Using a TOPSIS Method to Evaluate and Select AI Chatbots for Improving Customer Service Communication

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Received: October 25, 2025 Accepted: November 18, 2025 Online Published: November 26, 2025

doi:10.5430/jms.v16n2p28 URL: https://doi.org/10.5430/jms.v16n2p28

Abstract

Chatbot has become an innovation for business to connect with customers. People can communicate with technology devices in the same way they would with real people through Chatbots. Traditional Chatbots typically depend on already programmed principles and replies, while AI (artificial intelligence) Chatbots comprehend and dynamically respond to user inquiries utilizing natural language processing (NLP) and machine learning (ML). Chatbots powered by AI have an increased requirement to communicate with customers in a fast and effective way. People can communicate with technology devices like they were speaking to a real person, which are software programs that simulate human conversation which can be texts or speeches. Many criteria quantitative criteria, including frequently asked questions (FAQs), security, brands, improving efficiency, and enhancing engagement, etc., and quantitative criteria, including cost, bot analytics built-in templates and customer relationship management (CRM), etc., need to be considered when evaluating AI Chatbots for companies to enhance customer service. Moreover, criteria may have different importance. Therefore, evaluating AI Chatbots is a MCDM (multiple criteria decision making) problem. Many companies do not know how to select the most suitable one to serve their customers. To address this issue, the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), one of MCDM approaches, is used to evaluate AI Chatbots; and criteria weights will be produced by applying BWM (Best Worse Method). A numerical example will be used to present feasibility of the used method, and a comparison will be conducted to display its effectiveness.

Keywords: AI, Chatbot, AI Chatbot, BWM, TOPSIS

1. Introduction

Today, the Internet has become an important part of people's lives, affecting almost every daily activity. One of the major impacts is the way people now purchase business, leading to the huge growth of e-commerce. E-commerce is expanding rapidly, with online sales growing at a rate of 20-25% annually. For consumers, buying products or services online means speed, efficiency, a wide selection of options, and convenient choices that affect consumer habits and influence how businesses approach sales and marketing (Gunasekaran et al., 2002). ELIZA (Weizenbaum, 1966) and PARRY (Kenneth, 1972), the two most famous early Chatbots, were created specifically to imitate written conversations. Nowadays, modern Chatbots, such as ChatGPT, frequently rely on massive language models known as generative pre-trained transformers (GPT). They are built on a deep learning architecture called transformer, which includes artificial neurons and learns how to create text by training on a large text collection using a minimal amount of task-specific data (OpenAI, 2023). Faruk (2017) did research and found that 4 percent of businesses set up Chatbots. Based on 2016 research, 80% of organizations want to have Chatbots by 2020 (Business Insider, 2016). In 2016, Facebook Messenger enabled programmers to develop Chatbots for the platform (Constine, 2016).

In contrast to traditional Chatbots, which typically depend on already programmed principles and replies, AI Chatbots comprehend and dynamically respond to user inquiries utilizing natural language processing (NLP) and machine learning (ML) (Salesforce, 2024). Businesses now have an excellent opportunity to handle issues brought up in the quickly evolving marketplace of today thanks to artificial intelligence (AI) (Borges et al., 2021). For example, Chatbots powered by AI now have an increased requirement to communicate with customers in a fast and effective way (Chung et al., 2020). People can communicate with technology devices like they were speaking to a real person thanks to Chatbots, which are software programs that simulate human conversation which can be texts or speeches (Oracle, 2024). There are some Business Chatbots, for example Tidio, Chatfuel, Botsify, Drift, ManyChat, Ada, SnatchBot, etc. Businesses can choose the most suitable that best for their businesses by evaluating many criteria (Sapardic, 2024). Chatbots continue to become more proficient in conducting conversations (Wang et al., 2022) that allows businesses in responding to changes in economic conditions and customer needs (Chiu & Chuang, 2021). In the marketing sector, there are five key functions of Chatbots which have been identified, for example, interaction, entertainment, trendiness, customization, and problem-solving. These functions can be seen as important roles of Chatbots for customer service (Chung et al., 2020).

