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A Pentagonal Neutrosophic TODIM Approach for Multi-Criteria Decision-Making in Digital Banking Chatbot Assessment

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Abstract

"Chatty robots," or chatbots, are a mix of the terms "chat" (to converse) and "bots," which is short for robots. A robot is any machine that has been programmed and managed by a computer. As the banking business evolves into a 24/7 service sector, it is imperative that customers receive continuous help; nevertheless, human agents are unable to meet this demand alone. This resulted in the creation of automated systems, like chatbots, that can manage complex problems with the aid of built-in system rules or external human input. These machines efficiently do difficult, dangerous, and repetitive tasks that were previously impossible for people to accomplish. Robotic process automation, or RPA, is crucial to modern banking because it reduces human costs, minimises operational errors, and ensures continuous, high-efficiency service. Chatbots are an extension of RPA that enhances service delivery, optimises client interactions, and boosts operational efficiency. Given the increasing reliance on online banking, it is critical to understand the key factors that influence chatbot efficacy. This study examines important chatbot assessment criteria in the West Bengal banking sector using a Pentagonal Neutrosophic Number (PNN)-based TODIM technique for multi-criteria decision-making (MCDM). In order to demonstrate how RPA and AI-powered chatbots are transforming digital banking and customer relationship management while giving financial institutions useful data, this study looks at usability, security, flexibility, and customer satisfaction.

Keywords: Chatbots, Multi-Criteria Decision Making (MCDM), Pentagonal Neutrosophic Number, TODIM.

Introduction

In order to efficiently handle their wide variety of goods and services, banks have used chatbots for customer care. According to Takuma Okuda, chatbots start automatic, 24/7 consumer communication (1). These are software applications that let users communicate via messaging apps or chat windows (2). Banks are using AI to improve their decision-making skills in an effort to improve service quality and boost consumer satisfaction (3). Chatbots help banks evaluate and improve their services by collecting thorough client feedback. Additionally, they may answer questions via messaging apps like WhatsApp and Messenger, offering precise, prompt answers for a reasonable price. Banks may now provide more individualised services thanks to AI, which increases client pleasure, engagement, and loyalty and boosts income (4). Chatbots provide customers with easy access to useful information, and banks are increasingly using them to provide customised services. As computer usage increased, there was a need for natural language human-machine interaction, which led to the development of chatbots (5). Chatbots employ natural language technology to facilitate task-oriented, text-based interactions with users Christiane Volkle (6, 7). According to Licht and Euwen, these are AI-powered messaging tools that function as interactive services that are available via chat interfaces (8, 9). Joseph Weizenbaum, a scientist at MIT, created the first chatbot, ELIZA, in the 1960s. It functioned as a mental therapist and used simple keyword recognition (10). ELIZA's fundamental methodology is still the cornerstone of contemporary chatbots, despite being simplistic by today's standards. Chatbots are now

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indispensable in banking because of the tremendous advancements made in them by AI and machine learning since then (11). The study evaluates chatbots for online banking using a multi-criteria decision-making (MCDM) paradigm. The primary goal of the Pentagonal Neutrosophic TODIM approach is to assess chatbot effectiveness based on key performance metrics. Using a structured multi-criteria decision-making (MCDM) methodology, the main goal is to evaluate how Robotic Process Automation (RPA) might enhance the performance of digital banking chatbots. This study specifically intends to (i) identify and analyse important factors influencing chatbot efficiency in the banking industry, (ii) use the Pentagonal Neutrosophic Number (PNN)-based TODIM method to develop a robust decision-making framework, (iii) assess the effects of RPA-driven chatbots on banking operations and customer relationship management (CRM), and (iv) offer strategic insights for optimising chatbot deployment in financial institutions. By accomplishing these goals, this study improves customer service effectiveness and advances intelligent automation in digital banking. A thorough literature review is provided in Section II, which covers earlier studies on chatbot effectiveness, robotic process automation (RPA), and multi-criteria decision-making (MCDM) techniques in online banking. The mathematical preliminaries and methodology are described in Section III and IV, which also describes how the Pentagonal Neutrosophic Number (PNN)-based TODIM algorithm is used to assess chatbot performance. In-depth analysis and findings are presented in Section V, where the suggested model is used and important discoveries are explained. Section VI wraps up the study by outlining the main findings, going over its limitations, and making recommendations for further research.

Theory of Vagueness

Fuzzy set theory was first presented in response to the increasing ambiguity and uncertainty in human thought (12). Since then, it has been extensively used in a variety of scientific and industrial domains. More recently, researchers have developed fuzzy numbers that are pentagonal, hexagonal and heptagonal (13-15). Atanassov later presented the idea of the intuitionistic fuzzy set (IFS) (16). This notion combines membership and non-membership functions. Building on these advancements, the neutrosophic set (NS) was introduced (17). This set can better handle complicated situations since it has three membership functions: truth, falsity, and hesitation. In keeping with this direction, the concept of the pentagonal neutrosophic number (PNN) was evolved, leading to the creation of a categorization system for PNN in research settings (18-20).

