Engineering Applications of Artificial Intelligence 158 (2025) 111498

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

An integrated p,q-quasirung orthopair fuzzy decision-making approach for strategic selection of competitive intelligence platforms

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ARTICLE INFO

Keywords:
Competitive intelligence
Export performance
p,q-Quasirung Orthopair fuzzy sets
Website selection

ABSTRACT

In an increasingly globalized world, Competitive Intelligence (CI) plays a vital role for export-oriented businesses aiming to maintain a competitive advantage and identify opportunities in international markets. Accurate, timely, and comprehensive information is essential for understanding market dynamics, evaluating competitors, and analysing customer behaviour. However, selecting reliable commercial intelligence websites presents challenges, such as issues of data quality, pricing, usability, and coverage. This study addresses these challenges by introducing a scientific decision-making framework using a fuzzy Multi-Criteria Decision-Making (MCDM) approach to handle the uncertainty in the selection process. The research proposes a novel decision-making model based on p,q-Quasirung Orthopair Fuzzy Numbers (p,q-QOFNs), applying p,q-quasirung operators to calculate expert weights. It integrates the Simple Weight Calculation (SIWEC) and Multi-Attributive Border Approximation Area Comparison (MABAC) methods, called "p,q-quasirung-SIWEC-MABAC", to determine criteria weights and rank website alternatives. This model enhances the integration of subjective evaluations, improving both robustness and efficiency in decision-making. A case study validates the model's practical application in evaluating CI websites, supported by sensitivity and comparative analyses confirming the model's reliability across diverse scenarios. Findings highlight that data security and reliability are the most critical factors in CI website selection. Among the evaluated platforms, A3 emerges as the top choice due to its detailed insights into textile import trends and supplier analysis. This research contributes a unique methodology to CI literature by enhancing export decision-making processes through advanced fuzzy logic techniques, ultimately helping businesses navigate the complexities of global trade more effectively.

1. Introduction

The increasing competition in the globalizing world requires export-oriented companies to make strategic decisions to be successful in export markets. The basis of these strategic decisions is access to reliable and updated information (Cadogan et al., 2003). This is where foreign trade intelligence comes into play, which allows companies to gain a competitive advantage and take the right steps. Competitive Intelligence (CI) will enable businesses to deeply understand their target markets, analyse their competitors, evaluate customer demands and needs, and see opportunities and threats in the sector (Sharp, 2009). However, the diversification of sources from which CI is provided makes the process of selecting the most appropriate and reliable among these sources increasingly complex. Today, many platforms and websites offer export companies a variety of CI services such as market data, customer analysis, industry reports, and competitive information (Javalgi et al., 2004). However, the quality, accuracy, scope, and usability of the information provided by each platform can vary greatly. Therefore, determining which platform is most suitable for businesses is critical not only in terms of providing access to the data needed, but also in terms of evaluating the reliability, timeliness, and compatibility of this data with the company's specific goals (Fernandez et al., 2020). While some platforms offer a wide range of data, their accuracy and timeliness can be questionable. On the other hand, some sources may have highly reliable and

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https://doi.org/10.1016/j.engappai.2025.111498
Received 5 March 2025; Received in revised form 30 May 2025; Accepted 11 June 2025
Available online 24 June 2025
0952-1976/

accurate data, but may not be accessible to small and medium-sized businesses due to user-unfriendly interfaces or high costs (Graef et al., 2015). Therefore, the selection between CI platforms is not limited to the scope of the data alone; it also requires consideration of many different factors, such as the cost of the platform, user experience, the format of the data it provides, ease of use, and how well it aligns with the firm's specific strategic goals (Lapa et al., 2014).

Companies rely heavily on CI application components when making strategic decisions. This procedure entails methodically gathering, examining, and sharing information on market trends, rival activity, and any dangers (Graef et al., 2015). This information may be found on CI websites, which give companies useful information on the pricing tactics, new product launches, and marketing activities of their rivals. This enables companies to act proactively to obtain a competitive edge and promptly adjust to the changing needs of the market.

When making strategic decisions for a specific market, selecting the right source of information is as important as the accuracy of the data obtained from market research (Ruževičius and Gedminaitė, 2007). Relying on misleading or inadequate sources of information can lead to wrong strategic decisions and thus the failure of the company in the international arena. In this context, selecting the right CI source is of great importance for companies to fully understand market dynamics and achieve a strategic edge in their target market (Feenstra et al., 2010). This work is motivated by the urgent need to address these challenges through a structured, scientifically grounded approach. While existing literature has explored the importance of CI, there remains a critical gap in methodologies that systematically evaluate and rank CI websites under conditions of uncertainty. Current decision-making frameworks often fail to account for the nuanced, subjective preferences of experts or the inherent ambiguities in data quality and relevance. Our research seeks to bridge this gap by introducing a novel, multi-dimensional decision-making framework that leverages advanced fuzzy multi-criteria techniques through p,q-Quasirung Orthopair Fuzzy Sets (p,q-QOFSs).

The developed model takes advantage of Simple Weight Calculation (SIWEC) and Multi-Attributive Border Approximation Area Comparison (MABAC) methods integrated with p,q-Quasirung Orthopair Fuzzy Numbers (p,q-QOFNs). Compared to other fuzzy approaches, the p,q-QOFSs contribute to a broader and more flexible decision mechanism. Utilising the p,q-QOFNs combined with the SIWEC approach to calculate criteria weights improves accuracy in intricate decision-making processes and provides more consistent and dependable outcomes, particularly in multi-dimensional and uncertain problems. This method produces trustworthy criteria weights. Here, alternative websites for CI are ranked according to their significance employing the MABAC approach integrated with p,q-QOFNs. MABAC provides the evaluation of alternatives by creating a boundary approximation area. It also offers Decision-Makers (DMs) the ability to make a more robust analysis. The most important advantage of MABAC is that the calculation process is stable, and alternatives can be easily classified according to negative or positive criterion values. In addition, it is a robust method that works effectively on large data sets. In this way, the rankings of CI businesses, as the alternatives, are effectively obtained in the study. By employing p,q-QOFNs and combining SIWEC and MABAC techniques, this work suggests a model that not only enhances decision-making more robustly but also gives firms a useful tool for navigating the intricacies of international trade intelligence. Moreover, the fact that the study conducted two different sensitivity analyses prevents concerns about the reliability of the results. By offering DMs a method of selecting intelligence platforms that have been empirically verified, the aim is to help create more competitive, strategic, and informed business practices in the global marketplace. In other words, we hope to contribute to the scholarly conversation on CI while offering practical answers to the pressing problems that companies in global commerce confront.

All in all, the research renders a comprehensive and systematic approach to determining which platforms to use in research to be conducted on export markets. Exporting companies need reliable and up-to-date information to gain a competitive advantage in their targeted foreign markets. However, making the right selection among the platforms that provide access to this information is a critical step that can directly affect the strategic decisions of companies. The platforms that companies can use in their research on export markets are examined in detail by considering various criteria. These criteria include factors such as accuracy, scope, up-to-dateness of data provided by the platforms, user-friendly interfaces, cost-effectiveness, and suitability for the specific goals of the company. The study aims to optimize the strategic decision-making processes of companies by providing a guiding approach on which platforms can be employed most efficiently to increase the effectiveness of such research and ensure that companies achieve success in international markets. Therefore, the following Research Questions (RQs) will be answered.

***RQ* 1.** Which criteria and sub-criteria are most critical for evaluating competitive intelligence platforms under uncertainty, and how can they be robustly weighted using the p,q-Quasirung SIWEC method?
***RQ* 2.** How can the integrated p,q-Quasirung-SIWEC, and p,q-Quasirung-MABAC framework be applied to rank real-world CI platforms, and what insights emerge from the case study?
***RQ* 3.** How resilient are the resulting rankings to variations in expert judgments and criteria weights, and what does this imply for practical decision support?

The remainder of the manuscript is organized as follows. Section 2 reviews the literature with a special concentration on the CI applications and web service/product selection process. The developed model is described in Section 3. Section 4 presents the case study problem and findings. A comprehensive sensitivity analysis is then done in Section 5 where the managerial insights are provided in Section 6. Finally, Section 7 gives the concluding remarks and outlook for future studies.

2. Literature review

Studies that support the examination of selecting websites to be utilised in international trade are reviewed in this section. The first section focuses on research involving commercial and CI, and the second segment explores studies that focus on the selection process. A literature review was done by searching the terms "competitive intelligence", "commercial intelligence" and "website selection" in the Web of Science (WoS) and Scopus databases.

2.1. CI applications

CI is one of the concepts most frequently used and benefited by exporting businesses. In addition to the sector, there are important studies in the literature. Tao and Prescott (2000) conducted surveys and in-depth case studies to examine the development and structure of CI practices in China. It was also emphasized that the development of China's information infrastructure will play an important role in rapidly improving the information collection and analysis skills of CI professionals. Vedder and Guynes (2001) conducted a survey among CEOs and CIOs implementing a Likert scale regarding CI. The study revealed the perspectives of senior executives regarding CI. Viviers et al. (2002) investigated the development level and prevalence of CI applications in South African firms. The results showed that firms believed that CI could create a strategic advantage, but they were not sufficiently equipped in the areas of process, structure, and analysis. The study presented recommendations to improve the competitiveness of South African firms by increasing their CI awareness.De Pelsmacker et al. (2005) conducted surveys to compare the CI practices of exporting companies in South Africa and Belgium. The study revealed that exporters in both countries have a general awareness of CI but do not have the necessary equipment and configuration for effective CI practices. It was also observed that companies in South Africa have a longer CI tradition, and more personnel are involved in CI activities compared to Belgium. Cuyvers et al. (2008) examined the role and impact of CI in export-oriented firms. The findings demonstrated that export-intensive firms in South Africa give more importance to CI activities and that these activities contribute to export success. In addition, employee training, evaluation of information sources, and acceptance of CI as a critical element for business operations were recommended for the effective use of CI. Yap and Rashid (2011) investigated the level of CI practices in public companies in Malaysia and their relationship with firm performance. Data collected from 123 companies showed that CI was implemented at a moderate level and used for strategic decisions. It was also found that companies with formal CI units performed better in terms of growth and profitability. Mojarad et al. (2014) discussed how CI increases the export performance of firms. The study revealed that elements such as understanding the competitive environment, customer focus, and management skills of CI play an important role in strategic decision-making and export success. They concluded that with the effective use of these elements, firms can gain a competitive advantage in global markets, and their export success increases. Köseoglu et al. (2016) conducted interviews with hotel managers to assess the level of CI in the hotel industry in Minot, North Dakota. According to the outcomes, managers used CI mostly for tactical purposes and received insufficient training at the strategic level. A Competitive Optimality (CO) framework inspired by Captcha tests was developed by Bhatnagar (2021) to provide a probabilistic approach to evaluating AI systems under time and sample-size constraints. This framework formalized key concepts such as the turing gap and competitive inequity, offering a structured method for assessing AI performance, human-executability, and CI in real-world applications.

Iskandar et al. (2023) examined how CI contributes to strategic decision-making processes in the context of delivery services. It was demonstrated that CI helps companies increase their competitive advantage by analysing elements such as competitors' delivery speed, fleet capacity, pricing, and marketing strategies. It was also emphasized that CI plays an important role in adapting to demographic, economic, technological, and political changes in the context of Industry 4.0. Isichei et al. (2023) discussed how CI affects the export performance of SMEs. It was revealed that CI improves export results by improving strategic decision-making processes and that this relationship is further strengthened by a strong learning tendency in the firm. It was also concluded that creating an environment that encourages information sharing strengthens the role of CI in increasing export performance. Afanasyeva et al. (2024) addressed the activities of CI to collect and analyse information about competitors, market trends, and the competitive environment to improve the strategic decision-making processes of firms. They evaluated the benefits and challenges of CI by considering marketing, strategic, technological, and financial intelligence types. They also underscored the importance of implementing effective CI mechanisms to ensure economic security in dynamic markets.

