Role of WhatsApp chatbots in e-commerce

Abstract

It was necessary to create an educational chatbot that could able to answer the people query about any particular domain. The goal of this study is to investigate the possibility of developing a chatbot that can be used for instructional purposes in educational field by using artificial intelligence. Through the use of a question-and-answer structure, the chatbot is able to give users who are looking for information with communication that is reminiscent of human interaction. It is possible that the user, who is often anxious, will not be able to precisely identify the query at times. These features need to be updated and improved on a regular basis in order to give fresh contents and features. According to the findings, it is possible to develop an educational chatbot via the use of artificial intelligence. It is essential to test and evaluate the functioning of the chatbot.

Keywords: artificial intelligence; machine learning; natural language processing; chatbot; radiotherapy; Internet of Things; healthcare

1. Introduction

Also referred to as conversational agents, chatbots are also known as [1]. They are computer programmes replicating human communication by using technology such as artificial intelligence, natural language processing, and machine learning [2]. A broad variety of fields and applications have benefited from the introduction of chatbots, which have brought about new levels of ease and efficiency. Among these industries and uses are e-commerce, healthcare, finance, and education. But when these technologies are utilised more often, they also become more open to other security risks, which makes users' private and sensitive data less secure. The protection of sensitive information has been receiving an increasing amount of focus. The protection of sensitive data belonging to users is one of the most significant difficulties that chatbots face when it comes to information security. An increasing amount of personally identifiable information, financial information, and health information are being supplied by chatbots[3]: This makes chatbots an appealing target for cybersecurity criminals.

In a similar vein, an attacker may get permission to access client financial information, such as credit card numbers, bank account information, and transaction history, if a finance chatbot is breached. Preserving customers' confidence in these many kinds of technologies is an additional vital component of information security in chatbots. It is crucial that consumers utilising chatbots feel secure in the knowledge that their private data is protected [4].

When it comes to selecting a chatbot for customer assistance as opposed to connecting to a live agent, older persons seem to have a different preference than younger ones. This is an additional factor that should be taken into particular account for the purpose of establishing user confidence. It is possible that older individuals still place a higher value on the human touch. This would imply that depending primarily or mostly on chatbot communication might potentially alienate older customers, despite the fact that older consumers make up such a significant portion of the population.

Since this is the case, continuous study and development are required in order to recognise and eliminate new dangers. [5] GPT-4, which is superior than ChatGPT, was trained on the artificial intelligence supercomputers that are part of Microsoft Azure. It employs a method known as deep learning, which makes use of a greater amount of data and computing in order to generate language models that are ever more complex and competent. [6] For it to be able to predict outcomes, it has to be trained on vast datasets of information pertaining to the relevant domains (for example, information about patients and information about user conversations). Chatbots, on the other hand, are unable to learn from encrypted data. To add salt to injury, the development of secure chatbots calls for a strategy that is interdisciplinary in nature [7]. [8] This is a process that may be difficult to do and calls for the participation of users, developers, politicians, and security specialists.

In addition, the wide variety of chatbot situations and scenarios provides one-of-a-kind security concerns that call for individualised ways to address them. For instance, a chatbot that is used in the healthcare industry would need a distinct set of security precautions than one that is utilised in the financial sector or in online commerce. [10] This is why security has to be dealt with in a difficult way that considers the particular wants and needs of every use case. It's too important not to stress how important it is to make sure that robots have good information security [11].

2. Literature review/hypothesis development

The use of information and communication provided by mass media is also subject to the trend of integrated artificial intelligence development, which creates new challenges for retail communication design. Changes in the way that consumers receive and process information are brought about by the fact that they are constantly confronted with an uncontrolled amount of communication stimuli in the internet environment [12]. There is a tendency that is becoming more multidimensional in customer behaviour, and this phenomenon is particularly relevant to retail communication.

The usage of chatbots has been more prevalent in the field of customer service, as shown by the literature. [13] As a result, chatbots are typically used as digital voice assistants in instant messaging and as conversational user interfaces for online customers. Relatively few studies, meanwhile, have looked at how chatbots are really used throughout the channel choosing process.

Because they believe they do not get enough assistance, social connections, or individual guidance[15]. When it comes to the retail business, multichannel retailing systems have been a well-established component for a considerable length of time, as stated by Parboteeah et al. [16]. A high level of channel participation is often linked with proactive conduct, while a low level of engagement leads to more reactive action that is reliant on external inputs. It is becoming more common for customers to make extensive use of a variety of multimedia information channels, particularly during the information phase, prior to making a purchase or entering into a contract.[17] The main elements influencing the choice to purchase via a certain channel are the customer's personal characteristics and the item or service being purchased. On the other hand, the online shopping alternatives that are accessible are decided by the circumstances of the market and the quality characteristics of the relevant merchants.

2.1. Multichannel stores that sell good things

Since interactive channels may react quickly to the display of real-time information, they perform better in this assessment dimension than static information media, as shown by earlier studies on the behaviour of channel selection. [18] When evaluating the quality of certain shops and channel offers, the scope and depth of online offerings are crucial factors to take into account. Furthermore, the ability to tailor or alter the multimedia content and services provided on a channel according to the preferences of the specific user may also be very helpful in satisfying customer demands. In addition, the Internet provides much improved pricing transparency as a result of the almost limitless supply and price comparison tools that are available inside the channel. This is the reason why a considerable number of customers end up picking the online channel as their preferred method of transportation.

(H1) The first hypothesis. There is a positive correlation between the attractiveness of a multichannel retail channel and the quality of the offer.

(H2) second hypothesis. The quality of the offer has a positive effect on consumers' satisfaction levels in multichannel shopping.

2.2. Multichannel Retail Usability

When purchasing purchases online, one often needs to contend with the opportunity, time, distance, and effort that are the main components of this construct. The amount of time that an online client saves is correlated with an information channel that is easy to use and receive. A channel's ease of use is crucial, particularly for those who don't directly connect with corporate employees. Furthermore, consumers may find the location-independent features of the Internet to be especially important when certain products or services need a similar time commitment to get. The research's findings lend credence to the following theories:

(H3) The third hypothesis. When it comes to multichannel retail, the perceived ease of use has a favourable impact on the attractiveness of different channels.

(H4)fourth hypothesis. Customer satisfaction is positively impacted by the impression of ease of use in the context of multichannel buying.

Safety of Multiple Retail Channels

The adoption of secure transaction procedures and the conditions connected to responsible data usage have received a great deal of attention throughout the last several years. [19] In light of these obligations, more thought must be given to the many aspects pertaining to multichannel retail safety from the standpoint of the consumer. The fifth hypothesis is (H5). The degree of security offered by multichannel retail adoption affects the channel's desirability.

2.4. Consumer Satisfaction

Apart from the specific channel requirements of a given scenario, it's possible that prior online interactions with certain data and sales channels may also impact how those channels are used in the future. Consumers will also use their prior experiences—whether favourable or unfavorable—with that channel to the new online purchase flow, which they may access via the channel that best meets their needs. [19] The channel's own expectations influencing perceived quality qualities at the time of purchase and past channel experiences. This prompts the following assumptions to be made:

(H6) The sixth hypothesis. When it comes to multichannel retail, the level of customer satisfaction has a favourable impact on the attractiveness of different channels.

The seventh hypothesis (H7). Enhanced customer satisfaction positively influences channel choice in multichannel commerce.

2.5. Chatbots for Customers

The literature has been promoting chatbots as a significant technological advancement that enhances customer service for the last several years. The study's findings were published in [20] and showed that when a chatbot's personality is similar to their own, consumers prefer to utilise it for longer periods of time. Customers prefer chatbots when they have basic, daily queries, according to the results of other research. In point of fact, chatbots have the potential to enhance the customer experience by delivering prompt and individualised replies to inquiries from consumers, managing many customer interactions simultaneously, and operating around the clock, therefore providing customers with access to assistance whenever they need it.

2.6. Attractiveness of the Channel

The use of digital channels is expected to expand as internet speeds rise and as more excellent, easily accessible online services become available. Disruptive technologies continue to be developed and used, which further supports this tendency. The main factors taken into account while assessing a channel are its qualitative attributes in relation to the individual goals or purchase motives of the current client. The client uses a method akin to the traditional utility maximisation hypothesis to choose the channel that offers the most benefit. [21] A person's personal channel preferences may be influenced by a channel's perceived attractiveness [22]. To effectively integrate their channel's offers of products and services with online customers' demands, merchants must, in this context, understand as much as they can about situation-specific channel preferences. [23] Consequently, it is assumed that the following hypothesis is accurate:

When robots are used across multiple channels, personal information like gender, age, and level of schooling are often used as control factors. These things have a big effect on how people choose which station to watch. [24] The conceptual model is shown in Figure 1. This model is based on a survey of the existing literature as well as assumptions. [25]