Chatbots in Banking Industry

The banking sector was one of the first to use chatbots; by Juniper Research projects that 90% of bot interactions in banking would be successful. Unlike IVR systems, which often leave consumers waiting in lines, chatbots are advanced software applications created to interact with customers in a human-like way. By rapidly answering questions, chatbots greatly increase customer satisfaction. For common enquiries like account balances, utility payments, balance transfers, and ATM locations, customers like the real-time answers chatbots provide (21). Chatbots use predictive analytics to understand consumer intent and react appropriately. In the case of card theft, several banks have even created bots that may restrict a customer's card. Chatbots are strengthening client ties by providing 24/7 help. Chatbots are increasingly more action-oriented as their skills have grown, going beyond just responding to enquiries to personalising items according to user requirements and preferences. Chatbots answer consumer questions, freeing up bank staff to work on human-intensive activities. Banks can handle millions of requests per month at a fraction of the expense of human labour because to their ability to manage several enquiries at once. Thus, chatbots save a lot of money; according to Juniper Research, they might save banks more than USD 8 billion (22). The Evolution from Mobile Banking to Conversational Banking is mentioned in Figure 1.

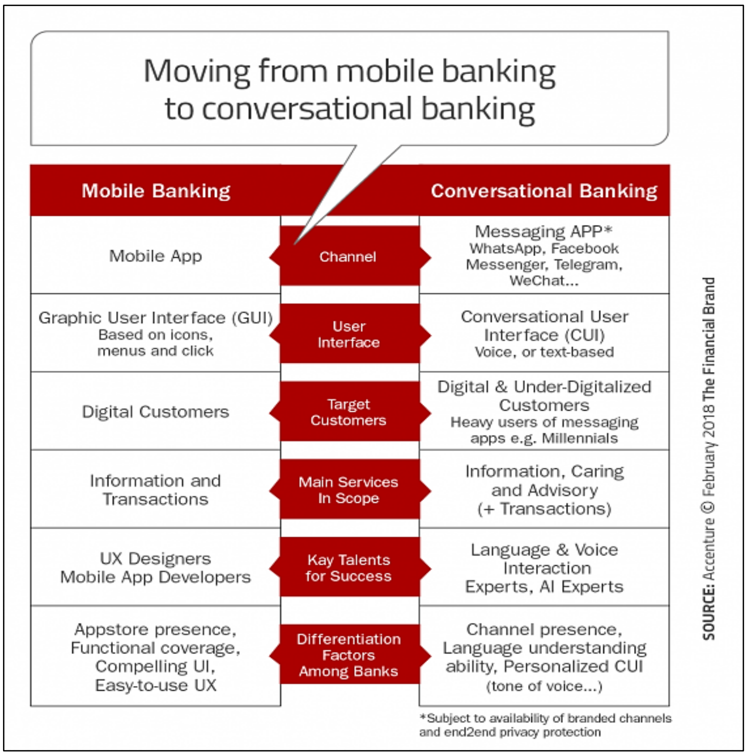

Figure 1: Evolution from Mobile Banking to Conversational Banking

Software applications called chatbot conversational agents are made to speak to users in natural language (9). AI chatbots in the banking sector enable automated customer-bank contact generating natural language replies (23, 24). Since their first application in online banking, chatbots have become more prevalent via mobile messaging interfaces, contributing to the growth of conversational commerce. With chatbots offering real-time guidance, alerts, and interactive call-to-action alternatives, this change enables consumers to purchase online (25). Modern chatbots, enhanced by AI, are able to understand the intents and emotions of customers and provide pertinent plans and goods based on personal preferences, thus increasing customer happiness and revenues via tailored services (26).

An Overview of Chatbots and Virtual Assistants Used in Indian Banking

State Bank of India (SBI): SBI's artificial intelligence-powered chatbot, SIA, can process 864 million questions per day and 10,000 requests per second, or about 25% of all queries handled. SIA's original purpose was to respond to enquiries on SBI's offerings, services, ATMs, and IFSC codes (27, 28).

HDFC Bank: HDFC's first AI-powered chatbot, EVA, responds to consumer questions in milliseconds using AI and natural language processing. With an accuracy record of more than 85%, EVA has processed more than 5 million enquiries from over a million customers. With a 90% accuracy rate, it handles 7,500 FAQs and facilitates over 16 million interactions in 20,000 daily conversations throughout the globe (29, 30).

ICICI Bank: With a 90% accuracy rate, ICICI's AI chatbot, iPal, has handled about 1 million monthly requests across its website and mobile applications, providing 6 million replies. Additionally, iPal has language and voice capabilities and is compatible with platforms such as Google Assistant, Siri, and Facebook Messenger (31).

Yes Bank: YES ROBOT has communicated with 9.8 million customers with a 90% accuracy rate, using AI and natural language processing. To provide customers a more complete experience, the bank is adding voice command capabilities to YES ROBOT (32).

IndusInd Bank: By integrating Indusassist, IndusInd'schatbot, with Amazon Alexa, users may access financial services by using voice commands. By connecting Indusassist with the Internet of Things, this initiative seeks to expand banking outside conventional channels (33).

Kotak Bank: With a 93% accuracy rate, Keya, Kotak's AI-powered chatbot, has responded to 3.5

million questions from more than 1 million clients. For customer service, it makes use of automated voice recognition and natural language processing (34).

Axis Bank: Axis Bank worked with Singapore-based tech startup Active AI to build its chatbot, Aha. This sophisticated chatbot can manage financial transactions via text and speech (35, 36).

Andhra Bank: Using AI and natural language processing, the chatbot ABHI provides services to Andhra Bank's 5 million clients. WhatsApp users may access ABHI, which improves user convenience (37, 38).