2.2. Web service/product selection using decision-making approaches

The subject of web service providers is among the subjects studied in the literature. Some of the studies implemented for foreign trade intelligence website selection are as follows. Al-Aomar and Dweiri (2008) developed a web-based Decision Agent (DA) and presented a customer-oriented approach to make the online product selection process user-friendly. The system, which directs users to one of three decision modules (i.e., Analytic Hierarchy Process (AHP), Simple Multi-Attribute Rating Technique (SMART), and Design Structure Method (DSM)) according to their Consistency Rates (CRs), was applied to mobile phone selection and showed that users achieved higher satisfaction with less effort. Khezrian et al. (2014) proposed the VIekriterijumsko KOmpromisno Rangiranje (VIKOR) method using a Quality of Service (QoS)-based approach for service selection. They determined the weights of the criteria in service selection by considering the DMs' confidence levels and user preferences. This approach, validated with a sample application, aims to help service consumers make a more efficient and appropriate service selection. Li and Sun (2020) employed MCDM methods to evaluate and prioritise the factors that are effective in the design of a successful Business-to-Consumer (B2C) e-commerce website. In the study, the important design factors were prioritised with Fuzzy AHP, and then five e-commerce websites were ranked with grey Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The results determined "service quality" as the most important design factor, while "Website-3″ was reported as the most successful website. Ouadah et al. (2018) proposed a framework to improve the selection of web services that offer the same functionality but provide different QoS (quality of service). The research area was narrowed down using the K-representative Skyline method, an improved version of fuzzy AHP was applied for QoS weighting, and the web services were ranked using the Promethee method. Experimental results showed that this framework found the best-ranked K-representative Skyline Web Services by better reflecting user preferences. Serrai et al. (2017) implemented MCDM methods by considering the quality (QoS) criteria in the selection of web services. First, they narrowed down the research area by eliminating less suitable web services with the Skyline method and then normalized the weights according to the QoS parameters with the Best-Worst Method (BWM). Then, they ranked the web services using the VIKOR, Simple Additive Weighting (SAW), TOPSIS, and Complex Proportional Assessment (COPRAS) methods and determined the best solution by evaluating the compatibility between these rankings with the Borda voting method.

Youssef (2020) offered a new approach using MCDM methods for the selection of Cloud Service Providers (CSPs). This method, which evaluates CSPs with the integration of TOPSIS and BWM, ranked the most suitable provider according to the criteria specified by the user. They also showed that this approach is more efficient and consistent than the widely used AHP method and that it surpasses AHP, especially in terms of computational complexity and consistency. Bączkiewicz (2021) examined the role of MCDM methods in product selection in e-commerce. In the study, TOPSIS, VIKOR, Preference Ranking Organization Method for Enrichment Evaluation II (PROMETHEE II), and Characteristic Objects Method (COMET) methods were applied to select the most suitable headphone model, and the contribution of these methods to the decision-making processes in online shopping was evaluated. It was shown that these MCDM methods are useful in product selection and have great potential in the field of online commerce. Kumar and Parimala (2020) extracted popular features from online product reviews of customers and analysed possible opinions based on these features. The process of selecting a product from combinations of different features was considered as an MCDM problem and priority scores were calculated for each product using the Weighted Sum Method (WSM). Bagga et al. (2019) evaluated the performance of different MCDM methods for users to select the best web service. Five different MCDM methods were applied in 50 and 100 web service scenarios and the services were ranked based on Quality of Service (QoS). Furthermore, the ranking deviations between the methods were evaluated using Spearman Rank Correlation (SRC) and the results helped the web service users to make the most appropriate selection. Hosseinzadeh et al. (2020) investigated in detail the MCDM techniques used in the service selection process. In the study, a taxonomy including MCDM-based service selection approaches in the literature was presented and the data sets, QoS criteria, and evaluation environments were explained. Polska et al. (2021) developed a method to compare the performance of the Logic Scoring of Preference (LSP) method with other MCDM methods for the selection of Web services. They examined the rankings obtained by SAW, AHP, TOPSIS, and VIKOR methods by comparing the weight calculations of the LSP method with other MCDM methods. The results confirmed that the LSP method produces efficient and accurate results when compared to other MCDM methods. Tomar et al. (2023) proposed a hybrid MCDM methodology to assist DMs in selecting CSPs. This approach evaluated CSPs by combining both subjective and objective criteria and ranked the service providers according to the prioritised list. The results, validated with a real case study, demonstrated that the suggested method provides higher accuracy and reliability in terms of user satisfaction.

Youssef and Saleem (2023) proposed a hybrid MCDM method for the evaluation of Web-based E-Learning Platforms (WELP). This method allowed WELPs to be ranked according to quality criteria using BWM, SAW, and Delphi techniques. It was also shown that the proposed approach is more efficient and reliable compared to the widely used AHP method. Ahemad et al. (2023) extended the COPRAS method using interval-valued q-rung orthopair fuzzy numbers to address MCDM problems. A new distance measure and projection-based weighting model were suggested to evaluate unknown criteria. The approach was validated through a solid waste management case in Indian cities with supporting sensitivity and comparative analyses. Mondal et al. (2023) developed a novel three-way MCDM model integrating regret and prospect theories to reflect behavioral decision-making dynamics. They applied q-rung orthopair fuzzy sets as well as a revised Mahalanobis distance to handle uncertainty and attribute weighting. Giri et al. (2023) proposed a Three-Way Decision (3WD) model based on regret theory and probabilistic interval-valued q-rung orthopair hesitant fuzzy sets to handle uncertainty in medical company evaluations. The model integrated psychological behaviors and imprecise fuzzy data to improve decision plausibility. Kaya (2023) applied a two-stage group decision-making model combining Picture Fuzzy Analytical Hierarchical Process (PF-AHP) and Grey Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS-G) methods to address railway material supplier selection in line with the circular economy approach. Bali et al. (2023) employed a model based on Intuitionistic Fuzzy Sets (IFSs) and TOPSIS method for commercial-off-the-shelf component selection in a group decision-making environment with various benefit and cost criteria. Mondal and Roy (2024) offered a novel three-way MCDM model incorporating Fermatean fuzzy sets and regret theory to address ambiguity and attribute interdependence. They integrated DMs' psychological behaviors through prospect theory to classify alternatives into acceptance, suspension, or rejection categories. Empirical analysis of supply chain datasets demonstrated the model's superior accuracy and robustness compared to existing approaches. Fan et al. (2025) introduced a comprehensive decision-making approach, integrating Picture Fuzzy Sets (PFSs), the CRiteria Importance Through Intercriteria Correlation (CRITIC) method, Interactive MCDM (TODIM) technique, and regret theory to address uncertainty, unknown criteria weights, and psychological behaviors in a group decision-making environment. Applied to green supplier selection problem, the proposed model represented superior consistency, adaptability, and reliability through comparative analysis and Spearman's correlation tests.

2.3. Research gaps

CI plays an increasingly important role in the strategic decision-making processes of companies in international markets. Studies on CI in the literature generally focus on the introduction of data sources (Best, 2011; West, 2010), the use of these data (Tuboalabo et al., 2024; Vashishth et al., 2024), and their effects (Isichei et al., 2023) on foreign trade performance. A large portion of these studies provide information on how to collect foreign trade data (Garcia et al., 2008; Williamson, 1999), which data sources are reliable, and how these data can be implemented in companies' market entry strategies (Levi, 2007; Singh, 2022), competitive analysis (Ismail, 2018; Tong, 2012), and risk management processes. In addition, there are some empirical studies on the use of databases employed in CI on a sectoral or regional basis (Cong and Xia, 2017; Tong, 2012). However, these studies are mostly limited to general analyses and do not comparatively examine the effectiveness of specific databases. The current gap in the literature stems from the lack of a detailed analysis, particularly in comparing the data offered by different CI providers in terms of criteria such as quality, reliability, timeliness, and ease of implementation. This study aims to fill the gap in the literature on measuring the effectiveness of websites in CI. A comprehensive comparative analysis will be presented on how effective different databases are on a sectoral and market basis, how these data are used in firms' export processes, and which data sources are more advantageous. Thus, strategic suggestions will be presented on how firms can use CI more efficiently, and an important contribution will be implemented in the academic literature.

The research on business intelligence, CI, and international trade intelligence are typically carried out employing surveys, as can be observed when examining the studies in Table 1. There are not many studies that implement the fuzzy MCDM approach. Because of that, this study is the first to apply CI and this specific fuzzy MCDM approach together.

2.4. Motivation of the study

The motivation of this research is to optimize the decision process in determining the websites that can help companies find effective export markets within the scope of CI. While there are very limited studies comparing the effectiveness of databases for CI in the literature, there is a lack of in-depth analysis on how SMEs can manage this process with limited resources. In this field where uncertainty and the MCDM process are inevitable, the aim is to direct companies to the right data sources by employing the fuzzy MCDM method. Thus, a guide will be presented for companies to determine which websites are more effective, accessible, and reliable, and an important gap in the literature will be filled in this work.

In the competitive arena of international trade, organizations increasingly depend on advanced tools to obtain actionable insights and sustain a strategic edge. CI websites have become essential resources, providing vital information on market trends, trade legislation, competitor actions, and global economic indicators (Afanasyeva et al., 2024). The increasing number of these platforms poses a considerable challenge: identifying the most suitable CI website that corresponds with certain organizational requirements and strategic goals. The intricacy of this selection process is heightened by the many evaluation criteria, which often include both quantitative considerations (e.g., data accuracy and coverage) and qualitative elements (e.g., user experience and customer assistance). The decision-making environment is characterized by uncertainty and subjectivity, arising from differing expert judgements and the intrinsic ambiguity of language evaluations (L.-C. Yang and Lu, 2012).

This research presents a novel decision-making framework that utilises sophisticated techniques, notably p,q-QOFSs inside an MCDM context to tackle these issues. This method is driven by the necessity to manage the imprecision and uncertainty intrinsic to expert assessments more efficiently than conventional crisp or standard fuzzy set

Table 1
CI and related studies.

Reference	Subject	Method
Chen and Hung (2021)	Gaining a competitive advantage in product development	Intuitionistic fuzzy numbers
Wang (2015)	Quality function deployment business-intelligence systems	Fuzzy AHP, Fuzzy DEMATEL
Isichei et al. (2023)	Export performance of SMEs	Survey method
Nunes and de Souza Lequain (2016)	Export market selection	Four-dimension analyses
Mohammadi et al. (2024)	CI based on export market orientation	Qualitative analysis
Tarek et al. (2016)	CI and the internationalization of North African SMEs	Survey method

techniques. The p,q-QOFSs enhance traditional fuzzy sets by providing a more adaptable representation of uncertainty and reluctance, encompassing both membership and non-membership degrees without the limitations of binary constraints (Zhao et al., 2024). This advanced modelling capability is essential when experts articulate their judgements using language concepts, as it offers a more nuanced and precise representation of their thoughts. Our methodology utilises the p,q-quasirung Orthopair Fuzzy Delphi (p,q-QOFD) method to iteratively enhance the evaluation criteria. This approach utilises the combined expertise of a varied panel of experts, including international trade experts, CI analysts, supply chain professionals, and academics—to evaluate the importance of different criteria. Experts can express their evaluations with enhanced precision by employing language scales aligned with p,q-QOFNs. The p,q-quasirung Orthopair Fuzzy Weighted Averaging (p,q-QOFWA) operator facilitates the aggregation of expert judgements by synthesizing individual evaluations into a unified group

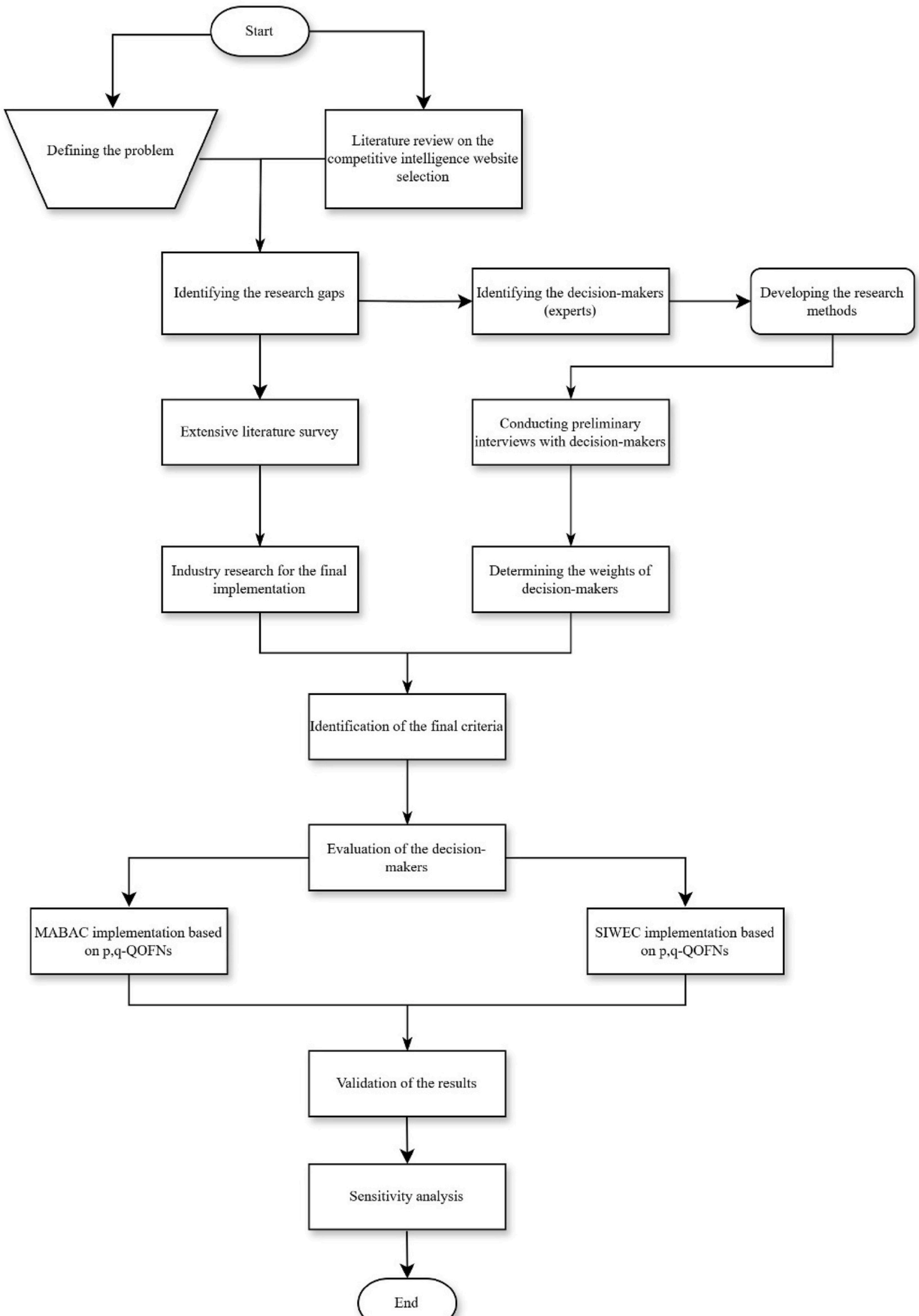

Fig. 1. Website selection methodology for the CI.

