Corporate Reputation Review

Integrated Learning with AI Enabled Customer Interactions by Fashion Retailers

--Manuscript Draft--

Manuscript Number:	CRRR-D-23-00041R1
Full Title:	Integrated Learning with AI Enabled Customer Interactions by Fashion Retailers
Article Type:	Original Article
Funding Information:	
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Response to Reviewers:	The response to the reviewer's feedback has been uploaded as supplementary material.

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ABSTRACT

This research highlights qualities and capabilities of new age interactive technologies like chatbots to satisfy the needs of customers as per their expectations. To address the gap in literature about utilisation of chatbots to improve customer engagement that hinges on several critical aspects such as responsiveness, accuracy, and personalisation related issues faced by fashion brands, this study conceptualises how AI can be used to simultaneously use chatbots with human intelligence to satisfy customers. It also reflects on responsiveness as a feature that addresses enquiries of customers promptly and engages them without any gender or privacy bias and with transparency. Findings of this research propose that advanced natural language processing algorithms can understand and process complex user queries and contexts, but should be applied with ethical considerations. Additionally, the integration of emotional AI with HI in features of chatbots can help in recognising and responding to users.

Keywords: AI-enabled Chatbots, New Age Communication Technologies, Customer Engagement, Customer Satisfaction, Interactive Technologies

INTRODUCTION

Fashion brands have been proactively engaging with customers for marketing their products via various ecommerce platforms, in addition to their own websites and offline stores. For this purpose, their technology and marketing managers have tried to apply their understanding to make online shopping easier and convenient for online shoppers. However, brand managers feel that online shopping by customers is resulting in a lack of personalisation that fashion

retailers offer and customers enjoy in an offline store. Importance of customer service and customer experience has been highlighted by many scholars in marketing literature (El Bakkouri, et al., 2022). These studies have been conducted in a context wherein conversations or engagement with customers were in person and not virtual or online or with machines. In the current technologically advanced business environment, wherein every company is making its best efforts to use technology to optimise not only their business efficiency but also marketing capabilities using technology, it becomes important to understand how AI-enabled communication technologies help fashion retailer recognise and meet the contemporary needs of their customers. While technological innovations are helping retailer in the fashion business to address customers with different requirements, a customer with higher need for empathetic or personalised understanding will find chatbot conversations less satisfying. The changing needs of customers underscore the need for AI-enable communication tools and their integral role in satisfying their needs at a rapid pace with the convenience demanded by modern lifestyles (De Cicco et al., 2020).

The growth and development of companies such as Google, Apple and Facebook during the last decade, has been due to an increase in the number of customers seeking information and companies trying to optimise the resources available to them to satisfy customers (Misischia et al, 2022). Adoption of new age communication technologies that use machine learning has helped fashion retailer also to offer information to customers that creates meaning and also improves their functional capabilities such as handling orders, payments and bookings, thus significantly improving their business efficiency (Brush and Scardina, 2021). New age technologies enable retailer selling fashion products to interact with customers at all times without using human resources and serve them efficiently even outside office hours regardless of their geographical limitations. These technologies are intelligent software or computer programmes written to aid engagement by promptly answering the queries and questions raised

by customers using a stored database of queries (Pillai & Sivathanu, 2020; Radzicki, 2020). Such coordinated use of information can range from simple programs that respond to customers in a single instance, to advanced virtual assistants that have the capability to offer personalisation of messages (Basu Mallick, 2022). While AI-enabled new age communication technologies are equipped to support engagement, they also have the capability to analyse conversational data being gathered during interactions with customers and provide meaningful insights that can help managers predict future behavioural trends of customers, enhancing business development activities (Sands et al., 2020; Cheung, 2021). Today, such technologies have given a new dimension to customer service because customers treat them as an alternative to human agents that can offer customer insights (Chung and Park, 2019). The evolution of AI-enabled communication technologies like chatbots continue to grow by combining machine learning and deep learning techniques. But how retailer can integrate their customer service with AI-enabled communication technology which mirrors its operational efficiency is still unknown.

The on-going debate in the literature about the need for retailer to use an *"intent-based approach"* for gathering and using information to create knowledge that relies on the capacity to learn independently and gather useful knowledge (Rosruen and Samanchuen, 2018 & Wyawahare et al., 2024). The innovative use of AI-enabled applications configured with network applications for gathering and creating knowledge, continues to grow. AI-enabled tools such as chatbots provide insights by accommodating views and experiences of all stakeholders' communities (Leivadeas and Falkner, 2022). A large number of fashion retailer that use AI-enabled communication tools like chatbots, use natural language processing, machine learning, image processing, video processing, or audio analysis for developing analytical capabilities (Satheesh et al., 2020 & Bouguelia, 2023). These technologies use intelligent communication systems that recognise the input information and deliver the output

based on the query made by the customer (Jetten, 2021). As an AI-enabled robotic agent, a chatbot tends to improve the customer service being offered by fulfilling their needs in real-time. Many scholars have investigated how customers like to engage with AI-enabled communication technologies, while some have proven that these technologies may be equally capable of communicating in an objective and trustworthy manner (Edwards & Barker, 2014; Pillai & Sivathanu, 2020; Bouguelia, 2023 & Wyawahare et al., 2024). According to research by Hill et al., (2015), AI-enabled chatbots can reduce time taken by companies to respond and provide an uninterrupted service.

Chung and Park (2019) conducted research to study if machine learning based tools have the capability to perform as a marketing communication tool and found that chatbots can be used to successfully deliver information to customers (Wyawahare et al., 2024). Cheng and Jiang (2020) studied the impact of AI-enabled tools on perceived amusement, attraction, and social presence. Authors such as Jetten (2021) explained that AI-enabled chatbots play the role of communicator that facilitates functions such as marketing and sales by aiding business development process for generating leads, collecting visitor information, and customer engagement through the lead pipeline. According to Huang and Rust (2018), there are four different types of tasks that AI-enabled communication technology can perform: mechanical tasks, like delivering a scripted response enabled on the customer's keywords; analytical tasks, like determining the type of problem the customer is experiencing by coordinated use of information; intuitive tasks, like creating meaning from information in the customer's complaint; and empathetic tasks, like making an effort to calm down an agitated customer. AI-enabled interactive communications through chatbots have been able to successfully build the communicative capability of retailer in many of the industry sectors, for example fashion, healthcare and tourism. Healthcare sector uses AI-enabled chatbots to gather information about conditions of the patient, and offer suggestions concerning the condition of the patient. Through

the chat function, it tries to deliver immediate relief to patients and if required act on transfer of information to relevant entities in case of an emergency, keeping the patient engaged (Chung and Park, 2019 & El Bakkouri et al, 2022).

Another school of thought advocates that service sector organisations are undergoing rapid technological changes despite being resistant to automation, because of the ability of AI to grasp and analyse the information from content generated by interactive tools such as chatbots using machine learning (Al-Jaroodi et al, 2020; Aklamanu et al., 2019). Academic literature offers evidence that chatbots work as digital service agents who play a vital role in resolving customer issues and shaping customer decisions (Godes et al., 2005; Hu et al., 2023). Chatbots, as service agents, facilitate a richer understanding based on interactions with an intuitive and compassionate approach combined with an analytical approach (Canhoto and Clear, 2020). It can therefore be assumed that the rich understanding of categories of AI-enabled communication technologies can enable businesses to better select, manage and innovate their capabilities of generating insights from coordinated use of information and improve their business efficiency. As pointed out by Serban et al. (2020), AI-enabled chatbots can be used by e-commerce platforms as service agents for a variety of reasons, including providing a pleasant experience to the customer or meeting customer expectations and co-creating value that strengthens the relationship between the customer and the company (Serban et al., 2018 & El Bakkouri et al., 2022).