Bank of Baroda: Bank of Baroda's Assisted Digital Interaction (ADI) chatbot answers questions about the bank's products using IBM Watson's API (39, 40).

Union Bank of India (UBI): UBI introduced UVA, a chatbot, on the occasion of its 99th anniversary. Nevertheless, UVA has not revealed precise engagement numbers or comprehensive information about its technology partners (41).

Canara Bank: Mitra and CANDI are two robots that Canara Bank has used for client service. Apart from answering enquiries, CANDI functions as a security robot with an HD camera and has two modes: a banking mode that responds to 215 specific requests and a standard one that answers general questions (42, 43).

Multi-criteria decision-making (MCDM), especially when numerous criteria are involved, has emerged as an important field of decision-focused study in recent years. Applications for multi-criteria group decision-making (MCGDM) issues are many, particularly when dealing with complicated criteria. In order to address these concerns, the attribute value of single-valued neutrosophic numbers (SVNN) was used in MCDM problems with the ELECTRE approach. A solution for MADM problems requiring intuitionistic neutrosophic sets (INS) was suggested based on the ELECTRE approach (44, 45). Additionally, a strategy was devised for addressing MCDM difficulties using the interval-valued neutrosophic EDAS process (46, 47). To rank options in MADM situations, Chiranjibe and Madhumangal presented a novel aggregation operator of single-valued neutrosophic (SVN) soft numbers (48). The Portuguese acronym for "interactive and multi-criteria decision-making," or TODIM, is a useful MADM technique that is based on the subjective assessments of the decision-makers. In order to address MCDM difficulties, Gomes and Lima first used the prospect theory-based TODIM model, which Krohling and Souza then modified for fuzzy TODIM policies (49, 50). For both interval and single-valued neutrosophic situations, Xu *et al*., expanded the TODIM technique (51). Other methods have also been developed to handle decision-making issues in neutrosophic contexts, notably in the social sciences where decision-making may be particularly challenging due to unclear data. These methods include VIKOR, TOPSIS, MOORA and GRA (52-55). In order to determine the most important chatbot variables in the digital banking industry, this research presents a PNN-based MCDM technique. Based on their online marketing reports, we collected data from a number of digital banks and discovered that this data is prone to ambiguity and swings. We invented PNN to better results in such uncertain contexts since these imprecisions required a sophisticated methodology. The approach also takes decision-makers' preferences into account and incorporates changing weights across various criteria. Lastly, the PNN framework was used to address a TODIM-based MCDM issue pertaining to digital marketing chatbots, providing a fresh method for handling MCDM difficulties in further studies.

Methodology

Mathematical Preliminaries

Neutrosophic Set: A set $\tilde{S}_N$is considered the universe of discourse for R and is recognized as a neutrosophic set if defined as:

$$S^{\sim}{}_{N} = \left\{\langle\sigma; \left[\phi^{\sim}{}_{R_N}(\sigma), \delta^{\sim}{}_{R_N}(\sigma), \emptyset^{\sim}{}_{R_N}(\sigma)\right]\rangle : \sigma \in R\right\} \quad [1]$$

where:

$$\varphi_{\widetilde{S_N}}(\sigma): R \to 0,1\ +\ represents\ the\ index\ of\ accuracy, \quad [2]$$

$$\delta_{\widetilde{S_N}}(\sigma): R \to 0,1\ +\ represents\ the\ index\ of\ confusion \quad [3]$$

$$\emptyset_{\widetilde{S_N}}(\sigma): R \to 0{,}1 + \text{ represents the index of inaccuracy in the decision} - \text{making process.} \quad [4]$$

These values satisfy the inequality constraint:

$$-0 \le sup\phi^{\sim}{}_{S_N}(\sigma) + sup\delta^{\sim}{}_{S_N}(\sigma) + sup\emptyset_{\widetilde{S_N}} \le 3+ \quad [5]$$

This formulation offers a sophisticated framework for managing uncertainty in decision-making situations by allowing the representation of correctness, confusion, and inaccuracy indices inside the neutrosophic set.

Single-Valued Neutrosophic Set: A Single-Valued Neutrosophic Set, denoted $(S^{\tilde{}}{}_{N})_{SV}$, if ∈ is a single-valued self-decisive variable. The set $(S^{\tilde{}}{}_{N})_{SV}$ is defined as:

$$(S^{\tilde{}}{}_{N})_{SV} = \{\langle \epsilon; [\partial_{S^{\tilde{}}_N}(\epsilon), \pi_{S^{\tilde{}}_N}(\epsilon), \theta_{S^{\tilde{}}_N}(\epsilon)] \rangle : \epsilon \in R\} \quad [6]$$

Where $\partial_{S^{\tilde{}}_N}(\in)$, $\pi_{S^{\tilde{}}_N}(\in)$ and $\theta_{S^{\tilde{}}_N}(\in)$represent the accuracy, confusion, and fallacy membership functions, respectively.