consensus. The next defuzzification via a scoring procedure converts the aggregated fuzzy values into precise scores, facilitating practical interpretation and comparison. Ultimately, we employ a quantile-based technique (percentiles) for effective prioritization of the criteria in the p,q-QOFD method. This statistical method categorizes the defuzzied criteria scores into three unique groups: "uncritical," "moderate," and "critical," according to their relative positions within the distribution.

The impetus for incorporating these sophisticated fuzzy set approaches stems from their capacity to represent intricate decision-making situations marked by ambiguity and subjectivity. Conventional MCDM methods may be inadequate when confronted with ambiguous data or linguistic evaluations, potentially resulting in suboptimal conclusions. The utilization of p,q-QOFSs improves the robustness and dependability of the assessment process, guaranteeing that nuanced expert insights are precisely recorded and represented in the results. Moreover, our study introduces a novel MCDM model that enhances the decision-making process by integrating both subjective assessments within the p,q-quasirung orthopair fuzzy framework. We employ the SIWEC method to ascertain subjective weights, effectively capturing expert judgments while minimizing inconsistencies in their evaluations. Then we utilise the MABAC method, which is a potent instrument of MCDM, utilised for ranking options in website evaluation processes. Our study enhances both theoretical and practical areas by underscoring the importance of choosing the ideal CTI website through this advanced approach. It demonstrates the practical use of sophisticated fuzzy set theory in real-world decision-making, offering organizations a methodical method to manage the difficulties of CI in international trade. The novelties aimed at being achieved in this study are in line with all these innovative approaches.

- Uncovering the importance of CI website platforms in export markets,
- Determining which criteria may be used for identifying CI platform selection,
- Identifying which CI websites provide more effective results in export market research,
- Practical demonstration showing that the CI website selection process yields more accurate results with the p,q-QOFSs based approach,
- Strengthening academic and industry connections with p,q-QOFSs based application for business intelligence website selection.

3. Developed model

In this section, we first introduce the fundamental concepts of p,q-QOFSs. Subsequently, the proposed MCDM model, incorporating SIWEC, MABAC, and p,q-quasirung orthopair fuzzy information, is described. This method is designated as the p,q-quasirung-SIWEC-MABAC method. The methodology and flow implemented in the website selection study for CI are also included in this section. Fig. 1 details the execution steps of the model. Moreover, Algorithm 1 represents the pseudocode of the suggested methodology.

Algorithm 1: p,q-Quasirung_SIWEC_MABAC_CI_Platform_Selection

INPUT:

- Initial high-level criteria and candidate sub-criteria (from literature review)
- Expert linguistic judgments on sub-criteria importance (mapped to p,q-QOFNs)
- Expert linguistic evaluations of alternatives (mapped to p,q-QOFNs)
- Parameters $p = 4$, $q = 3$ for score function

OUTPUT:

- w: Final weights for all sub-criteria (from SIWEC)
- R: Final ranking of CI platforms (from MABAC)
- Sensitivity analysis results

BEGIN

Step 1: Data & Criteria Preparation

(continued on next column)

(continued)

1.1 Compile initial criteria categories and collect relevant sub-criteria from the literature
1.2 Consolidate a broad list of candidate sub-criteria (e.g., 40 items) for CI platform evaluation.
1.3 Prepare expert questionnaire with linguistic scales for both sub-criteria importance and platform performance.

Step 2: p,q-QOFD
2.1 Translate each expert's linguistic rating into a p,q-QOFN.
2.2 Aggregate expert judgments using the p,q-QOFWA operator.
2.3 Defuzzify aggregated p,q-QOFNs via the score function to obtain crisp scores. // Eq. (2)
2.4 Compute the 25th and 50th percentiles of the defuzzified scores to classify sub-criteria as "uncritical," "moderate," or "critical" (Table 6).

Step 3: p,q-Quasirung SIWEC Weight Calculation
Input:

- Experts $E = \{e_1, \ldots, e_m\}$,
- Criteria $C = \{c_1, \ldots, c_n\}$,
- Linguistic evaluations L[e][c] → p,q-QOFN,
- Parameters $p = 4$, $q = 3$.

Output: weights w[1,…, n]
1. for each e in E, c in C:
2. (μ, ν) ← p,q-QOFN(L[e][c])
3. S[e][c] ← (1+f^p - h^q)/2//Eq. (2)
4. S_max ← max_{e,c} S[e][c]
5. for each e in E, c in C:
6. N[e][c] ← S[e][c]/S_max//Eq. (6) global normalization
7. for each e in E:
8. σ_e ← stdev_{c}(N[e][c])//DM dispersion
9. for each e in E, c in C:
10. M[e][c] ← N[e][c]×σ_e//Eq. (7)
11. for each c in C:
12. U[c] ← ∑_{e} M[e][c]//Eq. (8)
13. W_sum ← ∑_{c} U[c]
14. for each c in C:
15. w[c] ← U[c]/W_sum//Eq. (9)
16. return w

Step 4: p,q-Quasirung MABAC Ranking
Input:

- Alternatives $A = \{a_1, \ldots, a_k\}$,
- Criteria C and weights w[c],
- Expert evaluations aggregated into p,q-QOFN matrix G0[a][c],
- p,q parameters for defuzzification.

Output: ranking R of A
1. for each a in A, c in C:
2. x[a][c] ← score(G0[a][c])//Eq. (2)
3.//Normalize (all benefit criteria):
4. for each c in C:
5. x_min[c], x_max[c] ← min,max_{a}(x[a][c])
6. for each a in A:
7. n[a][c] ← (x[a][c] – x_min[c])/(x_max[c] – x_min[c])//Eq. (11)
8.//Apply weights:
9. for each a in A, c in C:
10. v[a][c] ← w[c] × n[a][c]//Eq. (13)
11.//Boundary proximity area:
12. for each c in C:
13. g[c] ←∏_{a} v[a][c]^(1/k)//Eq. (14)
14. for each $a$in A, $c$in C:
15. q[a][c] ← v[a][c] – g[c]//Eq. (16)
16. for each a in A:
17. Q[a] ← ∑_{c} q[a][c]//Eq. (18)
18. R ← rank alternatives by descending Q[a]
19. return R

Step 5: Validation & Sensitivity Analysis
5.1 Perform Consistency Check.
5.2 Sensitivity Analysis.
5.3 Compare the output of MABAC with alternative MCDM methods.
Step 6: Managerial & Practical Implications
END

3.1. Website selection criteria set for CI

Expert evaluation and extensive industry study led to the final set of selection criteria for CI websites. In practice, the gathering of criteria is examined in Table 2. The criteria's application meanings and the studies in which they are applied serve as evidence that the application is specifically designed to meet sectoral and academic demands. Table 2 lists the five high-level criteria and their associated sub-criteria as identified from the literature review. The initial results of the literature review served as input for the proposed p,q-QOFD refinement in Sub-section 4.1, which surveyed experts to winnow and prioritise a broader set of 40 candidate sub-criteria down to the final 20 (see Table 6). Importantly, the p,q-QOFD–SIWEC–MABAC framework can be easily expanded: any new main criteria or sub-criteria can be added to the original list and go through the same Delphi, weighting, and ranking processes.

3.2. Basic concepts

Definition 1. A $p,q-QOFS\ B$ on a universal set U is defined by Eq. (1):

$$B = \{\langle u, f_B(u), h_B(u)\rangle | u \epsilon U\}, \tag{1}$$

where $f_b : \mathrm{U} \rightarrow [0,1]$ and $h_b : \mathrm{U} \rightarrow [0,1]$ describe the membership and non-membership degrees, respectively, with the condition $0 \leq f_B(u) + h_B(u) \leq 1$.

Definition 2. The score function $p,q-QOFNs\ b = (f,h)$ can be defined as in Eq. (2):

$$\Theta(b) = \frac{1 + f^p - h^q}{2}. \tag{2}$$

Definition 3. $b_1 = (f_1, h_1)$ and $b_2 = (f_2, h_2)$ be two $p,q-$ $QOFNs$, some operations are as follows:

1. $b_1 \leq b_2$ if $f_1 \leq f_2$ and $h_1 \geq h_2$,
2. $b_1 = b_2$ if $f_1 = f_2$ and $h_1 = h_2$,
3. $b_1 \bigoplus b_2 = \left(\sqrt[p]{f_1^p + f_2^p - f_1^p f_2^p}, h_1 h_2\right)$,
4. $b_1 \bigotimes b_2 = \left(f_1 f_2 \sqrt[q]{h_1^q + h_2^q - h_1^q h_2^q},\right)$,
5. $rb_1 = \left(\sqrt[p]{1 - \left(1 - f_1^p\right)^r}, h_1^r\right)$, where $r(\geq 0) \in \mathbb{R}$,
6. $b_1^r = \left(f_1^r, \sqrt[q]{1 - \left(1 - h_1^q\right)^r}\right)$, where $r(\geq 0) \in \mathbb{R}$.

Definition 4. The aggregated result of a collection of $p,q-$ $QOFNs\ b_r = (f_{b_r}, h_{b_r})$ $(r = 1, 2, \ldots, k)$ using $p,q-QOFWA$ and p,q-Quasirung Orthopair Fuzzy Weighted Geometric ($p,q-QOFWG$) operators is also a $p,q-QOFN$:

$$p,q-QOFWA(b_1, b_2, \ldots., b_k) = \left(\sqrt[p]{1 - \prod_{r=1}^{k}\left(1 - f_{b_r}^p\right)^{Qr}}, \prod_{r=1}^{k} h_{b_r}^{Qr}\right), \tag{3}$$

$$p,q-QOFWG(b_1, b_2, \ldots., b_k) = \left(\prod_{r=1}^{k} f_{b_r}^{Qr}, \sqrt[q]{1 - \prod_{r=1}^{k}\left(1 - h_{b_r}^q\right)^{Qr}}\right). \tag{4}$$

3.3. p, q-quasirung SIWEC

The SIWEC method is an innovative method used in MCDM processes. The SIWEC method stands for a streamlined approach to criteria-weight profiling within the MCDM context. Basically, it refers to the development of an appropriate format for any given panel through the direct translation of weights from the more often linguistic evaluation provided by the panel into a unified weighting format. Several relative

Table 2
CI website selection criteria.