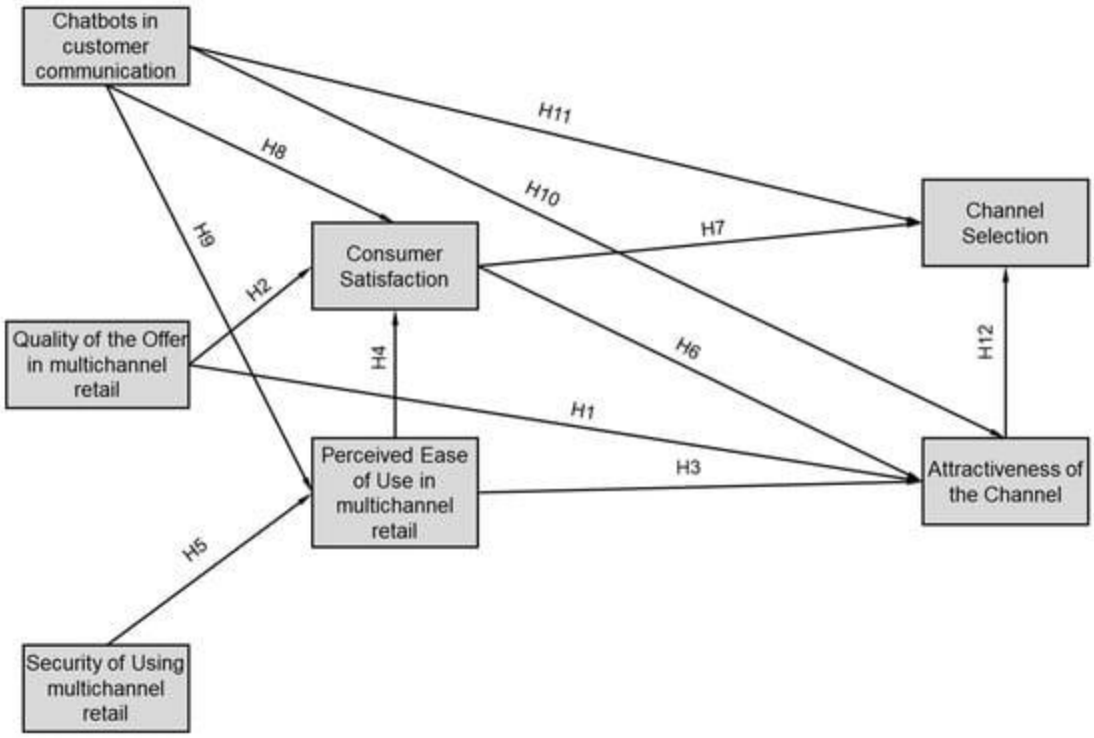

Figure 1. Conceptual model.

3. Materials and Methods

3.1. A Look at the Workflow

3.1.1. Labelling of the User Group

It is necessary to begin by determining the sorts of possible consumers and the requirements that they have in order to determine the scope of the project. For the purpose of gathering such information, seminars, meetings, and conferences are all viable options. Patients with cancer, members of the general public, including the patient's relatives, and radiation workers employed by the cancer centre are examples of individuals who may use radiotherapy. All of these individuals are users of radiotherapy. In order to solve the challenges, a chatbot may be developed when the demands of the customers have been understood. Through the use of the internet, the chatbot is intended to imitate discussion with as many different types of human users as possible. On display in Figure 2 is an illustration of the fundamental process of the chatbot. As seen in Figure 2, the chatbot starts out by asking questions to determine who the user is. Every one of the two user types has specific needs of its own. On the other hand, patients could be interested in gaining an understanding of certain fundamental words related to external beam radiotherapy, while radiation workers would wish to verify certain particular laws and procedures as they pertain to radiation safety.