Chatbots improves service quality and allows businesses to respond quickly, enhancing customer satisfaction and building loyalty. Consequently, Chatbots provide good service that consumers are willing to pay more for convenient and responsive brands (Chung et al., 2020). Therefore, business managers should choose the suitable Chatbot for their business. However, many criteria need to be considered when evaluating and selecting an AI Chatbot for companies to enhance customer service. Those criteria can be classified as qualitative criteria, such as frequently asked questions (FAQs), security, personalization, brands (Sapardic, 2024), improves efficiency and productivity, and enhances engagement and experience (Salesforce, 2024), etc. and quantitative criteria, such as cost, rating (Sapardic, 2024), bot analytics, built-in templates and customer relationship management (CRM) integration (Sapardic, 2024), etc. Therefore, evaluating AI Chatbots is a MCDM (multiple criteria decision making) problem. To address this issue, this research project proposes TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) to evaluate and select AI Chatbots and weights of criteria will be produced by using BWM (Best Worse Method) for enhancing customer service communication to improve company service.

The rest of this work is organized as follows. Section 2 introduces literature review. Section 3 introduces model establishment. Section 4 presents an example to show the feasibility of the suggested method, and a numerical comparison is conducted to show the effectiveness of the proposed method. Conclusion is finally made in Section 5.

2. Literature Review

2.1 AI

Traditional Chatbots typically rely on already programmed principles and replies, AI Chatbots comprehensively and dynamically responds to user inquiries by natural language processing (NLP) and machine learning (ML), allowing them to get involved in greater natural and contextually relevant conversations, adapting to user inputs over time, and dealing with many issues with more accuracy and efficiency (Salesforce, 2024).

AI has created a significant chance for businesses to find solutions to the difficulties faced by nowadays rapidly expanding marketplace (Chung et al., 2020). Businesses now have excellent opportunities to handle issues brought up in the quickly evolving marketplace of today thanks to AI (Borges et al., 2021). Nowadays, AI is applied in many fields. For example, Chatbots powered by AI now have an increased requirement to communicate with customers in a fast and effective way (Chung et al., 2020). In the education field which is about AI Chatbots' impact on teaching and learning strategies in higher education (Stöhr et al., 2024). Baffour Gyau et al., 2024 demonstrated that using artificial intelligence technology in banking and finance improves banks' return on assets, emphasizing its importance in boosting financial performance. Especially, ChatGPT has demonstrated the usefulness of GenAI-powered Chatbots in answering crisis-related inquiries in a timely and cost-effective manner, showing its potential to replace human roles in crisis communication (Xiao & Yu, 2025).

2.2 Chatbot

People can communicate with technology devices in the same way they would with real people through Chatbots, software that simulates human conversations through text or voice. Chatbots can range from simple programs that provide direct answers to a single question to sophisticated digital assistants that can learn and adapt as they collect and analyze more information to provide more personalized responses (Oracle, 2024). There are some Business Chatbots, for example Tidio, Chatfuel, Botsify, Drift, ManyChat, Ada, SnatchBot, etc. Companies can choose the most suitable Chatbot for their businesses by evaluating many criteria (Sapardic, 2024).

A number of criteria, including perceived value, perceived enjoyment, and the authenticity of the discussion, could affect users' acceptance of Chatbots based on the pleasure theory and the technology acceptance model (Rese et al., 2020). Chatbot has been applied in many different business fields, for instance online banking, e-service agents for luxury brands, airline carrier, travel agency, telecommunications, rail transport, furniture retailing, health insurance, mobile services, car rental, clothing company, hotel, and so on (Wang et al., 2022). Nowadays, Chatbot has become an innovation for business to connect with customers (Shumanov & Johnson, 2021). Through understanding of Chatbots' features and functionalities, some studies have begun to investigate the influence of Chatbot use on business results with a concentration on customer service (Rese et al., 2020). There were some researches that have examined the Chatbots using. For example, some earlier research has looked at the use of Chatbots in a variety of sectors, including apparel and communication services (Etemad-Sajadi & Ghachem, 2015). More recently, when a customer's personality matches with that of a Chatbot, they can use the Chatbot for longer that examined the way consumers used Chatbots perspective and within the framework of mobile services (Shumanov & Johnson, 2021). In addition, Chatbot has been studied by some authors using fuzzy set theory. For example, Sihotang et al. (2020) researched about answering Islamic questions with a Chatbot using fuzzy string-matching algorithm. Another study used fuzzy AHP approach to select Chatbot platform for health industry environment (Syamsuddin & Warastuti, 2021). Almansor and Hussain (2021) did research focusing on human thinking and reasoning to model Chatbot quality of services based on recognizing the breakdown using fuzzy prediction. Moreover, a study using fuzzy logic for more effective Chatbot for sickness and drug prediction by processing of natural languages was conducted by PhaniRaghava and Kumar (2022). Troussas et al. (2023) introduced fuzzy logic knowledge modeling for dynamic Chatbot adaptation for customized learners' assistance.

