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Research Article

# Application of Multi-criteria Decision-making Methods for Forensic Analysis of Mechanical Parts in Vehicle Accidents using q-Rung Orthopair Fuzzy Numbers

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**Keywords:** Forensic science; MCDM; Mechanical part analysis; q-Rung Orthopair Fuzzy Numbers, Evidence Analysis



## Abstract

This study explores the application of a Multi-Criteria Decision-Making (MCDM) approach based on q-rung orthopair fuzzy numbers to identify the origin of mechanical parts found at vehicle accident scenes. The primary objective is to determine the most likely vehicle to which these parts belong by evaluating key criteria such as compatibility, damage level, serial number matching, and color compatibility. Q-rung orthopair fuzzy numbers offer an advanced method to handle the inherent uncertainty and vagueness associated with forensic evaluations, particularly in scenarios where data is incomplete or imprecise. The proposed methodology involves defining the criteria, assigning membership and non-membership degrees using q-rung orthopair fuzzy sets, and applying an aggregation process to effectively rank alternatives. This approach facilitates flexible decision-making by accommodating different levels of confidence and uncertainty, making it particularly suitable for forensic applications where evidence is often ambiguous. The findings demonstrate that integrating q-rung orthopair fuzzy numbers into the MCDM framework significantly enhances the accuracy and reliability of identifying vehicle components involved in accidents. The proposed methodology provides a systematic tool to support forensic investigations, aiding in the determination of liability and contributing to more robust outcomes in mechanical evidence analysis.

## Introduction

Forensic analysis plays a pivotal role in vehicle accident investigations, particularly in determining the origin of mechanical parts found at accident scenes. Accurate identification of these parts is essential for reconstructing events, establishing liability, and ultimately administering justice. However, forensic evaluations often grapple with inherent uncertainties and ambiguities due to factors such as incomplete data, damaged evidence, and subjective expert interpretations. These challenges necessitate advanced analytical methods capable of handling imprecision and providing reliable decision support. The significance of addressing these uncertainties becomes even more critical in legal contexts where accurate and reliable forensic assessments can directly influence judicial outcomes. MCDM methods have been increasingly employed in forensic science to address complex decision problems involving multiple conflicting criteria. Traditional MCDM approaches, however, may not adequately capture the uncertainty and vagueness inherent in forensic evidence analysis. In particular, when forensic experts deal with fragmented or ambiguous data, the inability of traditional methods to fully incorporate varying degrees of confidence in their assessments can lead to less reliable conclusions. To overcome this limitation, researchers have integrated fuzzy logic into MCDM frameworks, allowing for a more nuanced representation of expert judgments and uncertain data.

Goala, et al. [1] utilized a fuzzy MCDM approach employing trapezoidal fuzzy numbers to aid criminal investigators in cases involving gunshot wounds. Their method aimed to correlate the physical properties of wounds and bloodstains with specific derivations, acknowledging that such characteristics do not manifest as isolated values but within specific ranges. They also proposed a ranking method based on the variance of degrees to evaluate alternatives, demonstrating the applicability of fuzzy MCDM in forensic contexts through a hypothetical case study. Similarly, Chinnasamy, et al. [2] applied the Decision Making Trial and Evaluation Laboratory (DEMATEL) method to develop forensic medical examinations for detecting injuries and using the findings as legal evidence. Their work highlighted the utility of MCDM techniques in structuring complex forensic assessments and enhancing the objectivity of medical examinations in legal cases. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has also been widely adopted in forensic science for solving MCDM problems. Lee and colleagues [3] employed the TOPSIS method to identify the most effective prediction model in a forensic case study. Their findings provided insights into how TOPSIS can be leveraged in other applied scientific domains to select optimal prediction models, emphasizing its versatility and effectiveness in handling multiple criteria. In the realm of network forensics, Samuel and colleagues [4] recognized the need for real-time investigation of network attacks and evidence acquisition for decision-making processes. They identified the prioritization of network attacks and risk selection as an MCDM problem characterized by ambiguity and incompleteness. To address this, they applied a fuzzy TOPSIS methodology, enabling multiple network forensic examiners to offer disparate evaluations while effectively handling uncertainty in their assessments. Rodrigues, et al. [5] presented a multicriteria decision-making model for evaluating the operational feasibility of forensic units within the Federal Police of Brazil. By combining Best-Worst Scaling (BWS) with TOPSIS, they conducted a comprehensive ranking of 23 local forensic units. Their sensitivity analysis demonstrated the robustness of the proposed solution, indicating that resource optimization can be achieved without compromising the quality of services provided to society.