The set $S^{\sim}{}_{NC}$ is termed neutrosophic-convex if it satisfies the following properties, indicating that $S^{\sim}{}_{NC}$ is a subset ofR:

$$\partial_{S^{\tilde{}}_N}(\omega k_1 + (1-\omega)k_2) \ge \left(\partial_{S^{\tilde{}}_N}(k_1), \partial_{S^{\tilde{}}_N}(k_2)\right) \quad [7]$$

$$\pi_{S^{\tilde{}}_N}(\omega k_1 + (1-\omega)k_2) \le \left(\pi_{S^{\tilde{}}_N}(k_1), \pi_{S^{\tilde{}}_N}(k_2)\right) \quad [8]$$

$$\theta_{S^{\tilde{}}_N}(\omega k_1 + (1-\omega)k_2) \le \left(\theta_{S^{\tilde{}}_N}(k_1), \theta_{S^{\tilde{}}_N}(k_2)\right) \quad [9]$$

Where$K_1, K_2 \in R$and $w \in R$

Single-Valued Pentagonal Neutrosophic Number: A Single-Valued Pentagonal Neutrosophic Number $P^{\sim}{}_N$ is designated as:

$$P^{\sim}{}_N = \langle [(v_1, v_2, v_3, v_4, v_5); \alpha], [(v_1, v_2, v_3, v_4, v_5); \beta], [(v_1, v_2, v_3, v_4, v_5); \gamma] \rangle \quad [10]$$

The following defines the uncertain membership function $(\emptyset_{\tilde{R}}): R \to [\beta, 1]$, the exactness membership function $(\varphi_{\tilde{R}}): R \to [0, \alpha]$, and the falseness membership function $(\mu_{\tilde{R}}): R \to [\gamma, 1]$:

$$\varphi_{\tilde{R}}(x) = \begin{cases} \dfrac{\alpha(x-v_1)}{(v_2-v_1)} & v_1 \le x \le v_2 \\ \dfrac{\alpha(x-v_2)}{(v_3-v_2)} & v_2 \le x < v_3 \\ \alpha & x = v_3 \\ \dfrac{\alpha(v_4-x)}{(v_4-v_3)} & v_3 < x \le v_4 \\ \dfrac{\alpha(v_4-x)}{(v_5-v_4)} & v_4 \le x \le v_5 \\ 0 & otherwise \end{cases} \quad [11]$$

$$\emptyset_{\tilde{R}}(x) = \begin{cases} \dfrac{v_2 - x + \beta(x-v_1)}{(v_2-v_1)} & v_1 \le x \le v_2 \\ \dfrac{v_3 - x + \beta(x-v_2)}{(v_3-v_2)} & v_2 \le x < v_3 \\ \beta & x = v_3 \\ \dfrac{x - v_3 + \beta(v_4-x)}{(v_4-v_3)} & v_3 < x \le v_4 \\ \dfrac{x - v_4 + \beta(v_5-x)}{(v_5-v_4)} & v_4 \le x \le v_5 \\ 1 & otherwise \end{cases} \quad [12]$$

$$\mu_{\tilde{R}}(x) = \begin{cases} \dfrac{v_2 - x + \gamma(x-v_1)}{(v_2-v_1)} & v_1 \le x \le v_2 \\ \dfrac{v_3 - x + \gamma(x-v_2)}{(v_3-v_2)} & v_2 \le x < v_3 \\ \gamma & x = v_3 \\ \dfrac{x - v_3 + \gamma(v_4-x)}{(v_4-v_3)} & v_3 < x \le v_4 \\ \dfrac{x - v_4 + \gamma(v_5-x)}{(v_5-v_4)} & v_4 \le x \le v_5 \\ 1 & otherwise \end{cases} \quad [13]$$

Proposed Score Function: To turn a neutrosophic fuzzy number into a crisp one, a scoring function is required in the pentagonal neutrosophic field. The truthiness, uncertainty, and falseness measures are the only factors that affect the scoring function. A novel scoring function in a pentagonal neutrosophic scenario is described here. Consequently, for each single pentagonal neutrosophic number that is written

$$\tilde{n}_{Neu} = (a_1, a_2, a_3, a_4, a_5; T_{Pt}, I_{Pt}, F_{Pt}) \quad [14]$$

We describe the score function as:

$$N_{Sc} = \frac{1}{15}(a_1 + a_2 + a_3 + a_4 + a_5) \times (2 + T_{Pt} - I_{Pt} - f_{Pt}) \quad [15]$$

A wide range of participants, including students and staff members from different West Bengali organisations, provided the data. The majority of these participants were from corporate, governmental, and public sector organisations, as well as the education and service sectors. A total of 628 people took part in the poll. A five-point Likert scale, with 1 denoting strong agreement and 5 denoting severe disagreement, was used. Men made up 59.08 percent of the responders, while women made up 40.90 percent.

Problem Definition: The research employs a multi-criteria decision-making (MCDM) framework to assess chatbots for digital banking. Using the Pentagonal Neutrosophic TODIM technique, the main objective is to evaluate chatbot efficacy according to key performance indicators.

Justification for the Selected Approach: The Pentagonal Neutrosophic TODIM method was selected due to its ability to manage imprecision and ambiguity in decision-making. The neutrosophic extension more accurately represents hesitancy, inconsistency, and partial truth in expert judgements than classic TODIM, which depends on clear or fuzzy values. Because of this, it is appropriate for subjective evaluations such as chatbot evaluation. TODIM incorporates psychological behaviour into decision-making, which makes it more in line with preferences in the actual world than other MCDM techniques (such as TOPSIS and VIKOR).

Research Tool: The Demographic Profile serves as the study's independent variable. Awareness of chatbots in the banking sector and a comparison between chatbots and mobile applications were the main topics of the inquiry.Respondents' demographic details are mentioned in Table 1 and acceptance of Chatbots is indicated in Table 2. Comparison of Effectiveness, Speed, Safety and Ease of Use is mentioned in Figure 2.

