A Methodology of DASs Benchmarking to Support Industrial Community Characteristics in Designing and Implementing Advanced Driver Assistance Systems Within Vehicles

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A Methodology of DASs Benchmarking to Support Industrial Community Characteristics in Designing and Implementing Advanced Driver Assistance Systems within Vehicles

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Abstract

This study presents a novel benchmarking methodology for Data Acquisition System (DAS) types to support industrial community characteristics in designing and implementing the advanced driver assistance systems within vehicles, which is considered multicriteria decision-making (MCDM) problems. Four issues support this claim. Multiple criteria need to be considered in the evaluation, data variation, trade-off and conflict. Thus, an MCDM solution is essential to overcome problem complexity. In the last years, MCDM developed methods have been studied and criticised from different theoretical aspects. The most recent method, fuzzy decision by opinion score method (FDOSM), has proven its power in solving other methods challenges. However, the FDOSM technique and its extension were based on traditional fuzzy set theory, which is limited and unable to deal with the membership and non-membership hesitation simultaneously and that affect the accuracy of final decision especial among the group of decision-makers. Therefore, this study extended FDOSM into an intuitionistic fuzzy environment that considers the hesitation index in the membership definition, then discuss the power of such membership in evaluating and benchmarking the DAS systems. The proposed methodology comprises two consecutive phases. In the first phase, a decision matrix is formulated based on the crossover of the 'DAS systems' and 'multiple evaluation criteria'. In the second phase, the new method (the intuitionistic FDOSM method) has two main stages (i.e. data transformation unit and data processing). The dataset was used to prove the concept. A total of 39 DASs were evaluated based on 14 DASs criteria, involving seven sub-criteria for "comprehensive complexity assessment" purpose and eight sub-criteria for "design and implementation" purpose, which highly affected the design of DAS when implantation occurred by industrial communities. The results of this study are as follows: (1) Individual results of benchmarking, which used three decision-makers are broad, with consensus on the DAS#1 system ranked as the best. (2) The results of the proposed GDMs proved quality in DASs benchmarking, and the DAS#1 system is also the best. (3) Intuitionistic FDOSM can deal with hesitation and uncertainty problems properly. (4) Significant differences were indicated among the groups' scores, which proves the validity of the intuitionistic FDOSM results.

Keywords: Multi-Criteria Decision Making; Fuzzy Decision by Opinion Score Method; Intuitionistic fuzzy; Data Acquisition System; Intelligent transportation system; Industry Community.

1. Introduction

Since its development, the intelligent transportation system (ITS) makes humans, vehicles and roads united and harmonic and establishes a wide-range, fully efficient, real-time and accurate information management system [1]. ITS relies on a wide range of technologies and functions, such as communications, geographical locations, geographical information system (GIS), data acquisition system (DAS), detection and classification, in-vehicle systems and digital mapping. Among others, DAS is a core part of large-sized application systems or an application platform that brings many advantages such as improved efficiency and reliability of processes or machinery, quality control and data entry; reduced data redundancy and reduced storage and retrieval costs [2]. DAS directly faces all kinds of data objects for data collection and standardised sorting and can provide a series of standardised data services for others in the overall ITS [3]. Recently, researchers and developers are increasingly focusing on the importance of utilisation of DAS given its capabilities for collecting driver behaviour dataset. This dataset can be used to understanding drivers' characteristic behaviour, which can contribute significantly to road safety, engage the user in saving fuel and correlate faults of the car with the driving style. DAS is crucial for the development of the vehicle industry by increasing the reliability and efficiency of designing driver assistance systems within vehicles [4]. Furthermore, the implementation of DAS can assess driver instructions (steer angle tuning, reversing, lane changing, rotating or passing a car), speed differences, traffic condition (high, medium or low) and driver status (focused, sleepy, heavy-eyed, hostile and distracted) [5][6][7]. The digital DASs and signals can be shown in Figure 1.