While these studies underscore the efficacy of integrating fuzzy logic and MCDM methods in forensic science, they primarily focus on traditional fuzzy sets and do not fully address the complexities introduced by higher degrees of uncertainty and hesitation in expert judgments. The introduction of more advanced fuzzy logic methods is necessary to enhance the reliability of forensic assessments, particularly in cases where evidence is ambiguous. Traditional fuzzy sets, such as intuitionistic and Pythagorean fuzzy sets, have limitations in modeling situations where the sum of membership and non-membership degrees does not capture the full extent of uncertainty. To overcome these limitations, q-rung orthopair fuzzy numbers (q-ROFNs) have been introduced as a more generalized and flexible approach. The q-ROFN framework allows the sum of the q-th power of the membership and non-membership degrees to be less than or equal to one, providing an enhanced capacity to model uncertainty and hesitation [6]. This characteristic makes q-ROFNs particularly suitable for forensic applications where evidence can be ambiguous, and expert opinions may vary significantly.

Despite the potential advantages of q-ROFNs, their application in forensic science, particularly in the analysis of mechanical parts in vehicle accidents, remains unexplored. The current study aims to fill this gap by integrating q-ROFNs into an MCDM framework tailored for forensic analysis. The proposed methodology focuses on identifying the origin of mechanical parts found at accident scenes by evaluating key criteria such as compatibility with vehicle models, damage level consistency, serial number and markings matching, and color and material compatibility. By employing q-ROFNs, the methodology captures the uncertainty and hesitation inherent in expert evaluations more effectively than traditional fuzzy sets. It allows forensic experts to express their judgments with a higher degree of nuance, accommodating varying levels of confidence and hesitation. This leads to more accurate and reliable assessments, which are crucial for legal proceedings where evidence must withstand rigorous scrutiny. In conclusion, this study aims to provide a systematic and novel approach to forensic analysis through the integration of q-ROFNs into an MCDM framework, contributing to more informed and defensible decisions in vehicle accident investigations. The originality of this study lies in its novel application of q-ROFNs within an MCDM framework for forensic analysis of mechanical parts in vehicle accidents. Unlike previous studies that utilized conventional fuzzy MCDM methods, this research leverages the enhanced modeling capabilities of q-ROFNs to address the complexities of forensic evidence evaluation under uncertainty. The integration of q-ROFNs not only improves the handling of imprecise and ambiguous data but also enhances the robustness and reliability of the decision-making process. In summary, this study contributes to the field of forensic science by:

1. Introducing a novel q-ROFN-based MCDM methodology for the forensic analysis of mechanical parts in vehicle accidents, addressing the limitations of traditional fuzzy MCDM approaches.
2. Enhancing the modeling of uncertainty and expert hesitation, providing a more nuanced and accurate representation of forensic evaluations.
3. Demonstrating the applicability and effectiveness of q-ROFNs in a practical forensic context, thereby expanding the toolkit available to forensic investigators.
4. Providing a systematic and transparent decision-making framework that can be adapted to various types of forensic evidence beyond mechanical parts.

The findings of this study have the potential to significantly improve the accuracy and reliability of forensic analyses, ultimately contributing to more informed legal decisions and the advancement of forensic methodologies.