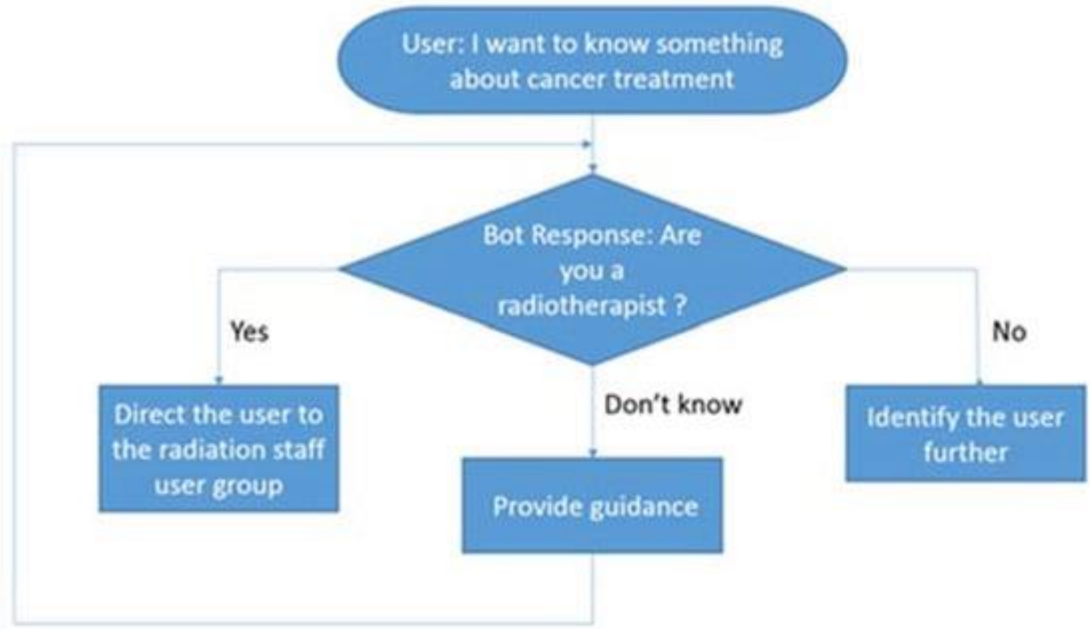

Figure 2. Basic chatbot process.

Figure 2 depicts the basic conversional flow of the chatbot and what occurs when a user asks for information about cancer treatment. It is possible for the deployment of artificial intelligence to assist the chatbot in precisely predicting the reaction (intent) from the user and providing a discussion that is more human-like.

3.1.2. Identification of Different Scenarios

It begins by determining the requirements of the user, and then it proceeds to choose an appropriate scenario that is personalised to the user depending on the requirements. For the purpose of developing an instructional chatbot for use in radiotherapy, we are conducting a pilot study with three different user groups: individuals in the general public, radiation professionals or students, and patients and their relatives. It is necessary to train the chatbot using the data that is collected from the scenario of each user group. This training should include both the input and the anticipated response. After that, the chatbot will be able to comprehend several people and answer to them in a suitable manner. These situations may be recognised by clinical workers and healthcare practitioners based on their experiences, which can be gathered via interviews, meetings, or seminars. In the near future, the chatbot's script and procedure will be modified to provide this help. The chatbot will learn from in order to become more intelligent via machine learning. A significant benefit of enhancing the chatbot via iterations is that it allows for the chatbot to be delivered in a timely manner while also undergoing continual development.

3.1.3. Dialogue Tree/Layered Communication Framework

The chatbot is capable of replying to open-ended inquiries made by users. This happens after the identification of the prevalent scenarios for each of the three user types. Artificial intelligence is able to learn from the queries and responses at this stage via machine learning.

The user will be prompted by the chatbot to choose the cancer-related websites that they are interested in. Assuming that the user chooses "Brain" in this scenario, Figure 3c will provide further information on the breakdown of such an item. In the event that "Brain Radiotherapy" is chosen, the chatbot will deliver material that is associated with the stated subject matter. It is not the same as websites since this is done via a question and answer session with the chatbot.

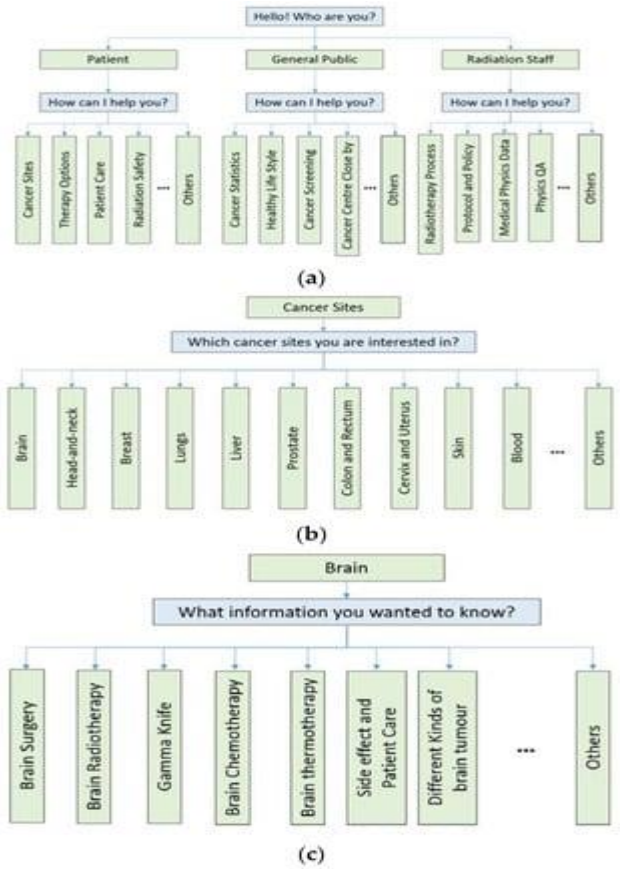

Figure 3. Chatbot logic for “Patient” users selecting “Cancer Sites” and “Brain”. The chatbot's question is blue and the user's choice is green.

