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Sustainable Model for Analyzing the Impact of Social Media on Customer Buying Behavior: A Case Study

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Abstract

In today's digital landscape, chatbots have become widely used across various applications, particularly in systems that provide intelligent assistance to users. To enhance user experience, these systems are often equipped with chatbots capable of processing user inquiries and delivering accurate, timely responses. This study proposes a structured framework for evaluating the impact of social media on customer buying behavior through a case study focused on selecting the most suitable Online Chatbot Platform (OCP). The selection of an optimal OCP is a complex multi-criteria decision-making (MCDM) problem, involving multiple interdependent and often conflicting factors. One of the key challenges in this process is the potential loss of critical decision information and underestimation of engagement complexity in a neutrosophic environment. To address this challenge, this paper introduces a hybrid MCDM framework that integrates Interval-Valued Neutrosophic Sets Analytical Hierarchy Process (IVNSs-AHP) with Weighted Aggregated Sum Product Assessment (WASPAS). The IVNSs-AHP method is employed to determine the relative importance of the evaluation criteria, while WASPAS is used to rank different OCP options. A comprehensive set of assessment criteria, grounded in the principles of sustainable development, was established through an extensive literature review and expert consultations to ensure the practical applicability of the proposed MCDM model. To validate the effectiveness of this approach, a real-world case study was conducted, successfully identifying the optimal OCP. Sensitivity and comparative analyses further demonstrate the robustness and reliability of the proposed decision framework. The conclusions of this study suggest that the proposed methodology can be effectively applied to similar regional decision-making scenarios, providing a structured and adaptable approach for evaluating intelligent chatbot systems in a dynamic business environment.

Keywords: Social Media Impact; Customer Buying Behavior; Chatbot; MCDM; Interval-Valued Neutrosophic Sets.

1 | Introduction and Literature Review

In today's digital world, social media platforms like Facebook, Instagram, Twitter, and TikTok have completely changed how people communicate, interact, and shop. These platforms are no longer just for entertainment; they have become powerful marketing tools that influence consumer behavior in significant ways. Businesses now rely on social media to advertise products, engage with customers, and build brand

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trust. Consumers, in turn, depend on these platforms to discover new products, read reviews, and compare options before making a purchase [1].

One of the biggest reasons for this shift is social proof—the idea that people are more likely to trust a product or service when they see others recommending it. Reviews, comments, and influence endorsements play a huge role in shaping consumer opinions. As a result, companies have adapted by integrating automated customer interaction tools like chatbots into their social media platforms to improve customer service and increase engagement [2].

Chatbots, powered by Artificial Intelligence (AI), have become an essential part of modern digital marketing. They allow businesses to provide 24/7 customer support, personalized product recommendations, and seamless shopping experiences without human intervention. However, selecting the best chatbot platform is not a straightforward task. Businesses must evaluate multiple factors, such as accuracy, response time, integration capabilities, and user experience [3]. This makes chatbot selection a Multi-Criteria Decision-Making (MCDM) problem that requires a structured approach.

This study aims to analyze how social media influences customer buying behavior and determine the best Online Chatbot Platform (OCP) for enhancing consumer interactions. To address the complexity of chatbot selection, we propose an MCDM-based framework that incorporates Neutrosophic Logic—a mathematical approach that helps deal with uncertainty and incomplete information in decision-making [4].

1.1 | The Role of Chatbots in Consumer Purchasing Decisions

Chatbots have transformed customer service by allowing businesses to interact with consumers in real time. These AI-driven systems simulate human conversations and help customers with product searches, FAQs, and purchase decisions [5]. As more people turn to online shopping, chatbots play a critical role in ensuring a smooth and efficient buying experience.

One of the key benefits of chatbots is their ability to provide instant and personalized responses. Studies show that customers prefer interacting with businesses that offer fast and relevant support. Chatbots can analyze customer preferences and suggest tailored recommendations, making the shopping experience more convenient [6]. Research by Cunningham-Nelson et al. (2023) found that AI-powered chatbots improve customer engagement and conversion rates, particularly in e-commerce platforms [7].

Despite their advantages, chatbots also have limitations. Studies suggest that when customers realize they are talking to a bot rather than a human, their trust levels may decrease, reducing the likelihood of completing a purchase [8]. Additionally, chatbots often struggle with understanding complex queries or handling emotionally sensitive interactions, which can lead to frustration [9]. These challenges highlight the importance of selecting the right chatbot platform—one that balances automation with human-like interaction.

1.2 | Multi-Criteria Decision-Making (MCDM) in Chatbot Selection

Selecting the best chatbot platform is a complex decision-making process because it involves multiple factors that influence performance and user experience. Businesses need to evaluate criteria such as response accuracy, user satisfaction, cost, integration with social media, and adaptability to different customer needs [10]. To address this challenge, researchers have developed Multi-Criteria Decision-Making (MCDM) models that help rank alternatives based on weighted factors.

Several MCDM techniques have been used in chatbot evaluation. Shemshadi et al. (2020) applied the VIKOR method to rank chatbot platforms based on objective performance metrics [11]. Mousavi-Nasab and Sotoudeh-Anvari (2021) demonstrated that TOPSIS and COPRAS are effective for evaluating AI-driven customer service tools [12]. Garg and Kumar (2021) improved the TOPSIS model by integrating exponential distance measures, resulting in more precise chatbot ranking [13].

Among these methods, Weighted Aggregated Sum Product Assessment (WASPAS) has emerged as a highly effective approach for chatbot selection. It combines weighted sum models and product assessment techniques, leading to more accurate and consistent rankings [14]. This study integrates Interval-Valued Neutrosophic Sets (IVNSs) into the MCDM framework to further refine the decision-making process and handle uncertainty in chatbot evaluation.

1.3 | Neutrosophic Logic and Its Role in Decision-Making

Neutrosophic Logic, introduced by Smarandache (1999), is an advanced mathematical approach for dealing with uncertainty, vagueness, and conflicting information in decision-making [15]. Unlike traditional fuzzy logic, which considers only degrees of truth and falsehood, neutrosophic logic adds a third dimension: indeterminacy. This makes it particularly useful for evaluating chatbot platforms, where customer experiences, user feedback, and chatbot performance metrics often involve incomplete and contradictory data. Each element in a neutrosophic set is characterized by:

- Truth (T): How true a statement or evaluation is.
- Indeterminacy (I): The level of uncertainty or ambiguity.
- Falsehood (F): How false a statement is.

This unique structure allows neutrosophic logic to handle inconsistencies in chatbot evaluations, ensuring a more balanced and reliable ranking process [16]. Research by Garg and Rani (2021) demonstrated that neutrosophic decision-making models significantly improve AI-based evaluations, making them ideal for chatbot selection [17]. By incorporating Interval-Valued Neutrosophic Sets (IVNSs) into AHP and WASPAS models, this study establishes a robust framework for selecting the most effective chatbot platform based on real-world conditions [18].

1.4 | Research Objectives and Contributions

This research aims to develop a structured approach for evaluating the impact of social media on consumer buying behavior through the selection of an optimal chatbot platform. The study introduces an MCDM-based methodology that integrates IVNSs-AHP and WASPAS, ensuring a systematic and objective decision-making process. A real-world case study is conducted to validate the framework, demonstrating its practical applicability and decision reliability. By incorporating Neutrosophic Logic, the study provides a more accurate and adaptive model for AI-driven decision-making in e-commerce.

1.5 | Study Organization

This study is structured as follows. Section 2 describes the materials and methods used, explaining the decision-making framework, the evaluation criteria, and the integration of Interval-Valued Neutrosophic Sets (IVNSs) with Analytical Hierarchy Process (AHP) and WASPAS. It also outlines how data was collected and analyzed to select the best chatbot platform. Section 3 presents the case study and results, applying the proposed model to evaluate different chatbot platforms. It demonstrates how social media influences customer buying behavior and identifies the most suitable Online Chatbot Platform (OCP) based on predefined criteria. Section 4 provides a sensitivity and comparative analysis, testing the robustness and reliability of the decision-making model. It compares the proposed approach with other methods like TOPSIS, VIKOR, and COPRAS to assess its effectiveness in chatbot selection. Section 5 concludes the study by summarizing key findings and suggesting future research directions. It highlights the impact of using Neutrosophic Logic in decision-making, acknowledges study limitations, and recommends further improvements to chatbot evaluation methods.