## Integration of q-rung orthopair fuzzy numbers into the mcdm framework

**Introduction to q-rung orthopair fuzzy numbers:** In the realm of decision-making, especially under conditions of uncertainty and imprecision, traditional fuzzy set theories like intuitionistic fuzzy sets and Pythagorean fuzzy sets have been extensively utilized. However, these theories have limitations in handling higher degrees of uncertainty. To overcome these limitations, q-rung orthopair fuzzy numbers (q-ROFNs) have been introduced as a more generalized and flexible approach. The q-ROFN framework extends the capacity to model uncertainty by allowing the sum of the q-th power of the membership and non-membership degrees to be less than or equal to one. A q-rung orthopair fuzzy number A on a universe of discourse X is defined as in Equation 1 [6]:

$$A = \{x, \mu_A(x), \nu_A(x) \mid x \in X\} \quad (1)$$

where:

$\mu_A(x) : X \to [0,1]$ is the membership degree of element $x$ in set $A$.

$\nu_A(x) : X \to [0,1]$ is the non-membership degree of element $x$ in set $A$.

These degrees satisfy the condition (Equation 2):

$$0 \le (\mu_A(x))^q + (\nu_A(x))^q \le 1, \ \textit{where} \ q \ge 1 \quad (2)$$

The parameter $q$ controls the allowable ranges of membership and non-membership degrees, providing flexibility in modeling uncertainty. Properties of q-ROFNs [6]:

**Indeterminacy degree** $(\pi_A(x))$: Represents the hesitation or uncertainty associated with the element $x$ (Equation 3):

$$\pi_A(x) = \left[1 - (\mu_A(x))^q - (\nu_A(x))^q\right]^{\frac{1}{q}} \quad (3)$$

**Complement of a q-ROFN:** The complement $A^c$ is defined as in Equation 4 [6]:

$$A^C = \{x, \nu_A(x), \mu_A(x) \mid x \in X\} \quad (4)$$

- **Boundary conditions:** When $q$ = 1, q-ROFNs reduce to intuitionistic fuzzy sets; when $q$ = 2, they become Pythagorean fuzzy sets.

## Aggregation operators and ranking methods

The q-ROFWA operator aggregates multiple q-ROFNs considering their associated weights, essential in multi-criteria decision-making [6]. Given q-ROFNs $A_i = \mu_{A_i}, \nu_{A_i}$ and weights $w_i$ where $\sum_{i=1}^{n} w_i = 1$, the aggregated q-ROFN $A$ is (Equation 5):

$$\mu_A = \left(\sum_{i=1}^{n} w_i (\mu_{A_i})^q\right)^{\frac{1}{q}}, \ \nu_A = \left(\sum_{i=1}^{n} w_i (\nu_{A_i})^q\right)^{\frac{1}{q}} \quad (5)$$

To compare and rank q-ROFNs, score and accuracy functions are defined.

- Score Function ($S(A)$) (Equation 6):

$$S(A) = (\mu_A)^q - (\nu_A)^q \quad (6)$$

A higher $S(A)$ indicates a preferable alternative.

- Accuracy Function ($H(A)$) (Equation 7):

$$H(A) = (\mu_A)^q + (\nu_A)^q \quad (7)$$

Used when score functions are equal, a higher $H(A)$ suggests greater certainty.

Benefits of q-ROFNs over MCDM are:

- **Efficient aggregation:** The q-ROFWA operator efficiently combines expert judgments across multiple criteria.
- **Robust ranking:** Score and accuracy functions provide a systematic approach to ranking alternatives under uncertainty.
- **Adaptability:** The methodology can be adapted by adjusting the $q$

q and weights according to the decision-making context.

## Integration into multi-criteria decision-making framework

MCDM involves evaluating and prioritizing alternatives based on multiple, often conflicting, criteria. It is widely used in various fields, including engineering, economics, and forensic science. The Steps for Integrating q-ROFNs into MCDM are as follows:

Step 1: Define Alternatives and Criteria

- **Alternatives (A):** The options or choices under consideration.
- **Criteria (C):** The standards or benchmarks used to evaluate the alternatives.

Step 2: Gather Expert Evaluations

Experts assess each alternative against each criterion, expressing their judgments as q-ROFNs $E_{ij} = \langle \mu_{ij}, \nu_{ij} \rangle$.

Step 3: Determine Criteria Weights

Assign weights $w_j$ to each criterion based on their relative importance.

Step 4: Aggregate Evaluations

Use the q-ROFWA operator to aggregate the q-ROFNs for each alternative.