Majority of AI-enabled communication technology available are developed utilising the algorithms using machine learning that allow response generation and management, whereas earlier versions of chatbots merely created an illusion of intelligence. Initially, built on menus and Buttons-based features, it has since moved on to using keywords, and context. According to Hussain et al. (2019), the previous AI-enabled communication technology employed much simpler versions of pattern matching and used string processing design

techniques to create the required interaction with customers. New technologies have enabled the use of more complex knowledge-based models that are based on machine learning, i.e. generalist task-oriented and specialist task-oriented that can be used for a variety of purposes, that are recognised as social and task-oriented communicative chatbots (Satheesh et al., 2020). These AI-enabled communicative chatbot technologies can be classified into two types based on their architecture, i.e. rule-based and data-based systems (Satheesh et al., 2020 & Hussain et al., 2019).

The foundation of AI-enabled chatbots as interactive communication tools needs a large amount of data to operate and can be divided into three main categories; 1) Rules or menus based Chatbots, 2) Context based Chatbots and 3) Conversational chatbots. Rule based category of AI-enabled chatbots lacks capability to self-improve using which the machine can represent and communicate as humans (Hussain et al., 2019). As a result, the quality of communication by this category of chatbots is not clear, therefore, capability of engaging customers is considered to be low. This category follows basic certain rules and becomes inefficient when input patterns don't match with any pre-identified rule, therefore, it is unable to offer answers which create meaning for the customer (Schanke et al., 2021). Context based AI-enabled chatbots also do not have any predetermined conditions or skills to communicate like a human being. To handle sequential data being generated, they use advanced machine learning models such as Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) types of recurrent neural networks, considering size of the dataset and computational resources available to handle the size. Content based chatbots use machine learning frameworks such as BERT, an open-source model that enables retailer to establish an ambiguous query by inferring from its surrounding content or DistilBERT with limited data handling, but higher performance capacity as compared to BERT (Brown, 2023). Furthermore, models such as RoBERTa offer even more sophisticated interpretation of human language (El Bakkouri et al., 2022). These

machine learning models have capability to self-improve their outputs, therefore, the quality of their communication is considered to be good (Xu et al., 2021). The conversational AI-enabled Chatbots that do not work with any predetermined conditions or capability to self-improve are unable to communicate and interact with customers like a human agent. However, they are able to manage a balance between implementation cost and also offer advantages like improving customer engagement, therefore, are preferred by some businesses (De Cicco et al., 2020).

Although previous literature on use of AI-enabled communication technologies refers to its abilities to serve as a human agent and its ability to demonstrate responsiveness in a user-friendly manner, there is a lack of understanding about use of chatbots as AI-based communication tools to satisfy customers. Although the ability of chatbots to promptly respond and engage customers without any gender or privacy bias with transparency, their ability to understand and process complex user queries and contexts is limited. Furthermore, it is challenging for retailer in the fashion industry to apply ethical considerations while recognising queries and responding to users' emotions when there is a need to consciously reflect under the lens of human sensitivity. The remainder of the paper addresses this gap in the literature by reviewing, conceptualising and discussing different functionalities of chatbots under the lens of different machine learning models with theoretical underpinning into the theory of coordinated management of meaning that offers guidance on how to coordinate, manage and create meaning from interactions performed in a rule based, flexible, open and evolving setting, where meaning is being inferred by constant coordination.

LITERATURE REVIEW

The communication technologies based on machine learning have advanced from simple conversational agents to new age actively responsive communication tools capable of interacting with customers as human agents of the company. Capability of AI-enabled

technologies to coordinate information from different sources and create meaning by simulating the communication with a focus on improving its effectiveness is much higher as compared to human analysts (De Cicco et al., 2020). Businesses have benefited from such technological advancements to manage meaning hidden in the information given by customers to the machine or vice versa and create explanations of the meaning of their practices for customers and for improving the effectiveness of their services. These technologies, when reviewed under the lens of coordinated management of meaning, explain the differences between functionalities offered by different machine learning models. Literature categorises functionalities of different AI-enabled machine learning communication tools that can be applied to engage customers into three types.

Rule-based Functionality

AI-enabled machine learning communication tools work on rule-based functionality with predetermined conditions using pre-identified information stored along the principles of decision tree methodology. These are recognised as AI-enabled Chatbots, one of the most preferred tools, with its foundation in top-down functionality (Gupta et al., 2020). The top-down functionality requires customers to enter the data in a format aligned with the predetermined rules to assist them in finding answers towards queries raised by them. This feature does not support customers asking context specific questions, as technology with top-down functionality does not have the capability to comprehend meaning from a context. According to Zhao et al. (2023), the use of AI-enabled communication tools with rule-based functionality has helped health organisations advance the perceived ease of use and enhance correction effectiveness while debunking false health claims. Smutny & Schreiberova (2020) found that AI-enabled chatbots with this feature are also useful for serving educational purposes. This functionality has also been used by public facing applications like Facebook to

run their Messenger platform for responding with personalised messages and recommending meaningful content. As a result, the conversation application of this category is not able to satisfy customers with its conversation application (Rosruen and Samanchuen, 2018). Keyword recognition-based AI-enabled chatbot is an improved version of the rule-based functionality, as they use recognised specific keywords to respond to the customers (Gupta et al., 2020). Hence, rule-based chatbots are able to help businesses accomplish the basic communication needs between retailer and customers. The rules pre-set by fashion retailer for example about size and colour of their product, enable machine learning models to answer 80% of queries from the customer, which is an effective solution to business communication. Nguyen et al. (2022) explained that the adoption of a chatbot is linked to the aim of businesses to enhance customer engagement with personalised customer interactions in comparison to the features offered by traditional menu-based web applications.

Literature also extends this knowledge to Button-based Chatbots that work on basic predefined rules provided as top-down menus from scripted choices that represent the needs of users (Martell et al., 2024). They enhance meaningful interactions with customers by continuing to prompt the user with a further set of options till the most suitable one is found (Nguyen et al., 2022). The button-based application works on answering users' repetitive, straight-forward questions. In case the enquiry of customers is not listed in the option, the application will then fail to respond and may create a feeling of dissatisfaction amongst the users (Saram, 2024). The effectiveness of the button-based category of AI-enabled chatbots is linked to the capability of the application to personalise a conversation with the customer (Longoni et al., 2020). This category is being commonly used by the banking sector to engage customers and offer customer services outside of the office hours. Few studies have raised a significant concern about the effectiveness of button-based category's communication and customer engagement capabilities, extending the concern to the issues related to privacy of the

customers (Ng et al., 2020). Research conducted by Crowder (2024), highlighted the gap in the literature about ethical considerations in its use, by alluding to the role played by cultural differences in different regions of the world.

Context-based Functionality

The contextual chatbots are advanced versions that use machine-learning models to enhance human-computer interaction (Gupta et al., 2020). The context-based functionality is capable of interpreting sentiments of customers using machine learning algorithms with features like voice recognition and speech-to-text conversion (Rosruen and Samanchuen, 2018). The contextual functionality is driven by the need of retailer to discover intentions of customers and offer an intelligent & meaningful response after interpreting the question for finding answers from patterns in the data available (Gupta et al., 2020). Rather than depending on keywords, this AI-enabled communication technology provides answers by self-improving the analysis of what customers ask and how they ask and matching the findings with the patterns in the data. For example, in a takeaway services business, a food delivery application provides a straightforward illustration of such a feature by looking at the transaction history, customer's payment options and delivery address, which are saved in the form of a database. These contextual tools examine customer perspective to provide suggestions based on previous orders and their preferences (Nguyen et al., 2022). Scholars such as Ramezani (2024) studied AI-enabled communication technologies-based tools to illustrate how communications tools with contextual functionality encompass everything from customer support service to personal assistance capability by utilising cutting-edge machine learning methods and advanced natural language processing. Businesses today are able to improve their business efficiency by processing and responding to intricate inquiries received using machine learning based

communication technology to achieve communicative conversation goals and deliver tailored experiences to customers (Ramezani, 2024).

