firms (Brock and Von Wangenheim 2019); thus, the challenges of the company are common.

7. Lessons Learned

Some of the lessons learned from this study are described below, which can serve as guidelines for future implementers of intelligent conversational agents.

(1) *Choose a partner with AI expertise* – As mentioned above, lack of skilled staff and knowledge is the main challenge in AI implementation. Thus, a company should seek an external partner for collaboration. The company should leverage its partner's experience, skills, and knowledge to realize successful conversational agent implementation.

(2) *Obtain top management support* – Intelligent conversational agents are relatively new to numerous companies. Thus, increased resources are required to handle the uncertainty in implementation. Top management support is a crucial success factor, as support from the top management can ensure the allocation of sufficient resources to the implementation. Moreover, when resistance to technological change arises, top management support can play a key role in resolving the issue. Apart from resource and funds allocation, the top management can show their support through their active involvement in the implementation.
(3) *Identify a clear use case and objective* – Apart from customer support automation on social media platforms, the proposed system can be applied to other use cases, such as internal staff training and personal sales assistants. However, after discussing the need to solve the problem, resource limitations, and possible benefits with the marketing department, it agreed to first limit the use case to one, with the objective of improving customer relationship and efficiency. The research team recommended the marketing department to define every detail in the use case to manage their expectations. Focusing on a clear use case with a simple, repeatable process, such as plucking a "low-hanging fruit," will allow the organization to realize returns quickly.
(4) *Involve users in the early stage* – Implementation of new technologies and changes in operation will understandably heighten users' hesitation and resistance. To relieve their concerns and increase their acceptance, they should be involved in the early stage of the project to enhance their understanding and awareness of the technology and system. In addition, they should be encouraged to express their opinions, requirements, and suggestions during the early stage to help make the system design realistic and practical.
(5) *Collaborate with different departments* – The conversational agent implementation requires close collaboration between the marketing department and IT department, especially in the data collection and system deployment stages. The implementation may involve accessing certain systems or social media accounts, which requires the involvement of the IT department. Hence, the research team should work closely with not only the marketing department but also the IT department for a successful implementation.
(6) *Retrieve sufficient high-quality training data* – One of the most important characteristics of AI-based systems is that they are data driven. Data are required for training the relevant models; thus, ensuring that the project team can retrieve the necessary training data if the system involves AI technology is essential. The training data should be high quality and without bias to avoid reproducing the bias in the algorithms in the system. Without sufficient training data, implementation will not be successful.
(7) *Involve humans in the loop* – When designing an automated system with AI technology, a company should consider involving its human staff in the loop. The system can leverage human and machine intelligence to generate optimum results and benefit the company and customers (Henkel et al. 2020; Wilson and Daugherty 2018). The division of labor between humans and machines can be realized in a way that the machines handle the repetitive and routine tasks, while the humans are responsible for the complex tasks that require creativity and high-level cognition.
(8) Minimize disruption in users' daily operation – To increase users' acceptance of the new system and operation, the system should lead to as little disruption as possible. In this case, the users are happy that they do not need to check social media frequently and answer questions repeatedly. However, the users are resisting learning the new tool to help the chatbot handle complicated questions. Therefore, the project team should integrate the system with the instant messenger application used by the staff to enable them to cooperate with the conversational agent without difficulties.

8. Concluding Remarks

To address the research gap identified in the literature, we proposed a KB design covering the customer knowledge required to manage customer relationship value cocreation and a system design that the KB will proactively improve. We evaluated the effectiveness of the designs through a case study of a leading international women's intimate apparel manufacturer.

Based on the user and expert evaluations, the results of the system prototype evaluation are satisfactory and support the contention that the system is effective. In our evaluation, we found that response time to customers was significantly shorter when the chatbot was used compared with before the chatbot was used. Moreover, human effort can be reduced significantly, while the accuracy of the chatbot was maintained at 100% in the test comparing the chatbot with the human staff. Therefore, the results of the evaluation showed that the designs can effectively improve efficiency in handling customer queries and thus customer relationship management.

8.1 Contributions of the study

This study considers the theoretical and practical implications of the contributions. The contributions of this research are two-fold in terms of design artifact. First, we have presented the intelligent knowledge-based conversational agent (a system architecture and its implemented prototype system). Second, we have provided a design framework of the KB for supporting chatbot conversation based on the customer knowledge management process, and the examination of how different types of customer knowledge can be applied to chatbot conversation.