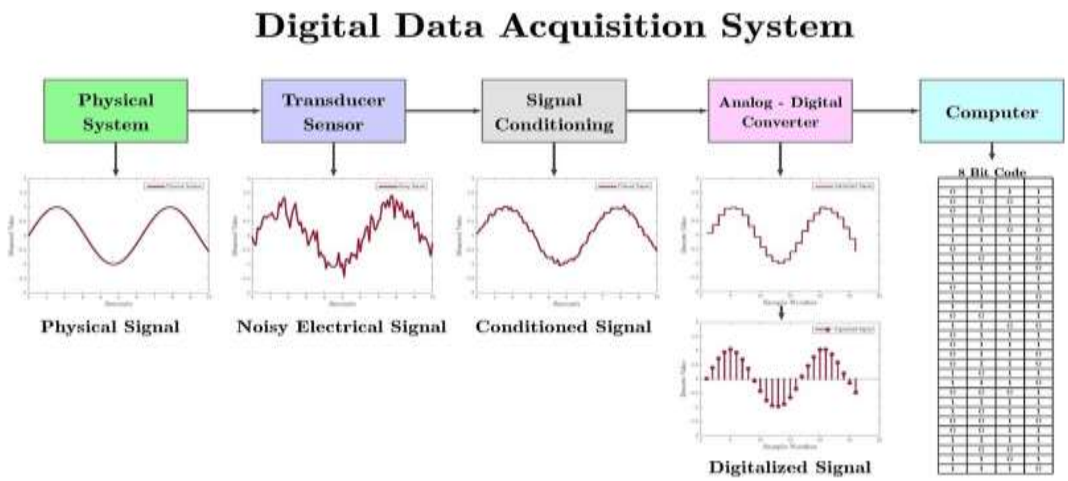

Figure 1 Digital DASs and Sensors [7]

Many characteristics are required for the DAS, such as the requirement for high acquisition speed and many analogue and digital inputs that enable us to use quarter vehicles and adequate resolution (bits) for the analogue inputs [8]. It must also be compact, economical and reliable; therefore, these DAS technologies apply to the automobile industry and guarantee the safe operation of vehicles [9]. Consequently, the complexity of the automotive electronic system inside vehicles is increasing daily [2]. Thus, the growth of scientific literature increasingly focuses on the importance of DAS applications and has gained considerable attention for supporting industrial community characteristics [10], such as smart vehicles manufacturing, which uses DAS and other computing platforms, communication technology, simulation, data-intensive modelling and predictive engineering [11]. Furthermore, many varieties in the types of DAS that companies can provide can be manufactured individually by developers through using Arduino or other technology for research experiments [12][13]: the plug-and-play type that prioritises flexibility and minimal set-up time, the data logger type that runs remotely and reliably with the option to add controls and a framework or industry DAS, which has high channel counts and the highest performance used for smart-factory platforms to reduce the defect rate and production cost in the die-casting industry [14] [15][16].

DAS's research is rapidly expanding, and reporters recent interests include the continual addition of new technologies, new processes for the acquisition of the data, new updating procedures for designing and implementing the DAS system. Nevertheless, all these terms explore some implications of ambiguity to give the decision for the best and accurate DAS system within vehicles. In particular, many DASs have been proposed in the literature on the basis of various approaches. Therefore, to obtain a clear view of the DAS' current state, challenges and related issues, criticism and gap analysis are conducted on the basis of academic literature. The introduction of this research must argue ninth sequential questions and lay out the appropriate answers to demonstrate and strengthen the contribution to DAS knowledge. The first question, **'*How can DAS Supporting Industrial Community Characteristics*?'**, describes the fundamental concepts of DAS considerations for the innovation of the automotive industry.

First, modern automotive electronic systems have become more complex than ever and have recently increased the importance of a vehicle total value in terms of electronic functionality and architecture. From the industry functional perspective, there is a wide range of emerging applications, including autonomous functions and advanced driver assistance systems, such as adaptive cruise control and lane-keeping assistance. To fulfil these applications, various DASs are designed and implemented to play important roles in sensing, signal processing, control and decision making [2]. The DAS system must guarantee data acquisition with the required characteristics (i.e. high frequency, easy installation in any vehicle without an aggressive vehicle modification and low-cost accelerometers in vehicle dynamics applications) [9]. Therefore, these technologies apply to the automobile industry, thereby supporting the industrial community with many benefits, such as reducing costs, parameter estimation and easily configurable system [9]. From the architectural perspective, the number of DASs in a standard car has recently gained attention [4][5]. However, the developing trend poses great challenges to the safety guarantee of the vehicles; thus, acquiring the real-time data inside the vehicles to implement the online diagnosis, cyber-security attacking detection and driver behaviour analysis is of great importance [6]–[7][8]. In this context, ***'What is the current scenario of available DAS in the academic literature and what are the critical analyses?'*** is the second research question that needs to be answered.

The academic literature shows variability in the types and complexity of used DASs. Some studies have used professional equipment, which is connected to the CAN-bus of the vehicle to access and collect the data directly [15][16][17][18][19][20][21][22][23]. However, the presented DASs in these studies are costly and require special tools to set up in the vehicle.

Reference [24] used simple software similar to a 'drive recorder' with a camera, front radar and GPS to collect the dataset. Consequently, the collection for the needed dataset required a more efficient approach to avoid incorrect prediction, which affects the route condition and traffic. Reference [25] used an old dataset from 1997, which generated from old DAS with limited resources, and the presented model cannot fully reproduce the fundamental diagram. The model needs more analysis to find the point where it deviates from real drives. In Reference [26], data were collected for more than 100 drivers through an instrumented vehicle, equipped with GPS, radar, cameras and other sensors for describing the road context and experimental procedure. Statistics and initial insights were also presented based on the large amount of data collected (more than 8000 km of observed trajectories and 120 hours of driving). In Reference [27], the authors analysed naturalistic driving data collected from 100 cars for one year by using cameras (forward road view, rearward road view and driver view), onboard sensors and the CAN-bus to collect continuous data at 10 Hz. However, few CAN-bus signals were selected, which were yaw rate, speed, gear, forward radar and line crossings. The DAS in this study used a complex configuration to integrate with all these signals and installing them in all 100 cars. In [28], the authors only mentioned the resource of collected data but did not clarify DAS details.

At this point, the academic literature has shown different variability in types and complexity for using the DAS without a clear understanding of its implementation or configuration concerning the required criteria as a whole. The studies demonstrated that the different DASs show diversity and confusion characterisation considering different criteria. Their assessment considered diversity for designing and implementing accurate advanced driver assistance systems within vehicles. Thus, the third question matches the literature scenario: '***Exactly how the criteria have been surrounded DASs' designing and implementation on the literature for supporting the industrial community?'.***

A big variance has been recognised in the presented DASs; in particular, some of them were presented based on rough criteria, such as performance, the number of channels, DAS communications method [15][16][17][18][19][20][21][22][23] and size of collected data [26][27]. Others limited their DAS design based on others' criteria, such as low-cost [25] and simplistic [24]. However, the development of DAS must meet the required number of criteria, whereas these criteria must be affected for the design and should comply with the standard requirements and guidelines for the development process within vehicles [29][30][31][32][33]. Therefore, the experience was limited in terms of the unified number of used criteria, which is confusing, inconsistent and detrimental to the field of driver behaviour studies that directly affect the industrial community, leading to an incomplete and inefficient dataset collected by a wrong DAS, which could also affect all driver behaviour domains' development. For example, if a study investigates driver behaviour for safety development and uses an incomplete dataset, unexpected accidents could happen. Thus, the development of an effective DAS for the industrial community is still crucial [34]. DAS should meet multiple criteria to be effective; for example, size is important when setting up a vehicle in a small room [35]. The communication method between the DAS and the vehicle should reach all the required data or sensors to collect live data, such as connecting on the can-bus network of the vehicle [36]. The throughput and the amount of data that can be produced with accurate results are important criteria [37][38]. Subsequently, the cost criteria, DAS, is usually costly because it is a complicated system and its mechanism contains many technologies; thus, many studies went for reducing the cost of DAS manufacturing and development [13][39]–[41]. Besides, DAS should be dynamic in reading the frequency because of the variety of sensor frequencies [40][42]. Thus, the fourth question is ***'What is the unified multi-criteria that can be affected for the evaluation of the available DASs for vehicles development to support the industrial community?'.***

No agreement had been made for the number of criteria used in the evaluation until previous work was contributed and collected the whole criteria [43]. The work presented a systematic literature review published in 'Vehicular Communications Journal' and examined the field of the car-following model, which collects the available DAS systems and the affected criteria systematically. The work determined the most important 15 criteria and categorised these criteria into two main categories. The first group was cost-efficiency, which contains eight criteria. The second category was 'complexity', which contains seven criteria. Besides, the criteria values were specified for the available DAS systems by the authors subjectively while the comparison as a benchmarking concept among DASs has not been presented. However, no key development process was produced in previous work in terms of the evaluation and benchmarking for the DASs. The scalability of DASs, the appropriate choice of board type and the consideration of the collected 15 criteria are necessary to develop robust, practical, cost-efficient, scalable and reliable DAS to support the industrial community. Thus, the fifth question is '***Can we evaluate and select of available DASs to support the industrial community?***'.

According to the above discussion, the scalability and availability of DAS boards over a long period are questionable. Literature shows a lack in the comparison between each proposed DAS considering the affected criteria in its design and implementation to support the industrial community [43]. When dealing with such DASs, we found that they are multi-cost effective. The selection process for the best available one is a problematic and complex but crucial task. Therefore, the selection of the best DAS for driver behaviour analyses and the required affected criteria to achieve this goal must be established to guarantee driver safety, improve traffic management and support the industries with a reliable design [44].

However, this process could not be accomplished without conducting accurate prioritisation stages based on the available criteria of evaluation. In these contexts, painting the full picture for the development of a novel methodology that favours the correct benchmarking of DASs and selection the best is an essential need to support the industrial community [45]. However, relatively little attention has been given to investigating this benchmarking process. Accordingly, before providing our direction, addressing the current issues for the selected solution, the sixth question must be explained: ***'What are the open issues making the evaluation and benchmarking DASs process challenging tasks to support the industrial community?'.***
To bridge the discussed gap of the selecting of DASs to support the industrial community, four benchmarking issues were faced: multi evaluation criteria, data variation, trade-off and conflict. The required evaluation and benchmarking for potential DASs were relayed on the basis of different evaluation criteria (eight criteria for cost-efficiency and seven criteria complexity), which present the first issue as multi evaluation criteria [44]. According to previous work, the subjective judgment values (i.e. high, medium and low) were achieved for each criterion for all available DASs, and these values varied from one criterion to another, resulting in data variation among the DASs because of the second issue [44]. Furthermore, optimal judgment values, in which some criteria are low, such as cost criteria, and others gain high value, such as scalability criteria, seriously affect the selection of the best DAS. The inverse relationship between criteria causes a trade-off because it is the third issue [45][46]. Finally, in the comparison procedure of DAS, a change in one of the DAS components is caused by the increase and decrease of some criteria's value. It is logically considered a conflict, producing the fourth issue [47][48]. Nevertheless, the literature has shown no valid attempt to consider the effect of each criterion on other criteria. Thus, according to the discussed issues, the evaluation and benchmarking of DASs is a complex multi-attribute decision-making problem falling under multicriteria decision-making (MCDM), in which each DAS is considered an alternative for the decision-maker. Thus, the present study raises the seventh question and provides an analytical response to address the above issues: '***What is the recommended solution for such issues?'.***
MCDA is 'an extension of decision theory that covers any decision with a complex multi-attribute decision-making problem. MCDA is a methodology for assessing alternatives on individuals, conflicting criteria and combining them into one overall appraisal' [49]. The technique involves various processes, including structuring, planning and solving different decision problems with the use of many criteria [50]. MCDM methods often require decision-makers (DMs) to provide qualitative and/or quantitative assessments to determine the performance of each alternative concerning each criterion and the relative importance of the evaluation criteria concerning the overall objective [51][52][53]. Thus, this study analyses the eighth question: ***'What is the best MCDM benchmarking method? Does it have any theoretical issues?'.***
In the literature, many MCDM methods are available with advantages and disadvantages [54]–[59]. However, in comparison with these existing methods, the fuzzy decision by opinion score method (FDOSM) based on traditional fuzzy logic theory in triangular membership forms the most recent technique (published in 2020), showing high efficiency and powerful implementation [59]. FDOSM succeeded in overwhelming many theoretical challenges of other weighting and ranking MCDM methods, such as the technique for order of preference by similarity to ideal solution and analytic hierarchy process by considering the idea of an ideal solution, avoiding two preferences, reducing the number of comparisons, preventing inconsistency, reducing vagueness, defining fair and implicit understandable comparisons and yielding a minimum number of mathematical operations [59]. In Reference [60], the extension of FDOSM introduced with different operators, such as direct aggregation, distance measurement and compromise rank, approaches with traditional fuzzy logic theory in triangular [60] and trapezoidal [61] membership forms to evaluate and benchmark active queue management methods. However, