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A multi-criteria decision analysis model for selecting an optimum customer service chatbot under uncertainty

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ABSTRACT

Chatbots are increasingly integrated into customer support systems due to recent developments in artificial intelligence. Chatbots can provide quick and tailored services to users, including employees and consumers. This paper presents a decision-making framework for chatbot selection in the telecommunication industry. The most suitable chatbot is chosen using a new combination strategy combining Combined Compromise Solution (CoCoSo) and analytic hierarchy process (AHP) in the context of single-valued neutrosophic sets (SVNSs). The proposed method uses the AHP to generate attribute weights (collected from previous studies), and CoCoSo ranks the options and selects the best chatbot. The AHP-CoCoSo is an efficient multi-criteria decision-making model for solving complex under uncertainty. The usefulness and viability of the proposed model are statistically demonstrated by solving an explanatory case study of chatbot selection in telecommunication. The method's resilience and strength are further demonstrated through sensitivity analysis and comparisons with previously proposed approaches. The findings of this study reveal that the approach used might lead to more realistic results when dealing with uncertain information.

1. Introduction

Technology "of the future", as depicted in science fiction literature and films by prior generations, is already available. Yes, even flying automobiles are possible. On the other hand, the modest chatbot is an example of modern technology that may appear simple to us now. Artificial Intelligence chatbots are already being used by 23% of customer support organizations. Despite this, 75% of customers still want businesses to adopt new technology to improve their experiences [1]. Customer service Chatbots are conversational software solutions used instead of, or in conjunction with, human agents to assist consumers with frequently asked questions (FAQs) and customer concerns. They generally appear to customers as a bot that answers a few important queries (think "please choose an option"). These simple chatbots are created with precise message flows behind the hood [2]. These flows frequently refer customers to a self-service online knowledge base or a live representative. Advanced chatbots employ some form of natural language processing (NLP), which may detect keywords in a conversational environment and select appropriate replies based on those keywords rather than depending on pre-programmed message flows [3].

Quick reaction times are one of the top considerations for the customer experience. When asked whether "a rapid answer" is vital or very important to them when they have a customer care query, 90% of Hubspot Research respondents said yes [4]. "Immediate reaction" means 10 min or less to them. That can be an issue in a globalized environment if you just have a contact center in one time zone with restricted availability. Chatbots can assist in providing immediate responses and, in certain situations, completing client contacts at any time of day. Chatbots are effective at answering frequently asked inquiries from customers. Companies have been forced to adjust and handle larger quantities of tickets for customer care personnel since the worldwide pandemic has altered the way customers and businesses engage. According to Digital Genius' study, 40% of support tickets are mindless and repetitious [5]. A support team's capacity to deal with more complicated issues is hampered when swamped with simple inquiries. Companies aware of the issue use chatbots to cope with the increased load and answer typical consumer concerns, resulting in speedier case processing times [6–8].

The use of these chatbots is fast-growing, much like instant messaging, and they are already being incorporated into common tasks like shopping and teaching [9]. The chatbot business is expected to expand from $2.6 billion to $9.4 billion between 2019 and 2026, with chatbots primarily utilized in customer service accounting for the most growth [10]. In 2018, it was estimated that over 300,000 chatbots were active on Facebook Messenger alone [11]. By 2022, customer service chatbots will account for 85 percent of all interactions [12].

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Nomenclature

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
CI	Consistency Index
CoCoSo	Combining Combined Compromise Solution
CR	Consistency Ratio
CRITIC	CRiteria Importance Through Inter-criteria Correlation
DMs	Decision Makers
MABAC	Multi-Attributive Border Approximation Area Comparison
MCDM	Multi-Criteria Decision Making
NLP	Natural Language Processing
NS	Neutrosophic sets
RI	Random Index
SVNNs	Single Valued Neutrosophic Numbers
SVNSs	Single Valued Neutrosophic Sets
SWARA	Stepwise Weight Assessment Ratio Analysis
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WPM	Weight Product Method
WSM	Weight Sum Method

According to a spate of recent studies [13,14], employing chatbots improves students' capacity to communicate with one another and learn more efficiently. Also, Retailers may use chatbots instead of human customer care representatives to connect with their consumers, market new items, and answer their customers' questions about their purchases and order status changes [15,16].

Although the term "chatbot" is often used to refer to all messaging bots, there are two distinct types: rule-based and AI chatbots. Rule-based chatbots are constrained because they follow a pre-determined set of rules and frequently need users to click through a sequence of buttons to obtain a meaningful result. On the other hand, artificial intelligence (AI) chatbots are more advanced and employ natural language processing (NLP) to identify client sentiment and give tailored service. While rule-based chatbots have their place in some instances, AI chatbots are typically better for businesses trying to boost productivity and improve customer service. Nonetheless, selecting the best chatbot is tricky, mostly due to multiple criteria and expectations [17–20]. Therefore, selecting an optimal chatbot can be considered a multi-criteria decision-making (MCDM) problem [21,22]. E.g.,

(i) Buying decision for a rule-based or AI chatbot depends on multiple things. As previously said, an AI chatbot has more advantages, but those advantages are not always necessary. A lot of brands can get by with a smaller selection. If you have a modest number of items or services to sell and receive few support queries, you could find that a rule-based chatbot is sufficient. Brands with a big catalogue of products and services, on the other hand, would certainly want to invest in an AI chatbot to help customers acquire the information they need without having to click through a long sequence of button prompts. Furthermore, an AI chatbot's machine-learning skills will allow it to scale automatically as the catalogue increases.

(ii) What does a decision-maker expect from the AI chatbot they choose? Are they seeking a customer service assistant or something that can deal with consumers on its own? Is it sufficient for the bot to greet consumers and offer basic information such as support hours, or does the decision-maker want it to gather data and assist in resolving inquiries? Determining the AI chatbot's intended purpose will aid decision-makers in making decisions since they will know what features it needs to have.

(iii) To guarantee no difficulties or service disruptions for clients, decision-makers must ensure that the AI chatbot they choose interacts seamlessly with their systems and workflows. For example, a retailer's AI chatbot should be able to look up past order information from their CRM and verify product availability through the brand's inventory management system. All of their systems should be able to interact with one another to give useful information to both consumers and employees.