2.3 AI Chatbot

In contrast to traditional Chatbots, which typically depend on already programmed principles and replies, AI Chatbots comprehend and dynamically respond to user inquiries utilizing natural language processing (NLP) and machine learning (ML). This allows them to get involved in greater natural and contextually relevant conversations, adapt to user inputs over time, and deal with a range of issues with more accuracy and efficiency. There are some common types of AI Chatbots in customer service, for example transactional Chatbots, informational Chatbots, problem-solving Chatbots, feedback and survey Chatbot and hybrid Chatbots (Salesforce, 2024). Chatbots powered by AI now have an increased requirement to communicate with customers in a fast and effective way (Chung et al., 2020). Nowadays, most people know ChatGPT that can answer crisis-related questions in a fast time and cost saving way showing its potential to replace human roles in crisis communication (Xiao & Yu, 2025). For example, Ghadge et al. (2022) did research about Medbot: An interactive Chatbot powered by artificial intelligence that helps with phone health checkups after COVID-19. Another study by Chang et al. (2023) investigates the elements that impact solo travelers' purchase intentions when utilizing AI Chatbots, focusing on the three primary aspects of marketing efforts, communication quality, and emotional characteristics. Utilizing AI-powered Chatbots would increase information sharing (Al-Emran et al., 2023). Other researchers demonstrated the fascinating potential of AI-powered Chatbots to revolutionize healthcare information delivery, focusing on the need for continuous improvement and user-centered evaluations to maximize their effectiveness (Truong & Doan, 2024). A study was researched about using generative AI Chatbots to increase online grocery shopping trust (Chakraborty et al., 2024). AI Chatbots' impact on teaching and learning strategies in higher education have been discussed by Stöhr et al., (2024). In addition, AI Chatbot has been studied by some authors using Fuzzy. Fuzzy set theory has been used in many studies about AI Chatbot in different business fields. For instance, research used the fuzzy AHP approach to evaluate AI Chatbot platform characteristics that businesses may use when choosing Chatbot installing solutions to improve company performance (Nguyen, 2021). Ghadge et al., (2022) applied Fuzzy IF-THEN rule base for their research about AI Chatbot for helping with the post-COVID-19 telephone health checkup service. A fuzzy-set qualitative comparative analysis of the impact of artificial intelligence Chatbots on Malaysian solo travelers' purchase intentions (Chang et al., 2023). Al-Emran et al. (2023) found that a fuzzy-set qualitative comparative analysis could influence the adoption of AI Chatbots, which can improve knowledge transfer.

2.4 TOPSIS

In order to handle challenges in making decisions involving different attributes, Hwang and Yoon (1981) developed Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). It depends on the idea that the chosen alternative should be most similar to the positive-ideal solution (PIS) and furthest from the negative-ideal solution (NIS) (Lai et al., 1994). Classical TOPSIS describes a (PIS) as one that maximizes benefits while minimizing costs, whereas a (NIS) minimizes benefits while increasing costs. The PIS and NIS are defined based on criterion values determined from comparing alternatives. However, this may not always be suitable if the Technical Experts know the input values beforehand. To compare alternatives to reference points (PIS and NIS), the Classical TOPSIS technique is modified to include PIS and NIS as dummy alternatives in the analysis (known as the "modified TOPSIS" approach). This technique is applied when rating or choosing one or more options (such as selection techniques) based on a number of criteria from a limited number of options (Yeh, 2002).