Table 1: Respondents' Demographic Details

Distinctiveness	Category	Occurrence	%
Gender	M	371	59.08
	F	257	40.92
Age	<25	309	49.23
	25-40	228	36.31
	>40	91	14.46
Occupation	Employed	245	39.08
	Professional	85	13.54
	Student	298	47.38

Table 2: Indicate Acceptance of Chatbots

Questions	Effectiveness	Speed	Safety	Ease of Use
Strongly Disagree	52	58	34	36
Disagree	150	156	174	148
Neutral	162	162	198	160
Agree	216	196	182	210
Strongly Agree	48	56	40	74

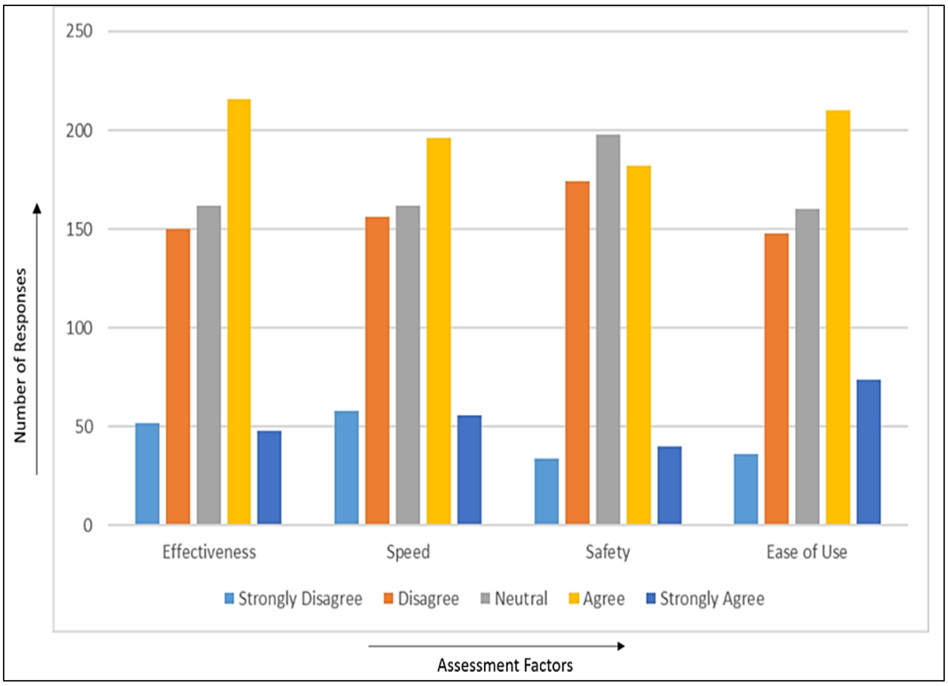

Figure2: Comparison of Effectiveness, Speed, Safety and Ease of Use

The MCDM Issue in a Pentagonal Neutrosophic Setting: The MCDM (Multi-Criteria Decision-Making) issue is an essential and trustworthy subject for handling ambiguity and imprecision in the complicated and uncertain modern world. Finding the best selection from a small number of possibilities based on certain characteristic criteria is the main goal of this strategy. As a result, MCDM guidelines, which are incredibly dependable for decision-making and improve communication and service delivery efficiency by guaranteeing better choice allocations, may be used to construct a strong decision-making process. Using known mathematical operators, a scoring function, and a proven algorithm, the procedure is systematically cautious in the context of a Pentagonal Neutrosophic Number (PNN) environment.

The Pentagonal Neutrosophic Number Environment:

A Multi-Criteria Decision Making Problem Using the TODIM Approach: This section considers the collection of m alternatives$A$= $\{A_1,A_2,A_3,\ldots\ldots A_m\}$ and the set of n criteria C=$\{C_1,C_2,C_3,\ldots\ldots C_n\}$. Additionally, the associated weight set requirement where each $\gamma_i \geq 0$ also meets the relation $r = \{r_1,r_2,r_3,\ldots.r_n\}$Therefore, we create a decision matrixD=$(d_{ij})_{mn}$in which each entry explains A_i over $C_j$and creates a pentagonal neutrosophic number. The stages that follow demonstrate how comprehensive the approach is.

Step-1: Here, we construct the decision matrix under the related finite alternatives and finite set of criteria. The remarkable point is that the entitiesd_{ij} of the matrix are all pentagonal neutrosophic numbers.Thus we develop the matrix which is given as follows:

$D = (. C_1\ C_2\ C_3 \dots C_m\ A_1\ d_{11}\ d_{12}\ d_{13} \dots . d_{1m}\ A_2\ d_{21}\ d_{22}\ d_{23} \dots d_{2m}\ A_3 . A_n\ \dots d_{n1}\ .. d_{n2}\ .. d_{n3}\ \dots \dots \dots .. d_{nm}\ )$ [16]

Step-2: constructing the criterion's matching weights $W_j (j = 1,2, .. n)$. [17]

Step-3: Compute the relative weight $\omega_j, j = 1,2, \dots n$ of each criterion by the defined equation $\omega_j = \frac{\Delta_j}{\Delta_{max}}$ where

$W_{max} = \max \{W_1, W_2, \dots W_n\}$ [18]

Step-4: Compute the score values of each alternative w.r.t the criterion utilizing the equation (1) and formulate the score valued decision matrix $\emptyset = (\emptyset_{ij})_{mn}$

$\emptyset = (\emptyset_{11}\ \emptyset_{12}\ \emptyset_{13} \dots . \emptyset_{1m}\ \emptyset_{21}\ \emptyset_{22}\ \emptyset_{23} \dots \emptyset_{2m}\ \dots \emptyset_{n1}\ .. \emptyset_{n2}\ .. \emptyset_{n3}\ \dots \dots \dots .. \emptyset_{nm}\ )$ [19]

Step-5: In this stage, we use the following established formula to calculate the dominance matrix of each option in relation to the criteria.