(iv) Budget is always a consideration when making a purchase, but it is worth noting that not all AI chatbots provide decision-makers with a plain sticker price. In reality, a number of approaches that impact costs may be used to price AI chatbots. For instance, one AI chatbot may charge depending on the number of site users or chat interactions, while another may charge based on the number of site users or chat interactions. Some AI chatbots even charge for extra features like conversation routing and form integration. When picking an AI chatbot, carefully look through the price model, note the features your company needs, and make sure it fits your budget.

(v) Almost all AI chatbots allow for personalization, although the amount and simplicity this can be done vary greatly from one option to the next. A tough back end-user interface, for example, may make it difficult for support teams to update regularly. Some AI chatbots may adapt replies depending on what a user says during a chat session, while more powerful AI chatbots may be able to propose items and services based on past user behaviors.

(vi) While all AI chatbots arrive with a pre-loaded data set, more complicated bots may require training at the outset and regularly to teach industry-specific terminology and other business-related knowledge such as new goods services, and policies. This is crucial to consider if you need an AI chatbot to be operational by a certain date, such as the start of the Christmas season.

(vii) A decision-maker may wish to collect data on the number of engagements, speed of resolution, CSAT, NPS, and other metrics related to the AI chatbot's interactions. He will be able to discover trends and gain insights about his clients by gathering this data, which will aid him in making changes to his customer service, among other things. Find out what data an AI chatbot will supply and how it will display it when selecting one. He will want the data structured in a style that is simple to interpret and evaluate for your team.

Unfortunately, more complex decision-making settings and hesitant decision-makers (DMs) can make overall decision-making more difficult, especially in confusing or uncertain situations. Consider a suitable uncertainty strategy between the classical sets and their extensions to improve decision-making. Various fuzzy set extensions, including indeterminacy, ambiguity, and uncertainty, can be used to address uncertainty in the chatbot data set. According to traditional set theory, an element may or may not be a member of a set; in optimization, there are only two options: feasible or not feasible; in Boolean logic, a proposition is either true or false; there is no in-between state [23]. Classical reasoning cannot account for everything in the actual world, which is less accurate than it seems. Zadeh [24] created the fuzzy sets theory to deal with this form of uncertainty. Since its initial release in 1965, it has received various modifications and expansions [25–27]. In addition, indeterminacy functions are employed in Neutrosophic Sets [27] to distinguish between degrees of belonging and non-belongingness and express absoluteness and relativeness. With this method, NS can cope with the system's uncertainty while also reducing the amount of ambiguous and incomplete data. The NS has a significant advantage over other fuzzy extensions in this aspect. Three NS functions yield a range area that may be utilized to do mathematical

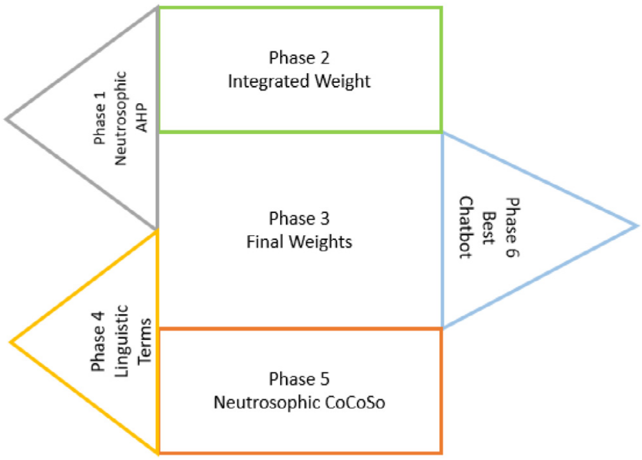


Fig. 1. The proposed framework for this paper.

operations with various degrees of uncertainty. As a result, the NSs offer a suitable, if questionable, paradigm for coping with uncertainty.

Another well-known strategy for dealing with intricate challenges is the Analysis Hierarchy Process (AHP), which breaks them into subtasks and then combines the answers to these sub-problems [28]. In this approach, which depends on expert pairwise judgment, the consistency of the judgments is crucial. Yazdani et al. [29] introduced the CoCoSo (combined compromise solution) technique as a sensible and common-sense way to deal with ambiguity. It has no paradoxical properties like division by zero or antilogarithm [30]. The recommended technique in this study is depicted in Fig. 1. This study comprises six primary phases, as shown in Fig. 1. The weights of chatbot characteristics are computed using the Neutrosophic AHP approach in phase one. The weight from the experts and the AHP approach are combined in Phase 2 using integrated weight. We get the final weights in Phase 3. We assign the linguistic terms in phase 4 to create the choice matrix. In step 5, we rate the alternatives (chatbots) using the neutrosophic CoCoSo. Finally, in phase 6, we deployed the smartest and most efficient chatbots in Egypt for customer care. In this work, three scientific contributions are provided:

(i) Only a few studies have been done on the CoCoSo approach, and none of them has developed a model to deal with the uncertainty of choosing the best chatbot. This research will contribute to closing the gap.
(ii) This study will be the first to integrate the CoCoSo methodology with chatbot selection and neutrosophic AHP techniques.
(iii) This paper develops a novel two-scale system for evaluating qualities and alternatives.

The structure of this paper is laid up as follows: Chatbot and neutrosophic AHP/CoCoSo approaches are examined in Section 2 of this paper. The proposed methodology is presented in Section 3. The case study and the findings of this investigation are presented in Section 4. The sensitivity and comparison analyses are presented in Section 5. The consideration of theoretical and managerial consequences begins in Section 6. Section 7 concludes with some last thoughts and ideas for further research.

2. Literature review

This section presented the previous studies related to the chatbot, neutrosophic AHP, and CoCoSo methods.