Criteria	Sub-Criteria	Description	Reference
C_1 (Data Quality)	Accuracy (C_{11})	Data is taken from reliable sources and reflects the truth.	(Shaar, 2019; Yang et al., 2023; Shaar, 2017)
	Up-to-dateness (C_{12})	How often data is updated and access to the latest data.	(Neumaier and Umbrich, 2016; Lucic, 2024; Jing et al., 2014)
	Reliability (C_{13})	Reliability of data sources and the reputation of data providers.	(Wang et al., 2010; Rozanski and Yeats, 1994)
	Scope (C_{14})	Level of detail provided by the data (sectoral, regional, or product-based).	(Wang and Chen, 2024; Yao et al., 2015)
	Data Consistency (C_{15})	The consistency and compatibility of data presented in different time periods.	(Rozanski and Yeats, 1994); **Expert Opinion**
C_2 (Scope and Reach)	Geographic Coverage (C_{21})	Accessibility of data at global, regional, or country level.	Maia (2015)
	Sectoral Coverage (C_{22})	Diversity of data provided for different sectors.	(Borchert et al., 2021; Maskus, 1989)
	User Friendly Interface (C_{23})	Ease of use of the website and speed of access to data.	(Giordano and Maiorana, 2004; Bordoloi, 2021)
	Access Time (C_{24})	How quickly data can be accessed (absence of problems such as slowness, interruptions, etc.).	(Chen et al., 2000; Fung and Wong, 2002)
C_3 (Cost and Ease of Access)	Subscription Cost (C_{31})	Costs required to access the website (paid subscription, free limited access).	(Bennett, 1996; Forte, 2011)
	Free Content Coverage (C_{32})	Extent and adequacy of data are provided free of charge.	**Expert Opinion**
	User Support (C_{33})	Quality of technical support and customer service.	(Herczeg et al., 2013); **Expert Opinion**
	Flexibility (C_{34})	Availability of different subscription options and affordable plans.	(Narkhede et al., 2017; Ali et al., 2014; Raut et al., 2019; Oly Ndubisi et al., 2005)
C_4 (Data Analysis Ability)	Trend Analysis (C_{41})	Ability to extract long-term trends from data and situations.	(Abiodun and Charlotte, 2022; Bhattacharyya and Choudhury, 2017)
	Customized Reporting (C_{42})	Reporting capabilities that can be customized according to user needs.	**Expert Opinion**
	Comparative Analysis (C_{43})	Ability to compare different markets or products.	(Yu and Ma, 2020; Wang and Choi, 2019)
	Graphical Visualization (C_{44})	Ability to present data in graphs, tables, or other visual formats.	(Chow et al., 2022; Skender and Manevska, 2022)
C_5 (Security and Privacy)	Data Security (C_{51})	Security measures to protect user data.	(Skender and Manevska, 2022; Chin and Zhao, 2022)
	Privacy Policy (C_{52})	Existence of reliable policies that ensure the confidentiality of user information.	(Meltzer, 2016; Mattoo and Meltzer, 2018)
	Security Certificates (C_{53})	Security certificates and protocols owned by the website	(Lotz et al., 2012; Kaluvuri et al., 2013)

Table 3
Linguistic inputs for the self-assessment of experts.

Linguistic variable	p,q-QOFNs
Very Low (VL)	(0.10, 0.90)
Low (L)	(0.30, 0.70)
Medium (M)	(0.50, 0.50)
High (H)	(0.70, 0.30)
Very High (VH)	(0.90, 0.10)

strengths of using the SIWEC weighting procedure are that by its very nature, it is rather straightforward, and its output will generally not be challenging to comprehend. It reduces computational complexity and is robust against inconsistencies in the expert evaluations, hence providing a reliable base for further decision analysis. Its simplicity also allows integration with other MCDM methods and can be easily extended for subjective factors. The SIWEC method consists of seven basic steps given in the following (Puška et al., 2024). Here, the SIWEC method is employed to identify the subjective weights of the criteria. Below are the implementation steps for the method.

Step 1: Constructing the initial decision matrix for each expert ($\mho^r$)

In this stage, specialists execute a linguistic appraisal for the decision alternatives using the linguistic scale. According to the scale, these assessments are then transformed into $p,q-QOFNs$. Following this process, each expert is assigned a foundational decision matrix $\mho^r = \left[\mho^r_{ij}\right]$, where $\mho^r_{ij} = \left(f^r_{ij}, h^r_{ij}\right)$, $(r = 1,2,\ldots,k;\ i = 1,\ldots,m;\ j = 1,\ldots n.)$ (5)

Step 2: Converting these linguistic evaluations into the $p,q-QOFNs$ aligned with the language scale This step leads to the acquisition of r into $p,q-QOFN$ matrices.

Step 3: Defuzzifying the $p,q-QOFNs$ and computing score values

During this phase, the $p,q-QOFNs$ matrix elements are defuzzified by applying Eq. (2).

Step 4: Normalizing the original matrix for decision-making

This normalization is different from the normalization employing multi-criteria analysis techniques because it divides the value corresponding to each criterion (x_{ij}) by the maximum value of all grades ($\max(x_{ij})$) rather than by the maximum value for specific criteria. The normalized formula is given in Eq. (6):

$$n_{ij} = \frac{x_{ij}}{\max(x_{ij})}. \tag{6}$$

Step 5: Calculating the standard deviation for normalized DM grades ($st.dev_j$) to provide preference to DMs with more dispersed ratings

Since not all criteria are equally important some must be better or worse than others, a higher divergence should encourage more realistic thinking.

Step 6: Multiplying the normalized grades by the standard deviation values

This step is done with the help of Eq. (7) for each DM:

$$v_{ij} = n_{ij} \times st.dev_j. \tag{7}$$

Step 7: Computing the weights of specific criteria added together

This phase involves adding the standard deviation values for certain criteria to all multiplied normalized grades. Eq. (8) calculates it as follows:

$$s_{ij} = \sum_{j=1}^{n} v_j. \tag{8}$$

Step 8: Calculating the final values of the criteria weights

To set the total weight of the criteria equal to 1, individual values s_j are divided by summary values s_j in this phase. It is computed using Eq. (9):

$$w_{ij} = \frac{s_{ij}}{\sum_{j=1}^{n} s_{ij}}. \tag{9}$$

3.4. p,q-quasirung MABAC

MABAC is a comprehensive technique that has been utilised in various decision-making studies for sorting alternatives. Based on the performance values of the alternatives and the weights of the criteria, this method generates a boundary approach area. The alternatives' distances to this location are determined and arranged in order of preference. It is a recommended approach in decision-making processes since it is straightforward and efficient (Pamučar and Ćirović, 2015). The method consists of six basic steps.

Step 1: Formulate the consolidated initial $p,q-QOFN$ decision matrix:

Let there be m options ($i = 1,\ldots,m$), n criteria ($j = 1,2,\ldots,n$), and r experts ($r = 1,2,\ldots,k$) in a group decision-making scenario. Each expert

Table 5
Linguistic inputs for the implementation of the p,q-QOFD method.

Linguistic variable	p,q-QOFNs
Not Important (NI)	(0.20, 0.98)
Slight Important (SI)	(0.50, 0.96)
Moderately Important (MI)	(0.45, 0.55)
Important (I)	(0.81, 0.42)
Very Important (VI)	(0.98, 0.15)

Table 4
Weights provided by the experts.

Expert	Q1	Q2	Q3	Q4	Q5	$Ⅎ_1$	$Ⅎ_2$	$Ⅎ_3$	$Ⅎ_4$	$Ⅎ_5$	ϱ_j
Exp1	VH	L	L	H	H	0.8276	0.3326	0.3326	0.6066	0.6066	0.1269
Exp2	H	H	M	H	VH	0.6066	0.6066	0.4688	0.6066	0.8276	0.1461
Exp3	L	M	H	M	M	0.3326	0.4688	0.6066	0.4688	0.4688	0.1100
Exp4	M	VL	H	VH	H	0.4688	0.1356	0.6066	0.8276	0.6066	0.1241
Exp5	H	VH	VH	VH	VH	0.6066	0.8276	0.8276	0.8276	0.8276	0.1837
Exp6	VH	L	VL	M	L	0.8276	0.3326	0.1356	0.4688	0.3326	0.0984
Exp7	VL	M	M	L	M	0.1356	0.4688	0.4688	0.3326	0.4688	0.0879
Exp8	M	H	H	L	H	0.4688	0.6066	0.6066	0.3326	0.6066	0.1229

Table 6
Experts evaluation to define the criteria.

Code	Exp1	Exp2	Exp3	Exp4	Exp5	Exp6	Exp7	Exp8	Score	Category
C1	VI	I	VI	MI	I	I	VI	I	0.826	Critical
C2	MI	VI	MI	VI	MI	MI	VI	VI	0.8442	Critical
C3	NI	NI	MI	SI	I	MI	I	NI	0.4151	Uncritical
C4	VI	VI	NI	NI	NI	MI	I	MI	0.7104	Critical
C5	VI	NI	VI	VI	MI	NI	I	VI	0.845	Critical
C6	VI	MI	VI	MI	I	MI	VI	I	0.8011	Critical
C7	SI	MI	SI	MI	I	I	SI	VI	0.6278	Moderate
C8	NI	MI	NI	I	I	VI	I	NI	0.6141	Moderate
C9	SI	MI	VI	VI	I	VI	I	I	0.8108	Critical
C10	NI	I	I	MI	I	SI	I	I	0.5852	Uncritical
C11	I	MI	SI	SI	MI	SI	MI	MI	0.4237	Uncritical
C12	NI	SI	SI	VI	VI	I	VI	VI	0.8569	Critical
C13	VI	I	I	MI	I	I	MI	NI	0.6948	Moderate
C14	I	NI	VI	MI	NI	MI	SI	SI	0.5335	Uncritical
C15	VI	VI	VI	I	NI	SI	I	I	0.8224	Critical
C16	I	SI	MI	VI	I	VI	SI	I	0.7461	Critical
C17	NI	SI	NI	MI	VI	I	VI	VI	0.7982	Critical
C18	SI	VI	SI	SI	NI	I	MI	NI	0.548	Uncritical
C19	NI	SI	VI	NI	SI	NI	I	SI	0.4543	Uncritical
C20	MI	SI	VI	NI	NI	VI	MI	SI	0.6155	Moderate
C21	VI	SI	MI	I	VI	I	VI	SI	0.8211	Critical
C22	I	MI	VI	VI	I	SI	VI	I	0.8104	Critical
C23	SI	SI	VI	SI	I	VI	I	VI	0.785	Critical
C24	NI	MI	VI	MI	NI	I	SI	VI	0.6822	Moderate
C25	MI	I	SI	VI	VI	SI	MI	I	0.7801	Critical
C26	I	NI	SI	MI	SI	VI	SI	VI	0.6662	Moderate
C27	SI	I	MI	MI	NI	SI	MI	NI	0.3692	Uncritical
C28	SI	SI	NI	I	VI	MI	SI	I	0.6617	Moderate
C29	VI	MI	VI	SI	I	I	I	VI	0.8218	Critical
C30	MI	I	MI	VI	MI	SI	MI	NI	0.6074	Moderate
C31	VI	MI	I	MI	I	VI	VI	SI	0.7895	Critical
C32	VI	SI	SI	MI	SI	MI	NI	NI	0.4995	Uncritical
C33	MI	NI	I	I	SI	MI	VI	SI	0.555	Uncritical
C34	VI	MI	I	VI	MI	MI	SI	NI	0.7173	Critical
C35	I	I	I	VI	VI	I	VI	I	0.8597	Critical
C36	SI	NI	VI	SI	SI	VI	I	NI	0.6151	Moderate
C37	I	NI	I	I	MI	I	SI	SI	0.517	Uncritical
C38	VI	VI	I	MI	MI	I	MI	VI	0.826	Critical
C39	I	MI	NI	VI	NI	NI	I	MI	0.5961	Moderate
C40	MI	I	I	VI	VI	I	VI	NI	0.8353	Critical

25th percentile: 0.5880; **50th percentile:** 0.7026.

does a linguistic evaluation for every choice by assessing each criterion. Subsequently, these linguistic evaluations are converted into the relevant $p,q-QOFNs$ on the linguistic scale, resulting in the acquisition of r $p,q-QOFN$ matrices. Subsequently, these matrices are consolidated utilising the $p,q-QOFWA$ operator as specified in Eq. (3). The consolidated initial $p,q-QOFN$ decision matrix is then produced. Finally, the elements of the consolidated matrix are converted into numerical (definite) scores using Eq. (2). Initial decision matrix is given in Eq. (10):

$$X = \begin{array}{c} A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}. \tag{10}$$

Step 2: Normalize the initial decision matrix to Eqs. (11) and (12):

$$n_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \ (\textit{benefit criteria}), \tag{11}$$

$$n_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \ (\textit{cost criteria}). \tag{12}$$

Step 3: The weighted matrix is given in Eq. (13):

$$b_{ij} = w_j \times (d_{ij} + 1). \tag{13}$$

Step 4: Obtain the boundary proximity area matrix with the help of Eq. (14):

$$g_i = \left(\prod_{i=1}^{m} b_{ij} \right)^{1/m}, \tag{14}$$

$$G = [g_i]_{1\times n}, \tag{15}$$

where g_i is the element of the boundary proximity area matrix (G):

Step 5: Calculate the distances of the alternatives to the boundary approach area matrix using Eq. (16):

$$Q = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & \cdots & v_{1n} - g_n \\ v_{11} - g_1 & v_{22} - g_2 & \cdots & v_{2n} - g_n \\ \cdots & \cdots & \cdots & \cdots \\ v_{11} - g_1 & v_{m2} - g_2 & \cdots & v_{mn} - g_n \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ q_{m1} & q_{m2} & \cdots & q_{mn} \end{bmatrix}. \tag{16}$$

Step 6: Determine the locations according to the border proximity area with the help of Eq. (17):

$$A_i \in \begin{cases} G^{+} \text{ if } q_{ij} > 0, \\ G \text{ if } q_{ij} = 0, \\ G^{-} \text{ if } q_{ij} < 0. \end{cases} \tag{17}$$

Step 7: Find the ranking of the alternatives using Eq. (18):

$$S_i = \sum_{j=1}^{n} q_{ij}. \tag{18}$$

3.5. Methodological advantages over existing fuzzy approaches

As can be understood from the literature, researchers have been developing various fuzzy MCDM methods to handle human judgement ambiguity. Traditional fuzzy MCDM techniques, such as fuzzy Analytic Hierarchy Process (AHP), fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy VIKOR, utilise linguistic scales mapped to triangular or trapezoidal fuzzy numbers to capture expert subjectivity. However, several extensions have been developed to handle uncertainty and imprecise information. Our integrated p,q-quasirung SIWEC-MABAC framework builds on these advances by offering a streamlined weight-derivation process and a boundary-based ranking mechanism that together improves both computational efficiency and robustness under uncertainty. Our methodological contribution is explained in detail below.