TOPSIS is applied for decision making of many different industries. In 2004, some authors applied the TOPSIS approach with the gray relational model to choose a host nation for expatriates. A real-world case study on expatriate assignment decision-making demonstrated how this integrated methodology offers a trustworthy and efficient evaluation framework (Chen & Tzeng, 2004). The Fuzzy Analytic Hierarchy Process (FAHP) and TOPSIS techniques are used to assess the performance of Turkish cement companies. Based on comments from decision-makers, the criterion weights are determined using the FAHP, and the businesses are then ranked using the TOPSIS method (Ertuğrul & Karakaşoğlu, 2009). In Turkey, some researchers analyzed company competition in domestic airline market applying the fuzzy TOPSIS which provided significant insights by evaluating major airlines based on essential success variables in the sector by Torlak et al. (2010). Kusi-Sarpong et al., 2015 conducted comprehensive evaluation of green supply programs using a set theory and fuzzy TOPSIS within the green supply chain practices framework for the mining industry. A study about quality e-Banking websites that used TOPSIS Method to identify the best e-banking websites through a selected multi-criteria approach and provided conclusions that could serve as a foundation for developing innovative and effective solutions in the field (Chmielarz & Zborowski, 2018). A modified TOPSIS was used to determine acceptable approaches in continuing monitoring for Avian Influenza in Canada (Allaki et al., 2019). Damle & Krishnamoorthy (2022) used TOPSIS technique for a complete ranking of indicators to improve decision-making in predicting levels and discovery of key technological drivers in the pharmaceutical business. TOPSIS explored Industry 4.0 technologies to improve manufacturing enterprise safety management in large food company (Forcina et al., 2024). Entropy and TOPSIS techniques were used to choose an intelligent and safe Internet of Things-based educational system. While TOPSIS was utilized to rank the smart school systems and assess the necessary parameters, entropy was utilized to ascertain the relevance of each criterion. The problem of finding a smart and secure IoT-based educational system was successfully solved by this strategy. The study determined which of the assessed educational systems was the most intelligent and secure (Khan et al., 2024). Chu & Nguyen (2025) suggested evaluating AI Chatbots via a MCDM method but algorithms are not displayed. However, there is no research about choosing a suitable AI Chatbot by TOPSIS. To fill this gap, this study applies TOPSIS method to evaluate an AI Chatbot, with criteria weights being determined through BWM.

3. Model Establishment

Assume that there are k decision makers ($D_{t,} t = 1,2,\dots,k$) who are responsible for evaluating m alternatives, AI Chatbot, ($A_i,\ i = 1,2,\dots,m$) u0.0nder *n* criteria ($C_j, j = 1,2,\dots,n$). Criteria can further be classified to benefit (B) and cost (C) ones. Benefit criteria have the characteristics of larger-is-better, while cost criteria have the characteristics of smaller-is-better. Further assume that weights of criteria are produced by BWM. The proposed BWM based TOPSIS method is established as the following steps.

Step 1. Determine criteria

Suppose the decision makers determine nine criteria as follows.

Quantitative Criteria:

1. Cost (C1): smaller-the-better
2. Response Time (C2): smaller-the-better
3. Recognition Accuracy (C3): larger-the-better
4. Completion Rate (C4): larger-the-better
5. User Satisfaction (C5): larger-the-better

Qualitative Criteria:

6. Adaptability and Learning (C6): larger-the-better
7. Complexity of Implementation (C7): smaller-the-better
8. Understanding Context (C8): larger-the-better
9. Response Flexibility (C9): larger-the-better

Step 2. Normalize values under criteria

Assume that x_{ij} represents the numerical value of alternative A_i under criterion $C_j, j = 1{\sim}n$. The normalized value, r_{ij} of x_{ij} can be obtained by applying the following two equations.

Large-the-better (LTB): $r_{ij} = \frac{x_{ij}-x_{ij}^{-}}{x_{ij}^{+}-x_{ij}^{-}}, i = 1\sim m, j = 1\sim n,\ j \in B$ (1)

Small-the-better (STB): $r_{ij} = \frac{x_{ij}^{+}-x_{ij}}{x_{ij}^{+}-x_{ij}^{-}}, i = 1\sim m, j = 1\sim n,\ j \in C$ (2)

where x_{ij}^{+} denotes the maximal value of alternative A_i under criterion $C_j C_j$; and x_{ij}^{-} denotes the minimal value of alternative A_i under criterion C_j.