2.1. Studies related to Chatbot

Customers' impressions of chatbots across retail industries and the influence chatbots have on consumers' expectations of additional online service experiences with human agents were investigated by Tran et al. [31]. They employed a hybrid automated sentiment analysis approach. As chatbots become more prevalent, they explore how retailers will need to learn more about them as a kind of customer service. According to their results, customers have a more positive view of their online interactions with chatbots than with human operators. They discovered that customers' impressions of online human agents had declined with the advent of chatbots. These findings might be linked to a lack of service quality and customer expectations. Meanwhile, Okonkwo and Ade-Ibijola [32] thoroughly reviewed previous studies on Chatbots in educational contexts. They examined 53 publications from well-known digital archives in total. They talked about the advantages and disadvantages of chatbots in teaching. Instant access to content, motivation and engagement, a large user base, and fast assistance are just a few benefits. Acceptance and use of chatbots in education may be limited by ethics, evaluation, attitude, supervision, and maintenance issues.

Nuruzzaman and Hussain [33] outlined the present status of chatbots and the strategies utilized to create them. They concentrated on the present chatbots' similarities, differences, and limitations. They compared 11 of the most popular chatbot application platforms and their features and technological specifications. According to their poll, many customers have had unsatisfactory customer service, and it is tough to come up with well-thought-out responses to their questions. They built AI chatbots with self-learning capabilities using advanced deep recurrent neural networks. Broeck et al. [34] investigated if and how the observed helpfulness and usefulness of a chatbot on the Facebook Messenger platform affects the pervasiveness of chatbot-initiated advertising. They looked at the link between patronage intentions and how intrusive you are seen by others (i.e. purchase and recommendation intention of the product). They looked at how message acceptance and perceived relevance functioned as moderators and how message acceptance functioned as a mediator. Rapp et al. [11] conducted a meta-analysis of 83 research on how individuals interact with text-based chatbots. During the last decades of research, they described how humans perceive the chatbot in terms of convenience, engagement, and trust, as well as whether and why they admit and use this technology, how emotionally invested they are, what types of drawbacks can be detected in human conversations, and how the chatbot is considered in terms of its humanness. From all these existing studies, it is evident that although there are a few studies related to chatbots and their functionalities, none of them has discussed a suitable way to select an optimal chatbot by considering multiple criteria together.

2.2. Studies related to neutrosophic AHP

The AHP method is common in MCDM literature in computing the weights of criteria in many problems and fields. Ilbahar et al. [35] used the intuitionistic fuzzy AHP to compute the weights of criteria to evaluate the risk of investing in renewable energy. Yilmaz et al. [36] used the spherical fuzzy AHP method to compute the weights of criteria in airport selection. Bak ır and Atal ık [37] proposed a fuzzy AHP method to compute the weights of criteria in assessing e-service quality in the airline industry. Ayyildiz and Gumus [38] proposed a Pythagorean fuzzy AHP approach for hazardous material transportation risk assessment. Their study's key flaw was that they did not account for indeterminacy in their calculations. As a result, the researchers visit the NS to cope with the indeterminacy and uncertainty in their computations. In healthcare enterprise training, Syamsuddin and Warastuti [39] provided a strategy for selecting the appropriate chatbot platform. To cope with ambiguity in calculating the weights of criteria, they adopted the fuzzy AHP technique. They just utilized six criteria and three options. The key flaws are that they do not account for indeterminacy in their calculations, use a limited sample size, and only use one method in their calculations. The AHP technique is excellent for calculating the weights of criteria, but not so much for determining the order of alternatives.

Gulum et al. [40] advocated that for the post-earthquake fire risk issue, the interval-valued neutrosophic-AHP be utilized to determine the weights of the criterion. In customer-oriented product design, Karasan et al. [41] suggested a neutrosophic AHP to weigh client demands. The Interval-Valued Neutrosophic AHP technique was used by Kavus et al. [42] to analyze sub-criteria for airline service quality.

2.3. Studies related to the CoCoSo method

Yazdani [43] presented the CoCoSo decision-making strategy, synthesizing a comparative ability series using an exponentially weighted product and simple additive weighting. It has been successfully utilized to examine industrial technology [29], employee information [44], sustainable supplier evaluation [45], solid waste disposal site selection [46], and OPEC country sustainability [47]. In addition, numerous research employed the CoCoSo in a hazy setting. Narang et al. [47] suggested a fuzzy framework with CoCoSo and the heronian mean operator to choose the best stock. Deveci et al. [48] suggested a fuzzy framework for autonomous vehicle priority in real-time traffic planning using the logarithmic technique, the Power Heronian function, and the CoCoSo methodology. Ulutaş et al. [49] recommended employing fuzzy PSI-PIPRECIA-CoCoCo MCDM to tackle the transportation company choice problem. Their research's fundamental flaw is that they do not consider the indeterminacy value.

Mishra and Rani [50] suggested a Single-valued neutrosophic set (SVNS), CoCoSo, and CRITIC approach for evaluating a third-party reverse logistics provider that is both financially and ecologically feasible. The criteria weights were calculated using the CRITIC approach, and alternatives were ranked using CoCoSo. The study's biggest flaw was that it did not include a significant number of attribute sets. To identify the finest Waste electrical and electronic equipment, Rani and Mishra [51] presented an SVNSs CoCoSo and similarity metric. The criteria weights are computed using the similarity measure, while the rank of alternatives is computed using CoCoSo. Rani et al. [52] presented the SVNSs CoCoSo, and SWARA approaches to choose the best renewable energy sources. The criteria weights were calculated using the SWARA approach, and the alternatives were ranked using CoCoSo. The study's fundamental flaw is that it does not account for subjective and objective factors. Turskis et al. [53] offered a novel model for dealing with uncertainty and ambiguity that included the q-neutrosophic CoCoSo approach with m-generalized. Yazdani et al. [54] suggested an interval-valued fuzzy neutrosophic CoCoSo and CRITIC for supplier selection and performance evaluation. CRITIC was used to calculate the weights of the criterion, and CoCoSo was used to rank the options. Peng and Smarandache [55] suggested a neutrosophic soft sets CoCoSo and CRITIC approach analyze China's rare earth sector security. To rank the options, the CoCoSo technique is employed. The weights of the criterion are calculated using CRITIC. Their study's biggest flaw is that they only employed one decision-maker instead of several decision-makers [56,57]. The CoCoSo was applied in many different industries [58–62]. On the other hand, Chatbot assessment does not employ NSs CoCoSo and AHP-based decision-making processes. It is the first time to introduce the AHP and CoCoSo under single-valued neutrosophic sets.