I. The p,q-QOFNs generalize IFSs by independently modelling membership and non-membership degrees. This richer representation captures expert ambiguity more flexibly than standard triangular/trapezoidal numbers often used in fuzzy AHP or TOPSIS,
II. The utilization of varying values for the two real numbers, p, and q, within the QOFS framework enhances flexibility and allows for a more detailed analysis of imprecise data. This approach adheres to the requirement that the degrees of membership and non-membership remain constrained within the interval of [0, 1],
III. SIWEC replaces fuzzy AHP's labor-intensive pairwise comparisons with direct linguistic-to-weight conversion, reducing computational complexity and minimizing consistency checks, while still reflecting DM dispersion,
IV. MABAC avoids the rank-reversal issues associated with distance-based methods (e.g., fuzzy TOPSIS) by evaluating each alternative's proximity to a boundary approximation area rather than ideal solutions. This yields more consistent classifications under small perturbations.

4. Case study problem and findings

The selection of commercial intelligence websites in this area was performed to get accurate and useful commercial intelligence for global commerce. The factors that are thought to be crucial for buying or using Web Resource-Based (WRB) websites were meticulously determined. These requirements covered things like accessibility, cost-effectiveness, data quality, and usability. The best software in the business intelligence industry was selected for this application based on the weight assigned to these factors. To ensure that the selected software fits the unique requirements and objectives for international trade activities, our selection process includes expert reviews.

4.1. Description of the case study

Here, experts initially assessed the criteria before the judges decided. The final criteria were created to be achieved after experts assessed the relationship between the research and its content prior to the criteria being implemented in this section.

4.1.1. *Phase 1:* obtain the expert weight

Accurate determination of expert weights is pivotal for the robustness and reliability of the MCDM framework employed in this study. This section delineates the systematic approach adopted to identify and aggregate the weights of experts, encapsulating their diverse expertise within the p,q-QOFNs framework. The process encompasses the formation of a decision-making group, the identification of relevant expertise criteria, the development and administration of structured questionnaires, and the subsequent translation and aggregation of expert evaluations.

I Formation of the Decision-Making Group

To ensure a comprehensive evaluation of CI websites, the decision-making group comprises experts from four key domains.

1. **International Trade Specialists**: Professionals with extensive knowledge of international trade dynamics, regulations, and market strategies,
2. **CI Analysts**: Experts skilled in competitor benchmarking, data analysis, and strategic foresight.
3. **Supply Chain and Logistics Experts**: Specialists in supply chain optimization, logistics management, and risk assessment,
4. **Academicians**: Scholars with expertise in international trade, export operations, operations management, and decision sciences.

This diverse panel ensures that evaluations are informed by a wide array of perspectives, enhancing the credibility and depth of the assessment process. As a result of the investigation, eight experts were accepted to support our research.

II Identification of Relevant Expertise Criteria

To encapsulate the multifaceted expertise of the group members within the p,q-QOFN framework, it is essential to identify and define the criteria that reflect their knowledge and skills. The following criteria were selected based on their relevance to the study's objectives.

1. **Understanding of International Trade Regulations (Q1):** Assesses the expert's knowledge of global trade laws, tariffs, and compliance requirements,
2. **Conducting Global Market Analysis (Q2):** Evaluates the ability to analyse international market trends and identify business opportunities,
3. **Developing Export Strategies (Q3):** Measures proficiency in formulating and implementing strategies to enhance export performance,
4. **Analytical Skills (Q4):** Gauges the capacity for critical thinking, data interpretation, and strategic decision-making,
5. **Competitor Benchmarking and Analysis (Q5)**: Assesses expertise in evaluating and comparing competitors' performance and strategies.

III Features of CI Websites Companies

The company took part in the application for the selection of CI websites. The characteristics of the companies subject to the application are as follows:

***Alternative* 1 (A1):** This CI company was established in the United States of America in 1990 and has been operating for around 35 years. The business provides a thorough database of workers, goods, and services, and contact details for several businesses throughout the entire world,

Founded in the US in 1990 and operating for nearly 35 years, the company offers an in-depth supplier and industrial resource database for businesses all over the world. Buyers have the potential to obtain access to contact information of millions of products, services, and potential business partners through this system. For example, a machine manufacturer in London can obtain access to and quotations from a US special steel supplier through this database.

***Alternative* 2 (A2)**: This platform has been providing annual trade statistics since 1962 and is run by the United Nations Statistics Division. It contains data on world commerce. The platform is an invaluable resource for scholars, DMs, and the business community since it includes import and export data for almost 200 nations.

UN Comtrade, in existence since 1962 through the United Nations Statistics Division, contains annual data on world trade. For example, an economist can examine the export and import quantity of Türkiye with Germany in 2024 in very much detail on this platform. An international logistics firm can also check trade flows between different nations and decide routes accordingly.

***Alternative* 3 (A3)**: This CI platform has been in operation for more than 20 years (established in 2001) to supply data on international commerce. The portal assists businesses with market research and examines global import and export trends. The system seeks to support the growth of international trade by offering data for several industries globally. It provides its consumers with current and comprehensive trade statistics thanks to its staff of professionals.

This global trade information platform, which was founded in 2001, helps a textile company, for example, discover its export potential in the Latin American region. Based on the latest information, the platform provides detailed textile import trends and leading suppliers of countries in this region. This allows the company to develop target market strategies.

***Alternative* 4 (A4)**: Established in 1972 in London, this independent market research firm first produced business reference guides and industry studies for the UK market. It currently has analysts in more than 100 countries and 16 international offices globally. Thousands of research professionals, data scientists, and technological specialists make up the company's research staff. The precise number of workers at the firm is unknown.

This independent market research firm is capable of producing comprehensive industry reports; for example, on Germany's renewable energy sector. Because it has a global network of qualified analysts, this report examines local market forces in combination with international trends, so DMs and investors can act sensibly. All these alternative website platforms are business intelligence that favors businesses willing to enter the global market through exporting. The IT companies provide information about foreign firms to export businesses overseas looking for it free of charge or for a fee. Such a channel makes it easier for businesses interested in exporting to have their foreign buyers easily, so they will not be buried with mountains of information. Due to this fact, such web platforms are extremely significant, particularly for businesses that seek foreign customers and markets.

IV Development of the Questionnaire

A structured questionnaire was designed to capture both the self-assessment of expertise and the evaluation of CI website criteria importance. The questionnaire comprises four main sections.

1. D**emographic and Background Information**: This section collects essential information about the experts, including their name, position, affiliation, years of experience, and area of expertise,
2. **Self-Assessment of Expertise**: Experts rate their proficiency in the identified expertise criteria using a predefined linguistic scale,
3. **Evaluation of CI Website Criteria Importance**: Experts assess the importance of various attributes of CI websites relevant to CI,
4. **Open-Ended Questions**: This section captures qualitative insights and additional factors considered critical by the experts.

Eight experts use the linguistic variables in Table 3 to express their self-assessment of expertise, which they then further transform into p,q-QOFNs. Then, Eq. (2) is applied to obtain the crisp values of the evaluations. Finally, we normalize the values to ensure that the sum of weights across all criteria is equal to 1. Table 4 presents the information assessment and the outcomes.

4.1.2. *Phase 2: refine the criteria*

Here, the p,q-QOFD method is employed as an advanced extension of the traditional fuzzy Delphi approach in order to meticulously refine the criteria for selecting CI websites. This method leverages p,q-QOFSs to allow experts to articulate their judgments with enhanced flexibility and precision, capturing both membership and non-membership degrees without necessitating binary decisions. A diverse panel of experts utilises a five-point linguistic scale presented in Table 5, ranging from "very important" to "not important," which are systematically translated into p,q-QOFNs. These experts evaluate the potential criteria based on their significance to CI in international trade. Subsequently, their assessments are aggregated implementing the p,q-QOFWA operator, ensuring a comprehensive synthesis of collective insights. The aggregated fuzzy vectors are then defuzzified through a score function, converting them into crisp numerical values. Finally, the criteria are categorized into distinct groups "uncritical," "moderate," and "critical"—using the quantile-based method (percentiles). This method involves calculating the 25th and 50th percentiles of the defuzzified criteria values to establish thresholds that effectively segment the criteria based on their relative importance. Utilising the 50th percentile, the median, instead of the 25th percentile for categorizing values into Critical, Moderate, and Uncritical offers a more balanced and representative division of the dataset. The 50th percentile effectively splits the data into two equal halves, ensuring that "Critical" encompasses the top 50 % of values, which provides a clear distinction based on the central tendency of the data. This approach minimizes the influence of outliers and skewed distributions that might disproportionately affect the 25th percentile, leading to a more equitable and meaningful categorization. By leveraging the median, the classification reflects a true midpoint, enhancing the reliability and interpretability of the categories for decision-making and analysis.

The carefully organized p,q-QOFD method employed the aggregated perspectives of experts. Experts assess a questionnaire in two or more defined stages. Specialists from 20 distinct firms conducted a survey employing a 5-point relevance scale to ascertain the essential elements among the 40 identified sub-criteria from the research evaluation. Nevertheless, merely 8 individuals from 14 distinct firms sent responses. The assessments of experts are given in Table 6. Criteria falling below the 25th percentile are classified as "uncritical," those between the 25th and 50th percentiles as "moderate," and those above the 50th percentile as "critical," thereby prioritizing the factors that most significantly influence the selection of CI websites. According to the results presented in Table 6, 20 criteria were defined as critical, 10 criteria as moderate, and the remainder as uncritical, respectively.

4.2. *Obtaining the weights of criteria by p, q-QOFSs-based SIWEC method*

The methodological framework was utilised to select an appropriate CI platform from the four alternatives identified in this study. A set of selection criteria comprising 20 factors was built up, as illustrated in Table 6. Subsequently, experts conducted linguistic evaluations based on the selection criteria outlined in Table 7. Table 8 presents the p,q-QOFNs assessment equivalent of experts. Linguistic assessments conducted by DMs were converted into p,q-QOFNs that correspond to the linguistic evaluation scale presented in Table 8. The score values of these evaluations were calculated using Eq. (2), as detailed in Table 9. The 20 sub-criteria obtained are classified under 5 main criteria. The multiplication matrix of the SIWEC method is given in Table 10. The calculation was done with the help of Eq. (7).

The s_{ij} and w_{ij} values of the main criteria were calculated with the

Table 7
Linguistic ratings of criteria.

Experts	C_1	C_2	C_3	C_4	C_5
Exp1	H	L	VL	VH	UA
Exp2	AA	EL	L	VL	AA
Exp3	H	L	VH	VL	L
Exp4	VL	VH	EL	EH	VH
Exp5	L	EL	VL	L	A
Exp6	EH	VH	VL	VH	VH
Exp7	EH	EH	VH	EL	UA
Exp8	AA	UA	UA	UA	AA

help of Eq. (8) and Eq. (9). The weights of the main criteria are C_1 (0.246), C_2 (0.214), C_3 (0.139), C_4 (0.1889) and C_5 (0.212) respectively. The same application process was applied to the sub-criteria. The weights of all criteria because of the calculations are given in Table 11.

4.3. Identifying ranking of platforms by p, q-QOFSs-based MABAC method

Following the determination of the criteria weights, the platforms were assessed utilising the linguistic terms presented in Table 5. Experts change linguistic terms given in Table 5 as "Very Bad (VB), Bad(B), Medium (M), Good (G), and Very Good (VG) for evaluating platforms. The linguistic assessments are presented in Table 12. These evaluations were converted to the p,q-QOFNs corresponding to the linguistic appraisal scale. The initial p,q-QOF decision matrices were aggregated using Eq. (3), resulting in the p,q-QOF decision matrix displayed in Table 13. Then, the exact number values with the help of Eq. (2), and given in Table 14.