2 | Materials and Methods

This research presents an effective evaluation framework for analyzing the impact of social media on customer buying behavior and selecting the optimal OCP through a case study. The proposed model consists of four phases. In the first phase, IVNSs are used to compute the weights for each evaluation criterion [28, 29].

In the second phase, AHP applies IVNSs, represented by linguistic variables, to manage uncertainties and ambiguities in expert judgments. To ensure reliability, the consistency of these judgments is tested [30].

The third phase utilizes WASPAS to rank the OCPs, while the final phase involves a comparative analysis, including a sensitivity assessment of threshold values and a methodological comparison to demonstrate the practicality of the proposed approach. The operations of IVNSs can be defined as [31, 32]:

Let two Interval-Valued Neutrosophic Numbers (IVNNs) be given, with operations such as:

$$A + B = \left([T_A^L(x) + T_B^L(x) - T_A^L(x)T_B^L(x), T_A^U(x) + T_B^U(x) - T_A^U(x)T_B^U(x)], [I_A^L(x)I_B^L(x), I_A^U(x)I_B^U(x)], [F_A^L(x)F_B^L(x), F_A^U(x)F_B^U(x)]\right)$$

$$AB = \begin{pmatrix} [T_A^L(x)T_B^L(x), T_A^U(x)T_B^U(x)], \\ [I_A^L(x) + I_B^L(x) - I_A^L(x)I_B^L(x), I_A^U(x) + I_B^U(x) - I_A^U(x)I_B^U(x)], \\ [F_A^L(x) + F_B^L(x) - F_A^L(x)F_B^L(x), F_A^U(x) + F_B^U(x) - F_A^U(x)T_B^U(x)] \end{pmatrix}$$

$$\frac{A}{B} = \left(\begin{bmatrix} \min\left\{\frac{T_A^L(x)}{T_B^L(x)}, \frac{T_A^L(x)}{T_B^U(x)}, \frac{T_A^U(x)}{T_B^L(x)}, \frac{T_A^U(x)}{T_B^U(x)}\right\}, \\ \max\left\{\frac{T_A^L(x)}{T_B^L(x)}, \frac{T_A^L(x)}{T_B^U(x)}, \frac{T_A^U(x)}{T_B^L(x)}, \frac{T_A^U(x)}{T_B^U(x)}\right\} \end{bmatrix}, \begin{bmatrix} \min\left\{\frac{I_A^L(x)}{I_B^L(x)}, \frac{I_A^L(x)}{I_B^U(x)}, \frac{I_A^U(x)}{I_B^L(x)}, \frac{I_A^U(x)}{I_B^U(x)}\right\}, \\ \max\left\{\frac{I_A^L(x)}{I_B^L(x)}, \frac{I_A^L(x)}{I_B^U(x)}, \frac{I_A^U(x)}{I_B^L(x)}, \frac{I_A^U(x)}{I_B^U(x)}\right\} \end{bmatrix}, \begin{bmatrix} \min\left\{\frac{F_A^L(x)}{F_B^L(x)}, \frac{F_A^L(x)}{F_B^U(x)}, \frac{F_A^U(x)}{F_B^L(x)}, \frac{F_A^U(x)}{F_B^U(x)}\right\}, \\ \max\left\{\frac{F_A^L(x)}{F_B^L(x)}, \frac{F_A^L(x)}{F_B^U(x)}, \frac{F_A^U(x)}{F_B^L(x)}, \frac{F_A^U(x)}{F_B^U(x)}\right\} \end{bmatrix}\right)$$

$$\pi A = \left(\left[1 - \left(1 - T_A^L(x)\right)^\pi, 1 - \left(1 - T_A^U(x)\right)^\pi\right], \left[\left(I_A^L(x)\right)^\pi, \left(I_A^U(x)\right)^\pi\right], \left[\left(F_A^L(x)\right)^\pi, \left(F_A^U(x)\right)^\pi\right]\right)$$

$$A^\pi = \left(\left[\left(T_A^L(x)\right)^\pi, \left(T_A^U(x)\right)^\pi\right], \left[1 - \left(1 - I_A^L(x)\right)^\pi, 1 - \left(1 - I_A^U(x)\right)^\pi\right], \left[1 - \left(1 - F_A^L(x)\right)^\pi, 1 - \left(1 - F_A^U(x)\right)^\pi\right]\right)$$

2.1 | Interval-Valued Neutrosophic Sets Analytical Hierarchy Process (IVNSs-AHP)

To address uncertainty in the quantification of expert judgments, this study employs IVNSs. These sets are characterized by three membership degrees: truth, indeterminacy, and falsity. The IVNSs-AHP method follows a structured sequence of steps to ensure accurate decision-making [33].

The first step involves constructing a pairwise comparison matrix, where experts evaluate criteria relative to one another. In the second step, a score judgment matrix is computed to quantify the evaluations. The third step aggregates expert opinions to form a single unified pairwise comparison matrix, ensuring consistency across multiple assessments. Finally, in the fourth step, the aggregated matrix is normalized to maintain coherence in the decision-making process. The normalization is performed as

$$N_{xy} = \frac{A_{xy}}{\sum_{x=1}^{e} A_{xy}} \tag{1}$$

Where A represents the aggregated comparison value, xy refers to the xth alternative in relation to the yth criterion, e denotes the number of alternatives, and f represents the number of criteria.

In the fifth step, the weights of the criteria (W) are determined by calculating the average row values of the normalized comparison matrix. This ensures that each criterion is assigned a proportional weight based on expert evaluations.

The sixth step involves conducting a consistency ratio test to verify the reliability of the judgments. This step ensures that the comparisons made in the decision-making process are logically consistent, minimizing potential errors in weight assignment and ranking.

$$CR = \frac{CI}{RI} \tag{2}$$

CR must be less than 0.1

$$CI = \frac{\lambda_{max} - f}{f - 1} \tag{3}$$

λ_{max} refers to the average weighted sum column.

2.2 | Interval-Valued Neutrosophic Sets Weighted Aggregated Sum Product Assessment (IVNSs-WASPAS)

The WASPAS technique, which was first introduced in 2012, is a mix of the WPM and the WSM[34]. This technique is stated as:

Step Seven, Build the decision matrix $M = [A_{xy}]_{ef}$ where A_{xy} is the performance of the xth alternative to the yth criterion, e is the number of alternatives and f is the number of criteria.

Step Eight, repeat steps 2 and 3 to obtain the aggregated decision matrix.

Step Nine, Normalize the aggregated decision matrix for benefit and cost criteria such as:

$$No_{xy} = \frac{A_{xy}}{\max\limits_{x} A_{xy}}, such\ that\ x = 1,2,3, \dots . e; y = 1,2,3, \dots f \text{ for benefit criteria} \tag{4}$$

$$No_{xy} = \frac{\min\limits_{x} A_{xy}}{A_{xy}}, such\ that\ x = 1,2,3, \dots . e; y = 1,2,3, \dots f \text{ for cost criteria} \tag{5}$$

Step Ten, by employing the WSM, it is possible to determine the relative relevance of the alternative:

$$R_x^{(1)} = \sum_{y=1}^{f} No_{xy}\, W_y\, , such\ that\ x = 1,2,3, \dots . e; y = 1,2,3, \dots f \tag{6}$$

where W_y is the yth criterion's weight (relative importance).

Step Eleven, the relative relevance of the option is then estimated using the WPM, which is like the following:

$$R_x^{(2)} = \prod_{y=1}^{f} (No_{xy})^{W_y}\, , such\ that\ x = 1,2,3, \dots . e; y = 1,2,3, \dots f \tag{7}$$

Step Twelve, The WASPAS model's integrated utility function is computed as:

$$R_y = Thd * R_x^{(1)} + (1 - Thd) R_x^{(2)} \tag{8}$$

$$Thd = \frac{\sum_{x=1}^{e} R_x^{(2)}}{\sum_{x=1}^{e} R_x^{(1)} + \sum_{x=1}^{e} R_x^{(2)}} \tag{9}$$

where Thd refers to the coefficient value or threshold value of the WASPAS approach.

Step Thirteen, arrange options based on the highest value of R_y.

3 | Case Study

This study employs two MCDM techniques to evaluate chatbot platforms. First, AHP is used to calculate the weights of the criteria, followed by WASPAS, which ranks the available options. To ensure a well-informed decision-making process, we selected three experts specializing in Chatbot and AI, social media impact on customer behavior, and decision-making frameworks. These experts identified the evaluation criteria and alternatives based on previous research.