Conversational Functionality

Conversational AI software agents use dialogues to activate machine learning models in AI-enabled communication technology with; Natural Language Processing (NLP) to interpret, understand and manipulate meaning from interactions in the most efficient way possible (Sharma, 2021). According to Mehri et al. (2019), multi-domain Wizard-of-Oz dataset (MultiWOZ), offers a fully labelled collection of human-human written conversations spanning over multiple domains and topics when used for training goal-oriented conversational agents like chatbots, to facilitate automated and personalised communication experiences using voice assistants with messaging apps (Hung et al., 2022). Such types of conversational chatbots are more effective in comparison to humans trying to reach out to a large audience through messaging apps. They retain a complete record of all interactions with customers to enhance the customer's experience by aiding comprehension of customer preferences and needs (Isa et al., 2024). They can handle complex dialogues with capability of understanding and responding to queries in a contextually rich environment. Machine learning models with conversational functionality when embedded in chatbots combine natural language processing (NLP) with principles of conversational design in their algorithm. NLP helps them understand the intent of the customer using the purpose or goal of the customer, for example “find a hotel near airport” or by matching specific information provided by the customers as input to infer from the context of the conversation and facilitate coherent interactions with customers. Algorithms using natural language generate appropriate human-like responses from contextually generated information using templates deep learning based transformers for pre-defining models that can answer specific queries. The interactive capability of conversational functionality when used

in chatbots allows seamless communication that is clear and relevant to the customer. The ability of NLP to extract intent by analysing human language for inferring meaning from inputs offered by the customers in their own language. Conversational functionality tends to bridge the gaps between human and machine in a natural and effective manner.

To summarise, machine learning based communication tools apply simple, straightforward and deterministic logic to perform by assigning tasks to classified text or labeled data for predicting customers' intent. Deep learning helps the prediction capability of machine learning to generate meaning from nuanced data with advanced neural network applications such as BERT, a bidirectional encoder representation for transformers, a neural networks-based technique that can understand ambiguous text by establishing context or GPT, a generative pre-trained transformer that applies generative AI framework or LLaMA, a large language open-source model of Meta AI. Neural network applications reinforce deep learning by optimising responses based on the feedback offered by customers during conversations. Conversations with multiple customers with their individual complexity helps deep learning track continuity and retain specific information in its memory systems and use it to personalise meaningful responses as per the preferences of the customer. Ability to adapt to every individual customer and scale the responses in a personalised manner requires fine-tuning of machine learning models and ensuring that they are trained on the specific domains, especially for specialised industries like food processing or supply chain. Applying these techniques in a global scenario will also require multilingual features such as the ability of the machine to translate conversations in multiple languages to be embedded in a machine learning model. Implementation of AI-enabled interactive communication tools is quite simplified by technology leaders like Microsoft with products like Microsoft Bot. These products offer simplified implementation and are available to businesses in the form of chatbots that enable advanced conversational capabilities by applying deep learning with OpenAI GPT or BERT

kind of models using NLP libraries like NLTK. Structured flow designed for intuitive conversations by these products enable interactions between the machine and the customer to become goal-oriented. These models are able to gracefully handle failures of machines to capture the intent of the customer and clarify the misunderstanding with personalised responses to customers, thereby, improving engagement and satisfaction of customers.

While these capabilities of machine learning are useful for businesses, we endorse that it is important to reduce the bias of the programmer in the training module designed to mitigate the personal bias in predictions. Ethical customer support considerations require use of chatbots as a capability developed for responding to queries of customers by guiding them through a process with transparency and respect for their privacy with data security and adherence to data regulatory frameworks such as General Data Protection Regulation (GDPR). Chatbots can assist customers beyond order tracking, product navigation and responding to their queries with tasks such as scheduling and reminders. Businesses in the healthcare sector can use machine learning for preliminary diagnosis or assessment of the health support required by the patients or evaluating mental health of the individual using the machine to reach out to the support providers. Fashion retailer engaged in e-commerce can extend use of machine learning from order tracking to better and quickly understand and navigate customer preferences. However, to explore the current understanding of the capabilities of machine learning based interactive communication tools for customer engagement, a scoping review was performed.

AI-enabled chabots have the capability of coordinating information from various touchpoints for the purpose of business development and use the meaning thus created from information for nurturing engagement and improving stakeholder satisfaction across various touchpoints. AI-enabled Chatbots can handle routine tasks without a feeling of burnout and handle multiple queries simultaneously. As the first point of contact, they are trained to respond to queries with personalised messages and interactions. Capabilities of AI-enabled chatbots to

create meaning from information received can support businesses and improve their response efficiency and scaleup the analysis of large amounts of data being gathered during interactions, for targeted marketing. Creating meaning from information received as insights or analysis of stakeholder data can help businesses share information to improve their product portfolio and customer engagement during a delivery process. AI chatbots quantify the qualitative data received to inform decision makers about the patterns and help them make informed strategic decisions. Chatbots can help managers evaluate, score and qualify leads. Machine learning applications offer assistance to make futuristic predictions from analysis of leads received. Combining AI with human intelligence (HI) can aid building of a personal rapport with customers through consistent and personalised interactions and smoothly handle and negotiate high-value leads received by analysing preferences of customers for making appropriate recommendations with detailed explanations. Information received when coordinated through chatbots can help fashion retailer to identify and use the gaps in the market for product innovation. Use of coordinated information gathered through chatbots can also help improve business efficiency with automation of tasks to support the backend systems such as managing traceability and tracking of orders. Combining AI with HI can improve performance and efficiently by managing repetitive queries received from stakeholders. Use of AI-chatbots to support HI with contextual data on the real-time dashboard with insights and trends can assist in finding resolution to the complexity in a query. On the operations front, coordinated information when used in a centralised system with aggregate data, can be used by companies to optimise utilisation and reduce the burnout of resources available, at times when load of queries from stakeholders is very high. Ability of AI to regularly update the dashboard with real-time insights and trends based on coordination between different types of data that flows between different systems of the organisation and provide information related to specific query

while addressing privacy concerns of the stakeholders in a way that is compliant with regulations under the data protection measures, such as (GDPR)

Methodology and data collection methods: Scoping Review

To explore, if integration of such functionalities of chatbots can enable retailer to improve the effectiveness of their machine learning applications on customer engagement and satisfaction from interacting with the machine, a scoping review was performed (Arksey & O'Malley, 2005; Levac et al., 2010). A scoping review has various definitions in the literature (Anderson et al., 2008; Davis et al., 2009). To achieve clarity and consistency, Davis et al. (2009) recommended researchers define scoping reviews as "a form of knowledge synthesis that addresses an exploratory research question aimed at mapping key concepts, types of evidence, and gaps in research related to a defined area or field by systematically searching, selecting, and synthesising existing knowledge. Scoping studies differ from systematic reviews because it is used when a topic has not yet been extensively researched or is of a complex or heterogeneous nature (Hanley & Cutts, 2013; Arksey & O'Malley, 2005; Levac et al., 2010). Table 1 distinguishes between scoping reviews and systematic reviews.

A scoping review is an approach which can be useful to explore areas which have not yet been compressively examined, or which have demonstrated considerable heterogeneity in terms of scope (Peters et al., 2015). Because of the lack of focus and exploration of how different types of chatbots cause different challenges, a scoping review on this area can therefore be seen to be justified; a more focussed time parameter for study inclusion shall also ensure that results are garnered from contemporary relevant sources only. Because of the combined flexibility and rigour of process inherent within the scoping review approach, this proposed piece of work will therefore have the potential to summarise and disseminate core

findings, to identify gaps in research within this field, and to make reliable & meaningful recommendations for future research directions (Peters et al., 2015).