Step 3. Determine weights by BWM

The Best–Worst method (Rezaei, 2015) is used to determine the weights of criteria as follows. Suppose decision makers determine a pairwise comparison vector for the best criterion in the structure by using Eq. (3), and that for the worst criterion by using Eq. (4).

$$E_B = (e_{B1}, \ldots, e_{Bi}, \ldots, e_{Bn}) \quad (3)$$

$$E_W = (e_{1W}, \ldots, e_{iW}, \ldots, e_{nW}) \quad (4)$$

where e_{Bi} indicates the preference of the best criterion *B* over criterion *i*, e_{Wi} indicates the preference of the criterion *i* over the worst criterion *W*.

The BWM model is shown as Eq. (5) (Rezaei, 2015):

$$\left|\frac{w_B}{w_i} - e_{Bi}\right| \le \xi, \text{ for all } i$$

$$\left|\frac{w_i}{w_W} - e_{iW}\right| \le \xi, \text{ for all } j \quad (5)$$

$\sum_i w_i = 1 \sum_i w_i = 1,\ w_i \ge 0$ for all *j*

And the consistency ration of the matrix is obtained by the Eq. (6)

$$CR = \frac{\xi^*}{CI} \quad (6)$$

where $\xi^*$is the optimal solution of Eq. (4), consistency index (CI) can be seen as in Table 1. The weights can be obtained using Eqs. (5) and (6).

Table 1. Consistency index (CI)

a_{BW}	1	2	3	4	5	6	7	8	9
CI	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

Step 4. Determine weighted normalized decision matrix

$V = [v_{ij}]$, $\mathbf{v_{ij}} = r_{ij} \otimes w_j$, $i = 1\sim m, j = 1\sim n.$

Step 5. Determine PIS and NIS

The positive ideal solution (PIS), s^{+}, and negative ideal solution (NIS), s^{-}, can be obtained by the following equations.

$$s^{+} = \left(v_1^{+}, \cdots, v_j^{+}, \cdots v_n^{+}\right) \text{ where} v_j^{+} = \max_i v_{ij},\ i = 1\sim m, j = 1\sim n. \quad (7)$$

$$s^{-} = \left(v_1^{-}, \cdots, v_j^{-}, \cdots v_n^{-}\right) \text{ where } v_j^{-} = \min_i v_{ij},\ i = 1\sim m, j = 1\sim n. \quad (8)$$

Step 6. Calculate distance of each alternative from PIS (d_i^+) and NIS (d_i^-)

$$d_i^+ = \sum_{j=1}^{n}\left(v_j^+ \quad v_{ij}\right) \tag{9}$$

$$d_i^- = \sum_{j=1}^{n}\left(v_{ij} \quad v_j^-\right) \tag{10}$$

Step 7. Determine ranking

The closeness coefficient, CC_i, of each alternative for ranking order all is shown as the following equation. The d_i^- is regarded as benefit criterion and is larger-better; while d_i^- is regarded as cost criterion and is smaller-better. The d_i^- and d_i^- may have different importance to different decision makers. Herein, we use AHP to produce the weights and conduct a sensitivity analysis to analyze the result behavior of the suggested method. And he larger CC_i value has higher ranking order.

$$CC_i = w_1 d_i^- - w_2 d_i^+ \tag{11}$$

where $w_1 + w_2 = 1, 0 \leq w_i \leq 1, i = 1 \sim 2$

4. Numerical Example

Suppose a company wants to buy an AI Chatbot to improve its customer service communication, three professional decision makers of this company form a committee to conduct this study. Further suppose the three decision makers have reached a consensus to screen out five alternatives for final evaluation and the nine criteria in Step 1 is used. Suppose the ratings of each alternative under each criterion is obtained as in Table 2.

Table 2. Ratings of Alternatives under Criteria

Criteria	A1	A2	A3	A4	A5
C1	200	100	150	170	140
C2	3.2	2.5	2.9	3.0	2.8
C3	88	91	85	84	89
C4	80	90	85	84	88
C5	75	85	95	78	86
C6	60	70	68	63	67
C7	3	2	2.5	2.8	2.7
C8	80	78	88	79	82
C9	70	65	72	71	67

By step 2, the normalized values can be obtained as shown in Table 3. By step 3, weights can be produced by BWM as shown in Table 4. By step 4, weighted normalized decision matrix can be produced as shown in Table 5.