Moreover, this study presents the system architecture in general terms and by focusing on the particular features of the rigorous system structure. Therefore, this study particularly contributes to an increasingly vital body of literature that examines knowledge base design for chatbot which is based on customer knowledge management process. We also demonstrate cooperation between humans and machines in handling customer queries and in the knowledge building and management processes. Human–machine cooperation can enhance understanding of the use of customer knowledge and chatbot conversation. These contributions can increase understanding and offer theoretical guidance for future research on how to design and develop an intelligent conversational agent in the e-commerce environment to support sales and marketing on chatbot design.

Regarding the practical implications for industrial practitioners and managers, this study can help better understanding of design an intelligent conversational agent based on different types of customer knowledge. We evaluate our proposed design in a case study to provide practitioners with empirical evidence on the effectiveness of the design. The results of our study are particularly useful to and timely for operations managers in terms of chatbot implementation, which is widely accepted in customer service. Through this study, managers can understand how chatbots can help enhance customer service efficiency and save human resources. Moreover, through this case study, we present a clear picture and examples to managers of how chatbots can benefit customer service in an operational environment. Furthermore, we demonstrate how AI or machines can cooperate with, rather than replace, humans in various operations to create value. With its strong data processing capacity, AI can augment human intelligence and replace human staff in well-defined and repetitive tasks. However, handling complicated questions effectively, solving problems creatively, or responding to complex customer emotions accurately are unlikely for AI and robots (Wirtz 2019). For such tasks, highly skilled employees are needed, as humans have an advantage in using intuition to deal with contradictory or uncertain information related to business and relationship-building aspects (Paschen et al. 2020). Managers can learn about how machines can handle well-defined and repetitive queries and how human agents can concentrate on dealing with complaints or other uncertain information. From the evaluation results of the system prototype, we can draw optimistic conclusions and determine that this intelligent system can be used to improve the services of conventional e-commerce applications in terms of product and service sales support.

8.2 Future research

This research can be extended to several areas for future work. First, additional case studies or tests can be conducted in different industries or companies for a holistic examination of the effectiveness of the design in terms of incorporating rich knowledge representation, machine learning, and retrieval techniques. Second, text-to-voice technology can be incorporated in the system to investigate response generation system designs for voice-based conversational agents, particularly in Chinese, owing to limited research in this context. Finally, a legacy system may be integrated in the conversational agent, such as an inventory system, to obtain knowledge on warehouse stocks and stock locations. This integration can provide the system with a competitive edge and capability to plan effectively, execute omnichannel strategies with customers predictably, and minimize labor costs and errors associated with manual reconciliation.

Acknowledgements

The authors are grateful for the constructive comments of the referees on an earlier version of this paper. The first author was supported in part by The Hong Kong Polytechnic University under a grant number ZVK9.

References

Acharya, A., Sneha, Y., Khettry, A. R., and Patil, D. 2020. "Athena an Avid Traveller Using Lstm Based Rnn Architecture," *Journal of Engineering Science and Technology* (15:2), pp. 1413-1428.

Adam, M., Wessel, M., and Benlian, A. 2020. "Ai-Based Chatbots in Customer Service and Their Effects on User Compliance," *Electronic Markets*, pp. 1-19.

Androutsopoulou, A., Karacapilidis, N., Loukis, E., and Charalabidis, Y. 2019. "Transforming the Communication between Citizens and Government through Ai-Guided Chatbots," *Government Information Quarterly* (36:2), pp. 358-367.

Bank of America. 2019. "Bank of America's Erica® Surpasses 10 Million Users, Introduces New Capabilities." Retrieved 5th November, 2020, 2020, from https://newsroom.bankofamerica.com/press-releases/consumer-banking/bank-americas-ericar-surpasses-10-million-users-introduces-new

Bhawiyuga, A., Fauzi, M. A., Pramukantoro, E. S., and Yahya, W. 2017. "Design of E-Commerce Chat Robot for Automatically Answering Customer Question," *2017 International Conference on Sustainable Information Engineering and Technology (SIET)*: IEEE, pp. 159-162.

Bojanowski, P., Grave, E., Joulin, A., and Mikolov, T. 2017. "Enriching Word Vectors with Subword Information," *Transactions of the Association for Computational Linguistics* (5), pp. 135-146.

Brock, J. K.-U., and Von Wangenheim, F. 2019. "Demystifying Ai: What Digital Transformation Leaders Can Teach You About Realistic Artificial Intelligence," *California Management Review* (61:4), pp. 110-134.