Table 1 distinguishes between scoping reviews and systematic reviews

Activity	Systematic Reviews	Scoping Reviews
Study Question	Focused	Often broad or exploratory
Inclusion/ Exclusion criteria	Defined a priori	Flexible, can be changed post hoc
Quality Judgement	Quality filters applied	Quality not an initial priority
Synthesis	Quantitative	Qualitative
Purpose	Detailed data extraction for knowledge accumulation	Identify parameters and gaps in the literature for mapping knowledge
Typical Questions	What is the effectiveness of x compared to.. in xxx patients	What is known about xxx in the literature

This study follows the guideline offered for use of SPIDER by Peters et al. (2015) for conducting a scoping review based on JBI guidance to report the results and offer a detailed recommendation. It encourages systematic thinking using the knowledge available. The framework requires five consecutive stages listed below in a structured manner` to analyse the information gathered by breaking it into smaller units and manageable parts for clarity followed by mapping them with the objective comprehensively for concluding. The consistency of the analytical process reflects on the reliability of the analysis and process in this approach mainly focuses on a complex issue by systematically breaking down the consistent information into manageable components for derivable insights that can be actioned. The accuracy of the findings received from the analysis combined with the consistency in the procedure applied reveal the reliability and validity of the analysis.

1) Identify the research questions

2) Identifying relevant studies

3) Selecting Studies

4) Charting the data

5) Collating, summarising and reporting results

6) Consultation with stakeholders

Stage One: Identifying the questions

The stage one of the SPIDER framework requires analysis of the consistent situation by defining the current state of the context, identifying the key stakeholders and the situation so that questions like what's happening and what are the intrinsic and extrinsic factors consistently influencing in a given context. To identify the review question, description of the population and context with concept approach was used for this proposed study. The context of the interactive technology settings with the concept of the measurement of its use and challenges in its use, along with the understanding of the population that the businesses mainly in the banking industry address for using chatbots. The overarching research question based on the review of literature with anecdotes and study of the context to be answered was identified as what is known about different types of AI-enabled machine learning based chatbots and how can AI-enabled interactive communication tools like chatbots be used to enable businesses to engage and satisfy customers?

Stage Two: Identifying relevant studies

The proposed stage for conducting a scoping review after identification of questions is about coming up with a Search Strategy using SPIDER framework (Peters et al., 2015). The SPIDER framework involves pinpointing the core issue or the challenge being faced with symptoms and root cause that differentiate the context from other similar situations. Therefore, raising questions like, “What's the challenge?” and, “Is there any evidence that reflects on the existence of the problem and consequences of not addressing the problem?” Thereafter, consideration of the sample, phenomenon of interest, design, evaluation, research type to help with the development of key words for the electronic search, and to inform the eligibility criteria within the study identification phase as described in a tabular format in Table 2.

Table 2: SPIDER Terms

Sample	Phenomenon of interest	Design	Evaluation	Research Type
Business organisations adopted chatbots	Use of Chatbots	Primary Research	Experiences	Primary Research
Chatbots enabled by Advanced AI	Challenges	Primary Research	Outcomes	Primary Research

Multiple electronic databases were used to incorporate a greater level of sensitivity and specificity within the search process (Xiao & Watson, 2019), including SCOPUS, Web of Science and Google Scholar. An additional approach of using cyclical search syntax helped to maximise sensitivity and specificity within this process. It is an advanced approach used to produce relevant and reliable returns via electronic searches (Xiao & Watson, 2019). An example of syntax applied is as follows: (((chatbot OR chatbots enabled by AI OR AI OR artificial intelligence OR business organisations OR e-banking or Banking OR chatbots types)))

Stage Three: The selection of studies

The purpose at this stage for the researchers is to assess the implications of the problem and to analyse how the problem may differently affect different stakeholders in different scenarios with identified resources and their outcomes. It raises questions such as what is the short or long-term impact of the issue in the given context and who will be most affected in a resource-based scenario. The papers returned by the searches using the above terms were* subjected to a manual process of study identification, as recommended by Xiao and Watson (2019). This consisted of a multi-phased approach in which eligibility criteria were applied to the body of returned work. These criteria used are given in Table 3 below and were first administered to the titles of all returned studies. Any paper which obviously did not meet eligibility criteria was then culled from further consideration; remaining papers were made to undergo the same process with their abstracts being examined in the next step (Xiao & Watson, 2019). The final phase involved reading of all the remaining studies being in their full text version, and the first author was responsible for making a decision as to keep or exclude them for further review. It was accepted that as a single-reviewer piece of work, during the identification phase this study may become subjective in nature and therefore, subject to potential personal bias of the researcher (Uttley & Montgomery, 2017). Hence, the final selection of papers may differ compared to selection by another individual or team, if they were to approach this process (Uttley & Montgomery, 2017). The results were then imported into RefWorks bibliography and database manager, then exported to the Covidence tool to reach an agreement with the research team and finally used to capture the PRISMA chart.

Table 3: Eligibility criteria

Inclusion criteria	Exclusion criteria

Primary research	Secondary research such as reviews or meta-analysis
Quantitative, qualitative or mixed methods	Commentaries, opinions or editorials
Published in the English, full text accessible	Published prior to 2012
Peer review Journals	Focus on retail and banks used chatbots
Chatbots types only	Based in banking sector

Stage Four: Charting the data

This stage involved exploration of potential solutions to the problems identified followed by evaluation of their alignment with the goals of the study and criteria used for decision making feasibility and impact reporting of the key study characteristics suggested by JBI Guidance for the Conduct of Scoping Reviews (Peters et al., 2015). Reporting involved extracting the data, author, year, research aim, theory applied, methodology, findings, implications for theory implications. No framework was conceptualised at this stage and no quality assessment tools were used at this stage. In contrast to systematic reviews, quality assessment is not needed for critical appraisal in scoping reviews, which aim to provide a wider overview of the evidence (Peters, 2022; Arksey & O'Malley, 2005; Levac et.al., 2010).

Stage Five: Submersing and reporting

At stage five the researcher plans to implement the proposed solution and ask questions such as how this can be implemented and managed after implementation. The purpose of this stage was to evaluate the effectiveness of the analysis performed and use the analysis to measure the outcomes by comparing them with the objectives defined in the beginning of the study. This action was performed by asking questions such as does the solution being offered resolve the issues being addressed by this study and if the approach chosen worked well or not and why it

did not work well, if it did not. The stage also needed extending the narrative to explaining the lessons that could be learnt, if the findings were to be applied to a future scenario. Table 4 presents the summary of the data extracted and reports the findings in a structured format.

Table 4: Summersing and reporting the data

Research	Core Argument	Methodology	Findings
Asbjørn Følstad et al. (2019)	A Two-Dimensional Typology	A sample of 57 chatbots according to the typology dimensions which are locus of control, duration of relation	Chatbots are still emerging as interactive technology, and their implications and purposes are only beginning to be seen on customer services
Vishal M and Prabhu V. (2022)	Critical comparison of different state-of-art technologies, natural language processing and dialogue management techniques	Literature review analysis of conversational AI-based research and development	Chatbots can be classified in four types of knowledge domain, service provided, goal-based, and response generation methods each one provides a different level of conversational AI. The developed versions of chatbots provided more capable and efficient agents leveraging the interaction to be more engaging and human-like
Rajabi et al. (2024)	The theoretical assumption that incorporating knowledge graphs might enhance the capabilities	Following a systematic literature review approach. Three knowledge graph-based chatbots have been used which are health care, education and business	The evidence supports the theoretical assumption suggesting that the use of knowledge graph-based chatbots was able to leverage extensive data retrieval. Its adoption improved the accuracy and enriched responses, which influenced positively on increasing user confidence and experience without investing on extensive training.
Inupakutika et al. (2024)	The natural language understanding (NLU) engine is the core service of the chatbots. Chatbots therefore is categorised based on the process of response creation, the field and length of conversation, and whether services include AI self-learning programs or not	Case study analysis of healthcare chatbot created for smoking related Symptom Assistance	The NLU applications demonstrate differences in handling automatic context, default alternative intent, pre-defined objectives and entities, and the availability of SDK/ webhook. Google Dialog Flow and IBM Watson Conversation platforms are the most suitable to integrate with chatbots. But Google Dialog flow demonstrated better performance in terms of recognising all the combined intents for complex sentences
Ndungi, and Siregar (2023)	The paper assumes that research studies since 2007 focused on popularising chatbots but since 2020 a growing presence of clever chatbots stimulating human behavior is reported	Mixed conversations and Graphical User Interface Chatbot on Facebook messenger was promoted for Kenyan citizens to access, a socio-technical initiative based on a crowdsourced platform during the presidential elections took place in	The research revealed gaps and pointed directions for further user-centred research studies. The empirical findings revealed that the participants' expectations were not met. The findings reported that the experience either to be disappointed or frustrated with the restricted natural language capabilities and the limited set of features offered by the chatbots