For example, in Phase 1, the chatbot's interaction logic asks the user what it can help them with after providing a brief introduction (see Figure 4: "Hi there! asks the RT Bot, myself. Figure 4 illustrates that the chatbot can respond to most of the questions posed about radiation. For example, the user may enter in "What is radiotherapy?" After providing a response, the chatbot will proceed to ask the user whether they are interested in learning the meaning of radiotherapy or how it works.

Figure 4. Customer chatbot responds “What is radiotherapy” Upon inquiry, the chatbot will give further information.

3.2. Chatbots use AI, or artificial intelligence.

Figure 5 The chatbot was created. The chatbot, which can be used on social networking sites or customised Internet of Things devices like smartphones, was created by the Watson Assistant. The IBM Cloud is linked to the Watson Assistant, which provides artificial intelligence functionalities including natural language processing (NLP). There is a further connection between the Cloud and other Watson services, such as the backend systems and speech-to-text interaction.

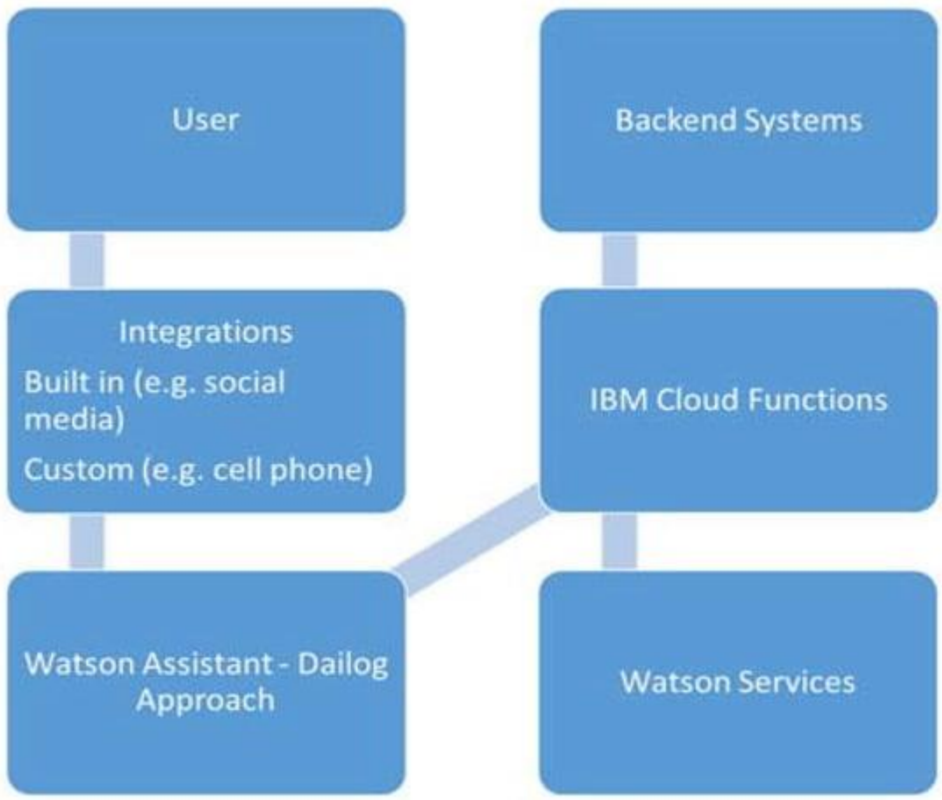

Figure 5. Architectural schematic of IBM Cloud-chatbot connection.

Artificial intelligence powers the chatbot by studying user responses and dissecting text or speech in order to identify patterns and create rules. Furthermore, this implies that the user's answer may be structured into a formatted form by the chatbot using machine learning. Natural language processing (NLP), which is a feature of many chatbot development platforms like IBM Watson Assistant, is one machine learning approach used in chatbots. Pattern matching and language analysis are both included in NLP. As an example, the IBM Watson Assistant is able to explicitly recognise keywords from the user's answer and then balance those keywords in order to establish the meaning of the text at hand. After then, the database of intentions is compared with this information in order to assess the answer that the chatbot is able to offer.