A total of twenty criteria and ten chatbot alternatives were considered in this study. The criteria used for evaluation include response accuracy, response speed, personalization, user engagement, conversation flow, natural language processing efficiency, multilingual support, integration with social media platforms, emotional intelligence, self-learning ability, recommendation accuracy, user satisfaction rate, trustworthiness, seamless handover to human agents, security and data privacy, reduction in customer drop-off rate, cost-effectiveness, ability to handle complex queries, feedback collection and analysis, and influence on purchase decisions.

The chatbot alternatives considered were rule-based chatbot, AI-powered chatbot, hybrid chatbot, e-commerce chatbot, social media chatbot, voice-enabled chatbot, transactional chatbot, healthcare chatbot, customer support chatbot, and lead generation chatbot. After selecting these criteria and alternatives, the experts assessed their significance to establish a structured evaluation. The dataset was compiled using questionnaires, interviews, articles, and surveys to ensure a well-rounded assessment.

The decision-making process followed a series of structured steps:

1. Creating the Comparison Matrix: A pairwise comparison matrix was constructed to compare the criteria based on expert opinions using linguistic terms.
2. Converting Linguistic Terms into IVNNs: The linguistic terms were replaced with Interval-Valued Neutrosophic Numbers (IVNNs). A score function was then applied to obtain a single representative value instead of multiple IVNN values.
3. Aggregating Comparison Matrices: The three expert-generated comparison matrices were aggregated into a single unified matrix, as presented in Table 1, where $OECC_1$, $OECA_1$, Alternative 1, etc., represent the evaluated parameters.
4. Normalizing the Comparison Matrix: Using Eq. (1), the aggregated matrix was normalized, as shown in Table 2.
5. Calculating the Criteria Weights: The weights for each criterion were determined using the row average method, as illustrated in Figure 1. The results indicate that $OECC_{19}$ has the highest weight, while $OECC_2$ has the lowest weight, suggesting its relative importance in decision-making.
6. Checking Consistency Ratio: The Consistency Ratio (CR) was calculated using Eqs. (2) and (3). With a CR value of 0.088, the expert evaluations were confirmed to be logically consistent.

After establishing the criteria weights, the WASPAS method was applied to rank the chatbot platforms and determine the most suitable Online Chatbot Platform (OCP) based on the selected evaluation criteria.

Table 1. The aggregated comparison matrix by the AHP method.

Criteria/ Criteria	$OECC_{1}$	$OECC_{2}$	$OECC_{3}$	$OECC_{4}$	$OECC_{5}$	$OECC_{6}$	$OECC_{7}$	$OECC_{8}$	$OECC_{9}$	$OECC_{10}$	$OECC_{11}$	$OECC_{12}$	$OECC_{13}$	$OECC_{14}$	$OECC_{15}$	$OECC_{16}$	$OECC_{17}$	$OECC_{18}$	$OECC_{19}$	$OECC_{20}$
$OECC_{1}$	0.5	0.857635	0.77654	0.887804	0.596493	0.724823	0.621825	0.832172	0.832172	0.857635	0.554976	0.617782	0.514476	0.415653	0.802003	0.802003	0.747034	0.458844	0.614221	0.492573
$OECC_{2}$	1.176585	0.5	0.647288	0.57103	0.540861	0.677457	0.400261	0.836878	0.625999	0.625999	0.77654	0.592319	0.677457	0.832172	0.415653	0.540861	0.614221	0.669191	0.349465	0.492573
$OECC_{3}$	1.291516	1.992678	0.5	0.467111	0.600536	0.716865	0.651994	0.393749	0.836878	0.218359	0.218359	0.836878	0.836878	0.836878	0.836878	0.218359	0.657852	0.347934	0.746372	0.218359
$OECC_{4}$	1.128286	2.431541	2.760472	0.5	0.746372	0.77654	0.802665	0.304129	0.394363	0.555638	0.452332	0.610607	0.625999	0.260938	0.239649	0.651994	0.239649	0.746372	0.304129	0.554976
$OECC_{5}$	2.398225	2.47984	2.371446	1.339815	0.5	0.570368	0.857635	0.651994	0.540861	0.747034	0.43043	0.40914	0.600536	0.436942	0.434603	0.467111	0.570368	0.716865	0.282227	0.621825
$OECC_{6}$	1.688016	1.944379	1.39991	1.291516	2.419746	0.5	0.832172	0.687359	0.643728	0.772497	0.777203	0.467111	0.458844	0.806709	0.394363	0.746372	0.630705	0.640776	0.415653	0.492573
$OECC_{7}$	2.025994	3.563601	1.977695	1.269996	1.176585	1.209901	0.5	0.69936	0.643728	0.747034	0.777203	0.592319	0.458844	0.621825	0.28284	0.621825	0.600536	0.677457	0.570368	0.592319
$OECC_{8}$	1.209901	1.194918	4.270132	3.320201	1.977695	1.460004	1.721332	0.5	0.554546	0.510915	0.836878	0.218359	0.746372	0.777203	0.208865	0.746372	0.436942	0.407435	0.208865	0.282227
$OECC_{9}$	1.209901	2.338131	1.194918	3.499676	2.47984	1.802946	1.802946	1.971435	0.5	0.687359	0.716865	0.467111	0.467111	0.467111	0.218359	0.913267	0.282227	0.394363	0.746372	0.282227
$OECC_{10}$	1.176585	2.338131	4.579607	2.840918	1.35161	1.318295	1.35161	2.314377	1.460004	0.5	0.887804	0.777203	0.657852	0.570368	0.532644	0.77654	0.746372	0.289351	0.887804	0.304129
$OECC_{11}$	2.829123	1.291516	4.579607	3.292254	3.515302	1.303311	1.303311	1.194918	1.39991	1.128286	0.5	0.772497	0.772497	0.747034	0.514476	0.836878	0.806709	0.400261	0.806709	0.584053
$OECC_{12}$	2.052773	2.086088	1.194918	2.747508	3.860754	2.760472	2.086088	4.579607	2.760472	1.303311	1.318295	0.5	0.828128	0.613559	0.772497	0.746372	0.436942	0.437555	0.802003	0.621825
$OECC_{13}$	2.504109	1.944379	1.194918	2.338131	2.371446	2.585723	2.585723	1.339815	2.760472	1.520099	1.318295	1.23668	0.5	0.724823	0.74299	0.70292	0.657852	0.74299	0.415653	0.746372
$OECC_{14}$	3.154223	1.209901	1.194918	3.888701	2.808771	1.243217	2.025994	1.303311	2.760472	2.419746	1.35161	1.851246	1.688016	0.5	0.857635	0.772497	0.669191	0.747034	0.647288	0.77654
$OECC_{15}$	1.2582	3.154223	1.194918	4.234154	3.827439	3.499676	3.665654	5.052909	4.579607	2.194482	2.504109	1.318295	1.378389	1.176585	0.5	0.554546	0.477795	0.862341	0.554976	0.802665
$OECC_{16}$	1.2582	2.47984	4.579607	1.977695	2.760472	1.339815	2.025994	1.339815	1.09497	1.291516	1.194918	1.339815	1.911063	1.318295	1.971435	0.5	0.536378	0.471284	0.480747	0.747034

$OECC_{17}$	1.35161	1.863041	1.520099	4.234154	2.419746	2.323147	2.371446	2.808771	3.543249	1.339815	1.243217	2.808771	1.520099	1.769631	3.258939	2.281061	0.5	0.828128	0.857635	0.802003
$OECC_{18}$	2.585723	1.769631	2.874107	1.339815	1.39991	2.699209	1.944379	2.868865	3.499676	3.851984	3.563601	2.931176	1.378389	1.35161	1.161602	3.072609	1.23668	0.5	0.746372	0.747034
$OECC_{19}$	1.863041	3.969148	1.339815	3.320201	3.543249	3.154223	2.419746	5.052909	1.339815	1.128286	1.243217	1.2582	3.154223	1.992678	2.829123	2.362676	1.176585	1.339815	0.5	0.802003
$OECC_{20}$	2.727156	2.727156	4.579607	2.829123	2.025994	2.727156	2.086088	3.543249	3.543249	3.320201	1.91134	2.025994	1.339815	1.291516	1.269996	1.35161	1.2582	1.35161	1.2582	0.5

Table 2. The normalized comparison matrix by the AHP approach.