		October 2017. The research targeted 16 first time users and evaluated 8 popular chatbots	
Schlesinger et al. (2018)	The paper discusses why chatbots have trouble handling race-talk. So, chatbots cannot handle race talk	Literature review analysis to answer questions How can chatbots handle race in dialog in new and improved ways? and 2) Why is race-talk so difficult for chatbots?	The context of database corpora, the syntactic focus of language processing, and the un-adjustable nature of deep learning algorithms made chatbots limited in handling race talk. In addition, the questions on how chatbots can handle race talk have not been revealed given the complexities in the problem space of race and chatbots,
Smestad and Volden (2019)	Using the five-factors model, an assumption regarding the effects of personality is investigated through measuring the effects of chatbot agents, with levels of personality, on the user experience.	Case analysis depends on the model of five factors. By using AttrakDiff form, a group of 25–40 years of age, 8 females and 8 males were selected. The group was devised to include couples living together, either married or unmarried. 12 individuals out of 16 had young children. Participants evaluated the two chatbots by completing a series of tasks using each chatbot	The research examines the impact of a match in personality between a chatbot and the user and concludes that the personality does affect the user experience of chatbot interfaces
Skjuve et al. (2023)	The paper aims to present a new way of measuring user experience in terms of ICC—the interpersonal competence in chatbots. The 10 ICC skills and the ICC scale were used to measure interpersonal competence in human–human interaction it as used and adjusted to fit the context of human–chatbot interaction	Observing the impact of interpersonal competencies while using chatbots	Chatbots in the past have taken abuse from the users. Hence ICC might be viewed as a necessary competence for regulating the behavior of the user when it is inappropriate. In addition, chatbot context may need some alteration where the emphasis is more on the ability to express confidence more so than to “feel” relaxed. Chatbots need to focus more on the ability to demonstrate availability though push messages and active listening
Følstad et al. (2021)	Chatbots conversations need to expand beyond the individual’s perception and discipline	The research uses deliberative research analysis process among workshops’ participants discussing chatbots	Theories should be developed around the knowledge about the users’ experience and the effect of the chatbots’ design. In addition, the theories should use such knowledge to improve chatbot user experience in different industrial applications
Schei et al. (2024)	Explore how chatbots empowered by AI shaped the students’ learning experience within higher education context	Using five steps scoping review methodology, 24 empirical articles published between 1 January 2022 and 5 September 2023 on	Science, technology, and education (English as a Foreign Language) are emerging fields interested in chatbots. Less interests appeared in medicine and pharmacy. Asia came first in 14 articles published in cases from Saudi Arabia, China, Turkey in the lead. Little research adopted qualitative research methods.

		students' perceptions and use of chatbots empowered by AI in higher education context	Majority of the research focused on the usefulness and adoption of chatbots as well as the use of it in the learning process
Alshibly et al. (2024)	Explore the mediating role of customer empowerment in chatbot usability and customer engagement in Jordanian commercial banks' context using technology acceptance model	Using surveys as a tool to serve quantitative research inquiry, bank customers in Jordan. Snowball sampling targeted adult users of chatbots who had utilised a chatbot service within the preceding six months from the beginning of the research. Online questionnaire was distributed through bank branches and social media groups	The research proved the positive correlation between customer-empowerment and customer engagement in the context of chatbots. There are specific chatbot capabilities such as knowledge empowerment cultivating empowerment and satisfaction, Responsiveness surprisingly did not demonstrate link to customer empowerment.
Chaouali et al. (2024)	Resistance to use or adopt chatbots in the banking sector, focusing on the role of gender in the resistance using complexity theory.	For the data analysis the fsQCA approach was employed.Using a snowball method involving 385 French users of chatbots usage, value, risk, tradition and image barriers, as well as two gender conditions were used to assess the resistance to chatbots.	Four different grouping were reported to explain the resistance: First usage, value, risk and cultural obstacles, second a group of value, risk, cultural and image obstacles, third a mixture of usage, value, risk and image obstacles, along with the male gender and forth a obstacle of usage, value, tradition and image barriers, along with the female gender.

DISCUSSION

AI-enabled machine learning based interactive communication tools such as Chatbots enable delivery of service with convenience beyond the capabilities humans can offer. retailer in the fashion industry can use a combination of human agents and declarative robots for contextual functionality in AI enabled chatbots that have the capability to create authentic connections during conversations by coordinated use of information (El Bakkouri, et al., 2022). While human agents are deficient of multitasking capability and can serve a limited number of customers at a time, with limitation of work hours with break time or downtime, they are capable of striking a deal by assessing customers' emotions in a real-time context and offer a personalised and pleasurable experience to the customer during the conversation (Nguyen et

al., 2022). Simultaneously inability of human agents to offer a timely response may influence perceptions of customers and their experiences with the company. Studies by Handelsman et al. (2005) and Radke et al. (2020) highlight the importance of achieving a motivated and personally fulfilling conversations through the reciprocal interaction between the customer and the technology. This concept aligns with the service-dominant logic, suggesting that value is co-created through interactions involving the service recipient. In line with this, Hollebeek et al. (2021) also subscribe to the idea of customer engagement as the investment of emotional, cognitive and physical resources for interactions within service systems, underscoring the subjective nature of customer engagement evaluation. According to Forbes, 80% of marketers have started using AI-enabled communication tools such as chatbots (Forbes, 2019), indicating the acceptance of chatbots as a mode of communication by customers. Daniels et al. (2017) classified the customer engagement of chatbots into seven categories: usability, utility, availability, search-friendliness, trustworthiness, value, and desirability; hence, the values which AI adds to functionality of chatbots based on the needs and the context where the technology is adopted.

In addition, the ability of AI-enabled communication technologies to offer opportunities for strengthening customer relationships, their actual impact on customer engagement remains a complex challenge (Saikia and Bhattacharjee 2024). Within the ambit of online marketing, considerable emphasis has been laid on the mechanisms through which interactions with customers via digital platforms translate into customer loyalty (Cheung et al., 2021). Nevertheless, what is often construed as customer engagement might not stem from a genuine interest in the brand but rather from the interactive experience facilitated by the technology itself (Hollebeek et al., 2021). For example, banking chatbots save an average of four minutes per inquiry compared to traditional handling by call centres (Oracle, 2020; Drift, 2021).

The declarative chatbot and the contextual chatbot are able to communicate with customers 24/7 and handle customers' common questions or simple transactions; for example, answering where to download specific content, or replying to an item of the purchase process, etc. The 24/7 availability of chatbots would reduce the waiting time for customers looking for help and allow retailer to reduce the cost of setting up round-the-clock communication services. However, declaration and contextual chatbots are ideal only for questions for which the answers are planted in the system. (Aggarwal and Singh, 2024; Gupta et al., 2020; Rani et al., 2024; Shah, and Kavathiya, 2024 & Assayed et al., 2024). As regards the interaction quality, customers often weigh the convenience of automated services in comparison to the quality delivered by interactions with humans. For instance, in banking, customers might choose interacting with an employee cashier instead of a self-service option, which includes interacting with chatbots. The selection of customers often depends upon factors like speed, efficiency, and the quality of engagement.