When the chatbot is interacting with the user via the usage of the question and answer method, the questions are included into the conversation nodes in a separate manner. In spite of the fact that every node is independent, it also causes the next issue to arise. The user is granted access to the discussion tree via the use of the dialogue tool. Because of this, the tree is able to exert total control on the dialogue nodes. The IBM Watson Assistant's conversation tree is seen in Figure 6, which features the assistant. The chatbot builder may add a new node above or below any conversation tree node by using the choice button on each node. This enables the conversation tree's overall flow to be built by the developer. Furthermore, every node has the capacity to have offspring nodes, which is a crucial attribute to possess considering the many ways a user might answer a query.

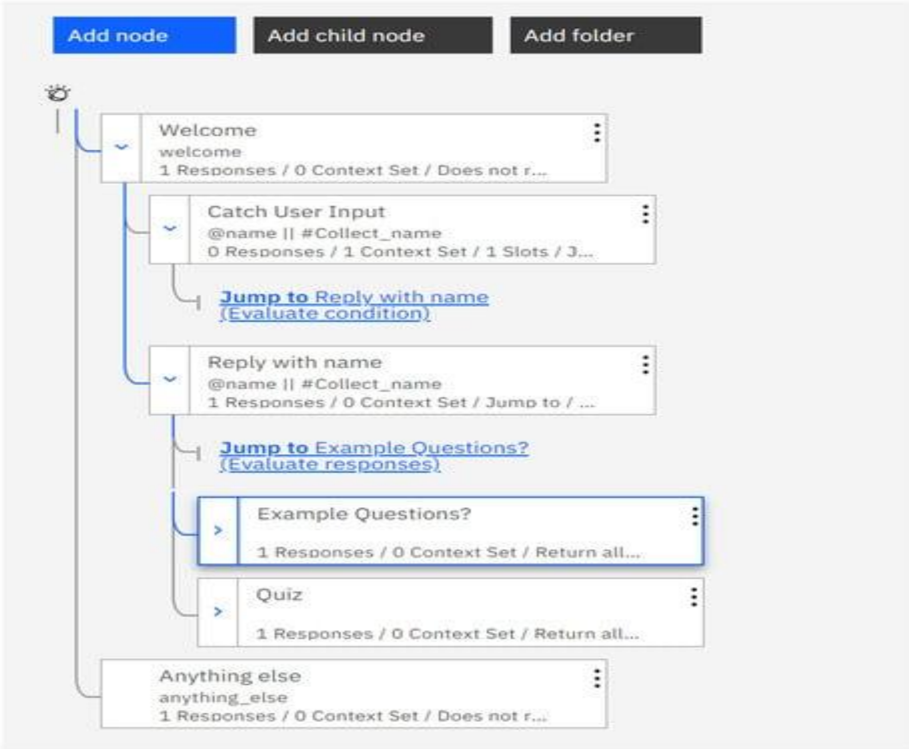

Figure 6. IBM Watson Assistant conversation tree.

During the process of building the chatbot, the IBM Watson Assistant offers a sophisticated feature known as the Intent. This tool enables the chatbot to evaluate the input from the user and to make predictions about the user's intentions.ML and NLP capabilities of the platform are able to provide assistance for this tool. As can be seen in Figure 7, in order for the chatbot to be able to access certain nodes of the discussion, it must first recognise the precise intentions that are included inside the user's input. For instance, the Hint node is a node that will appear when the user is unable to comprehend the question that is being asked by the chatbot. This node may only be accessible by the user when they have specifically requested assistance. It is feasible for the Intent node to generate the node in order to assess the various user inputs that may be conceivable in response to that node. Consider the following scenario: the user responds to a query posed by the chatbot by typing "help" or "hint," which triggers the execution of an intent known as "#Hint." Through the process of providing the chatbot with samples of the purpose, this and additional intents may be developed.

It should be brought to your attention that some intentions call for less than a few instances. This is due to the chatbot's expectation that the user would respond with "Yes" or "No" given the restricted expression alternatives. Regarding the Entities tool, the function may be seen as a database that the chatbot can access and use for data extraction and cross-referencing. As seen in Figure 7, the chatbot is able to extract names when it recognises the "#Collect_name" intent that is associated with it.