$\pi_k(d_i, d_j) = \{ \sqrt{\frac{\omega_k \delta(\tilde{d}_{ik}, \tilde{d}_{jk})}{\sum_{k=1}^{n} \omega_k}}, \text{if} \tilde{d}_{ik} > \tilde{d}_{jk}\ 0\ , \text{if} \tilde{d}_{ik} = \tilde{d}_{jk}\ - \frac{1}{\theta} \sqrt{\frac{\sum_{k=1}^{n} \omega_k \delta(\tilde{d}_{ik}, \tilde{d}_{jk})}{\omega_k}}, \text{if} \tilde{d}_{ik} < \tilde{d}_{jk}$ [20]

Where θ denotes the decay factor and $\theta > 0$.

Step-6: In this stage, we use the formula below to get the aggregate dominance value of each option.

$\vartheta(d_i, d_j) = \sum_{k=1}^{n} \pi_k(d_i, d_j)$ [21]

Step-7: In this phase, we use the method below to calculate each alternative's dominance degree, Q_i.

$\tau_i = \frac{\sum_{j=1}^{n} \vartheta(d_i, d_j) - \min_{1 \le i \le m} (\sum_{j=1}^{n} \vartheta(d_i, d_j))}{\max_{1 \le i \le m} (\sum_{j=1}^{n} \vartheta(d_i, d_j)) - \min_{1 \le i \le m} (\sum_{j=1}^{n} \vartheta(d_i, d_j))}$ [22]

for$i = 1,2, \dots m$.

Step-8: The options Q_i are ranked in this phase according to their degree of dominance. The best option is the one with the greatest degree value.

Step-9: The process of TODIM method's pseudocode is described in Figure 3.

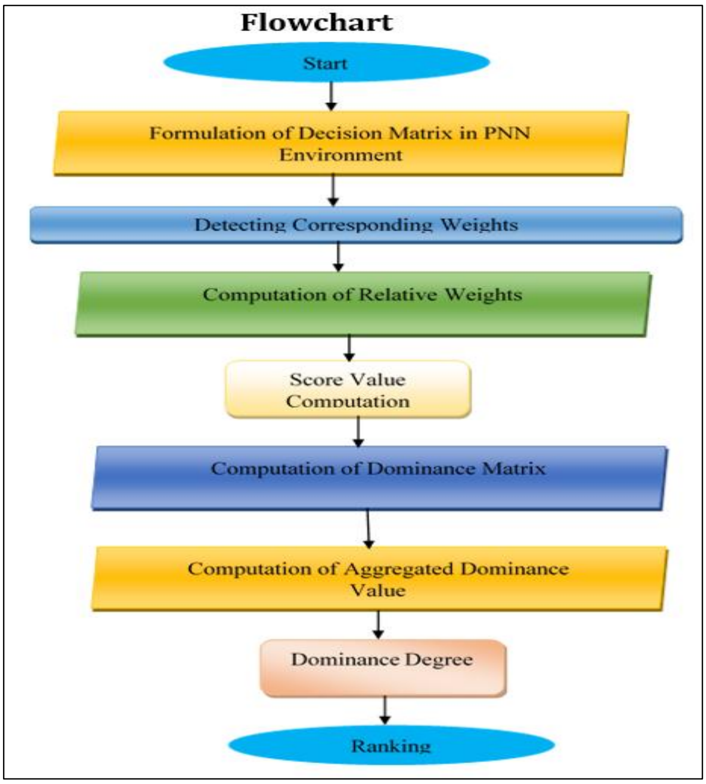

Figure 3: The TODIM Method's Pseudocode

Input: Alternatives A_i, Criterion C_j, Weights W_j, Hamming distance δ_{ij};
Output: Ranked Alternatives A_i
Begin
Step 1: Formation of Decision Matrix via PNN
1.1 Construct decision matrix D by calculating PNN expressions for each alternative-criterion pair (A_i, C_j).
Step 2: Compute Relative Weight Vector
2.1 Compute the relative weight vector ω_j for each criterion using the given weights $W_j$as per Equation.
Step 3: Score Matrix Calculation
3.1 Calculate the PNN decision matrix Q by expressing the score-valued matrix using the score function defined in Equation.
Step 4: Compute Dominance Matrices
4.1 For each criterion C_j, compute the dominance matrix π_j using the distance measure formula $\delta_{i,j}$ and weight vector W_j.
Step 5: Aggregate Dominance Values
5.1 Calculate the dominance matrix $\vartheta_{i,j}$ by aggregating the dominance values across all criteria.
Step 6: Compute Aggregated Dominance Degree
6.1 Derive the aggregated dominance value $\tau_i$for each alternative A_i based on $\vartheta_{i,j}$.
Step 7: Rank Alternatives
7.1 Rank the alternatives $A_i$in descending order based on the aggregated dominance degrees τ_i.
End
Return: The best alternative A_i with the highest τ_i.