AI-enabled chatbots have the ability to synergise operations with customer service that can enable retailer to establish a stable relationship with their customers (Assayed et al., 2024 & Shah, and Kavathiya, 2024). AI-enabled chatbots are capable of learning and responding based on learning at a very fast pace with optimised self-communication skills. They can process a wealth of data within a relatively shorter time and provide fast, comprehensive and personalised responses during interactions with customers (Luo et al., 2019; Cha, 2020; Belanche et al., 2020; Ratchford, 2020). The quality of interaction is good when both customer and service provider are able to engage in a meaningful dialogue. Incase of AI-enabled chatbots representing the service provider, they are not recognised as sincere to the customer (Jeong, and Shin, 2024). Customers seeking engagement with human agents do not trust AI-enabled chatbots. The declarative vs AI chatbots in comparison to human agents is presented in Table 5.

Table 5: The comparisons of AI chatbot and other common interaction methods

Human Agent	Declarative Chatbot	AI-based Chatbot
Offers personalised conversation (Agarwal et.al., 2025)	Can answer customers questions 24/7 (Assayed et al., 2024)	Provide round-the-clock support to customers (Assayed et al., 2024)
Provide real personal communication to enhance the authenticity (Gupta et al., 2020)	Handle customers' queries, common questions or simple transactions (Shah and Kavathiya, 2024)	Contact with unlimited number of customers (Shah and Kavathiya, 2024)
Serve a limited number of people at one time (Aggarwal et.al., 2025)	Ideal for already known types of enquiries that customers will ask (Aggarwal et.al., 2025)	Reduces customer waiting time and provides immediate response to a variety of enquiries from customers (Aggarwal et.al., 2025)
		Supports personalised service (Rani et al., 2024)

Hollebeek et al. (2021) proposed that the interaction between technology applications and their usage contexts can generate a spectrum of engagement manifestations, targeting specific actors or entities. Majid et al. (2024) argued that chatbots promote a different understanding of the concept of business sustainability. Literature also discusses the rise in online transactions via e-commerce platforms. Global e-commerce sales in 2019 were $26.7 trillion in 2019, which is equivalent to 30% of the global gross domestic product (GDP) that year (United Nations Conference on Trade and Development UNCTAD, 2021). While scholars recognise that E-commerce has broadened new channels for conducting business, they also report that these platforms have created new challenges for fashion retailer trying to maintain exclusiveness and differentiation as the opportunity of conducting business via e-commerce on public platforms is available to every company (Shah, and Kavathiya, 2024). Therefore, retailer are focussing on feedback from customers about how to refine the capabilities of AI-enabled chatbots. The adaptability of retailer to incorporate the feedback has become crucial for maintaining the relevance and effectiveness of the technology. Another critical aspect

important for fashion retailer to consider is the ability of AI-enabled chatbots to provide personalised experiences of products using advanced data analytics to tailor interactions for individual customers based on their anticipations and preferences. The level of personalisation offered by a company when customers expect accurate responses, and relevant support enhances customer engagement and fosters customer loyalty. Addition of convenience and effectiveness in such an interaction to the conversation creates differentiation for the company in a competitive market (Aggarwal and Singh, 2024).

Unlike chatbots that worked in the past on predefined questions and answers corresponding to the questions, today AI-enabled chatbots are powered with Natural Language Processing (NLP), Machine Learning (ML) and Deep Learning (DL) techniques that help in capturing, understanding and analysing heterogeneous information such as linguistics, contexts, behaviours, buying habits etc. from multiple dimensions like words, voices, photographs, videos etc. (Luo et al., 2019; Cha, 2020; Belanche et al., 2020; Ratchford, 2020). Capability of these new age AI-enabled machine learning based chatbots to offer in-depth interactions with the individual customer in real-time for efficiently delivering services with the help of virtual assistants has led to a change in attitude of the customers. A shift study by Help Shift (in Chakraborty, 2022) The survey conducted by Help shift discovered that 79% of people prefer live chat to other channels that can provide personalised service without any limitation of time. A conversational chatbot that uses neural connections to learn continuously can constantly offer better service, reduce operational costs, perform routine and ordinary tasks without complaining (Chotia, 2022). These AI-enabled chatbots can handle a large number of enquiries enabling retailer to improve utilisation of human resources and also analyse the purchase intentions of individual customers and help retailer to efficiently manage their future supply chain (Kalaiyarasan et al., 2023).

Literature reports that customer contact centre agents suffer from risk of burnout, especially those who are diligent because they handle a high number of queries (Chotia, 2022). Introduction of new age AI-enabled chatbot in such a setting reduces the average workload for human agents as they can swiftly improvise based on the needs of the customers, by providing them with the required information (Luo et al., 2019; Bock et al., 2020). Although AI chatbots cannot replace human agents, retailer intend to use them as the first point of contact (Jiménez et al., 2021). When smartly integrated into the communication service delivery process, swiftness of the AI-enabled chatbots make it hard for customers to differentiate between a chatbot and a real person providing services (Hollebeek et al., 2021; Sidaoui et al., 2020). The knowledge and understanding created by AI-enabled chatbots in the form of customers' intent, tone, emotions and habits works as input to consequently provide relevant responses. In the event when AI chatbots cannot identify the needs of the customers, they can be trained to engage a human agent into the conversation. In addition, AI-enabled chatbots can be used to deal with potential scenarios of unpleasant human-to-human interactions (Aggarwal and Singh, 2024). The capability of AI-enabled chatbots to act as a central point for information storage and dispatch systems has become useful for businesses aiming to improve communications with customers (Figure 1). Furthermore, supported by the ability of AI-enabled chatbots to capture, organise and analyse heterogeneous information from different touch points in a format when converted into knowledge highly suitable for different stakeholders along the supply chain or to relevant delivery ports, can offer context specific suggestions for modification of the route being followed for product delivery or optimisation of resources. By acting as a central information system as shown in Figure 1, AI-enabled chatbots strengthen the smooth flow of goods along a supply chain that can result in a transaction channel with least friction.

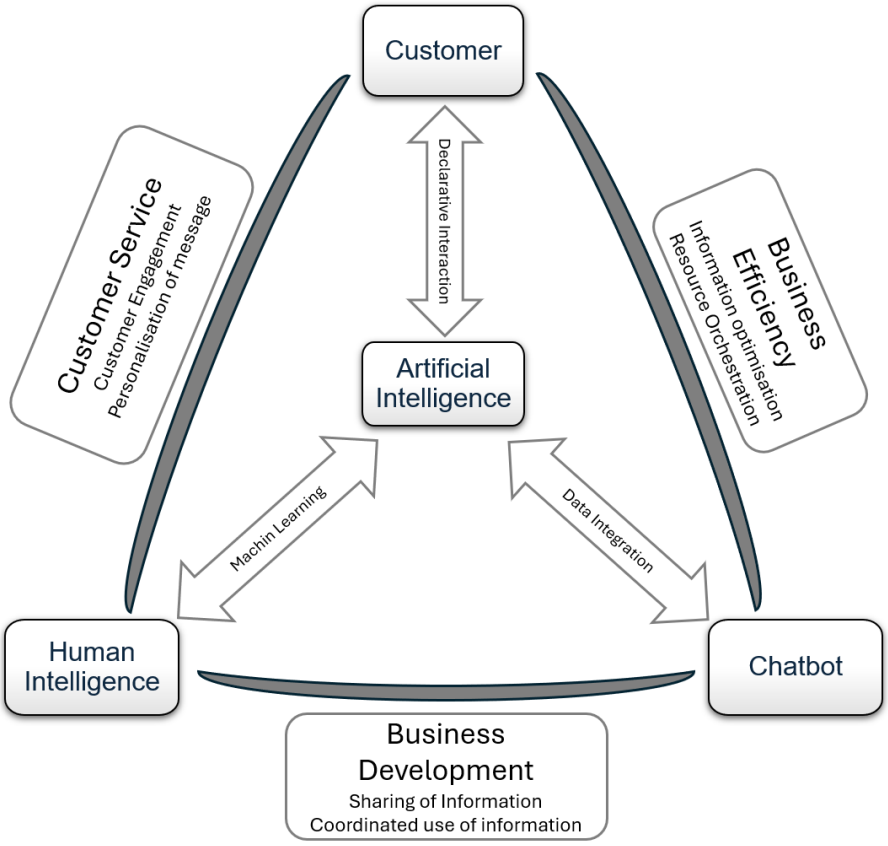

Fig 1: AI based Learning empowered by Intelligence

The framework above (Figure 1) explains how AI enabled chatbots can create the linkages between customers, AI and HI for ensuring its best possible use for customer engagement, business efficiency and business development. The engagement of customers with the company via Chatbot facilitates the interaction that generates data. Using this data AI can engage customers and create meaning to enhance their experience. Integration of AI with machine learning when applied to use of AI-enabled chatbots, provides opportunities of new learning and allows personalisation of the messages with empathy in the conversation. Indeed, business development opportunities are offered by AI-enabled chatbots with its ability to share information with its coordinbranated use by human intelligence and artificial intelligence.