Table 3. Normalized Ratings of Alternatives under Criteria

Criteria	A1	A2	A3	A4	A5
C1	0.000	1.000	0.500	0.300	0.600
C2	0.000	1.000	0.429	0.286	0.571
C3	0.571	1.000	0.143	0.000	0.714
C4	0.000	1.000	0.500	0.400	0.800
C5	0.000	0.500	1.000	0.150	0.550
C6	0.000	1.000	0.800	0.300	0.700
C7	0.000	1.000	0.500	0.200	0.300
C8	0.200	0.000	1.000	0.100	0.400
C9	0.714	0.000	1.000	0.857	0.286

Table 4. Weights of Criteria Produced by BWM

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
Weights	0.199	0.100	0.028	0.080	0.199	0.242	0.050	0.044	0.057

Table 5. Weighted Normalized Ratings

Criteria	A1	A2	A3	A4	A5
C1	0.000	0.199	0.100	0.060	0.119
C2	0.000	0.100	0.043	0.029	0.057
C3	0.016	0.028	0.004	0.000	0.020
C4	0.000	0.080	0.040	0.032	0.064
C5	0.000	0.100	0.199	0.030	0.109
C6	0.000	0.242	0.194	0.073	0.169
C7	0.000	0.050	0.025	0.010	0.015
C8	0.009	0.000	0.044	0.004	0.018
C9	0.041	0.000	0.057	0.049	0.016

By step 5, the positive ideal solution (PIS), s^{+}, and negative ideal solution (NIS), s^{-}, can be obtained as displayed in Table 6.

Table 6. PIS (s^+) and NIS (s^-)

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
s^+	0.199	0.100	0.028	0.080	0.199	0.242	0.050	0.044	0.057
s^-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

By step 6, the distance of each alternative from s^+ and s^- can be obtained as follows.

Table 7. Distances d_i^+ and d_i^-

Distance	A1	A2	A3	A4	A5
d_i^+	0.933	0.201	0.294	0.713	0.411
d_i^-	0.066	0.799	0.705	0.286	0.588

Finally, the closeness coefficients can be produced by step 7 as shown in Table 8.

Table 8. Closeness Coefficients

Distance	A1	A2	A3	A4	A5
CC_i	0.066	0.799	0.706	0.286	0.589

According to Table 8, CC_2 has the largest value, 0.799. Therefore, A2 is our choice. Now we conduct a comparison with various weights for w_1 and w_2 using AHP as follow.

Table 9. Weights by AHP

(a_1,a_2)	(1,1)	(2,1/2)	(3,1/3)	(4,1/4)
(w_1,w_2)	(0.5,0.5)	(0.667,0.333)	(0.75,0.25)	(0.8,0.2)
(5,1/5)	(6,1/6)	(7,1/7)	(8,1/8)	(9,1/9)
(0.833,0.167)	(0.857,0.143)	(0.875,0.125)	(0.889,0.111)	(0.9,0.1)
(a_1,a_2)	(1,1)	(1/2,2)	(1/3,3)	(1/4,4)
(w_1,w_2)	(0.5,0.5)	(0.333,0.667)	(0.25,0.75)	(0.2,0.8)
(1/5,5)	(1/6,6)	(1/7,7)	(1/8,8)	(1/9,9)
(0.167,0.833)	(0.143,0.857)	(0.125,0.875)	(0.111,0.889)	(0.1,0.9)

Table 10. $(a_1, a_2) = (1,1)$

w_1	0.5
w_2	0.5

Distance	A1	A2	A3	A4	A5
CC_i	-0.434	0.299	0.206	-0.214	0.089

Table 11. $(a_1, a_2) = (2,1/2)$

w_1	0.667
w_2	0.333

Distance	A1	A2	A3	A4	A5
CC_i	-0.267	0.466	0.372	-0.047	0.255

Table 12. $(a_1, a_2) = (3,1/3)$

w_1	0.75
w_2	0.25

Distance	A1	A2	A3	A4	A5
CC_i	-0.184	0.549	0.455	0.036	0.338

Table 13. (a_1, a_2) = (4,1/4)

w_1	0.8
w_2	0.2

Distance	A1	A2	A3	A4	A5
CC_i	-0.134	0.599	0.505	0.086	0.388

Table 14. (a_1, a_2) = (5,1/5)