Step 5: Compute Score and Accuracy Functions

Calculate $S(A_i)$ and $H(A_i)$ for each alternative to facilitate ranking.

Step 6: Rank Alternatives and Make Decisions

Rank the alternatives based on the computed scores and select the best option.

Step 7: Sensitivity Analysis (Optional)

Analyze how changes in weights and parameters q affect the ranking to ensure robustness.

The Advantages of the Integrated Approach are as follows:

- **Accommodates uncertainty:** Handles the inherent uncertainty in expert judgments effectively.
- **Flexible modeling:** The parameter $q$ allows for adjusting the fuzziness level to suit specific situations.
- **Comprehensive evaluation:** Considers multiple criteria and integrates them into a single evaluative framework.

## Application of q-rofns-based mcdm in forensic analysis

**Overview of the forensic analysis problem:** In vehicle accident investigations, identifying the source vehicle of mechanical parts found at the scene is crucial. This determination aids in:

- **Establishing liability:** Identifying responsible parties for legal proceedings.
- **Accident reconstruction:** Understanding how the accident occurred.
- **Evidence correlation:** Linking physical evidence to involved vehicles.
- **Uncertainty in evidence:** Parts may be damaged or lack clear identifying features.
- **Multiple potential sources:** Several vehicles might be similar, complicating identification.
- **Expert hesitation:** Experts may be unsure due to incomplete or ambiguous data.

## Criteria definition and importance weighting

The following criteria are defined for the forensic analysis:

1. **Compatibility with vehicle model ($C_1$):** Degree to which the part matches specific vehicle models.
2. **Damage level consistency ($C_2$):** Alignment of the part's damage with expected patterns from the accident.
3. **Serial number and markings matching ($C_3$):** Correlation of identifying numbers or marks with vehicle records.
4. **Color and material compatibility ($C_4$):** Consistency of the part's color and material with those of potential source vehicles.
5. **Wear and tear patterns ($C_5$):** Similarity of wear patterns to those expected from a specific vehicle's usage.
6. **Environmental residue analysis ($C_6$):** Presence of residues that match the environment where a vehicle is typically located.

Weights $w_j$ are assigned based on the criteria's significance:

- **Expert consultation:** Engage forensic experts to determine the relative importance.
- **Legal considerations:** Some criteria may carry more weight legally (e.g., serial number matching).
- **Normalization:** Ensure $\sum_{j=1}^{m} w_j = 1$.

For instance:

- w1 = 0.25
- w2 = 0.20
- w3 = 0.30
- w4 = 0.10
- w5 = 0.10
- w6 = 0.05

## Expert evaluation and uncertainty handling

Experts evaluate each alternative $A_i$ against each criterion $C_j$, providing q-ROFNs:

- **Membership Degree ($\mu_{ij}$):** Confidence that the part matches the criterion.
- **Non-Membership Degree ($\nu_{ij}$):** Confidence that the part does not match the criterion.

The indeterminacy degree $\pi_{ij}$ captures the experts' hesitation due to:

- **Incomplete data:** Missing information about the part or vehicles.
- **Ambiguous evidence:** Conflicting signs or markings.
- **Subjective interpretation:** Differences in expert opinions.

## Step-by-step methodology implementation

Step 1: Identification of Alternatives and Criteria

- Alternatives ($A$): Potential vehicles $A_1, A_2, A_3, \ldots, A_n$
- Criteria ($C$): $C_1, C_2, C_3, C_4, C_5, C_6$

Step 2: Expert Assessment Using q-ROFNs

- Experts provide $E_{ij} = \langle \mu_{ij}, v_{ij} \rangle$ for each $A_i$ and $C_j$
- For example, for $A_1$ and $C_1$:

$$E_{11} = \mu_{11} = 0.85, \nu_{11} = 0.05$$

Step 3: Assigning Weights to Criteria

- Weights are assigned as per the importance determined earlier.