The art of communication is a concern for designers of AI-enabled communication technology. Certain behaviours are more morally or socially acceptable than others in society.

One question being raised is about the ability of chatbot to recognise and not respond to negative language when dealing with customer abuse? Passively accepting the abuse may improve customer behaviour and minimise the gravity of the situation (Code Academy, 2022). Although the chatbot may be developed to identify similar sentiment features indicating violence (e.g., via certain keywords) and intensity (e.g., usage of capital letters and exclamation points), it is likely to have trouble with humour and irony (Canhoto and Padmanabhan, 2015). This concern has long existed and will continue to be an uncomfortable source for customers.

Another issue that machine learning based communication technology faces is technological incapability. Some unstructured data, such as images with low resolution, may be unusable; or the chatbot could struggle to attract all sources of information available because of a shortage of processing power (Canhoto and Clear, 2020). AI programmers are also concerned about cultural adaptation. AI-enabled chatbots when trained to be multilingual in order to communicate with customers from different countries can highlight cultural differences and accommodate the collective psychological traits of customers from various countries (Chen et al., 2022). In summary, there are ethical issues with use of AI-enabled communication technologies in relation to the communication process and diverse cultural situations, other than protection of data privacy and rights of customers. Addressing these issues is important to make customers feel secure so that they can comfortably embrace the technology after they have built their expectations based on exposure and encountered some poor outcomes (Bhardwaj et al., 2024; Cameron et al., 2017). A poor or not so favourable encounter can make customers conclude that technology they are using prevents similar outcomes.

AI-enabled communication tools should focus on improving or incorporating additional features in the algorithm to assess conversational performance holistically and create a better contextual understanding of the customer's experiences, including the measurement of

complicated indicators such as feelings and expectations. Scholars focusing on the services sector (Edwards & Barker, 2014; Pillai & Sivathanu, 2020 & Hussain et al., 2019) suggest that AI-enabled communication technology works as virtual personal shopping assistants who help in personalising a shopping experience. This technological capability facilitates customer-brand relationships and empower fashion retailer to design products and services tailored to customer demands. A few research studies also reflect on customer's hesitancy in adoption of the AI-enabled communication tools such as chatbots, suggesting the gap in our knowledge about customer expectations and experiences in the context of usability of AI-enabled chatbots. (De Cicco et al., 2020 & El Bakkouri, et al., 2022).

CONCLUSION

Different types of chatbots including declarative chatbots, contextual chatbots, and AI-enabled chatbots, have their strengths. For example, a rule or menu-based chatbot can provide customers with direct, accurate answers regarding popular questions. In contrast, an AI-enabled chatbot can help businesses in many different ways, for example addressing common queries through chatbots can enable the sales team to focus on high-intent conversations (Drift, 2021). Therefore, the selection of chatbot to use from types available by retailer will depend on the goals of the company. Simultaneously, paying attention to ethical aspects is important while employing chatbots to communicate is a significant concern. More specifically, AI researchers need to consider the ability of customers to understand how chatbots work, follow the explanations given by chatbots after a malfunction, and understand the following steps to recover from a malfunction (Khurana et al., 2021). Also, chatbot self-training needs to be carefully monitored to avoid behaviours such as racism, sexism, or the use of abusive language.

LIMITATIONS

Numerous studies show that data-driven NLP systems are vulnerable to unintentional learning biases inherent in datasets (Lee et al., 2019). Simultaneously, gender bias reflects in the roles being allocated to different AI-enabled chatbots such as Apple's Siri and Amazon's Alexa, which have been disproportionately given female names or voices (Feine et al., 2020). It again reinforces ongoing issues related to how gender roles perpetuate the "subservient female" stereotype. Therefore, chatbot developers should be cautious and avoid any gender bias in the bot's design. Feminised chatbots are frequently sexually harassed with no apparent consequences. The design of the bots can influence by actively combating the harassment related to gender bias by possibly employing humour and wit to turn the unpleasant situations around (Jin & Eastin, 2023). For example, their name (e.g., Alexa, Cortana, Siri), voice (e.g., Alexa and Cortana's voices are exclusively female), and how they are advertised (e.g., "Alexa lost her voice") frequently cause female gender associations. This can result in the embodiment of gender stereotypes, which should be exercised with caution, with training for the bot to ensure that it behaves appropriately. If not trained properly, the chatbot may exhibit racism, sexism, or the use of abusive language (Jin & Eastin, 2023).

FUTURE RESEARCH

AI enabled chatbot can understand what the company is attempting to achieve by stimulating the HI and customer interaction for information optimisation and resource orchestration. Researchers recommend that the concept of customer service should be regularly evaluated to improve its practice and effectiveness. Future researchers should focus on how the capability to learn from mistakes, share lessons and develop solutions be integrated in a chatbot because the core of chatbots enabled by AI is to enhance the customer engagement. According to a study conducted by Ashfaq et al. (2020), customers preferring human connection would appreciate the service approach of humans and prefer human interactions to human human-computer interactions

(David-Ignatieff et al., 2023), particularly when it comes to highly customised services (Dabholkar and Bagozzi, 2002). Those with limited understanding about the quality of services delivered by AI-enabled chatbots, will value human interaction and will not see any value in their interactions via chatbots (Ashfaq et al., 2020). Therefore, a shift in the disparity in chatbot usage scenarios can be noticed in behaviour of consumers. Hence, the future research should be concerned with developing chatbots versions that are capable of understanding and generating responses in multiple languages, and that are sensitive to cultural nuances, which could vastly broaden the applicability of chatbots with features that enhance customers' and services providers' interests. More inclusive and accessible conversational chatbots are required to enhance the customer's experience and improve the values of customers' engagement across diverse communities.