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. J., and Mavrommatis, A. 2020. "From Data to Action: How Marketers Can Leverage Ai," *Business Horizons* (63:2), pp. 227-243.

Carter, D. 2018. "How Real Is the Impact of Artificial Intelligence? The Business Information Survey 2018," *Business Information Review* (35:3), pp. 99-115.

Catapang, J. K., Solano, G. A., and Oco, N. 2020. "A Bilingual Chatbot Using Support Vector Classifier on an Automatic Corpus Engine Dataset," *2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*: IEEE, pp. 187-192.

Cha, S.-C., Li, Z.-X., Fan, C.-Y., Tsai, M., Li, J.-Y., and Huang, T.-C. 2019. "On Design and Implementation a Federated Chat Service Framework in Social Network Applications," *2019 IEEE International Conference on Agents (ICA)*: IEEE, pp. 33-36.

Chakrabarti, C., and Luger, G. F. 2012. "A Semantic Architecture for Artificial Conversations," *The 6th International Conference on Soft Computing and Intelligent Systems, and The 13th International Symposium on Advanced Intelligence Systems*: IEEE, pp. 21-26.

Chakrabarti, C., and Luger, G. F. 2014. "An Anatomy for Artificial Conversation Generation in the Customer Service Domain," *MAICS*, pp. 80-85.

Chakrabarti, C., and Luger, G. F. 2015. "Artificial Conversations for Customer Service Chatter Bots: Architecture, Algorithms, and Evaluation Metrics," *Expert Systems with Applications* (42:20), pp. 6878-6897.

Computing Technology Industry Association. 2020. "2020 Emerging Technology Top 10 List." Retrieved 12 Mar 2021, 2021, from https://connect.comptia.org/content/infographic/2020-emerging-technology-top-10-list

Cui, L., Huang, S., Wei, F., Tan, C., Duan, C., and Zhou, M. 2017. "Superagent: A Customer Service Chatbot for E-Commerce Websites," *Proceedings of ACL 2017, System Demonstrations*, pp. 97-102.

Doherty, D., and Curran, K. 2019. "Chatbots for Online Banking Services," *Web Intelligence*: IOS Press, pp. 327-342.

Gibbert, M., Leibold, M., and Probst, G. 2002. "Five Styles of Customer Knowledge Management, and How Smart Companies Use Them to Create Value," *European Management Journal* (20:5), pp. 459-469.

Grønsund, T., and Aanestad, M. 2020. "Augmenting the Algorithm: Emerging Human-in-the-

Loop Work Configurations," *The Journal of Strategic Information Systems* (29:2), p. 101614.

Grice, H. P. 1975. "Logic and Conversation," in *Speech Acts*. Brill, pp. 41-58.

Griol, D., and Molina, J. M. 2016. "A Proposal to Manage Multi-Task Dialogs in Conversational Interfaces," *Advances in Distributed Computing and Artificial Intelligence Journal* (5:2), pp. 53-65.

Gunawan, D., Putri, F. P., and Meidia, H. 2020. "Bershca: Bringing Chatbot into Hotel Industry in Indonesia," *Telkomnika* (18:2), pp. 839-845.

Henkel, A. P., Bromuri, S., Iren, D., and Urovi, V. 2020. "Half Human, Half Machine–Augmenting Service Employees with Ai for Interpersonal Emotion Regulation," *Journal of Service Management*).

Herrera, A., Yaguachi, L., and Piedra, N. 2019. "Building Conversational Interface for Customer Support Applied to Open Campus an Open Online Course Provider," *2019 IEEE 19th International Conference on Advanced Learning Technologies (ICALT)*: IEEE, pp. 11-13.

Hill, J., Ford, W. R., and Farreras, I. G. 2015. "Real Conversations with Artificial Intelligence: A Comparison between Human–Human Online Conversations and Human–Chatbot Conversations," *Computers in Human Behavior* (49), pp. 245-250.

Johnson, J., Douze, M., and Jégou, H. 2021. "Billion-Scale Similarity Search with Gpus," *IEEE Transactions on Big Data*, (7:3), 535 - 547.

Kerlyl, A., Hall, P., and Bull, S. 2006. "Bringing Chatbots into Education: Towards Natural Language Negotiation of Open Learner Models," *International Conference on Innovative Techniques and Applications of Artificial Intelligence*: Springer, pp. 179-192.

Kurachi, Y., Narukawa, S., and Hara, H. 2018. "Ai Chatbot to Realize Sophistication of Customer Contact Points," *Fujitsu Scientific and Technical Journal* (54), pp. 2-8.