Step 4: Aggregation of Evaluations

Using $q = 2$ (for simplicity), aggregate the evaluations for each $A_i$ (Equation 8):

$$\mu_i = \left( \sum_{j=1}^{6} w_j \left( \mu_{ij} \right)^2 \right)^{\frac{1}{2}}, \quad \nu_i = \left( \sum_{j=1}^{6} w_j \left( \nu_{ij} \right)^2 \right)^{\frac{1}{2}} \tag{8}$$

Step 5: Calculation of Score Functions Compute (Equation 9):

$$S\left( A_i \right) = \left( \mu_i \right)^2 - \left( \nu_i \right)^2 \tag{9}$$

Step 6: Ranking the Alternatives

- Rank alternatives based on $S(A_i)$.
- Use $H(Ai)$ if necessary.

Step 7: Decision Making

- Select the alternative with the highest score as the likely source vehicle.
- Document the process for transparency.

## Mathematical example with detailed calculations

Assume three potential vehicles $A_1$, $A_2$, $A_3$ and the weights as previously defined. These values are given in Table 1.

Calculations for $A_1$

Aggregated Membership Degree $\mu_1$:

$$\mu_1 = \left(0.25\times0.85^2+0.20\times0.80^2+0.30\times0.70^2+0.10\times0.65^2+0.10\times0.75^2+0.05\times0.60^2\right)^{\frac{1}{2}}$$
$$=(0.25\times0.7225+0.20\times0.64+0.30\times0.49+0.10\times0.4225+0.10\times0.5625+0.05\times0.36)^{\frac{1}{2}}$$
$$=(0.180625+0.128+0.147+0.04225+0.05625+0.018)^{\frac{1}{2}}=(0.572125)^{\frac{1}{2}}\approx0.757$$

Aggregated Non-Membership Degree $\nu_1$:

$$\nu_1 = \left(0.25\times0.05^2+0.20\times0.10^2+0.30\times0.20^2+0.10\times0.25^2+0.10\times0.15^2+0.05\times0.30^2\right)^{\frac{1}{2}}$$
$$=(0.25\times0.0025+0.20\times0.01+0.30\times0.04+0.10\times0.0625+0.10\times0.0225+0.05\times0.09)^{\frac{1}{2}}$$
$$=(0.000625+0.002+0.012+0.00625+0.00225+0.0045)^{\frac{1}{2}}=(0.027625)^{\frac{1}{2}}\approx0.166$$

Score Function $S(A_1)$:

Similar calculations are performed for $A_2$ and $A_3$. For brevity, let's assume the following results:

**Table 1:** Expert Evaluations Decision Making.

| Criteria | $A_1$ | $A_2$ | $A_3$ |
|---|---|---|---|
| $C_1$ | 0.85,0.05⟩ | ⟨0.60,0.30⟩ | ⟨0.90,0.05 |
| $C_2$ | 0.80,0.10⟩ | ⟨0.65,0.25⟩ | ⟨0.85,0.10 |
| $C_3$ | 0.70,0.20⟩ | ⟨0.50,0.40⟩ | ⟨0.95,0.02 |
| $C_4$ | 0.65,0.25⟩ | ⟨0.55,0.35⟩ | ⟨0.80,0.15 |
| $C_5$ | 0.85,0.05⟩ | ⟨0.60,0.30⟩ | ⟨0.85,0.10 |
| $C_6$ | 0.60,0.30⟩ | ⟨0.50,0.40⟩ | ⟨0.70,0.20 |

$$\mu_2 \approx 0.611, \nu_2 \approx 0.361, S\left(A_2\right) = 0.273$$

$$\mu_3 \approx 0.859, \nu_3 \approx 0.102, S\left(A_3\right) = 0.726$$

Ranking the Alternatives

First Place: $A_3$ with $S(A_3) = 0.726$.

Second Place: $A_1$ with $S(A_1) = 0.5444$.

Third Place: $A_2$ with $S(A_2) = 0.273$.