w_1	0.833
w_2	0.167

Distance	A1	A2	A3	A4	A5
CC_i	-0.101	0.632	0.538	0.119	0.421

Table 15. (a_1, a_2) = (6,1/6)

w_1	0.857
w_2	0.143

Distance	A1	A2	A3	A4	A5
CC_i	-0.077	0.656	0.562	0.143	0.445

Table 16. (a_1, a_2) = (7,1/7)

w_1	0.875
w_2	0.125

Distance	A1	A2	A3	A4	A5
CC_i	-0.059	0.674	0.580	0.161	0.463

Table 17. (a_1, a_2) = (8,1/8)

w_1	0.889
w_2	0.111

Distance	A1	A2	A3	A4	A5
CC_i	-0.045	0.688	0.594	0.175	0.477

Table 18. (a_1, a_2) = (9,1/9)

w_1	0.9
w_2	0.1

Distance	A1	A2	A3	A4	A5
CC_i	-0.034	0.699	0.605	0.186	0.488

Table 19. (a_1, a_2) = (1/2,2)

w_1	0.333
w_2	0.667

Distance	A1	A2	A3	A4	A5
CC_i	-0.600	0.132	0.039	-0.380	-0.078

Table 20. (a_1, a_2) = (1/3,3)

w_1	0.25
w_2	0.75

Distance	A1	A2	A3	A4	A5
CC_i	-0.683	0.049	-0.044	-0.463	-0.161

Table 21. (a_1, a_2) = (1/4,4)

w_1	0.2
w_2	0.8

Distance	A1	A2	A3	A4	A5
CC_i	-0.733	-0.001	-0.094	-0.513	-0.211

Table 22. (a_1, a_2) = (1/5,5)

w_1	0.167
w_2	0.838

Distance	A1	A2	A3	A4	A5
CC_i	-0.771	-0.035	-0.129	-0.550	-0.246

Table 23. (a_1, a_2) = (1/6,6)

w_1	0.143
w_2	0.857

Distance	A1	A2	A3	A4	A5
CC_i	-0.790	-0.058	-0.151	-0.570	-0.268

Table 24. (a_1, a_2) = (1/7,7)

w_1	0.125
w_2	0.875

Distance	A1	A2	A3	A4	A5
CC_i	-0.808	-0.076	-0.169	-0.588	-0.286

Table 25. (a_1, a_2) = (1/8,8)

w_1	0.111
w_2	0.889

Distance	A1	A2	A3	A4	A5
CC_i	-0.822	-0.090	-0.183	-0.602	-0.300

Table 26. (a_1, a_2) = (1/9,9)

w_1	0.1
w_2	0.9

Distance	A1	A2	A3	A4	A5
CC_i	-0.833	-0.101	-0.194	-0.613	-0.311

According to from Table 10 to Table 26, CC_2 always has the largest value which is consistent to the traditional method showed in Table 8. Therefore, A2 is our choice.

5. Conclusion

Chatbots powered by AI have an increased requirement to communicate with customers in a fast and effective way. People can communicate with technology devices like they were speaking to a real person, which are software programs that simulate human conversation which can be texts or speeches. Many criteria must be considered so it is a MCDM Problem. This paper suggests TOPSIS to evaluate AI Chatbots for company to select the most suitable one. A numerical example has shown the feasibility of the used TOPSIS method and a comparison is conducted to display the robustness of the used method.

Acknowledgments

The authors would like to sincerely thank the Editor, Ms. Catherine and anonymous reviewers for providing helpful comments. Their comments led to a better presentation of the ideas in this paper. This work was supported in part by the National Science and Technology Council, Taiwan, under Grant NSTC 113−2410−H−218−011.

Authors' contributions

Ms. Thi Bao Tram Nguyen was responsible for study design and revising. Ms. Thi Bao Tram Nguyen was responsible for data collection. Ms. Thi Bao Tram Nguyen drafted the manuscript and Prof. Ta-Chung Chu revised it. Prof. Ta-Chung Chu provided budget to pay APC. All authors read and approved the final manuscript. In this paragraph, Ms. Thi Bao Tram Nguyen contributed 80% and Prof. Ta-Chung Chu contributed 20% to the study.

Funding.

This work was supported in part by the National Science and Technology Council, Taiwan [Grant NSTC 113-2410-H-218-011].

Competing interests

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

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of Sciedu Press.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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