Kwizera, F., Markus, I., Mugambi, P., and Diriye, A. 2017. "Use of Twitter Data toward the Development of an English and Swahili Question Answering Agent for the Kenyan Customer Service Market," *Proceedings of the Ninth International Conference on Information and Communication Technologies and Development*, pp. 1-5.

Lahey, M. 1988. *Language Disorders and Language Development*. Macmillan.

Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., and Lau, A. Y. 2018. "Conversational Agents in Healthcare: A Systematic Review," *Journal of the American Medical Informatics Association* (25:9), pp. 1248-1258.

Luo, X., Tong, S. Fang, Z, Qu, Z. 2019. "Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases". *Marketing Science*, 1192.

Nuruzzaman, M., and Hussain, O. K. 2020. "Intellibot: A Dialogue-Based Chatbot for the Insurance Industry," *Knowledge-Based Systems* (196), p. 105810.

Oh, K.-J., Lee, D., Ko, B., and Choi, H.-J. 2017. "A Chatbot for Psychiatric Counseling in Mental Healthcare Service Based on Emotional Dialogue Analysis and Sentence Generation," *2017 18th IEEE International Conference on Mobile Data Management (MDM)*: IEEE, pp. 371-375.

Paikens, P., Znotiņš, A., and Bārzdiņš, G. 2020. "Human-in-the-Loop Conversation Agent for Customer Service," *International Conference on Applications of Natural Language to Information Systems*: Springer, pp. 277-284.

Paschen, J., Wilson, M., and Ferreira, J. J. 2020. "Collaborative Intelligence: How Human and Artificial Intelligence Create Value Along the B2b Sales Funnel," *Business Horizons* (63:3), pp. 403-414.

Pradana, A., Sing, G. O., and Kumar, Y. 2017. "Sambot-Intelligent Conversational Bot for Interactive Marketing with Consumer-Centric Approach," *International Journal of Computer Information Systems and Industrial Management Applications* (6:2014), pp. 265-275.

Putri, F. P., Meidia, H., and Gunawan, D. 2019. "Designing Intelligent Personalized Chatbot for Hotel Services," *Proceedings of the 2019 2nd International Conference on Algorithms, Computing and Artificial Intelligence*, pp. 468-472.

Sain, S., and Wilde, S. 2014. *Customer Knowledge Management. Leveraging Soft Skills to Improve Customer Focus*. Springer, Cham.

Saygin, A. P., and Cicekli, I. 2002. "Pragmatics in Human-Computer Conversations," *Journal of Pragmatics* (34:3), pp. 227-258.

Schanke, S., Burtch, G. and Ray, G. 2021, "Estimating the Impact of "Humanizing" Customer Service Chatbots", *Information Systems Research*, Forthcoming.

Subramaniam, S., Aggarwal, P., Dasgupta, G. B., and Paradkar, A. 2018. "Cobots-a Cognitive Multi-Bot Conversational Framework for Technical Support," *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pp. 597-604.

Van den Broeck, E., Zarouali, B., and Poels, K. 2019. "Chatbot Advertising Effectiveness: When Does the Message Get Through?," *Computers in Human Behavior* (98), pp. 150-157.

Wang, Z., Wang, Z., Long, Y., Wang, J., Xu, Z., and Wang, B. 2019. "Enhancing Generative Conversational Service Agents with Dialog History and External Knowledge," *Computer Speech & Language* (54), pp. 71-85.

Wilde, S. 2011. *Customer Knowledge Management: Improving Customer Relationship through Knowledge Application.* Springer Science & Business Media.

Wilson, H. J., and Daugherty, P. R. 2018. "Collaborative Intelligence: Humans and Ai Are Joining Forces," *Harvard Business Review* (96:4), pp. 114-123.

Wirtz, J. 2019. "Organizational Ambidexterity: Cost-Effective Service Excellence, Service Robots, and Artificial Intelligence," *Organizational Dynamics* (100719).

Zarouali, B., Van den Broeck, E., Walrave, M., and Poels, K. 2018. "Predicting Consumer Responses to a Chatbot on Facebook," *Cyberpsychology, Behavior, and Social Networking* (21:8), pp. 491-497.

Zhao, G., Zhao, J., Li, Y., Alt, C., Schwarzenberg, R., Hennig, L., Schaffer, S., Schmeier, S., Hu, C., and Xu, F. 2019. "Moli: Smart Conversation Agent for Mobile Customer Service," *Information* (10:2), p. 63.