## Implications and advantages in forensic sciences

The methodology developed in this study offers significant implications and advantages for forensic sciences, particularly in the effective handling of uncertainty and imprecision inherent in forensic analysis. By incorporating q-rung orthopair fuzzy numbers (q-ROFNs) into the multi-criteria decision-making (MCDM) framework, the approach captures expert uncertainty and hesitation that often arise due to ambiguous evidence and subjective judgments. Physical evidence in forensic investigations may not always be clear-cut, leading to varying interpretations among experts. The q-ROFN-based methodology allows experts to express their confidence levels along with their hesitation, providing a more nuanced and accurate representation of their assessments. Furthermore, the methodology promotes a systematic and transparent evaluation process. It offers a structured, step-by-step framework that ensures all relevant criteria are considered comprehensively. The explicit nature of the calculations and rankings enhances transparency, facilitating review and validation by other experts or stakeholders. This transparency is crucial in forensic investigations, where the credibility and reproducibility of the analysis can significantly impact legal outcomes. Another key advantage is the enhanced reliability of conclusions derived from the methodology. The mathematical rigor introduced by the use of q-ROFNs adds precision to the analysis, ensuring that the findings are grounded in robust quantitative methods. This rigor enhances the defensibility of the results in legal contexts, as quantitative outcomes can effectively support expert testimony and withstand scrutiny in judicial proceedings. The ability to present clear, mathematically substantiated conclusions strengthens the overall quality and impact of forensic evidence. Lastly, the methodology exhibits considerable flexibility and adaptability, making it suitable for a wide range of forensic applications. The parameters within the model, such as the q-value and the weights assigned to different criteria, can be customized to fit the specific requirements of individual cases. This adaptability allows the methodology to accommodate the unique characteristics of different forensic scenarios, whether they involve mechanical parts, biological samples, or digital evidence. Additionally, the scalability of the approach means it can be extended beyond the analysis of mechanical parts to various types of forensic evidence, thereby broadening its applicability and usefulness in the field.

In summary, the integration of q-rung orthopair fuzzy numbers into the MCDM framework provides a powerful tool for forensic analysis. It effectively addresses the challenges of uncertainty and imprecision, offers a systematic and transparent evaluation process, enhances the reliability and defensibility of conclusions, and provides the flexibility to adapt to diverse forensic contexts. These advantages contribute to more accurate, reliable, and robust outcomes in forensic investigations, ultimately supporting the pursuit of justice.

## Results and discussion

The integration of q-rung orthopair fuzzy numbers (q-ROFNs) into the multi-criteria decision-making (MCDM) framework represents a significant advancement in the forensic analysis of mechanical parts involved in vehicle accidents. This methodology addresses the inherent uncertainties and imprecisions that often complicate forensic investigations, particularly when dealing with incomplete, ambiguous, or conflicting evidence. By utilizing q-ROFNs, experts can express their judgments with a higher degree of nuance, capturing both their confidence and hesitation levels. This leads to a more accurate and reliable assessment of the potential source vehicles. In the detailed application presented, the methodology was implemented through a systematic, step-by-step process. The identification of critical criteria—such as compatibility with vehicle models, damage level consistency, serial number and markings matching, color and material compatibility, wear and tear patterns, and environmental residue analysis—ensured a comprehensive evaluation of all relevant factors influencing the origin determination of the mechanical part. The assignment of weights to these criteria, reflecting their relative importance, added depth to the analysis by emphasizing the most critical aspects of the forensic evidence.

The aggregation of expert evaluations using the q-ROFWA operator allowed for the effective combination of multiple assessments, each capturing varying degrees of certainty and hesitation. The use of the score function provided a quantitative basis for ranking the alternatives, leading to a clear and justifiable conclusion. In the example, Alternative emerged as the most probable source of the mechanical part, supported by the highest aggregated membership degree and the lowest non-membership degree among the alternatives. This outcome underscores the methodology's capability to discern subtle differences between potential sources, enhancing the precision of forensic conclusions. Moreover, the methodology's adaptability is noteworthy. By adjusting the parameter qqq and the criteria weights, the approach can be tailored to the specific nuances of different forensic cases. This flexibility ensures that the methodology remains relevant and effective across a wide range of scenarios, whether dealing with different types of mechanical parts, varying accident contexts, or diverse forms of forensic evidence. The scalability of the approach extends its applicability beyond mechanical part analysis to other domains within forensic science where uncertainty and multi-criteria evaluation are prevalent. The enhanced reliability of conclusions derived from this methodology has significant implications for legal proceedings. The mathematical rigor and transparency inherent in the approach strengthen the defensibility of forensic findings. Quantitative results, grounded in robust mathematical models, can bolster expert testimony, providing clear evidence that can withstand rigorous cross-examination and judicial scrutiny. This not only aids in the pursuit of justice but also reinforces the credibility of forensic science as a discipline. Furthermore, the systematic nature of the methodology contributes to the standardization of forensic analysis procedures. By providing a clear framework for evaluating evidence, it reduces the potential for subjective bias and inconsistency in expert assessments. This standardization is crucial for ensuring that forensic analyses are conducted with the highest levels of integrity and reliability, fostering trust in forensic findings among legal professionals and the public.