CONTRIBUTION

This study contributes to the literature on customer service using AI-enabled chatbots; ability to interact autonomously and serve customers by responding to queries raised by them (Sands et al., 2020), which improves the efficiency and effectiveness of communication while helping organisations to reduce costs (Chotia, 2022). Authors adopt an optimisation perspective to suggest that adopting AI-enabled chatbots for engaging customers with human agents, only if required, can reduce the workload of human capital of the company and improve quality of their work, which can improve the outcomes and satisfaction of customers from the interaction (De Cicco et al., 2020; Singh, 2021; Kumar et al., 2019). When fashion retailer adopt AI-enabled chatbots to act as the first point of contact for the customers followed by human agents when setting up the interaction and communication program, they can strategically maintain consistency in their interactions with customers, which could lead to an e-commerce capability building opportunity for their business (Alt et al., 2021; Sidaoui et al., 2020). Our research

highlights that AI-enabled communication technologies face a significant challenge in dealing with various types of miscommunications, such as misconceptions and false assumptions. They frequently suffer from speech recognition errors, so preventing miscommunication becomes a major issue (Aggarwal et al., 2025). Simultaneously, privacy concerns of customers are an important consideration in the context of chatbot based interactions. The unpredictability and transparency issues associated with AI technology highlighted by this study are in line with Zarifis et al. (2023), who escalated customers' concerns about use of technology for communications. Addressing these concerns has become essential for building the trustworthiness of customers in chatbots. Lack of transparency is another factor that we recommend that managers should focus upon as they can acts as a barrier in building customers' trust (Khurana et al., 2021). Our study also explains the importance of transparency when dealing with customers using technology should be weaved in the process when information is being gathered and being used for social or commercial purposes with the consent of the customer (Code Academy, 2022). Therefore, utilisation of AI-enabled chatbots in customer service is not merely a technological challenge but also poses psychological and emotional challenges. Therefore, a combination of technological sophistication in terms of linguistics and response accuracy, coupled with the understanding of human psychology in terms of empathy, privacy, and personalisation, can lead to delivery of a holistic and satisfying customer service experience through chatbots. Task-oriented chatbots with "black-box" orientation makes it challenging for customers to comprehend what went wrong and why (Khurana et al., 2021). Implementing a data governance framework like the GDPR of the European Union can offer customers better control over their personal data (Code Academy, 2022). Full disclosure may also entail informing customers that they are connected with a bot (ibid) as customers may not always recognise that they are interacting with a chatbot as chatbots as humans have been developed and they behave very much lifelike. The ability of customers to comprehend

explanations offered by chatbot after a breakdown with information about the path to recovery from a breakdown should be explained to customers' as it will improve their impressions of transparency (Khurana et al., 2021).

Findings of our study recommend that Adoption of AI-enabled chatbots by fashion retailer can result in common discrepancies such as inability to fully understand and process complex customer requests with lack of an empathetic response because when retailer integrate advanced NLP algorithms to address such gaps, chatbots can improve the interaction quality with understanding, decision-making capabilities, superior recognition and responding ability to connect with emotions. We recommend retailer to focus on training and updates based on customer feedback, because they can ensure that chatbots evolve in line with customer expectations and experiences. Using AI-enabled chatbots to engage customers in seamless interactions for handling multiple queries simultaneously with immediate and consistent response to inquiries will enhance satisfaction from engagement. Furthermore, personalisation of interactions via chatbots when based on customer data analysis will make customers feel valued and understood, thereby deepening their engagement. However, there are still gaps in our knowledge about long-term effects of chatbot interactions which can be addressed empirically using data on chatbots effectiveness in handling complex issues. There is also a lack of research focusing on the integration of emotional intelligence in new age AI-enabled chatbots.

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Reviewer's feedback	Response to the Reviewer's feedback
Reviewer 1	
Despite the potential novelty of the topic, the paper presents very general information about the phenomenon. There is no clear indication of why the study should have been conducted. The research problem, from both scholarly (theoretical) and practical perspectives, is not explained clearly. In-text citations are not provided to support strong claims/statements.	Thank you for your feedback. The motivation of the study has been updated. The introduction section has been revised with clear identification of the importance of the study on Page 1 Line 12 to 19. The research problem has been explained on Page 7 Introduction section Para 8 In-text citations have been updated
Ensure that every paragraph in your paper explains why chatbots urgently need to be studied (by presenting the research problem) and supports statements with appropriate in-text citations.	Proper explanation has been provided for the urgent study of chatbots with appropriate citations.
The aim presented is insufficient, very weak, and too generic. Please revise it to be more specific and consider providing a framework for scholars and practitioners regarding how chatbots work and the repositioning of your paper. Specify the contributions explicitly and ensure they are meaningful.	The aim has been revised and specified on Page 1 Abstract section. Framework has been created to position it with the contribution to make it more meaningful.
The literature review reads like a textbook and is very descriptive. It needs to be revised according to the revised research problem, objectives, and contributions.	The literature review section has been revised based on the research problem, objectives and contribution. Changes have been made on Page 7 & 12 to 14.
A stronger theoretical standpoint is needed to apply to chatbots, or at least highlight the limitations of previous theories that you are extending or developing.	The limitations of previous theories and studies have been highlighted and listed on Page 13 & 14.
Indicate the exact tension in the literature to justify the importance of this study and	The required changes have been made to justify the importance of

connect them more critically with your revised aim.	the study in the literature review section
The methodology is missing. Although this is a conceptual paper, a rigorous methodology still needs to be applied. Ensure you provide the techniques used to arrive at your findings. Consider a systematic literature review (SLR) or bibliometric review style.	The methodology section has been expanded with further description of how techniques were defined, and articles were selected with the five stages of scoping review. Changes have been made on Page 15 to 23.
The findings need to connect with the revised research objectives/questions	The required changes have been made to connect findings with the research question and objectives.
Special Issue Fit Which aspect of chatbots addresses the issue "Responsible Corporate Branding". Which aspect of chatbots addresses this? Ensure to make this connection clear.	Matter has been considered during the revision and has been ensured to make this connection clear.
The conclusion is another weak part. Based on the synthesis and contributions, there should be two clear sections with dedicated support from the earlier parts: Theoretical Contribution and Managerial Implications. This needs to be written transparently and clearly, with support for future research.	Clear sections have been provided and the conclusion have been rewritten from Page 27 to 35.
The research problem is not clearly identified from both theoretical and practical perspectives; hence no research gaps are highlighted.	The research gap has been highlighted. The problem has been discussed in the Introduction section from Page 2 to 5.
The theoretical and practical contributions are not clearly stated despite the potentially interesting topic.	The theoretical and practical contributions have been stated on Page 28 & 29
The methodology lacks information - please revise to an SLR or bibliometric style with rigorous reporting.	The methodology has been revised and rewritten. Changes have been made on Pages 15 to 23.
There is no guiding framework provided.	Thank you for your feedback. Guiding framework has been provided.
The conclusion requires clarity and a stronger theoretical standpoint, indicating which theory the study is bridging or developing based on previous theoretical limitations and its practical implications.	Stronger theoretical standpoint has been indicated on Page 34

Finally, the current study's fit to the special issue needs to be clarified. How does the chatbot represent an ethical issue or which aspect the study is exploring with regards to the fit of special issue.	The special issue has been clarified and represented on Pages 13, 23, and 34.

Reviewer 2	
The academic rationale/ motivation for undertaking this study is not clear. I would have expected a novel research model and set of propositions to have been developed following the review of the extant literature.	Thank you for your feedback. A novel research model and set of propositions have been developed following the review of the extant literature.
In the abstract and introduction section, the rationale for and the aim/motivation of the study has not been stated, the rationale (academic underpinning) for conducting this study is not strong and is currently weak. E.g. What is the originality of this study?	Thank you for your feedback. The rationale for and the aim/motivation of the study has been stated in abstract and introduction
The paper provides a somewhat adequate review of extant studies surrounding chatbot use in the business context. The literature review needs to be strengthened by developing a taxonomy highlighting the various alternative models/theory in this context other than describing the use of different types of chatbots and the research gap this study is seeking to address.	Thank you for your feedback. All the literature sections were rewritten Done
There is no research methodology applied for the study and therefore lacks academic justifications to support a review paper based on extant literature and case studies. There is a need to provide a robust methodology even if the paper is based on literature and the consideration of	A robust methodology has been provided. The methodology section has been expanded with further description of how techniques were defined, and articles were selected with the five stages of scoping review. Changes made on Page 15 to 23.

alternatives and justification of methods selected for data collection and data analysis, support-ed by appropriate references needs to be provided.	
An interesting area of research but the results do not report anything new, and the findings are very vague and do not delve into the peculiarities of the findings discussed in detail. I am left with the same question throughout the discussion section and therefore don't see how this study has added anything new to the existing literature of corporate reputation review.	Results have been reported in Table 4 and the findings have been discussed in detail with provision of framework.
The paper also lacks theoretical and managerial implications section.	Improvements have been made to the texts in literature and conclusions to demonstrate the theoretical and managerial implications section.