3. A framework for SVNSs MCDM approach combining AHP and CoCoSo

In this section, the proposed framework was applied which consist of three phases namely data collection from the previous studies such as criteria and alternatives, then the proposed AHP method was sued to compute the weights of criteria, and finally, the CoCoSo method was used to rank and select best chatbot. The neutrosophic sets were sued to overcome the vague and uncertain information. Fig. 2 shows the phases of the proposed framework in this study. The steps of the proposed framework are shown in Fig. 3. The steps of the proposed framework are explained as follows

Table 1
The SVNSs MCDM matrix.

	st_1	st_2	$\cdots$	st_y
ch_1	(c_{11}, d_{11})	(c_{12}, d_{12})	$\cdots$	(c_{1y}, d_{1y})
ch_2	(c_{21}, d_{21})	(c_{22}, d_{22})	$\cdots$	(c_{2y}, d_{2y})
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
ch_x	(c_{x1}, d_{x1})	(c_{x2}, d_{x2})	$\cdots$	(c_{xy}, d_{xy})

Table 2
The neutrosophic linguistic values for assessment attributes by experts.

Variables of linguistic	SVNNs
Poor	(0.15, 0.90, 0.85)
Moderate poor	(0.30, 0.80, 0.70)
Moderate	(0.50, 0.50, 0.50)
Moderate perfect	(0.75, 0.30, 0.35)
Perfect	(0.95, 0.15, 0.20)

3.1. Description of parameters and variables

Suppose ch is a collection of Chatbot (alternatives) $ch = ch_1, ch_2, \ldots, ch_x$, and that st is a set of standards (attribute) $st = st_1, st_2, \ldots., st_y$, and that G is a weight $G = g_1, g_2, \ldots, g_y$ with the range $[0, 1]$, with $\sum_{b=1}^{y} g_b = 1$. For example, use an SVNSs matrix $M = \left(m_{ab}\right)_{x\times y} = (c_{ab}, d_{ab})_{x\times y}$ (where the values of the input variables are $a = 1, 2, \ldots, ., ., x$; $b = 1, 2, \ldots, ., ., y$) to represent the assessment of Chatbot , ch_a in relation to the attribute , st_b. Table 1 shows the evaluation values for each alternative. Fig. 2 depicts the steps for the created methodology. Fig. 3 shows the steps of the AHP and CoCoSo methods.

3.2. Compute the weights of the criteria

3.2.1. The AHP method used to compute the objective weight

It is possible to use attributes as a substantial source of information when making decisions. Attributes of importance "objective weights" are weights that show all of the information stored in them. To deal with uncertainty, the neutrosophic extension AHP method. The following are the steps involved in using this technique:

Step 1: Collect a group of experts, a list of attributes, and data.

A group of decision-makers and experts is identified. The decision-makers are selected by their degree of experience in the field of AI and chatbots. The decision-makers had a Ph.D. and master.

Step 2: Let experts and decision-makers evaluate a list of attributes and build the comparison matrix. Table 2 shows the values for these evaluations.

Step 3: Aggregate the values of experts by the average method and apply the score function as:

$$SC = \left(SC_{ab}\right)_{x\times y} = \frac{2 + T - I - F}{3} \tag{1}$$

Where T,I,F refers to the truth, indeterminacy, and falsity membership degrees.

Step 4: Normalize the comparison matrix f_b as:

$$f_b = \frac{SC_b}{\sum_{b=1}^{y} f_b} \tag{2}$$

Step 5: Compute the weights g_b of attributes:

$$g_b = \frac{\sum_{a=1}^{x} f_{ab}}{y} \tag{3}$$

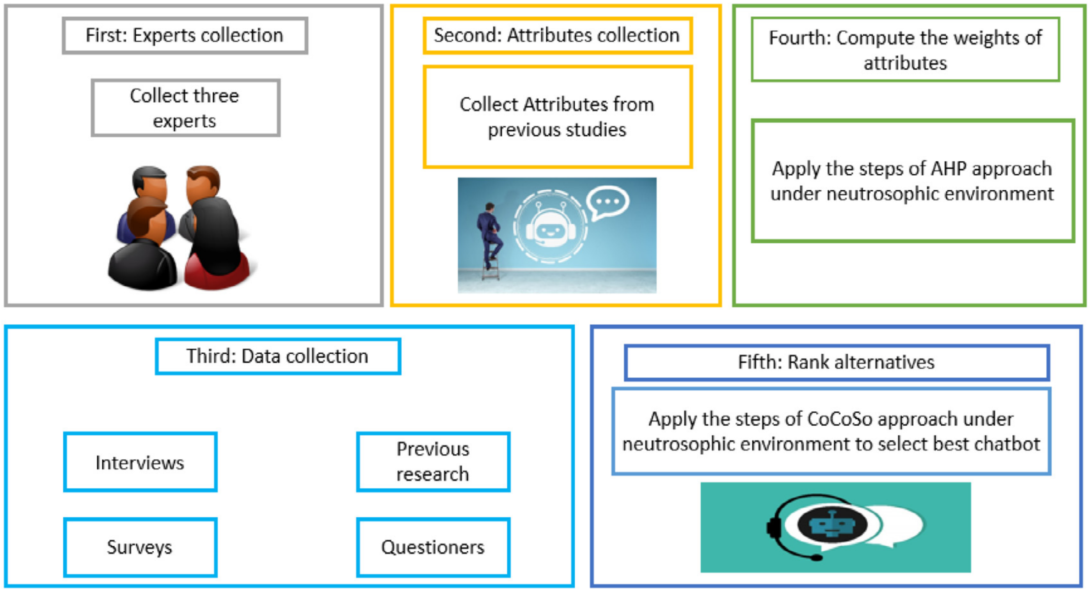


Fig. 2. The steps of the methodology of this study.