Criteria /Criteria	$OECC_1$	$OECC_2$	$OECC_3$	$OECC_4$	$OECC_5$	$OECC_6$	$OECC_7$	$OECC_8$	$OECC_9$	$OECC_{10}$	$OECC_{11}$	$OECC_{12}$	$OECC_{13}$	$OECC_{14}$	$OECC_{15}$	$OECC_{16}$	$OECC_{17}$	$OECC_{18}$	$OECC_{19}$	$OECC_{20}$
$OECC_1$	0.014129	0.020354	0.01736	0.019221	0.014576	0.021706	0.019398	0.021742	0.024252	0.033345	0.024581	0.028559	0.025078	0.023736	0.043959	0.040781	0.056243	0.035216	0.050366	0.04297
$OECC_2$	0.033247	0.011866	0.014471	0.012363	0.013217	0.020287	0.012486	0.021865	0.018243	0.024339	0.034395	0.027382	0.033023	0.047521	0.022782	0.027503	0.046244	0.051359	0.028656	0.04297
$OECC_3$	0.036495	0.047292	0.011178	0.010113	0.014675	0.021467	0.020339	0.010287	0.024389	0.00849	0.009672	0.038688	0.040793	0.04779	0.04587	0.011103	0.049529	0.026703	0.061203	0.019049
$OECC_4$	0.031882	0.057707	0.061713	0.010825	0.018239	0.023254	0.025039	0.007946	0.011493	0.021603	0.020035	0.028228	0.030514	0.014901	0.013135	0.033154	0.018043	0.057283	0.024939	0.048413
$OECC_5$	0.067767	0.058854	0.053016	0.029007	0.012218	0.01708	0.026754	0.017034	0.015762	0.029045	0.019065	0.018914	0.029273	0.024952	0.023821	0.023752	0.042942	0.055018	0.023143	0.054245
$OECC_6$	0.047699	0.046146	0.031297	0.027961	0.059129	0.014973	0.025959	0.017958	0.01876	0.030035	0.034424	0.021594	0.022366	0.046067	0.021615	0.037953	0.047485	0.049178	0.034084	0.04297
$OECC_7$	0.057249	0.084574	0.044214	0.027495	0.028751	0.036232	0.015597	0.018272	0.01876	0.029045	0.034424	0.027382	0.022366	0.035509	0.015503	0.03162	0.045213	0.051994	0.04677	0.051671
$OECC_8$	0.034188	0.028359	0.095463	0.071882	0.048327	0.043722	0.053696	0.013063	0.016161	0.019864	0.037067	0.010095	0.036382	0.044382	0.011448	0.037953	0.032897	0.03127	0.017127	0.02462
$OECC_9$	0.034188	0.05549	0.026714	0.075767	0.060598	0.053992	0.056242	0.051506	0.014571	0.026724	0.031752	0.021594	0.022769	0.026674	0.011968	0.046439	0.021248	0.030267	0.061203	0.02462
$OECC_{10}$	0.033247	0.05549	0.102382	0.061505	0.033028	0.039478	0.042163	0.060466	0.042548	0.01944	0.039323	0.035929	0.032067	0.032571	0.029195	0.039487	0.056193	0.022207	0.0728	0.026531
$OECC_{11}$	0.079943	0.030651	0.102382	0.071277	0.085901	0.039029	0.040656	0.031219	0.040797	0.043868	0.022146	0.035712	0.037655	0.04266	0.028199	0.042555	0.060736	0.030719	0.06615	0.05095
$OECC_{12}$	0.058006	0.049509	0.026714	0.059483	0.094342	0.082666	0.065075	0.119648	0.080447	0.050673	0.058391	0.023114	0.040367	0.035037	0.042341	0.037953	0.032897	0.033582	0.065765	0.054245
$OECC_{13}$	0.070759	0.046146	0.026714	0.05062	0.057949	0.077433	0.080661	0.035004	0.080447	0.059101	0.058391	0.05717	0.024372	0.041391	0.040724	0.035743	0.049529	0.057023	0.034084	0.06511
$OECC_{14}$	0.08913	0.028714	0.026714	0.08419	0.068636	0.03723	0.0632	0.034051	0.080447	0.09408	0.059866	0.085581	0.082282	0.028553	0.047008	0.039281	0.050382	0.057334	0.053078	0.067741
$OECC_{15}$	0.035553	0.074859	0.026714	0.091669	0.093528	0.104802	0.114348	0.132014	0.133461	0.085321	0.110913	0.060943	0.067189	0.067189	0.027405	0.028198	0.035972	0.066183	0.045508	0.07002
$OECC_{16}$	0.035553	0.058854	0.102382	0.042817	0.067456	0.040122	0.0632	0.035004	0.03191	0.050214	0.052926	0.061938	0.093154	0.075282	0.108056	0.025425	0.040383	0.03617	0.039421	0.065167
$OECC_{17}$	0.038193	0.044215	0.033983	0.091669	0.059129	0.06957	0.073976	0.073383	0.103259	0.052092	0.055065	0.129846	0.074097	0.101055	0.178625	0.115991	0.037644	0.063557	0.070326	0.069963
$OECC_{18}$	0.073065	0.041998	0.064254	0.029007	0.034209	0.080831	0.060654	0.074953	0.101989	0.149765	0.157841	0.135505	0.067189	0.077184	0.063668	0.156241	0.093108	0.038374	0.061203	0.065167
$OECC_{19}$	0.052644	0.094199	0.029953	0.071882	0.086584	0.094457	0.075483	0.132014	0.039046	0.043868	0.055065	0.058165	0.153752	0.113792	0.155067	0.120141	0.088583	0.102828	0.041	0.069963
$OECC_{20}$	0.077062	0.064723	0.102382	0.06125	0.049508	0.081668	0.065075	0.092572	0.103259	0.129089	0.084658	0.093659	0.065309	0.073752	0.06961	0.068729	0.094728	0.103734	0.103173	0.043617

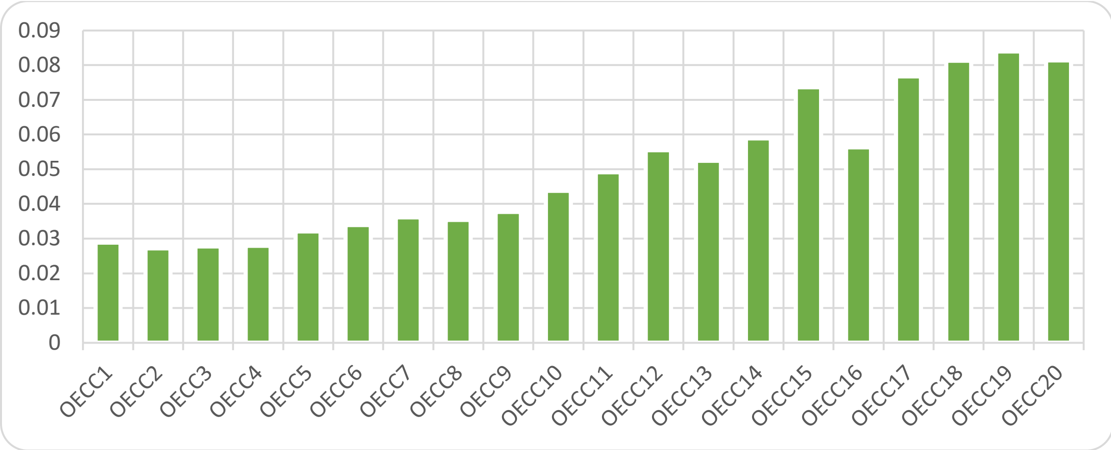

Figure 1. The weights of principles.

In the second phase, the WASPAS technique is applied to rank the OCP alternatives. The evaluation process follows a structured sequence to ensure an accurate and consistent ranking.

First, decision matrices are constructed based on expert opinions, as presented in Table A1. Next, the experts' opinions are transformed into Interval-Valued Neutrosophic Numbers (IVNNs) and then converted into crisp values for easier computation. These values are then aggregated into a single unified matrix, as shown in Table 3.

Once the aggregated matrix is obtained, it is normalized using Equations (4) and (5), with the resulting values presented in Table 4. Following normalization, the Weighted Sum Model (WSM) and Weighted Product Model (WPM) are calculated using Equations (6) and (7), as outlined in Table 5.