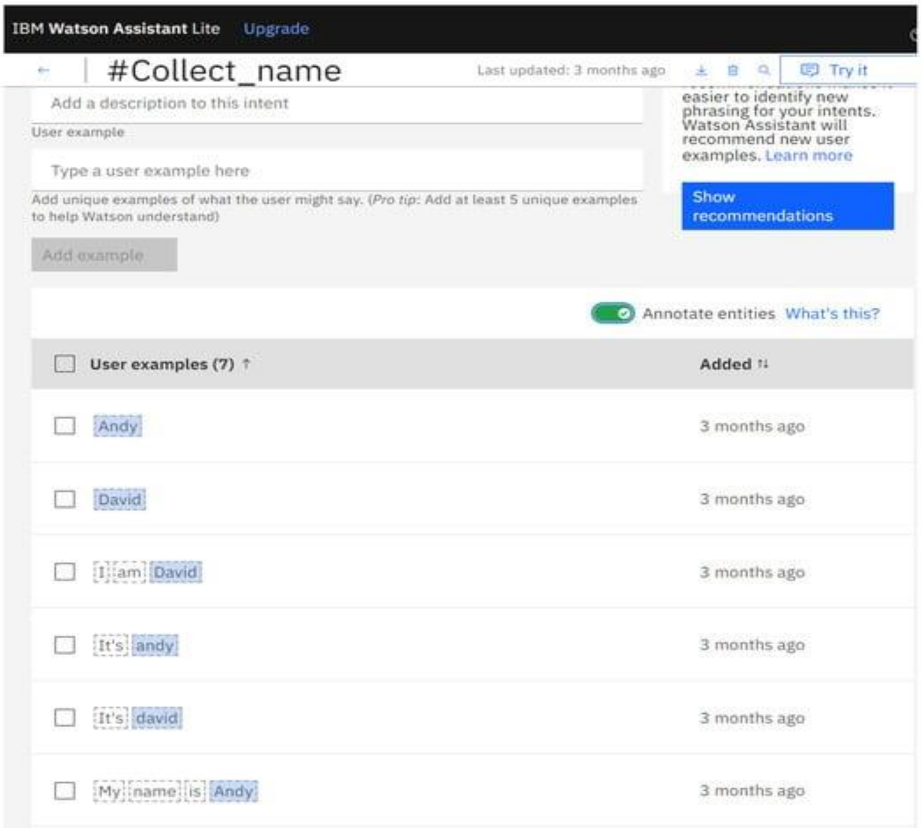

Figure 7. IBM Watson Assistant's “#Collect_name” intent node. The chatbot just wants the blue-boxed user names.

4. Results

4.1.1 Analysis of Measurement Models

The α values of all the items ranged between 0.84 and 0.90, suggesting a good too high degree of reliability (>0.7) and had a reliability coefficient (CR) above 0.90. It was necessary to determine the average extracted variance (AVE) for every concept in order to assess convergent validity. The seven constructions yielded values ranging from 0.68 to 0.83, above Hair et al.'s cutoff value of 0.5. This demonstrates that each construct can account for a minimum of 50% of the variations among its constituents.

Table 1. Analysis of measurement model.

Construct	Indicator (In)	Indicator Loadings	α	CR	AVE	R^2	R^2 Adjusted	Q^2
Perceived Ease of Use	In 1	0.85	0.88	0.92	0.73			
	In 2	0.90						
	In 3	0.88						
	In 4	0.80						
Perceived Usefulness	In 1	0.85	0.86	0.90	0.70			
	In 2	0.87						
	In 3	0.79						
	In 4	0.84						

Calculating the discriminant validity is the last stage in the process of analysing a measurement model. This measure evaluates a structural model construct's ability to be separated from other constructs that evaluate different ideas. According to Hair et al.'s reasoning, the square root of the AVE's optimal value for any given construct should be greater than the correlations between that particular construct and every other construct in the structural model. The HTMT ratios must have a lower value of 0.85 in order to demonstrate discriminant validity.

Table 2. Analysis of discriminant validity and correlation matrix.

Constructs	1	2	3	4	5	6	7
1. Perceived Ease of Use	0.86						
2. Perceived Usefulness	0.61 (0.69)	0.84					
3. Perceived Enjoyment	0.53 (0.59)	0.55 (0.62)	0.91				
4. Perceived Risk	−0.10 (0.11)	−0.07 (0.07)	−0.03 (0.07)	0.89			
5. Attitude	0.60 (0.69)	0.63 (0.73)	0.59 (0.68)	−0.08 (0.08)	0.82		
6. Perceived Value	0.61 (0.79)	0.51 (0.57)	0.65 (0.73)	−0.09 (0.09)	0.67 (0.77)	0.89	
7. Chatbot Acceptance	0.56 (0.63)	0.50 (0.56)	0.62 (0.68)	−0.12 (0.09)	0.65 (0.79)	0.63 (0.76)	0.84

4.2. Model Structure Analysis

Before looking at the structure model, we checked to see if the measuring model would work. It was necessary to look at the adjusted path coefficients (²), standard error (SE), t-values (t), and significance levels (p-values) for each theory in order to finish this job. We followed Hair's instructions when we did this study. The results of testing the eleven theories can be found in Table 3 and Figure 8. It was shown that theories 4 and 6 were not true. The truth of hypotheses 3 and 7 is supported by these findings.