Table 14 is also the initial decision matrix of the MABAC method. All criteria in the application were considered as benefit criteria. Therefore, the values were standardized using Eq. (11). Then, the weighted matrix in Table 15 was obtained with the help of Eq. (13).

The g-matrix was created utilising Eq. (14), while the q-matrix was rendered using Eq. (16). The q-matrix is given in Table 16. The final scores of the alternatives were calculated with the help of Eq. (18). The scores and rankings of the alternatives are given in Table 17. Alternative 3 is the best and most selected CI platform.

5. Reliability and Stability

Understanding the outcomes of many scenarios is essential when selecting the right commercial intelligence platforms. As such, the study included two different sensitivity analyses. In the first sensitivity analysis, 200 alternative scenarios were generated by altering the weights of the criteria applied when selecting the CI platforms. In the second sensitivity study, 80 distinct scenarios were generated by altering the DMs' expert weights. The formulas employed in sensitivity analysis calculations are given in Eqs. (19)–(21):

$$w_{fv}^{1} = w_{pv}^{1} - \left(w_{pv}^{1} \times m_v\right). \tag{19}$$

Table 9
Definite number of ratings.

Experts	C_1	C_2	C_3	C_4	C_5
Exp1	0.658	0.278	0.160	0.795	0.375
Exp2	0.552	0.015	0.278	0.160	0.552
Exp3	0.658	0.278	0.795	0.160	0.278
Exp4	0.160	0.795	0.015	0.980	0.795
Exp5	0.278	0.015	0.160	0.278	0.463
Exp6	0.980	0.795	0.160	0.795	0.795
Exp7	0.980	0.980	0.795	0.015	0.375
Exp8	0.552	0.375	0.375	0.375	0.552

Table 10
Multiplication matrix of the SIWEC method.

Experts	st.dev	C_1	C_2	C_3	C_4	C_5
Exp1	0.271	0.182	0.077	0.044	0.219	0.104
Exp2	0.244	0.137	0.004	0.069	0.040	0.137
Exp3	0.281	0.189	0.080	0.228	0.046	0.080
Exp4	0.440	0.072	0.357	0.007	0.440	0.357
Exp5	0.169	0.048	0.003	0.028	0.048	0.080
Exp6	0.321	0.321	0.260	0.053	0.260	0.260
Exp7	0.432	0.432	0.432	0.350	0.007	0.165
Exp8	0.099	0.056	0.038	0.038	0.038	0.056

Eq. (20) calculates the w_{fv}^{1} value, which represents the adjusted weight of the jth factor:

$$w_{nv}^{2} = \frac{\left(1 - w_{fv}^{1}\right)}{n-1} + w_{pv}^{2}. \tag{20}$$

In Eq. (21), w_{nv}^{2} refers to the new values of the remaining criteria, n refers to the number of criteria, and w_{pv}^{2} stands for the previous value of the remaining criteria:

$$w_{fv}^{1} + \sum w_{nv}^{2} = 1. \tag{21}$$

5.1. Sensitivity analysis of the criteria weights

The influence of sub-criteria on the selection of strategic selection of CI platform outcomes is computed by implementing sensitivity analysis by varying the weight ratios. There are 200 different situations in the sensitivity analyses. Variations in the weight of each criterion are employed to examine the impact of various circumstances on CI platform selection. The weight of each criterion is increased by 10 % throughout the sensitivity analysis. To make the weights of the remaining elements equal to 1, the weight sums are adjusted sensitivity. Implementing Eqs. (19)–(21), calculations are accounted for the sensitivity applications. The sensitivity analysis calculations produce 200 alternative scenarios and the results are depicted in Fig. 2.

A3 comes out on top in practically every situation when examining the sensitivity analysis. In several situations, though, it comes in second. The second-ranked commercial intelligence online platform received an

Table 8
p,q- QOFNs assessment equivalent of ratings provided by the experts.

Experts	C_1		C_2		C_3		C_4		C_5	
	f	h	f	H	f	h	f	h	f	h
Exp1	0.77	0.33	0.33	0.77	0.22	0.88	0.88	0.22	0.44	0.66
Exp2	0.66	0.44	0.11	0.99	0.33	0.77	0.22	0.88	0.66	0.44
Exp3	0.77	0.33	0.33	0.77	0.88	0.22	0.22	0.88	0.33	0.77
Exp4	0.22	0.88	0.88	0.22	0.11	0.99	0.99	0.11	0.88	0.22
Exp5	0.33	0.77	0.11	0.99	0.22	0.88	0.33	0.77	0.55	0.55
Exp6	0.99	0.11	0.88	0.22	0.22	0.88	0.88	0.22	0.88	0.22
Exp7	0.99	0.11	0.99	0.11	0.88	0.22	0.11	0.99	0.44	0.66
Exp8	0.66	0.44	0.44	0.66	0.44	0.66	0.44	0.66	0.66	0.44

Table 11
Weights of all criteria.

Main Criteria		Sub-Criteria	Weights	Global Weight	Rank
C_1 Data Quality	0.246	Accuracy (C_{11})	0.197	0.049	10
		Up-to-dateness (C_{12})	0.150	0.037	15
		Reliability (C_{13})	**0.320**	**0.079**	**2**
		Scope (C_{14})	0.132	0.033	16
		Data Consistency (C_{15})	0.198	0.049	9
C_2 Scope and Reach	0.214	Geographic Coverage (C_{21})	0.218	0.047	12
		Sectoral Coverage (C_{22})	**0.353**	**0.076**	**3**
		User Friendly Interface (C_{23})	0.279	0.060	6
		Access Time (C_{24})	0.148	0.032	17
C_3 Cost and Ease of Access	0.139	Subscription Cost (C_{31})	0.226	0.032	18
		Free Content Coverage (C_{32})	0.354	0.050	8
		User Support (C_{33})	0.278	0.039	14
		Flexibility (C_{34})	0.140	0.020	20
C_4 Data Analysis Ability	0.188	Trend Analysis (C_{41})	0.212	0.040	13
		Customized Reporting (C_{42})	0.316	0.060	7
		Comparative Analysis (C_{43})	0.338	0.064	5
		Graphical Visualization (C_{44})	0.131	0.025	19
C_5 Security and Privacy	0.212	**Data Security (C_{51})**	**0.427**	**0.091**	**1**
		Privacy Policy (C_{52})	0.346	0.074	4
		Security Certificates (C_{53})	0.226	0.048	11

A1 analysis. Selecting the A1 platform is crucial for the commercial intelligence operations of companies involved in international trade in locations where the A3 platform is not selected.

5.2. Sensitivity analysis of the expert weights

In the sensitivity analysis, 80 distinct scenarios are determined by the DMs' expert weight. The expert weights are reduced by 10 % in each scenario, and computations are performed in this sensitivity analysis. The findings are calculated with the help of Eqs. (19)–(21) and the results are displayed in Fig. 3.

In many situations, it is evident that the A3 alternative platform company comes first. Differences between scenarios were greatest in scenarios between 37-45 and 76–80.

5.3. Comparative analysis

Here, a comparative analysis is done with the help of various MCDM methods and the same case study problem, including alternative ranking techniques derived from VIKOR, TOPSIS, and Weighted Aggregated Sum Product Assessment (WASPAS). The obtained ranking results are shown in Fig. 4 and Table 18.

It is clear that the results do not change wherein the alternatives ranking is obtained as A3 ≻ A1 ≻ A2 ≻ A4 using the applied methods. Moreover, the results of Spearman's rank correlation test (outlined in Table 19) indicates that the methods provide consistent results, suggesting the reliability of our framework.

6. Managerial implications

The findings yielded indicate that privacy and security are the most critical criteria in the selection of a data source with the highest global weight. This is a scenario that highlights how important it is for users to protect their sensitive information and privacy. When considering the

Table 12
Linguistic assessments of the p,q-QOFN alternative website evaluation.

Experts		C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}	C_{41}	C_{42}	C_{43}	C_{44}	C_{51}	C_{52}	C_{53}
EXP1	A1	VG	M	G	G	VB	B	G	M	VG	G	VG	VG	B	B	G	B	B	M	B	VB
	A2	VG	VG	B	VG	B	VB	VB	G	VB	M	B	M	G	VG	VG	VB	VG	VG	VG	B
	A3	VB	B	M	VG	B	B	B	M	B	B	VG	G	B	B	VG	B	VB	G	VB	G
	A4	G	G	G	G	M	VG	VB	G	VG	VG	B	VB	B	G	VB	M	M	M	B	G
EXP2	A1	B	G	B	M	VG	VG	VG	G	VB	VB	B	VB	M	VG	VG	VG	M	VB	VB	G
	A2	B	VB	M	G	M	VG	VG	M	VG	VB	VG	G	G	VG	M	VG	VB	M	B	B
	A3	VG	M	M	VG	B	VB	VG	VB	G	M	VG	M	B	G	B	VG	B	B	G	G
	A4	B	VB	G	VG	VG	G	VG	B	VB	B	M	M	G	B	VG	G	M	VG	VG	VB
EXP3	A1	G	M	B	M	VG	VG	M	G	B	VG	M	M	VB	VG	VB	VB	B	M	VB	B
	A2	G	VB	B	B	B	VB	G	VB	B	VG	G	VB	G	VG	G	VB	VB	VG	B	VB
	A3	VB	G	VB	G	M	VG	VB	B	VB	VG	VB	VB	B	B	VB	M	B	B	G	G
	A4	VB	M	M	G	B	VG	VG	VG	G	B	VB	VB	VB	VB	VG	M	B	B	M	B
EXP4	A1	G	G	B	B	M	M	B	VB	G	VB	B	VG	VB	M	M	B	VB	VG	VB	B
	A2	M	VG	G	B	G	VG	M	VB	M	M	G	B	M	G	G	VG	M	M	M	VG
	A3	G	M	VG	VB	B	B	VB	M	B	B	G	M	G	G	G	VG	M	G	G	M
	A4	VB	M	M	G	B	M	M	M	B	M	B	VB	G	G	VB	M	G	VG	VB	VB
EXP5	A1	M	VG	B	G	B	M	VG	VG	G	VB	B	VG	VB	VB	B	B	M	VB	B	M
	A2	B	M	B	B	VG	M	M	VG	B	VG	VG	M	M	B	B	VB	VG	M	VG	VG
	A3	G	VG	VB	M	M	VG	G	M	B	VB	G	G	VG	VG	VB	M	B	G	VG	VB
	A4	VG	VG	M	G	VB	VB	G	M	VB	G	M	G	B	VB	G	B	G	M	VB	VG
EXP6	A1	VG	VG	G	B	VB	G	G	B	G	VB	B	VB	M	B	G	VB	B	B	VG	M
	A2	VB	G	VB	VG	G	M	VB	VB	G	G	VB	VB	VB	B	G	G	G	VB	B	VB
	A3	B	G	VG	VB	B	B	VB	G	VG	VB	VG	M	B	G	VB	B	G	VB	VB	B
	A4	M	M	G	B	VG	M	VB	VB	M	VG	G	VB	B	B	VG	M	G	M	M	VG
EXP7	A1	VG	G	VG	VB	B	G	VB	G	G	G	G	VB	VG	VB	VG	G	VG	B	VG	B
	A2	VB	B	M	G	G	G	B	G	VB	G	B	G	VG	B	M	VB	M	VB	B	VB
	A3	VB	G	VG	VB	VB	G	G	VG	VG	M	M	M	M	VG	G	VB	VB	G	G	VB
	A4	VG	B	G	VG	B	B	B	B	B	G	VB	M	VB	VB	VB	VG	M	VB	B	B
EXP8	A1	B	VB	B	VB	M	VB	VB	B	VG	VB	G	VB	M	B	M	G	VB	VG	VG	M
	A2	M	M	B	B	M	G	VG	B	M	G	B	B	B	M	B	VB	VG	VG	VB	B
	A3	G	M	M	B	VB	M	G	G	VB	VG	G	G	VB	B	G	B	M	G	B	M
	A4	B	G	VB	M	M	B	VB	G	VG	VB	G	B	VB	B	VB	G	B	B	G	B

Table 13
Integrated values for the alternatives.