Previous studies such as Goala, et al. [1] applied a fuzzy MCDM approach using trapezoidal fuzzy numbers to assist criminal investigators in cases involving gunshot wounds. Their work showed how fuzzy logic can help handle uncertainties in forensic contexts. However, the q-rung orthopair fuzzy numbers used in this study provide a more advanced mechanism for handling higher levels of uncertainty and hesitation, which is particularly useful when evidence is incomplete or ambiguous. Chinnasamy, et al. [2] utilized the DEMATEL method for forensic medical examinations, emphasizing structured decision-making(Research Paper). While their approach provided valuable insights for medical forensics, our use of q-ROFNs offers greater flexibility and adaptability, especially when handling mechanical evidence with various degrees of ambiguity. In the domain of network forensics, Samuel, et al. [4] applied fuzzy TOPSIS to manage uncertainty in network intrusion investigations(Research Paper). Their findings demonstrated how fuzzy logic could address ambiguity in forensic assessments, similar to how this study uses q-ROFNs to refine and improve the precision of forensic evaluations in mechanical part identification.

In conclusion, the application of q-rung orthopair fuzzy numbers within the MCDM framework offers a powerful and versatile tool for forensic scientists. It effectively addresses the challenges posed by uncertainty and imprecision, providing a structured and transparent method for evaluating complex evidence. The methodology enhances the accuracy and reliability of determining the origins of mechanical parts in vehicle accidents, ultimately contributing to more robust and defensible outcomes in forensic investigations. Its flexibility, scalability, and rigorous mathematical foundation make it a valuable addition to the field of forensic science, with the potential to improve investigative processes and support the administration of justice.

Future Research Directions: While the application of q-rung orthopair fuzzy numbers (q-ROFNs) within the MCDM framework offers a novel approach to forensic analysis, there remain several areas for further exploration. One area for future research is the integration of objective data-driven techniques, such as machine learning algorithms, to further support and enhance expert evaluations. These techniques could provide more quantitative measures to complement the subjective expert judgments, reducing potential biases. Another avenue for future research involves extending the methodology to group decision-making processes, where multiple experts contribute collectively to the analysis. This could lead to a more comprehensive and balanced evaluation, particularly in complex forensic cases where multiple perspectives are valuable. Additionally, future studies could investigate the application of this approach to other forensic evidence types beyond mechanical parts, such as biological or digital evidence, where uncertainty and ambiguity are also prevalent. Expanding the application of q-ROFNs to these areas could further validate and strengthen its effectiveness in diverse forensic contexts.

## Conclusion

In this study, we introduced the q-ROFNs into the MCDM framework for forensic analysis, specifically addressing uncertainties in evaluating mechanical parts in vehicle accidents. The proposed methodology enables experts to express both confidence and hesitation, providing more accurate and reliable assessments compared to traditional fuzzy methods. By systematically defining criteria, assigning weights, and aggregating expert evaluations, the q-ROFN-based approach significantly improves decision-making in complex forensic contexts. The novelty of this study lies in applying q-ROFNs to forensic science, enhancing the robustness, flexibility, and reliability of forensic conclusions. This method offers adaptability across various forensic scenarios, evidence types, and different forensic environments. While this study provides a solid foundation, future research could explore integrating objective data-driven techniques and group decision-making processes to further improve reliability and reduce biases. Overall, this methodology contributes significantly to forensic science, improving the quality of forensic investigations and supporting judicial decision-making with more accurate and defensible conclusions.

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