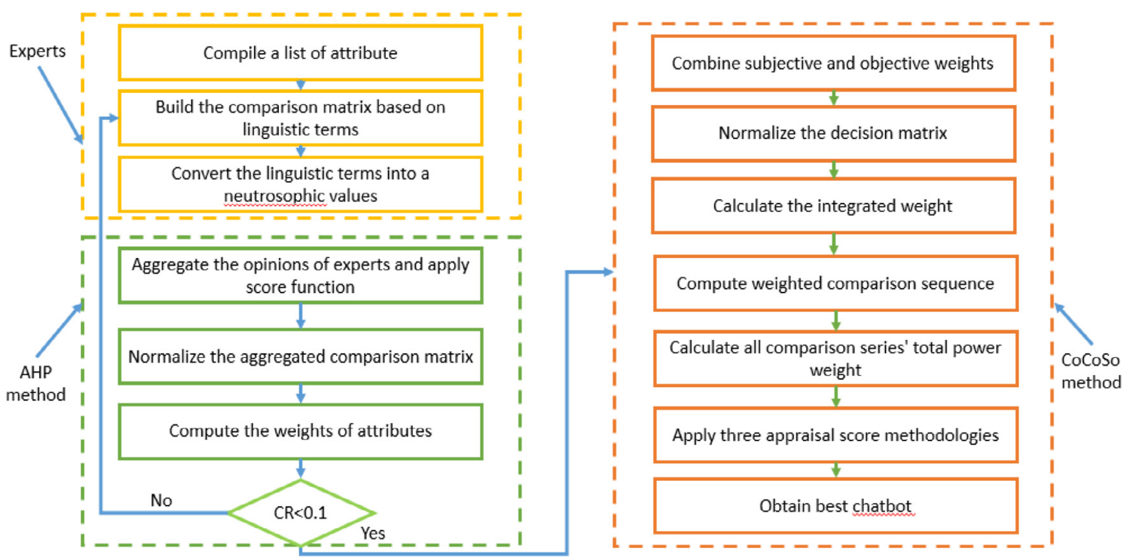


Fig. 3. The steps of the methodology.

Step 6: Check the consistency ratio CR as:

The AHP method is used to compute the consistency to make sure the opinions of experts are consistent by computing the consistency ratio. The consistency ratio is computed by dividing the consistency index and the random index. The consistency ratio must be less than 0.1. If the consistency ratio is less than 0.1, the opinions of experts are consistent, and if the consistency is greater than 0.1, the opinions of experts must be revised again.

$$CR = \frac{CI}{RI} \tag{4}$$

Where CI is the consistency index and RI is the random index.

3.2.2. Calculate the integrated weights using a complete linear weighted technique

Assume that the experts' subjective weight is $S = s_1, s_2, \ldots, s_y$ where $\sum_{b=1}^{y} s_b = 1,\ 0 \le s_b \le 1$. The weight of the objective is computed by Eq. (4) $G = g_1, g_2, \ldots, g_y$ where $\sum_{b=1}^{y} g_b = 1,\ 0 \le g_b \le 1$. So, we can compute the integrated weight $I = i_1, i_2, \ldots, i_y$ as:

$$i_b = \frac{s_b * g_b}{\sum_{b=1}^{y} s_b * g_b} \tag{5}$$

where $\sum_{b=1}^{y} i_b = 1,\ 0 \le i_b \le 1$

A nonlinear weighted synthesis technique combines subjective and objective weights. As the multiplier effect is applied, the greater a weight's subjective or objective weight is, the greater the integrated weight.

3.3. The neutrosophic CoCoSo approach

Yazdani et al. [43] have introduced a successful MCDM method, the Combined Compromise Solution (CoCoSo) method. SAW and EWP models are used as a framework for the proposed method, which might serve as a general summary of the compromise solution. We attempt to present an N-CoCoSo approach to address the MCDM problem in a neutrosophic environment.

The steps of the N-CoCoSo approach are organized as follows:

Table 3
Neutrosophic Linguistic values to evaluate alternatives over attributes.

Variables of Linguistic	SVNNs
More poor	(0.10, 0.85, 0.75)
Poor	(0.25, 0.70, 0.60)
Moderate poor	(0.35, 0.60, 0.55)
Moderate	(0.50, 0.50, 0.50)
Moderate perfect	(0.65, 0.40, 0.45)
Perfect	(0.85, 0.3, 0.40)
More perfect	(0.9, 0.20, 0.30)

Step 7: Build the decision matrix $E = \left(E_{ab}\right)_{x \times y} (a = 1, 2, 3, \ldots, x; b = 1, 2, 3, \ldots, y)$ based on the linguistic values in Table 3 to assess the alternatives and attributes

Step 8: Change the linguistic terms matrix into SVNS decision matrix $M = \left(m_{ab}\right)_{x \times y} = (c_{ab}, d_{ab})_{x \times y}$

Step 9: Aggregate the decision matrix and apply the score function as in Step 2.

Step 12: Normalize the decision matrix as:

$$N_{ab} = \begin{cases} \frac{SC_{ab} - \min_b SC_{ab}}{\max_b SC_{ab} - \min_b SC_{ab}} & for\ positive\ attributes \\ \frac{\max_b SC_{ab} - SC_{ab}}{\max_b SC_{ab} - \min_b SC_{ab}} & for\ cost\ attributes \end{cases} \tag{6}$$

Step 11: Calculate the integrated weight by Eq. (5).

Step 12: A weighted comparison sequence should be calculated for every alternative q_a as:

$$q_a = \sum_{b=1}^{y} i_b * N_{ab} \tag{7}$$

Step 13: Calculate all comparison series' total power weights for every alternative

$$o_a = \sum_{b=1}^{y} \left(N_{ab}\right)^{i_b} \tag{8}$$

Step 14: The next aggregating procedures are used to obtain the relative weights of the options. Eqs. (9)–(11) are used to calculate the relative weights of other alternatives in this stage, utilizing three appraisal score methodologies.

$$h_{a1} = \frac{q_a + o_a}{\sum_{a=1}^{x} (q_a + o_a)} \tag{9}$$

$$h_{a2} = \frac{q_a}{\min_a q_a} + \frac{o_a}{\min_a o} \tag{10}$$

$$h_{a3} = \frac{\lambda q_a + (1 - \lambda) o_a}{\lambda \min_a q_a + (1 - \lambda) \min_a q_a}, 0 \leq \lambda \leq 1 \tag{11}$$

Weight sum method (WSM) and Weight product method (WPM) scores are represented by the arithmetic mean (h_{a1}), a comparison of the best scores (h_{a2}) of WSM and WPM, and a balanced compromise (h_{a3}) between the top scores from each model (WSM and WPM).