	C_{11}		C_{12}		C_{13}		C_{14}		C_{15}		C_{21}		C_{22}		C_{23}		C_{24}		C_{31}	
	f	h	f	H	f	h	f	h	f	h	f	h	f	h	f	h	f	h	f	h
A1	0.89	0.40	0.88	0.37	0.76	0.68	0.65	0.65	0.84	0.52	0.86	0.82	0.57	0.86	0.59	0.85	0.66	0.82	0.32	0.95
A2	0.76	0.61	0.85	0.47	0.57	0.76	0.85	0.52	0.84	0.45	0.87	0.83	0.50	0.86	0.46	0.90	0.46	0.91	0.60	0.76
A3	0.83	0.52	0.83	0.43	0.86	0.44	0.86	0.48	0.46	0.82	0.87	0.90	0.49	0.90	0.49	0.83	0.49	0.93	0.44	0.92
A4	0.86	0.50	0.83	0.46	0.70	0.52	0.88	0.37	0.83	0.53	0.84	0.88	0.47	0.90	0.54	0.85	0.46	0.92	0.58	0.86

	C_{32}		C_{33}		C_{34}		C_{41}		C_{42}		C_{43}		C_{44}		C_{51}		C_{52}		C_{53}	
	f	h	f	h	f	h	f	h	f	h	f	h	f	h	f	h	f	h	f	h
A1	0.79	0.60	0.91	0.41	0.69	0.67	0.84	0.56	0.85	0.45	0.80	0.62	0.69	0.92	0.43	0.92	0.43	0.94	0.46	0.89
A2	0.89	0.43	0.62	0.67	0.78	0.50	0.90	0.40	0.80	0.51	0.85	0.54	0.91	0.84	0.51	0.80	0.54	0.91	0.47	0.94
A3	0.91	0.32	0.69	0.52	0.81	0.59	0.88	0.43	0.80	0.58	0.85	0.49	0.55	0.93	0.62	0.85	0.58	0.87	0.46	0.88
A4	0.62	0.67	0.58	0.73	0.64	0.77	0.63	0.79	0.89	0.43	0.76	0.51	0.69	0.79	0.53	0.84	0.43	0.92	0.50	0.92

sub-criteria, the highest global weight is for data security, which highlights the essentiality of having access to trustworthy information and data integrity. Data reliability and scope of the sector, which have high global weights, also suggest that the availability of correct and complete information is among the minimum requirements of users (Schmidthuber et al., 2023). Therefore, it can be said that security, reliability, and comprehensiveness must be prioritised in data source evaluation processes.

The importance of this research lies in the fact that it can solve the multi-dimensional and uncertain environment of CI, where critical decisions depend upon accurate and reliable data. The proposed framework allows a finer capture of expert judgments by integrating p,q-QOFSs into both weighting and ranking processes. It emphasizes data security, reliability, sectoral coverage, privacy policy, and comparative analysis as relevant selection criteria for the best commercial intelligence platforms. In this respect, it offers a novel and robust approach that would afford managers and researchers further insight, with a lesser risk of biased or inconsistent evaluations. Finally, it will allow better more transparent, strategically rational decision-making in international trade environments.

The purpose of this research is to extend the current literature on MCDM by incorporating p,q-QOFSs into the SIWEC and MABAC methods. The proposed p,q-QOFS framework overcomes the drawbacks of the previous fuzzy approaches by allowing more flexible expressions of uncertainty and expert hesitation. Further refinement will be afforded to enhance the capacity to capture nuanced judgments about the selection criteria for CI platforms. The theoretically rigorous proposed SIWEC method, which confirms data security, reliability, sectoral coverage, privacy policy, and comparative analysis as the most important criteria, will provide a basis for identifying the critical factors in evaluating and ranking platforms. These developments form the foundation for further research around incorporating higher-order fuzzy logic into MCDM and point to the prospect of increased precision and strength in decision-making involving uncertainty.

Managerially, the results of this study provide useful guidelines for organizations and decision-makers who are engaged in the selection of commercial intelligence websites. The identification of data security, reliability, sectoral coverage, privacy policy, and comparative analysis as the most critical factors allows managers to target investments and improvements in these areas. The p,q-QOFS-based MABAC analysis, which identifies A3 as the most suitable platform, gives a clear and justifiable ranking process that managers can rely on when making strategic decisions about resource allocation. The adoption of the framework proposed herein enables firms to more confidently navigate complex trade intelligence options and sustain competitive advantages (Luis Casarotto et al., 2021). It also calls on website providers to respond to highlighted priority criteria that, in turn, would bring their services in line with market needs and improve user satisfaction in the competitive domain of international trade intelligence (Katsikea et al., 2019). These findings specifically suggest that decision-makers should prioritise platforms offering transparent data encryption protocols and real-time sector-specific analytics. Moreover, integrating user-centric dashboards could further differentiate a platform in this competitive market (Da Xu et al., 2014).

Security of data is considered one of the essential issues in website selection for CI, as this platform contains sensitive information regarding trade data, business intelligence, and corporate strategy (Khoje, 2023). Possible information breaches or unauthorized access to such information may result in financial losses, reputational damage, or legal liabilities. Consequently, ensuring strong data security protocols, including encryption, and multi-factor authentication among others, is paramount for organizations seeking to protect their trade information and maintain competitiveness (Chen and Zhao, 2012). Reliability signifies the consistency and dependability of intelligence data and services. A website is considered reliable if it has proper, timely information with minimum or no breakdowns and other technical errors

Table 14
Exact numbers for the evaluation of platforms.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}
A1	0.776	0.778	0.508	0.456	0.676	0.498	0.234	0.248	0.318	0.073
A2	0.560	0.703	0.333	0.691	0.697	0.495	0.216	0.152	0.150	0.346
A3	0.663	0.702	0.736	0.715	0.247	0.420	0.160	0.247	0.123	0.134
A4	0.711	0.684	0.550	0.775	0.665	0.417	0.158	0.236	0.133	0.235

	C_{32}	C_{33}	C_{34}	C_{41}	C_{42}	C_{43}	C_{44}	C_{51}	C_{52}	C_{53}
A1	0.584	0.803	0.460	0.660	0.717	0.585	0.221	0.132	0.099	0.171
A2	0.776	0.425	0.622	0.798	0.644	0.683	0.551	0.280	0.166	0.110
A3	0.832	0.545	0.617	0.763	0.606	0.697	0.140	0.265	0.231	0.181
A4	0.423	0.362	0.351	0.333	0.778	0.603	0.369	0.240	0.133	0.138

Table 15
Weighted matrix of the MABAC method.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}
A1	0.097	0.074	0.113	0.033	0.096	0.094	0.151	0.120	0.064	0.032
A2	0.049	0.045	0.079	0.057	0.098	0.092	0.133	0.060	0.036	0.063
A3	0.072	0.044	0.158	0.059	0.049	0.048	0.077	0.119	0.032	0.039
A4	0.082	0.037	0.121	0.065	0.094	0.047	0.076	0.112	0.034	0.050

	C_{32}	C_{33}	C_{34}	C_{41}	C_{42}	C_{43}	C_{44}	C_{51}	C_{52}	C_{53}
A1	0.069	0.078	0.028	0.068	0.098	0.064	0.030	0.091	0.074	0.089
A2	0.092	0.044	0.039	0.080	0.073	0.119	0.050	0.181	0.111	0.048
A3	0.099	0.055	0.039	0.077	0.060	0.127	0.025	0.172	0.147	0.096
A4	0.050	0.039	0.020	0.040	0.119	0.074	0.039	0.156	0.093	0.067

Table 16
q-matrix of the MABAC method.

	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}
A1	0.024	0.026	−0.001	−0.019	0.014	0.027	0.047	0.021	0.024	−0.013
A2	−0.024	−0.004	−0.035	0.005	0.017	0.025	0.029	−0.039	−0.003	0.019
A3	−0.001	−0.004	0.043	0.007	−0.032	−0.018	−0.027	0.020	−0.008	−0.006
A4	0.010	−0.011	0.007	0.014	0.013	−0.020	−0.029	0.013	−0.006	0.006

	C_{32}	C_{33}	C_{34}	C_{41}	C_{42}	C_{43}	C_{44}	C_{51}	C_{52}	C_{53}
A1	−0.006	0.026	−0.003	0.004	0.014	−0.028	−0.005	−0.054	−0.029	0.017
A2	0.018	−0.008	0.009	0.016	−0.012	0.027	0.015	0.036	0.008	−0.024
A3	0.024	0.003	0.009	0.013	−0.025	0.035	−0.010	0.027	0.044	0.024
A4	−0.025	−0.013	−0.011	−0.024	0.035	−0.018	0.004	0.011	−0.010	−0.006

Table 17
Value and ranking of the alternatives.

Alternative	Value	Rank
A1	0.0867	2
A2	0.0759	3
A3	**0.1201**	**1**
A4	−0.0595	4

(Lee et al., 2022). For international trade, which depends on the most correct and timely data, reliability would ensure the certainty that at any instance a user would have real insight and unhindered access to information, thus minimizing the risk due to incomplete or incorrect information (Y. Wang et al., 2016). Sectoral coverage refers to the breadth and depth with which the commercial intelligence website presents industry-specific data and analyses. In international trade, very specific trends, regulations in place, or market dynamics often require informed decision-making at the sectoral level. Strong sectoral coverage thus enables a platform to cater to a wider audience, from niche SMEs to diversified multinational corporations, by providing access to more specialized and granular insights for targeted strategies (A. Xu et al., 2024).

These insights highlight that firms should prioritise platforms offering customizable access controls and industry-specific alert systems to preempt data risks and support agile decision-making. Additionally, providers that integrate AI-driven verification of data accuracy and expand real-time sectoral monitoring will likely become preferred partners for trade-focused enterprises. Ultimately, targeted investment in these functionalities can enhance operational resilience and strategic foresight.

A clear and transparent privacy policy is the basis of user trust and conformance to regulatory requirements. It describes how the collection, storage, sharing, and protection of user data and proprietary information are carried out (Ghahremani and Nguyen, 2024). Considering the stringent international legislation related to data handling, e.g., GDPR, a sound privacy policy acts as a significant enabler in assuring legal compliance and the trust of stakeholders who share sensitive trade data with the website. Comparative analysis allows benchmarking of data across regions, sectors, or competitors. In the competitive environment of international trade, the ability to compare different markets, suppliers, or business strategies is a key differentiator in identifying opportunities, detecting risks, and formulating competitive strategies (Morris Mbabu, 2024). An effective comparative analysis tool synthesizes large volumes of data into actionable insights that drive strategic decisions on market entry, product differentiation, and pricing strategies.

The developed p,q-QOFD–SIWEC–MABAC hybrid method provides a structured framework for managers to strategically assess and rank CI

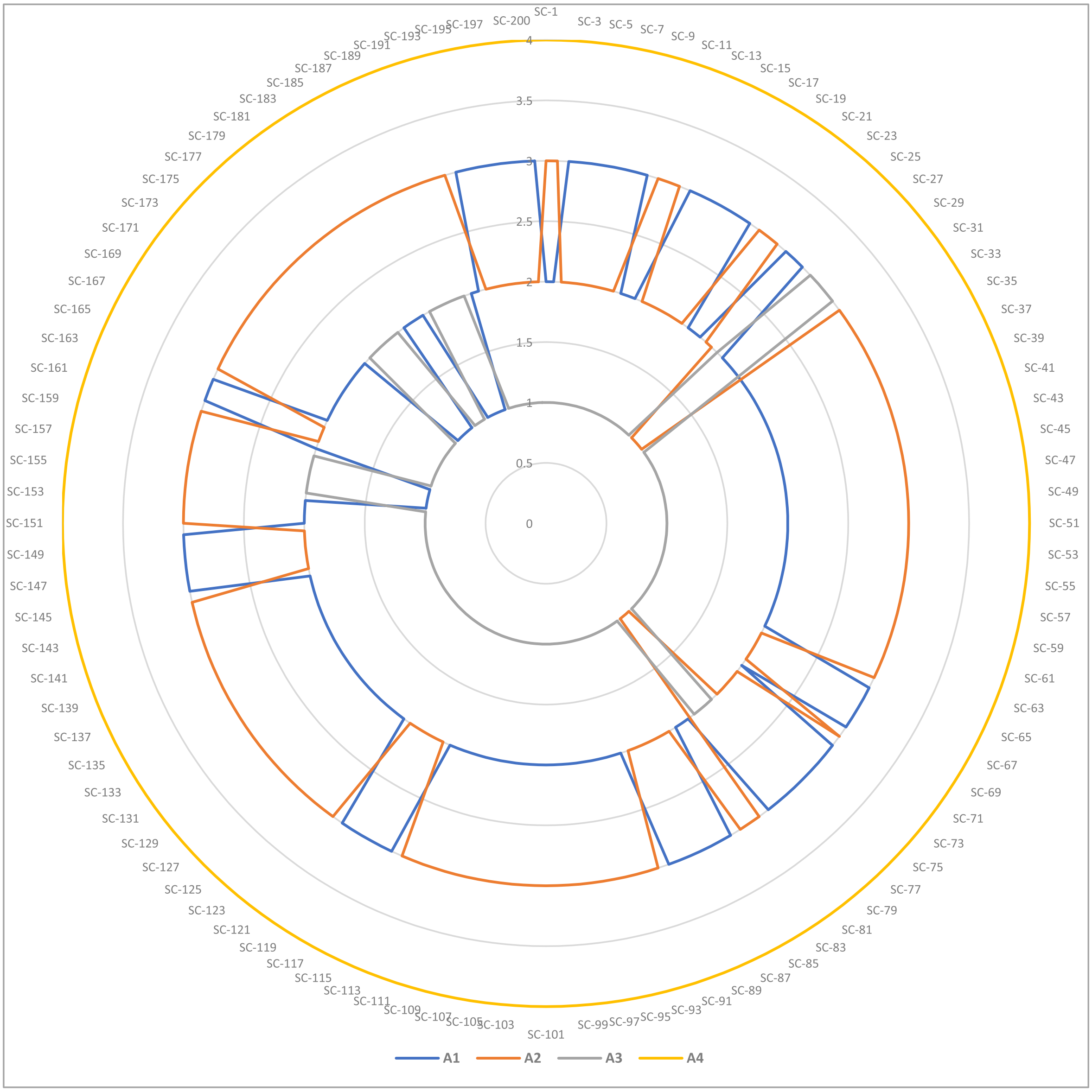

Fig. 2. Sensitivity analysis of the criteria weights.