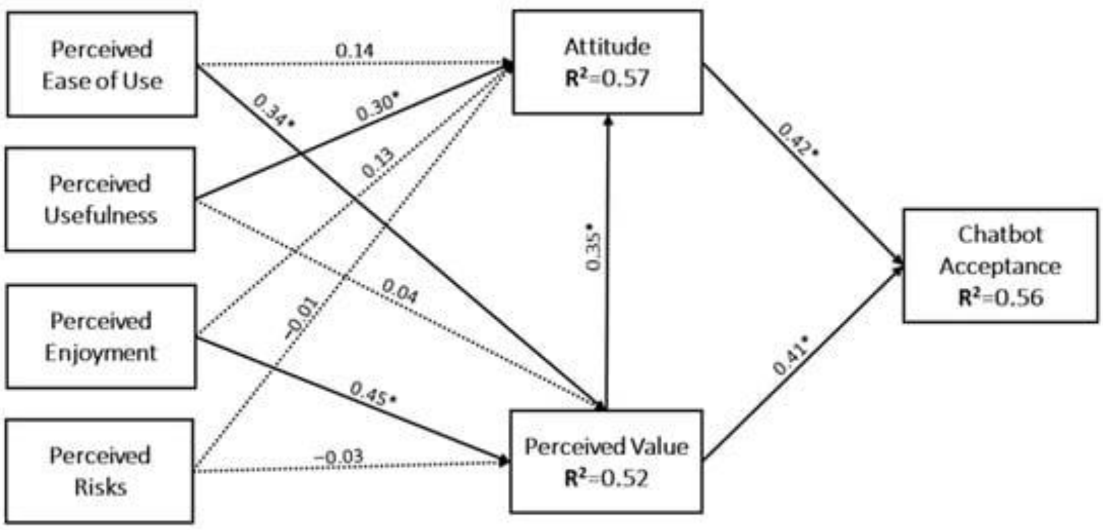

Figure 8. *P-value < 0.001 indicates significant standardised path coefficient findings.

Table 3. Results of hypothesis testing.

H	Independent Variables	Path	Dependent Variables	Path Coefficients (β)	Standard Errors (SE)	*t*-Values	*p*-Values
H1	Perceived Ease of Use	→	Attitude	0.14	0.08	1.73	0.08
H2	Perceived Usefulness	→	Attitude	0.30	0.06	4.51	0.00 *
H3	Attitude	→	Chatbot Acceptance	0.42	0.09	4.62	0.00 *
H4	Perceived Usefulness	→	Perceived Value	0.04	0.07	0.56	0.57
H5	Perceived Enjoyment	→	Perceived Value	0.45	0.06	7.28	0.00 *
H6	Perceived Risk	→	Perceived Value	−0.03	0.06	0.59	0.55
H7	Perceived Value	→	Chatbot Acceptance	0.41	0.08	4.97	0.00 *
H8	Perceived Ease of Use	→	Perceived Value	0.34	0.08	4.19	0.00 *
H9	Perceived Enjoyment	→	Attitude	0.13	0.08	1.68	0.09
H10	Perceived Risk	→	Attitude	−0.01	0.06	0.19	0.84
H11	Perceived Value	→	Attitude	0.35	0.10	3.50	0.00 *

Henseler et al. recommended that the R2 value be used to measure the predictive power of the research model. The amount of variance in the dependent construct that the independent constructs can explain is shown in this image. As evaluating students' acceptance of chatbots in the classroom was the study's main objective, the R2 value was used to determine the research model's predictive capacity.

A model with a higher Q2 value has more predictive significance outside of the sample, as shown by its Q2 value. Hair et al.'s results indicate that Q2 values of 0.35 and above are regarded as noteworthy. The values are as follows: acceptance of chatbots = 0.44, perceived value = 0.51, and attitude = 0.49. This suggests that the model has a high degree of accuracy in predicting students' approval of utilising chatbots in the classroom.

5. Conclusions

A layered structure and conversation tree technique may be used in the development of a chatbot that is incorporated into the Internet of Things (IoT) for instructional purposes in the field of radiotherapy. The chatbot can interact with people from a range of backgrounds and help those who struggle to learn new things by using the question and answer format. It has been determined that the chatbot is not a one-time completed product; rather, it is something that must be regularly updated and enhanced in order to meet the requirements of the user and to stay up with the rapid improvements in computer technology and radiation. Two of the things that will be done in the future are giving the chatbot more useful features and enabling it to handle languages other than English.

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