Step-1: Construction of decision matrix:
A finite set of criteria and a finite number of options make up the decision matrix, which is created in this stage. A pentagonal neutrosophic number is used to represent each item in the decision matrix.

The following is the structure of the criteria:

Features (standards): These criteria, which are represented by C_1, C_2, C_3, respectively, represent the views of corporate, students, and teachers.

Other Options: Effectiveness, speed, safety, and ease of use are represented by A_1, A_2, A_3 and A_4. Therefore, the matrix assesses each option based on the above criteria, using pentagonal neutrosophic values to represent different degrees of hesitancy, imprecision, and ambiguity in the decision-making process.

$$D = \begin{pmatrix} . & C_1 & C_2 & C_3 \\ A_1 & <0,1.9,5.3,5.9,7.6;0.6,0.5,0.1> & <2.3,3.2,8.3,10.1,28.2;0.6,0.4,0.2> & <2.3,4.7,6.9,9.3,9.5;0.7,0.2,0.3> \\ A_2 & <0,1.6,6.6,8.8,10.6;0.8,0.1,0.1> & <2.7,3.2,6.7,8.8,17.6;0.7,0.4,0.2> & <2.3,4.2,6.2,7.7,21.8;0.7,0.2,0.1> \\ A_3 & <0,1.9,4.4,5.8,10.6;0.7,0.2,0.1> & <2.4,3.6,5.8,7.8,20.14;0.6,0.3,0.3> & <2.6,3.5,6.7,8.7,11.9;0.6,0.3,0.2> \\ A_4 & <0,2.8,2.9,5.3,8.8;0.4,0.3,0.1> & <3.2,3.6,4.5,8.8,14.1;0.45,0.35,0.3> & <2.7,3.5,6.2,8.2,16.4;0.7,0.3,0.2> \end{pmatrix} \quad [23]$$

Step-2: Incorporation of the weight vector:
We apply a weight vector to the criteria established in this phase, which is provided as follows.
Δ_1=0.35, Δ_2=0.32 andΔ_3 =0.33 [24]

Step-3: Computation of the relative weight:
The following relative weights are obtained in this phase by using equation to calculate the relative weight of each criteria.
$\omega_1 = 1, \omega_2 = 0.91, \omega_3 = 0.94$ [25]

Step-4: Computation of scored valued matrix:
The following score-valued matrix is produced in this stage by using formula to calculate the score values of the aforementioned decision matrix.

$$S=\begin{bmatrix}2.76 & 6.95 & 4.80\\ 4.78 & 5.46 & 6.75\\ 3.63 & 5.30 & 4.68\\ 2.64 & 4.10 & 5.43\end{bmatrix} \quad [26]$$

Step-5: Computation of Dominance matrices:
In this stage, we use equation to generate the dominance matrices according to the criteria and alternatives stated.

$$\pi_1=\begin{bmatrix}0 & -2.40 & -1.48\\ 0.84 & 0 & 0.65\\ 0.55 & -1.85 & 0\\ -1.39 & -2.58 & -1.80\end{bmatrix},\ \pi_2=\begin{bmatrix}0 & 0.74 & 0.75\\ -2.28 & 0 & 0.14\\ -2.36 & -1.74 & 0\\ -3.07 & -2.07 & -2.06\end{bmatrix},\ \pi_3=\begin{bmatrix}0 & -3.48 & 0.38\\ 0.68 & 0 & 0.36\\ -1.95 & -1.83 & 0\\ 0.54 & 0.52 & 0.40\end{bmatrix} \quad [27]$$

Step-6: Computation of Aggregated Dominance Values:
Using equation, we calculate the aggregated dominance values of each option in this stage, yielding the following results.

$$\vartheta(d_1,d_1)=0 \quad \vartheta(d_1,d_2)=-5.14 \quad \vartheta(d_1,d_3)=-0.35$$
$$\vartheta(d_2,d_1)=-0.76 \quad \vartheta(d_2,d_2)=0 \quad \vartheta(d_2,d_3)=1.15$$
$$\vartheta(d_3,d_1)=-3.76 \quad \vartheta(d_3,d_2)=-5.42 \quad \vartheta(d_3,d_3)=0$$
$$\vartheta(d_4,d_1)=-3.92 \quad \vartheta(d_4,d_2)=-4.13 \quad \vartheta(d_4,d_3)=-3.46 \quad [28]$$

Step-7: Computation of Dominance Degree:
Using equation, we determine the dominance degree of each option in this stage, yielding the following results.
τ_1 =0.51,τ_2 =1.00, $\tau_3 = 0.20$ and $\tau_4 = 0$. [29]
Step-8: Ranking of the Alternatives:
The options are ranked in this stage according to their dominance values. In this case, $\tau_1 > \tau_2 > \tau_3 > \tau_4$. The possibilities are thus ranked as follows: $A_1 > A_2 > A_3 > A_4$.

Results

Over the last ten years, technical improvements have played a major role in the increasing acceptance of chatbots. These advancements—from text-based interfaces to graphical interfaces, smartphone applications, and now conversational interfaces—have made it possible for chatbots to play a big part, particularly in the banking industry. This research compares the user experience of chatbot-based and social media-based banking, assesses the influence of chatbots in banking, and examines the advantages they provide to transactions. The research also takes into account the uncertainty that is inherent in banking calculations due to their complexity. Our goal was to evaluate the system's operation and the ways in which different features affect chatbot banking's acceptability. Our research also investigates new results about accuracy and scoring functions. Numerous methods have been used in the research on chatbot application in banking, however many findings are still unknown. The following goals are addressed by this study:

Identifying crucial characteristics that are necessary for banking with chatbots. Examining the advantages of using chatbots in the banking sector.

Comparing chatbots and mobile apps to find the best option for consumers. The adoption of chatbots is graphically shown depending on key attributes. The finest social media networks to integrate chatbots with are chosen by solving an MCDM issue using a pentagonal neutrosophic number-based TODIM algorithm. Together, these goals seek to provide a more thorough understanding of the function and versatility of chatbot technology in banking. With a focus on a variety of demographics, including professionals, employed people, and students, this research sought to explore people's opinions about the use of chatbots for banking transactions in West Bengal. This study supports earlier research on AI-driven chatbots' capacity to improve customer experience, decrease response time, and minimise human interaction by offering insightful information about the function of robotic process automation (RPA) and chatbot efficiency in digital banking. Our results demonstrate that key elements impacting chatbot success include answer accuracy, security, flexibility, and user pleasure. Because it takes into consideration psychological decision-making behaviours and assessment uncertainty, the Pentagonal Neutrosophic TODIM methodology sets this research apart from others by providing a more sophisticated evaluation framework than conventional MCDM techniques like TOPSIS and VIKOR. The research also shows that security and adaptability have the biggest effects on chatbot effectiveness, highlighting the need of strong security features and dynamic learning in banking chatbots. A significant demographic trend is also identified by the analysis: younger, tech-savvy people under 40 make up the majority of adopters, which is consistent with worldwide banking trends. Financial institutions must take advantage of chatbot banking's potential to improve client happiness and sustained engagement, since it is still underutilised in West Bengal. In order to increase transparency and consumer trust, banks and chatbot developers are encouraged to give explainable AI (XAI) approaches top priority in light of these results. This study's geographical emphasis limits its usefulness, however, and for a more accurate assessment of chatbot efficacy, future research should enlarge the dataset and investigate hybrid MCDM models that include machine learning. In conclusion, this research offers a new methodology for evaluating chatbots, highlighting the importance of consumer involvement, flexibility, and security in digital banking automation. These models should be further refined in future studies to conform to changing user requirements and legal environments.

Discussion

According to the report, when interacting with banks, consumers place a high value on three key factors: safe, private transactions, convenience of access, and improved and quicker service. In addition to wanting individualised services and offers, modern consumers are also prepared to provide personal information in exchange for customised financial solutions. This requirement is met by chatbots, which greet users when they access their accounts, provide personalised support, and use cutting-edge technology like sentiment analysis and natural language processing to identify tone and purpose. By giving encounters a more human touch, this degree of individualised connection may increase client pleasure and, eventually, loyalty.
The results of the research highlight that:
Chatbots are becoming widely accepted, particularly among younger audiences.
In all important aspects, they are favoured over mobile banking applications.

- Adoption of chatbots is strongly influenced by speed, which is weighed as the most important aspect.
- The adoption of chatbots in banking is mostly dependent on client satisfaction, which is influenced by the four qualities of usability, speed, security, and convenience of use.
- By growing the client base without needing more physical branches and lowering operating expenses, a well-executed chatbot might boost bank earnings.
- Because chatbots don't need downloads and provide a highly customised connection, they give a more smooth and intuitive experience than conventional banking applications.

All things considered, using chatbots methodically might revolutionise banking customer service, promoting growth, loyalty, and satisfaction at a reasonable cost.

Conclusion

According to the research, chatbots have the potential to revolutionise banking by greatly improving a range of customer support tasks. Because of their speed, ease of use, and improved privacy features, chatbots are becoming more and more popular in the area, where almost all of the main banks have used them to increase client interaction. According to the survey's findings, speed was the most coveted attribute, with participants pointing to shorter wait times and increased productivity as key benefits. The preference for chatbot banking was also primarily driven by security and privacy, indicating that consumers are open to using chatbots for transactions as long as data protection is guaranteed.

Customers are driven to chatbots due of convenience, curiosity, and a rising knowledge of technical breakthroughs, according to the report. In light of these favourable opinions, banks are urged to use chatbot technology as a means of establishing more intimate, tailored connections with their clientele. In the next years, chatbot banking is expected to become a more popular alternative due to technological advancements and growing client familiarity with chatbots. This research has several limitations in spite of these contributions. Despite its diversity, the sample size is restricted to West Bengali banking professionals and consumers, which might affect how broadly the findings can be applied. For more accurate chatbot assessment, future studies might broaden the dataset to include a larger demography and investigate hybrid MCDM techniques that integrate machine learning models with Neutrosophic TODIM.

Abbreviations

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Author Contributions

Susovan Paul: Conceptualization, Avishek Chakraborty: Conceptualization, Shubhendu Banerjee: Software Assistance, Data Curation, Availability of Resources, Soumya Bhattacharya: Software Assistance, Data Curation, Availability of Resources, Nidhi Singh: Original Draft, Review, Editing for worthy visualization. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors of this work state that they have no conflicts of interest about its publication.

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