To finalize the ranking, the WASPAS model's integrated utility function is computed using Equation (8), with a threshold value of Thd = 0.5 applied in this study. The ranking is then determined based on the highest value of R_y, where the alternative with the highest score is considered the most optimal. The ranking of alternatives is illustrated in Figure 2, which indicates that $OECA_3$ is the best-performing alternative, while $OECA_8$ ranks the lowest.

Table 3. The aggregated decision matrix.

Criteria/Alternatives	$OECC_1$	$OECC_2$	$OECC_3$	$OECC_4$	$OECC_5$	$OECC_6$	$OECC_7$	$OECC_8$	$OECC_9$	$OECC_{10}$	$OECC_{11}$	$OECC_{12}$	$OECC_{13}$	$OECC_{14}$	$OECC_{15}$	$OECC_{16}$	$OECC_{17}$	$OECC_{18}$	$OECC_{19}$	$OECC_{20}$
$OECA_1$	0.647288	0.832172	0.77654	0.640776	0.656168	0.536378	0.621825	0.806709	0.832172	0.802003	0.400261	0.56215	0.514476	0.621825	0.613559	0.832172	0.802665	0.514476	0.584053	0.617782
$OECA_2$	0.802665	0.647288	0.458844	0.621825	0.386146	0.621825	0.591657	0.806709	0.625999	0.600536	0.621825	0.621825	0.592319	0.77654	0.540861	0.772497	0.584053	0.480747	0.681631	0.492573
$OECA_3$	0.77654	0.393749	0.621825	0.621825	0.777203	0.77654	0.77654	0.615313	0.806709	0.394363	0.424532	0.836878	0.862341	0.862341	0.777203	0.449995	0.74299	0.45124	0.746372	0.394363
$OECA_4$	0.625999	0.621825	0.615313	0.832172	0.591657	0.832172	0.887804	0.643728	0.625999	0.640776	0.452332	0.610607	0.471284	0.647288	0.681631	0.677457	0.28284	0.802003	0.304129	0.554976
$OECA_5$	0.581101	0.245546	0.400261	0.724823	0.673897	0.806709	0.610607	0.802665	0.511355	0.806709	0.640776	0.615313	0.625999	0.436942	0.625999	0.489013	0.669191	0.77654	0.455893	0.56215
$OECA_6$	0.772497	0.419212	0.489013	0.647288	0.617782	0.832172	0.621825	0.747034	0.77654	0.772497	0.836878	0.651994	0.647288	0.621825	0.600536	0.802003	0.57103	0.862341	0.445821	0.681631
$OECA_7$	0.610607	0.400261	0.525469	0.673897	0.772497	0.647288	0.640776	0.862341	0.832172	0.717527	0.836878	0.777203	0.28284	0.832172	0.467724	0.806709	0.887804	0.70292	0.540861	0.617782
$OECA_8$	0.540861	0.400261	0.489013	0.857635	0.467111	0.832172	0.70292	0.857635	0.532644	0.69936	0.651994	0.449995	0.591657	0.651994	0.36358	0.802003	0.282227	0.492573	0.610607	0.647288
$OECA_9$	0.458844	0.555638	0.467111	0.677457	0.777203	0.862341	0.647288	0.617782	0.828128	0.74299	0.832172	0.651994	0.445821	0.436942	0.424532	0.913267	0.492573	0.449995	0.857635	0.647288
$OECA_{10}$	0.772497	0.647288	0.429338	0.458844	0.532644	0.621825	0.70292	0.617782	0.857635	0.639684	0.510915	0.747034	0.370754	0.540861	0.617782	0.832172	0.613559	0.422163	0.677457	0.514476

Table 4. The normalized combined decision matrix.

Criteria/Alternatives	$OECC_1$	$OECC_2$	$OECC_3$	$OECC_4$	$OECC_5$	$OECC_6$	$OECC_7$	$OECC_8$	$OECC_9$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_1$	$OECC_2$
$OECA_1$	0.806424	1	1	0.747143	0.844269	0.622003	0.951484	0.935488	0.614482	0.491723	1	0.671723	0.596604	0.72109	0.789446	0.911204	0.904102	0.596604	0.681004	0.906329
$OECA_2$	1	0.77783	0.590883	0.725047	0.496841	0.72109	1	0.935488	0.816861	0.656686	0.643687	0.74303	0.686873	0.900503	0.695907	0.845861	0.657862	0.55749	0.79478	0.72264
$OECA_3$	0.967452	0.473158	0.800764	0.725047	1	0.900503	0.761914	0.713538	0.633877	1	0.942828	1	1	1	1	0.492731	0.836886	0.523274	0.870267	0.578559
$OECA_4$	0.779901	0.747232	0.792378	0.97031	0.761265	0.965015	0.666427	0.746489	0.816861	0.615447	0.884883	0.729626	0.546518	0.750618	0.877031	0.741796	0.318584	0.930031	0.354614	0.814188
$OECA_5$	0.723964	0.295066	0.515441	0.845141	0.86708	0.935488	0.968964	0.930799	1	0.488855	0.62465	0.735249	0.72593	0.506693	0.805452	0.535455	0.75376	0.900503	0.531569	0.824714
$OECA_6$	0.962414	0.503756	0.629733	0.754736	0.794879	0.965015	0.951484	0.866286	0.658503	0.510505	0.478279	0.779079	0.750618	0.72109	0.77269	0.87817	0.643194	1	0.519826	1
$OECA_7$	0.760725	0.480983	0.67668	0.785761	0.993945	0.750618	0.923344	1	0.614482	0.549615	0.478279	0.928693	0.327991	0.965015	0.601804	0.883323	1	0.81513	0.630642	0.906329
$OECA_8$	0.673831	0.480983	0.629733	1	0.601015	0.965015	0.841713	0.994543	0.960031	0.563892	0.613903	0.537707	0.686106	0.756075	0.467806	0.87817	0.317893	0.571205	0.711967	0.949617
$OECA_9$	0.571651	0.667696	0.601528	0.789913	1	1	0.914054	0.716401	0.617482	0.530779	0.480983	0.779079	0.51699	0.506693	0.546231	1	0.554823	0.52183	1	0.949617
$OECA_{10}$	0.962414	0.77783	0.552885	0.535011	0.685334	0.72109	0.841713	0.716401	0.596238	0.616497	0.783419	0.892644	0.42994	0.627201	0.794879	0.911204	0.691098	0.489555	0.789913	0.754772

Table 5. The WSM and WPM values.

Alternatives	WSM	WPM
$OECA_1$	0.777867	0.762985
$OECA_2$	0.737952	0.727729
$OECA_3$	0.807769	0.783309
$OECA_4$	0.716556	0.682314
$OECA_5$	0.725072	0.701503
$OECA_6$	0.761031	0.740374
$OECA_7$	0.761917	0.732473
$OECA_8$	0.688682	0.657804
$OECA_9$	0.710842	0.683802
$OECA_{10}$	0.708808	0.694161

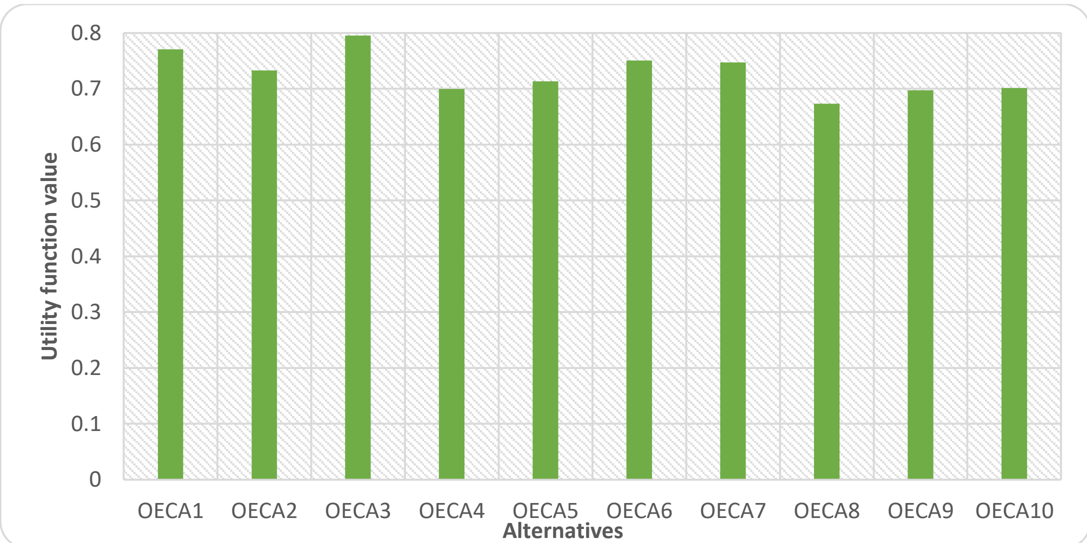

Figure 2. The order of options by the WASPAS technique.

4 | Sensitivity and Comparative Analysis

4.1 | Sensitivity Analysis

A sensitivity analysis of the preference coefficient and index weights is achieved to demonstrate the proposed MCDM model's robustness and stability.

4.1.1 | Change in the Value of Threshold λ Parameter of WASPAS Method

In previous related studies, the threshold value (Thd) was set at 0.5 for base-case analysis. However, this fixed assumption does not accurately represent real-world scenarios, where expert preferences may vary. To address this, the preference coefficient of the WASPAS model in this study fluctuates within a range from 0 to 1, increasing in increments of 0.1, as shown in Table 6.

Figure 3 illustrates the results of this sensitivity analysis, demonstrating how changes in the Thd value affect the ranking of alternatives. The findings indicate that, regardless of fluctuations in the preference coefficient (Thd), the most suitable OCP remains unchanged. Specifically, $OECA_3$ consistently ranks as the top-performing chatbot for takeover operations, maintaining its position across all tested values. Similarly, $OECA_1$ remains the second-best alternative, making it a strong and viable choice compared to other options. In contrast, $OECA_8$ consistently ranks as the least favorable alternative in all scenarios, highlighting its relative inefficiency in this evaluation.

Table 6. The $thershold$ values of the WASPAS method.

Thd values	$OECA_1$	$OECA_2$	$OECA_3$	$OECA_4$	$OECA_5$	$OECA_6$	$OECA_7$	$OECA_8$	$OECA_9$	$OECA_{10}$
Thd=0	0.762985	0.727729	0.783309	0.682314	0.701503	0.740374	0.732473	0.657804	0.683802	0.694161
Thd=0.1	0.764473	0.728751	0.785755	0.685738	0.70386	0.74244	0.735417	0.660891	0.686506	0.695626
Thd=0.2	0.765961	0.729773	0.788201	0.689162	0.706217	0.744506	0.738362	0.663979	0.68921	0.69709
Thd=0.3	0.76745	0.730796	0.790647	0.692586	0.708574	0.746571	0.741306	0.667067	0.691914	0.698555
Thd=0.4	0.768938	0.731818	0.793093	0.696011	0.710931	0.748637	0.744251	0.670155	0.694618	0.70002
Thd=0.5	0.770426	0.73284	0.795539	0.699435	0.713288	0.750702	0.747195	0.673243	0.697322	0.701485
Thd=0.6	0.771914	0.733862	0.797985	0.702859	0.715645	0.752768	0.750139	0.676331	0.700026	0.702949
Thd=0.7	0.773403	0.734885	0.800431	0.706284	0.718002	0.754834	0.753084	0.679418	0.70273	0.704414
Thd=0.8	0.774891	0.735907	0.802877	0.709708	0.720359	0.756899	0.756028	0.682506	0.705434	0.705879
Thd=0.9	0.776379	0.736929	0.805323	0.713132	0.722715	0.758965	0.758972	0.685594	0.708138	0.707344
Thd=1	0.777867	0.737952	0.807769	0.716556	0.725072	0.761031	0.761917	0.688682	0.710842	0.708808

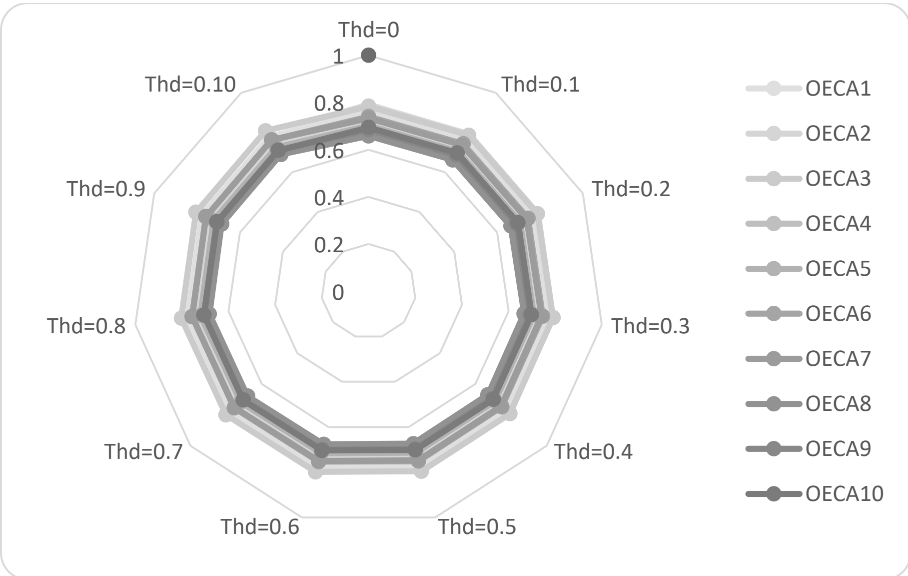

Figure 3. The sensitivity analysis when changing the value of λ.

4.1.2 | Change the Weights of Criteria

In this sub-section, we adjusted the weights of the criteria to observe changes in the ranking of alternatives. Table 7 presents the variations in rankings when the weight of a single criterion is increased to 0.1, while the other weights are proportionally reduced. This adjustment allows for an assessment of how changes in criterion importance impact the ranking of alternatives. The fluctuations in weights for each scenario are detailed in Table 7, highlighting the effect of different weight distributions on the decision-making process. Figure 4 illustrates the ranking of alternatives after modifying the criteria weights, providing a visual representation of the sensitivity analysis results. In this study, we proposed twenty different scenarios, as shown in Table 7. The results indicate that $OECC_3$ consistently ranks as the best alternative across all twenty scenarios, while $OECC_1$ remains the second-best alternative in every case. These findings demonstrate the stability and robustness of the proposed decision-making framework under varying weight conditions.

Table 7. The modifications applied to the dependence weights for each of the distinct scenarios.

Criteria	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12	Case 13	Case 14	Case 15	Case 16	Case 17	Case 18	Case 19	Case 20
$OECC_1$	0.028879	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_2$	0.027211	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_3$	0.027756	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_4$	0.027917	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_5$	0.032083	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_6$	0.033883	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_7$	0.036132	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_8$	0.035398	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_9$	0.037716	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.043803	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.04916	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.055513	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.052419	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.058875	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.07359	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736	0.04736
$OECC_1$	0.056272	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736	0.04736
$OECC_1$	0.076782	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736	0.04736
$OECC_1$	0.08131	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1	0.04736
$OECC_1$	0.083924	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.1
$OECC_2$	0.081378	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736	0.04736

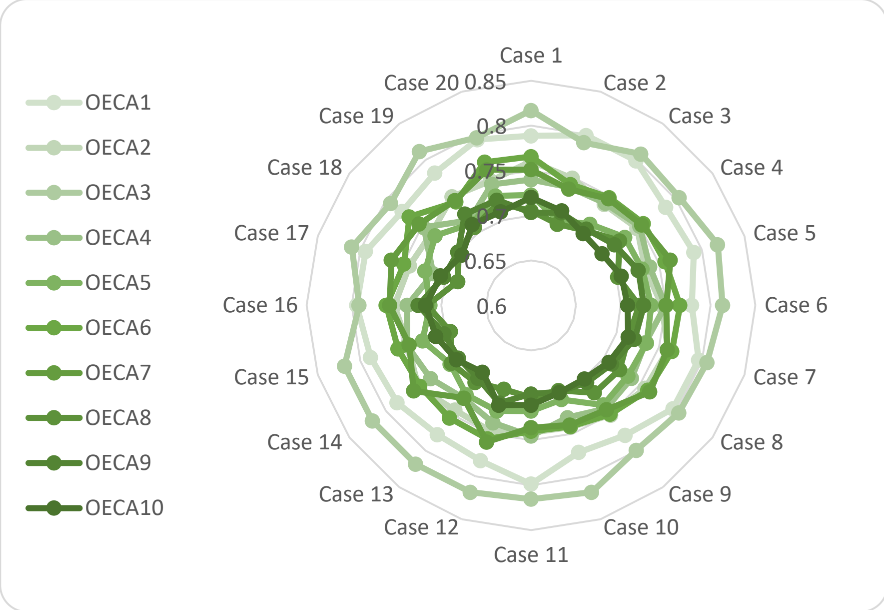

Figure 4. The sensitivity analysis of change in the weights of principles.

4.2 | Comparative Analysis

According to the MCDM methodology, it is essential to validate the applicability and reliability of the proposed techniques by comparing them with well-established, stable, and efficient methods commonly used in relevant studies. This research examines how the ranking of OCPs generated by the IVNSs-AHP and WASPAS model compares with other integrated models, specifically Single-Valued Neutrosophic (SVNSs)-AHP-MABAC and Interval-Valued Intuitionistic Fuzzy (IVIF)-AHP-WASPAS [35].

The comparative results, presented in Table 8 and illustrated in Figure 5, highlight the rankings obtained using four different ranking algorithms. When comparing the IVNSs-AHP-WASPAS with SVNSs-AHP-MABAC, it is evident that the best and worst-ranked OCPs remain consistent, with $OECA_3$ being the most suitable option and $OECA_8$ being the least favorable. However, when comparing IVNSs-AHP-WASPAS with IVIF-AHP-WASPAS, a slight variation is observed in the best-ranked alternative, where the ranking shifts between $OECA_3$ and $OECA_1$, while $OECA_8$ remains the least favorable in all methods. To further validate the consistency of the rankings, Spearman's correlation coefficient was computed for the three models. The correlation between IVNSs-AHP-WASPAS and SVNSs-AHP-MABAC was 0.91, between IVNSs-AHP-WASPAS and IVIF-AHP-WASPAS was 0.85, and between IVIF-AHP-WASPAS and SVNSs-AHP-MABAC was 0.89, resulting in an average correlation of 0.88 across all models. These high correlation values indicate strong consistency between the ranking methods, supporting the reliability of the proposed framework.

Figure 6 presents the criteria weights under different methodologies, including IVNSs-AHP, SVNSs-AHP, and IVIF-AHP. The findings confirm that all compared models assign the same ranking to the criteria, where $OECC_{19}$ holds the highest weight, while $OECC_2$ has the lowest weight. This consistency further reinforces the robustness of the proposed approach. Based on the analysis, the IVNSs-AHP-WASPAS model proves to be both reliable and validated, demonstrating its effectiveness in OCP selection. Given its robustness and credibility, this model serves as a valuable tool for managers, decision-makers, stakeholders, and administrators in selecting the ideal OCP. Additionally, its applicability extends beyond chatbot selection, offering a structured approach for decision-making in various sectors requiring MCDM frameworks.

Table 8. The comparison of the three kinds of MCDM method.

	Proposed Model	**SVNSs-AHP-MABAC**	**IVIF-AHP-WASPAS**
$OECA_1$	9	7	10
$OECA_2$	6	6	6
$OECA_3$	10	10	9
$OECA_4$	2	5	3
$OECA_5$	3	3	4
$OECA_6$	8	8	7
$OECA_7$	7	9	8
$OECA_8$	1	1	1
$OECA_9$	4	4	5
$OECA_{10}$	5	2	2

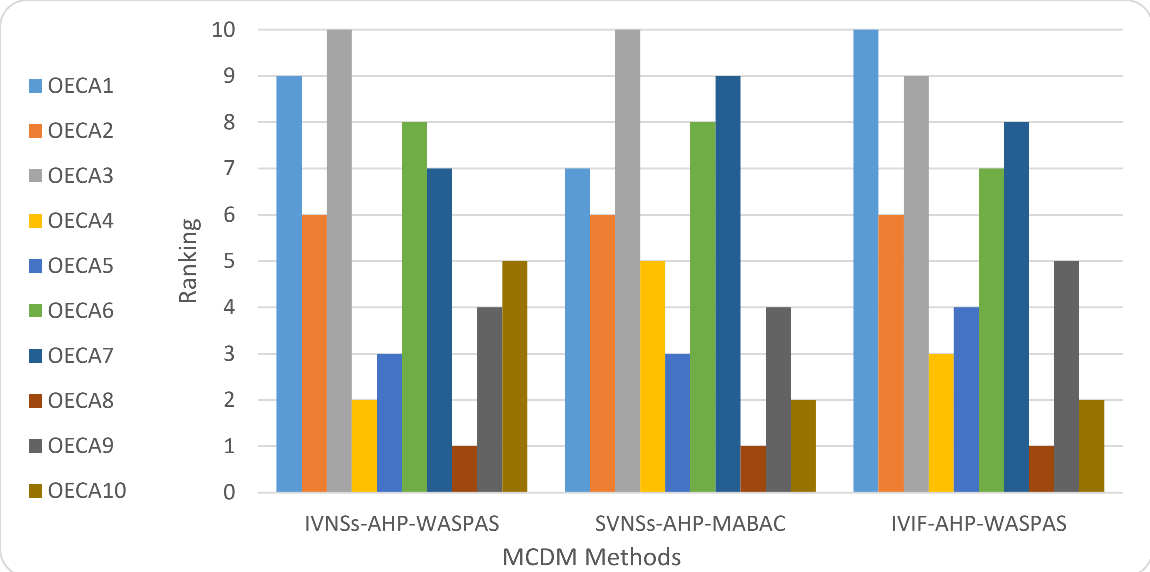

Figure 5. The rank of MCDM methods.

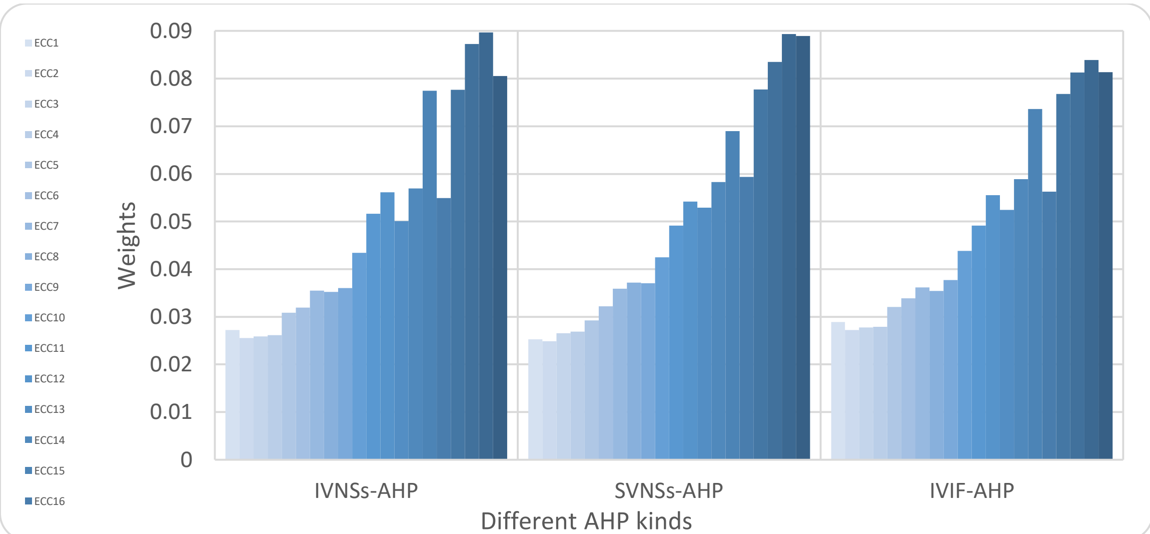

Figure 6. The weights of standards under three types of the AHP technique.

When comparing IVN-TOPSIS [36] and Fuzzy-VIKOR [37] using the same criteria weights as in this study, the rankings of alternatives are presented in Table 9. The results indicate that under IVN-TOPSIS, $OECA_1$ emerges as the best alternative, while $OECA_8$ ranks as the worst alternative. However, in the Fuzzy-VIKOR method, $OECA_7$ is identified as the top-ranked alternative, while $OECA_4$ is considered the least favorable option. These findings highlight the sensitivity of ranking results to the weighting of criteria, as evident when comparing Table 8 and Table 9. The variations in rankings across different MCDM techniques emphasize the importance of selecting appropriate criteria weights, as even slight changes can significantly influence the final decision.

Figure 7 visually illustrates the ranking differences between the proposed IVNSs-AHP-WASPAS model and other MCDM techniques, further reinforcing the impact of criteria weighing on alternative selection.

Table 9. The comparison of three kinds of MCDM method.

	Proposed Model	IVN-TOPSIS	Fuzzy-VIKOR
$OECA_1$	9	10	9
$OECA_2$	6	4	5
$OECA_3$	10	2	6
$OECA_4$	2	6	1
$OECA_5$	3	9	7
$OECA_6$	8	7	8
$OECA_7$	7	8	10
$OECA_8$	1	1	4
$OECA_9$	4	3	2
$OECA_{10}$	5	5	3

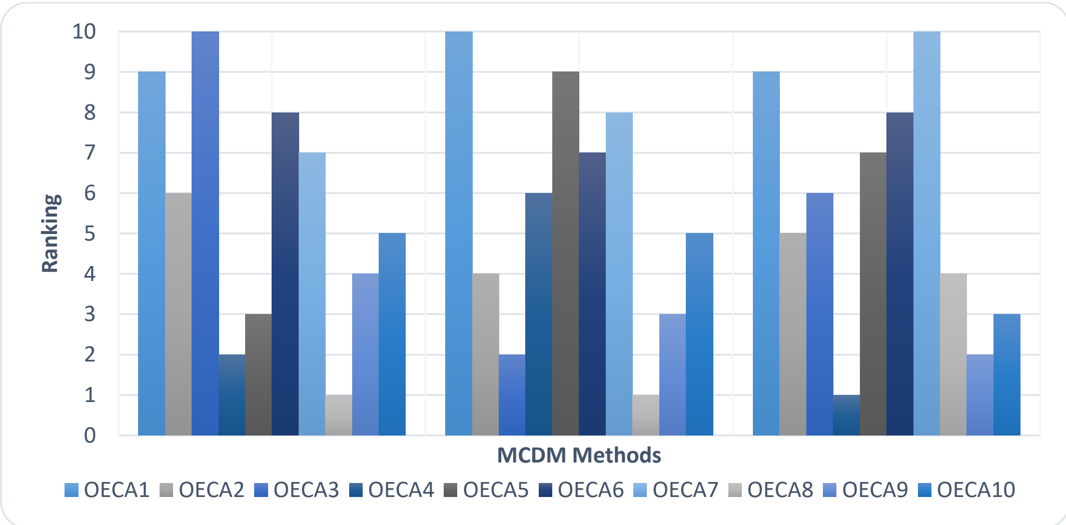

Figure 7. The rank among the suggested framework and IVN-TOPSIS and fuzzy-VIKOR.

4.3 | Challenges

There are several challenges in analyzing the impact of social media on customer buying behavior for OCP selection. One of the primary challenges is that chatbots often struggle with understanding complex queries and conversations, leading to incomplete or irrelevant responses. When discussions become too intricate, chatbots may provide inaccurate answers, frustrating customers and limiting their ability to make informed decisions.

Another challenge is the lack of motivation and support, which can reduce customer engagement. If chatbots fail to offer interactive and personalized experiences, users may lose interest, leading to lower effectiveness in customer assistance. Additionally, technical issues in chatbot software can introduce errors, affecting system reliability and negatively impacting the overall user experience.

Limited interaction capabilities can also be a drawback, as chatbots are unable to fully replace human customer service representatives. This restriction can reduce the depth of engagement and minimize the effectiveness of chatbot-driven decision-making. Furthermore, security and privacy concerns pose a significant challenge, as chatbots collect and process vast amounts of customer data. Cyberattacks and data breaches can compromise customer privacy, making security a crucial factor in chatbot implementation.

4.4 |Managerial Implications

Analyzing social media's impact on customer buying behavior for OCP selection has significant benefits for managers, customers, and administrators. One of the key advantages is that OCPs help customers adapt to content, enhance their skills, and improve their overall performance. Customers can ask questions at any time and receive instant responses without the need for human instructors, making the system highly convenient and accessible.

Additionally, OCPs facilitate customer feedback, enabling users to correct errors and adapt to new learning or shopping experiences. This continuous feedback loop improves engagement and enhances decision-making processes. Another managerial advantage is cost reduction, as OCPs minimize the need for direct human intervention, lowering operational expenses for businesses and reducing customer reliance on instructors and institutions.

OCPs also offer multilingual support, ensuring accessibility for users from different linguistic backgrounds. They accommodate multiple content formats, including text, audio, images, and videos, providing a versatile and inclusive platform for customer interactions. Furthermore, OCPs can track user interactions and generate valuable data insights, helping businesses understand customer preferences, optimize marketing strategies, and improve chatbot efficiency.

5 |Conclusions and Future Work

This study introduces a comprehensive Multi-Criteria Decision-Making (MCDM) framework for OCP selection by integrating IVNSs-AHP and WASPAS, applied to a real-world case study on analyzing social media's impact on customer buying behavior. The model addresses challenges associated with expert evaluations that involve uncertainty and ambiguous language, ensuring that decision-makers retain critical information during assessment. By incorporating sustainability considerations and leveraging expert knowledge, the framework expands on previous chatbot evaluation methodologies.

The IVNSs-AHP method is employed to determine the significance of evaluation criteria, while WASPAS ranks the OCP alternatives based on these weighted criteria. The proposed model has been compared with various MCDM techniques, and a sensitivity analysis was conducted to assess its robustness. Although this framework provides valuable insights for decision-makers in selecting the optimal chatbot platform, additional measurement tools may further enhance its effectiveness.

Future research could explore different Fuzzy Set (FS) extensions, such as intuitionistic, hesitant, and Pythagorean FSs, to better capture uncertainty in decision-making. Additionally, alternative MCDM techniques, including ELECTRE, ANP, VIKOR, and PROMETHEE, could be applied to evaluate criteria and rank alternatives more effectively. Beyond chatbot selection, the proposed framework has potential applications in robot selection, supply chain optimization, autonomous vehicle decision-making, supplier evaluation, aircraft type selection, and other complex MCDM challenges.

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Author Contributions

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Appendix

Table A1. The opinions of experts.

	$OECA_1$	$OECA_2$	$OECA_3$	$OECA_4$	$OECA_5$	$OECA_6$	$OECA_7$	$OECA_8$	$OECA_9$	$OECA_{10}$
OECC$_1$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_2$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_3$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_4$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_5$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_6$	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩
OECC$_7$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_8$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_9$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_{10}$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_{11}$	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩
OECC$_{12}$	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_{13}$	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_{14}$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9
OECC$_{15}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_{16}$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩
OECC$_{17}$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_{18}$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩
OECC$_{19}$	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩
OECC$_{20}$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
	$OECA_1$	$OECA_2$	$OECA_3$	$OECA_4$	$OECA_5$	$OECA_6$	$OECA_7$	$OECA_8$	$OECA_9$	$OECA_{10}$
OECC$_1$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩

OECC$_2$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_3$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
OECC$_4$	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_5$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_6$	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_7$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_8$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_9$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_{10}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_{11}$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
OECC$_{12}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_{13}$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_{14}$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_{15}$	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_{16}$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_{17}$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
OECC$_{18}$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_{19}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_{20}$	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
	$OECA_1$	$OECA_2$	$OECA_3$	$OECA_4$	$OECA_5$	$OECA_6$	$OECA_7$	$OECA_8$	$OECA_9$	$OECA_{10}$
OECC$_1$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_2$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_3$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_4$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
OECC$_5$	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_6$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_7$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
OECC$_8$	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩
OECC$_9$	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_{10}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
OECC$_{11}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
OECC$_{12}$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩
OECC$_{13}$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩
OECC$_{14}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_{15}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩
OECC$_{16}$	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩
OECC$_{17}$	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.8, 0.95], [0.15, 0.2], [0.2, 0.35]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩

$OECC_{18}$	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.4, 0.45], [0.25, 0.3], [0.6, 0.85]⟩
$OECC_{19}$	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.1, 0.3], [0.05, 0.15], [0.85, 0.99]⟩	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩
$OECC_{20}$	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.2, 0.35], [0.15, 0.2], [0.8, 0.95]⟩9	⟨[0.7, 0.9], [0.2, 0.25], [0.3, 0.4]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.85, 0.99], [0.05, 0.15], [0.1, 0.3]⟩	⟨[0.6, 0.85], [0.25, 0.3], [0.4, 0.45]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩	⟨[0.3, 0.4], [0.2, 0.25], [0.7, 0.9]⟩

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