platforms under uncertainty. This model aids decision-makers in identifying and weighting critical criteria (e.g., data security, reliability, sectoral coverage), enabling them to make robust, long-term platform investment decisions. Also, firms can tailor the linguistic scales, sub-criteria set, and sensitivity parameters to reflect their industry-specific information needs and risk tolerances, ensuring the model remains aligned with unique strategic goals. Managers can leverage these outputs to negotiate stronger metrics, monitor vendor performance metrics, and build fallback plans, thereby boosting overall CI resilience. Finally, executives, Information Technology (IT), procurement, and marketing teams can use the model's sensitivity analyses and boundary-proximity visuals to build consensus, justify budget allocations, and demonstrate methodological rigor in CI platform selection.

7. Conclusions and future studies

This research presents a novel p,q-quasirung orthopair fuzzy-based decision-making framework that significantly advances the evaluation of CI, providing websites in international trade. By integrating the p,q-quasirung orthopair fuzzy SIWEC method with the MABAC ranking approach, the study offers an innovative mechanism to capture and synthesize expert judgments in a highly uncertain environment, effectively identifying critical criteria such as data security, reliability, sectoral coverage, privacy policy, and comparative analysis. The framework not only enhances decision-making robustness through advanced fuzzy set techniques but also bridges the gap between subjective assessments and objective performance indicators, thereby providing a comprehensive tool for both academics and practitioners. A concise summary of our most important findings is presented as follows.

1. **Critical Selection Criteria:** Among the 20 sub-criteria, the top five-Data Security (global weight 0.091), Reliability (0.079), Sectoral Coverage (0.076), Privacy Policy (0.074), and Comparative Analysis (0.064)-emerged as most decisive for CI platform evaluation,
2. **Platform Ranking:** In the case study, the third alternative (A3) achieved the highest MABAC score (0.1201) and was consistently ranked first, followed by A1 (0.0867), A2 (0.0759), and A4 (−0.0595),
3. **Robustness via Sensitivity:** Two sensitivity analyses (200 criterion-weight scenarios; 80 expert-weight scenarios) showed A3 remained top in over 90 % of cases, confirming the model's robustness. Furthermore, the correlation test indicates that the methods yield

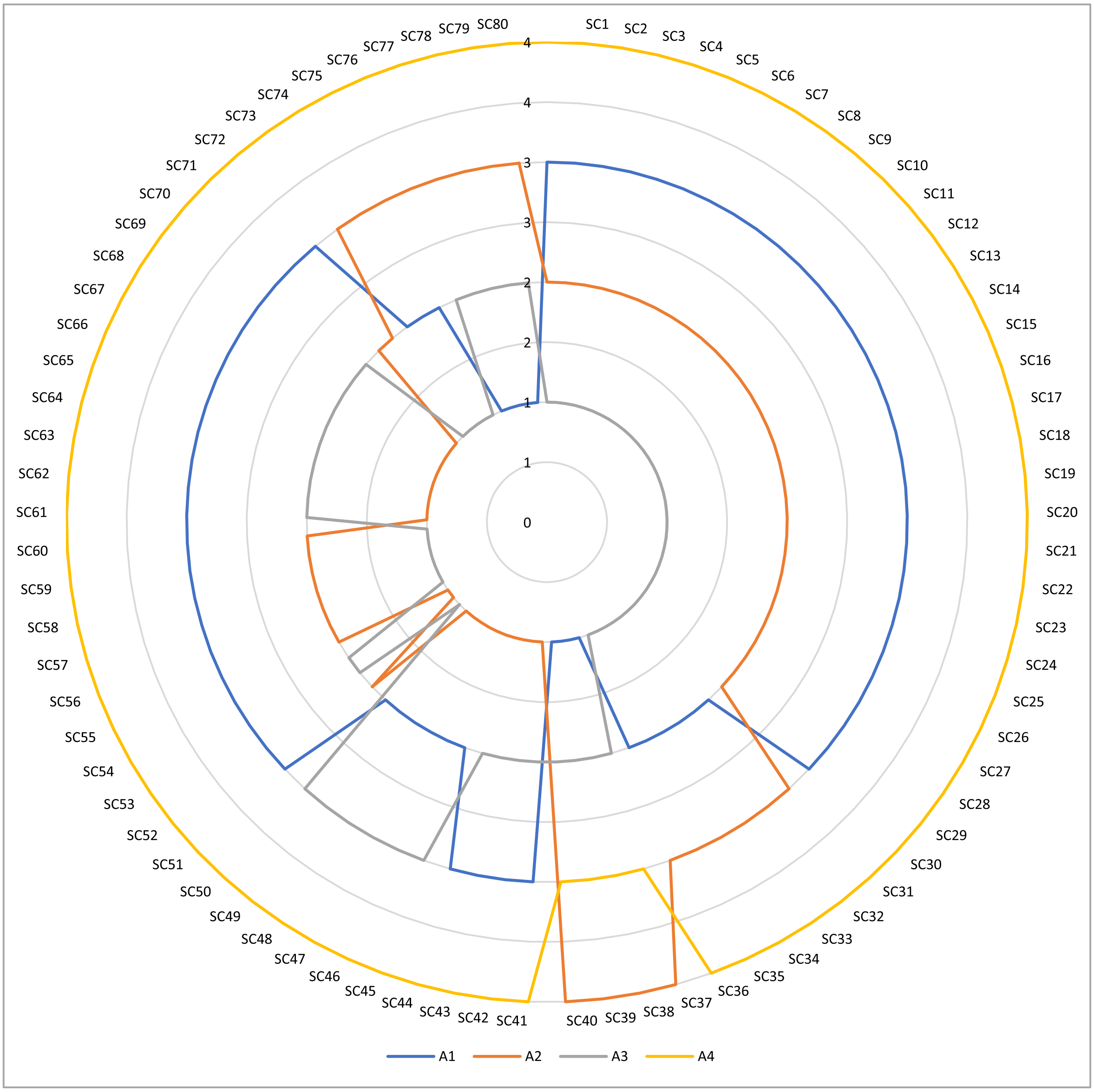

Fig. 3. Sensitivity analysis of the expert weights.

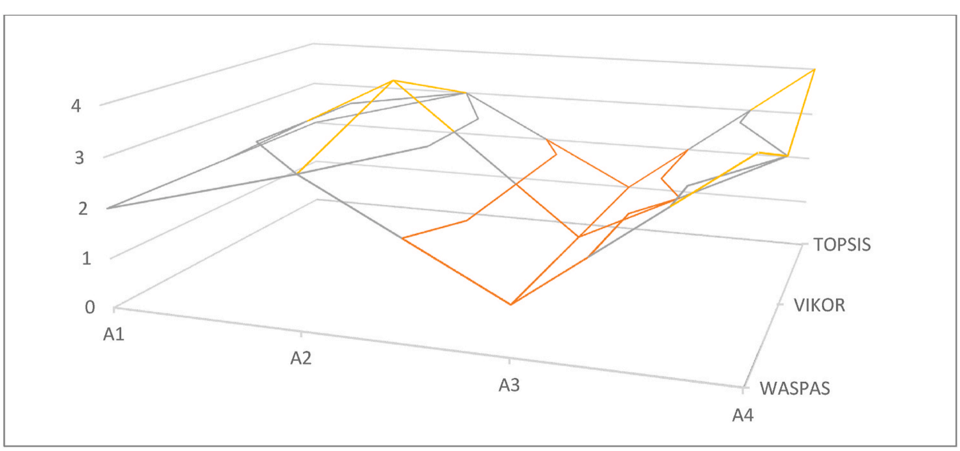

Fig. 4. Comparative analysis results.

Table 18
Comparative analysis of the proposed method and other MCDM methods.

Alternatives	Methods			
	p,q-quasirung-SIWEC-MABAC	WASPAS	VIKOR	TOPSIS
A1	2	2	2	2
A2	3	3	4	3
A3	1	1	1	1
A4	4	4	3	4

Table 19
Spearman's rank correlation coefficient values.

	WASPAS	VIKOR	TOPSIS
MABAC	1.000	1.000	0.600

consistent outcomes, thereby suggesting the reliability of our framework,

4. **Methodological Contribution:** The integrated p,q-Quasirung SIWEC-MABAC framework reliably captures expert uncertainty and delivers stable, interpretable rankings under varying conditions.

7.1. Theoretical insights

i. **Subjectivity and Aggregation Bias:** Although p,q-QOFNs capture hesitation more flexibly than standard fuzzy sets, they still rely on expert-provided linguistic inputs; biases or misinterpretations at the Delphi stage can propagate through SIWEC and MABAC.
ii. **Parameter Sensitivity:** The choice of the p and q parameters, as well as the linguistic scale definitions, may affect the defuzzification scores. However, further work is needed to explore adaptive parameter tuning or alternative membership functions.
iii. **Static Criterion Structure:** Our model assumes a fixed set of criteria and sub-criteria. In rapidly evolving trade environments, new factors (e.g., AI-driven analytics, and sustainability metrics) may emerge that require dynamic criterion updating mechanisms.

7.2. Practical insights

i. **Data and Resource Requirements:** Implementing p,q-Quasirung SIWEC-MABAC requires access to a sufficiently diverse expert panel and software capable of orthopair fuzzy computations, which may not be available in all organizations.
ii. **Computational Complexity:** While SIWEC simplifies weight derivation versus pairwise AHP, large criterion sets (e.g., >30 sub-criteria) still entail nontrivial Delphi rounds and matrix operations that can strain time and technical capacity.
iii. **Integration with Procurement Processes:** Embedding the framework into existing vendor-selection workflows may face organizational resistance, particularly where procurement teams are unfamiliar with fuzzy logic methods.

7.3. Limitations and future work

Whereas the study has its merit, there are a number of limitations. First, the framework proposed in this paper relies heavily on expert input, which, even with the use of fuzzy logic to overcome uncertainties, is subjective and may be biased. Second, although the case study is illustrative, it cannot capture the wide diversity of industries and regions that participate in global trade. More interestingly, a future extension to more contexts of this framework; e.g., sectors, geographies, or intelligence platforms, needs to be engaged in. It also incorporates artificial intelligence-machine learning algorithms that automatically make improvements or fine-tunings of weights and rankings on the model and increase its predictive accuracy and effectiveness. Lastly, the dynamic nature of foreign trade intelligence, such as real-time updates of data and changing market trends, may also provide further insight into how to adapt the framework for more agile decision-making.

Therefore, this research furthers not just the academic cause of understanding how to make a decision under uncertainty but also aids in practical aspects by providing specific tools for enhancing business foreign trade intelligence strategies. Addressing these limitations and giving future directions may serve as fertile ground for continuous innovation in the field and therefore provide businesses with an opportunity to succeed in this ever-changing world marketplace. Future research should focus on expanding empirical validations across diverse industries, refining parameter optimization procedures, and exploring dynamic, real-time applications of the proposed model to further improve its practical relevance and theoretical contributions in the context of international trade intelligence.

CRediT authorship contribution statement

Sinan Çizmecioğlu: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Ahmet Çalık:** Writing – review & editing, Validation, Project administration, Methodology, Investigation, Conceptualization. **Erfan Babaee Tirkolaee:** Writing – review & editing, Validation, Supervision, Investigation, Formal analysis, Data curation.

Declaration of competing interest

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

Acknowledgement

The Scientific and Technological Research Council of Türkiye (TÜBİTAK) has supported Ahmet Calik with an International Postdoctoral Research Fellowship to conduct this study. This fund is hereby appreciated with gratitude.

Data availability

Data will be made available on request.

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