Step 15: Calculate the evaluation value h_a as:

$$h_a = \sqrt[3]{h_{a1} h_{a2} h_{a3}} + \frac{h_{a1} + h_{a2} + h_{a3}}{3} \tag{12}$$

Step 16: Rank the alternatives according to their diminishing h_a evaluation values.

4. Case study in Egypt

Human capital is the most valuable asset in any firm. For example, the bigger a company's human resource capacity, the more likely it is to achieve its goals and objectives. In telecommunications firms, this is a challenging task. An Egyptian telecommunications business with millions of clients was used as a case study. Due to a large number of clients, employees are assigned many jobs, such as answering their queries at any time, meeting their wants, and so on. The effectiveness of the human agent deteriorates from time to time, and consumer complaints rise. As a result, this paper offers the main solution for a telecommunication business in Egypt to pick the finest chatbot to assist it in achieving its objectives.

In this section, the outcomes from the proposed AHP and CoCoSo methods under neutrosophic sets are explained. The AHP method was applied to compute the weights of the criteria. The CoCoSo method was applied to rank the alternatives.

Step 1: Fig. 4 shows the attributes (all attributes are positives) for this study collected by three experts. They have expertise in Chatbots and decision-making. The data was collected from previous research, interviews, questions, and surveys.

Step 2: Build the comparison matrix.

Step 3: Obtain one matrix by applying the average method. Then apply the score function in Eq. (1) to obtain SC_{ab} values.

Step 4: Apply Eq. (2) to obtain the f_b normalization values

Step 5: Using Eq. (3) to obtain the weights of attributes g_b as:

$g_1 = 0.021839, g_2 = 0.032536, g_3 = 0.038038, g_4 = 0.086758, g_5 = 0.104356, g_6 = 0.138716, g_7 = 0.155136, g_8 = 0.194131, g_9 = 0.22849$

Step 6: Apply Eq. (4) to check the consistency ratio. From the calculations, the CR is 0.079. Hence the CR is less than 0.1. Hence, experts' opinions are consistent, and then we are ready to apply the CoCoSo method to rank the alternatives.

Step 7: Use linguistic terms in Table 3 to create the decision matrix that contains the linguistic terms.

Step 8: Change the linguistic terms matrix into the SVNNs decision matrix.

Step 9: Aggregate the decision matrix and apply the score function as presented in Table 4 to obtain the decision matrix after the aggregation process.

Step 10: Normalize the decision matrix using Eq. (6) as presented in Table 5.

Step 11: Calculate the integrated weight by Eq. (5).

Step 12: A weighted comparison sequence should be calculated for every alternative q_a using Eq. (7) as presented in Table 6.

Step 13: Calculate all comparison series' total power weights for every alternative o_a using Eq. (8) as presented in Table 6.

Step 14: Eqs. (9)–(11) are used to calculate the relative weights of other alternatives in this stage, utilizing three appraisal score methodologies as presented in Table 6.

Step 15: Calculate the evaluation value h_a using Eq. (12) as presented in Table 6.

Step 16: Rank the alternatives according to their diminishing h_a evaluation values as:

$$ch_2 \succ ch_7 \succ ch_3 \succ ch_5 \succ ch_1 \succ ch_8 \succ ch_6 \succ ch_4$$

In this paragraph, the discussion of the previous steps are explained. In the first part of the results, the AHP method is integrated with neutrosophic sets to compute the weights of criteria. There are nine criteria collected from previous studies namely security, speed, responsiveness, satisfaction, reliability, assurance, tangibility, engagement, and empathy. There are three experts to evaluate the criteria. The experts used single-valued neutrosophic numbers to evaluate the criteria. The single-valued neutrosophic numbers included three values (true, indeterminacy, and false membership values). The experts built the pairwise comparison matrix on the data collected from previous studies. From the steps of the AHP method, criterion 9 is the highest importance and criterion 1 is the lowest importance. The data are consistent by the consistency ratio. From the results the consistency ratio is less than 0.1 so, the data is consistent.

In the second part of the results, the CoCoSo method was applied to rank the alternatives. The three experts evaluate the criteria and alternatives. There are eight chatbots collected to choose the best one. The CoCoSo ranked the second chatbot as the best one, followed by the seventh chatbot, followed by the third chatbot, followed by the fifth chatbot, followed by the first chatbot, followed by the eighth chatbot, and the worst chatbot is the fourth chatbot.

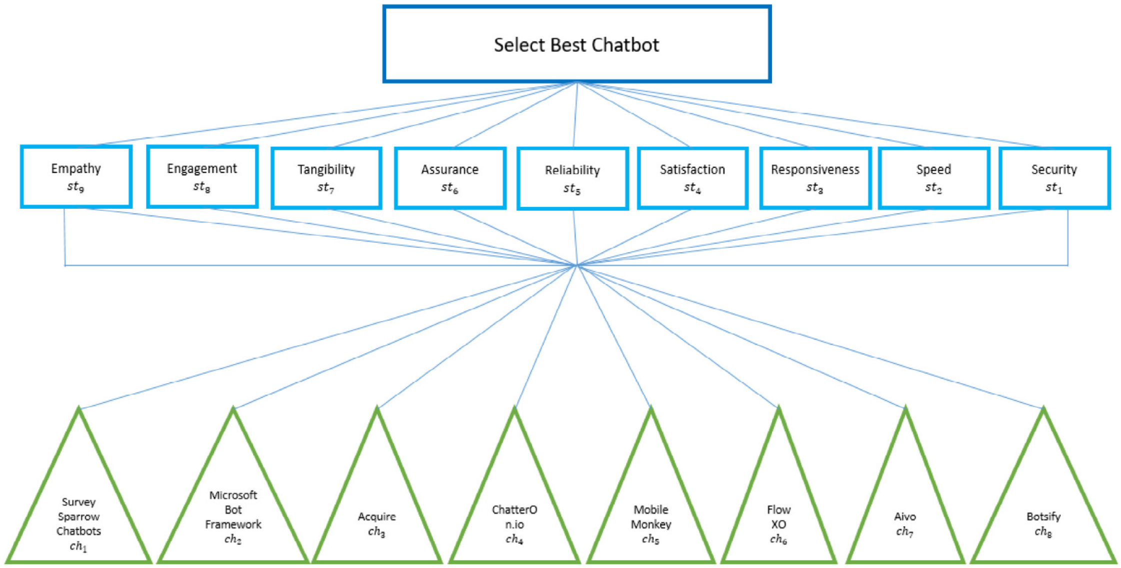


Fig. 4. The attributes and alternatives for this study.

Table 4
Aggregated decision matrix.

ch_x/st_y	st_1	st_2	st_3	st_4	st_5	st_6	st_7	st_8	st_9
ch_1	0.7667	0.5722	0.5442	0.4778	0.6109	0.6773	0.3056	0.7053	0.4833
ch_2	0.5829	0.6000	0.6389	0.6000	0.6000	0.8000	0.5829	0.8000	0.5555
ch_3	0.3611	0.3167	0.6000	0.6944	0.4111	0.5056	0.3389	0.7773	0.7160
ch_4	0.5056	0.4111	0.5222	0.4942	0.3167	0.3611	0.3611	0.4498	0.4111
ch_5	0.5829	0.7160	0.6389	0.3167	0.6944	0.6000	0.7160	0.8000	0.3833
ch_6	0.3167	0.5555	0.5555	0.6722	0.7160	0.8000	0.5111	0.3833	0.4111
ch_7	0.6109	0.8000	0.6000	0.3611	0.7440	0.3611	0.6389	0.8000	0.7160
ch_8	0.6000	0.6773	0.6389	0.3833	0.5111	0.3833	0.6000	0.5829	0.4778

Table 5
Normalized decision matrix.

ch_x/st_y	st_1	st_2	st_3	st_4	st_5	st_6	st_7	st_8	st_9
ch_1	1.0000	0.5287	0.1887	0.4265	0.6885	0.7205	0.0000	0.7728	0.3007
ch_2	0.5916	0.5862	1.0000	0.7500	0.6630	1.0000	0.6757	1.0000	0.5177
ch_3	0.0987	0.0000	0.6667	1.0000	0.2210	0.3291	0.0812	0.9456	1.0000
ch_4	0.4198	0.1954	0.0000	0.4700	0.0000	0.0000	0.1353	0.1595	0.0836
ch_5	0.5916	0.8262	1.0000	0.0000	0.8840	0.5443	1.0000	1.0000	0.0000
ch_6	0.0000	0.4942	0.2857	0.9412	0.9345	1.0000	0.5008	0.0000	0.0836
ch_7	0.6538	1.0000	0.6667	0.1176	1.0000	0.0000	0.8121	1.0000	1.0000
ch_8	0.6296	0.7462	1.0000	0.1764	0.4550	0.0506	0.7174	0.4790	0.2840

Table 6
Values of q_a, o_a, h_{a1}, h_{a2}, h_{a3} and, h_a .

ch_x	q_a	o_a	h_{a1}	h_{a2}	h_{a3}	h_a
ch_1	0.473748	7.475195	0.129138	5.255748	0.839707	2.903963
ch_2	0.760248	8.706078	0.15379	7.758206	1	4.031293
ch_3	0.607652	7.313349	0.128684	6.273881	0.836756	3.290553
ch_4	0.127359	4.866734	0.081134	2	0.527564	1.310293
ch_5	0.594865	6.888719	0.121578	6.086227	0.790548	3.169114
ch_6	0.441633	6.383968	0.110889	4.779368	0.72104	2.596102
ch_7	0.735345	7.774207	0.138246	7.371198	0.898929	3.773983
ch_8	0.415035	7.989553	0.136541	4.900435	0.88784	2.81558

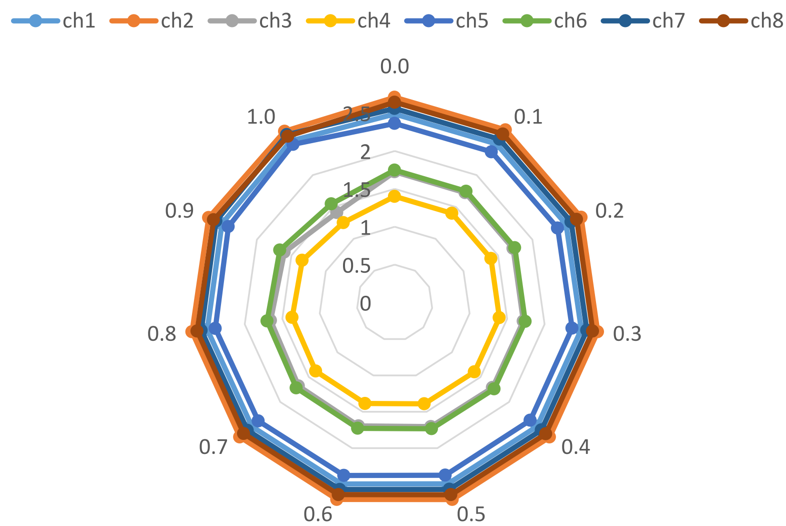
5. Further analysis

To justify the practicability and robustness of the proposed MCDM technique, this study further analyzed its sensitivity and then compared it against a few state-of-the-art MCDM techniques.

5.1. Sensitivity analysis

We developed a λ with a value of 0.5 in the proposed model. But in this subsection, we will change the λ between 0 and 1 to show the effect on the rank alternatives in Fig. 5. We conclude with chatbots $(ch_1, ch_3, ch_4, ch_5, ch_6 and, ch_8)$ decision values are reduced when the parameter λ is increased. We can conclude that chatbot (ch_7) decision values increased when this parameter λ is increased and chatbot (ch_2) never changed after increasing or decreasing the value of λ, hence the chatbot (ch_2) not sensitive. We can conclude that the rank in all cases never changed as.

$$ch_2 \succ ch_7 \succ ch_3 \succ ch_5 \succ ch_1 \succ ch_8 \succ ch_6 \succ ch_4$$



λ	ch_1	ch_2	ch_3	ch_4	ch_5	ch_6	ch_7	ch_8
0.0	2.916	4.031	3.293	1.329	3.170	2.604	3.770	2.835
0.1	2.915	4.031	3.293	1.327	3.170	2.603	3.770	2.833
0.2	2.913	4.031	3.292	1.324	3.169	2.602	3.771	2.830
0.3	2.911	4.031	3.292	1.321	3.169	2.601	3.772	2.826
0.4	2.908	4.031	3.291	1.316	3.169	2.599	3.773	2.822
0.5	2.904	4.031	3.291	1.310	3.169	2.596	3.774	2.816
0.6	2.898	4.031	3.290	1.302	3.169	2.592	3.776	2.807
0.7	2.890	4.031	3.288	1.289	3.169	2.587	3.779	2.794
0.8	2.876	4.031	3.286	1.267	3.168	2.578	3.783	2.772
0.9	2.847	4.031	3.281	1.220	3.167	2.559	3.792	2.726
1.0	2.753	4.031	3.265	1.050	3.164	2.499	3.821	2.576

Fig. 5. The rank of alternatives after changing in the λ value.

Table 7
Ranking outcomes from comparison methods.

Approaches	Ordering	Best Chatbot
SVN-MABAC	$ch_2 \succ ch_7 \succ ch_3 \succ ch_5 \succ ch_1 \succ ch_6 \succ ch_8 \succ ch_4$	ch_2
Pythagorean fuzzy CoCoSo	$ch_2 \succ ch_3 \succ ch_7 \succ ch_5 \succ ch_1 \succ ch_6 \succ ch_8 \succ ch_4$	ch_2
interval-valued neutrosophic TOPSIS	$ch_2 \succ ch_7 \succ ch_3 \succ ch_5 \succ ch_6 \succ ch_8 \succ ch_1 \succ ch_4$	ch_2
Proposed model	$ch_2 \succ ch_7 \succ ch_3 \succ ch_5 \succ ch_1 \succ ch_8 \succ ch_6 \succ ch_4$	ch_2

Table 8
Spearman's rank correlation test outcomes.

Methods	Correlation
Proposed method and SVN-MABAC method	0.97619
Proposed method and Pythagorean fuzzy CoCoSo method	0.95238
Proposed method and interval-valued neutrosophic TOPSIS method	0.904762

5.2. Comparative analysis

Comparing the created MCDM framework to existing approaches demonstrates its usefulness and viability. SVN-MABAC [63], Pythagorean fuzzy CoCoSo [30], and interval-valued neutrosophic TOPSIS [64] methods are used to compare the Chatbot choice problem using the same weight information to demonstrate the suggested method's applicability. Table 7 shows the rank of different methods. We compared the proposed model with the SVN-MABCA, and we found the ch_2 is the best chatbot also in our proposed model. When comparing interval-valued neutrosophic TOPSIS and the proposed model, we found the best chatbot is ch_2.

Table 8 shows that the Pythagorean fuzzy CoCoSo and SVN-CoCoSo techniques generate essentially equal results. The proposed method's outcomes have been verified. The Pythagorean fuzzy CoCoSo, on the other hand, does not take the indeterminacy value into account in their computations. As a result, our suggested approach handles uncertainty and ambiguity information more effectively. Our judgment was also validated using the SVN-MABAC approach. The SVN-MABAC results reveal that the ch_2 is the best chatbot. The test with our technique is 0.98, as shown in Table 8. Our suggested model and interval-valued neutrosophic TOPSIS correlate by 0.91, indicating a strong relationship between the two approaches.

The larger the disparity, the more indecisive the experts are. However, if the experts' indecision grows, the results will be hard to verify. The neutrosophic notion, which considers indeterminacy, can help decision-makers distinguish between absolute and relative realities.

6. Managerial implications

Our research provides recommendations and cautions for businesses and service managers interested in using the finest chatbots in their organizations. Chatbots can reduce operational costs for organizations while also responding to consumers' demands for speed and convenience [65]. According to our studies, customer satisfaction may be improved by utilizing the best chatbot rather than exclusively human personnel. Firms must carefully assess the current degree of technology maturity and its potential impact on other customer service efforts to deploy chatbots successfully. Security, timeliness, and consumer expectations of service quality, according to our results, are the most important customer demands and are similar across diverse service offerings. Choosing the finest chatbot can raise customer expectations and satisfaction while reducing human agent mistakes. Managers should keep this in mind when they train front-line personnel to meet consumers' changing expectations for service delivery. According to our findings, customers' demands will be met by picking an appropriate customer service chatbot.

7. Conclusions

The use of chatbots is fast-growing, much like instant messaging, and they are already being incorporated into common tasks like shopping, customer service, and teaching. Selecting a chatbot from a pool of candidates based on various criteria is a difficult and risky MCDM problem. Using SVNNs data, the article proposes an MCDM framework for addressing the chatbot evaluation problem. To do so, a new NS-AHP-CoCoSo methodology is created, which combines the regular CoCoSo method, SVNSs operations, and the AHP framework with SVNSs conditions. The weights of the qualities were evaluated using the AHP method. The CoCoSo method was used to rank and select the best chatbot. The AHP is an effective model due to computing the consistency of the pairwise comparison (opinions of experts). After then, a case study of the chatbot customer service assessment and selection problem was investigated using SVNS contexts, proving the applicability and practicality of the proposed technique. The suggested technique's efficacy has been established compared to existing methodologies. Finally, sensitivity analysis and comparative analysis were used to show that the new approach was stable and the robustness of this model. The results show that the second chatbot is the best than the seventh chatbot.

Another MCDM approach, such as BWM, SWARA, or CRITIC, might be used in the future to combine with the CoCoSo method to solve this problem. Other uncertainty problems, such as robot selection, renewable energy selection, and others, will be addressed using the suggested technique.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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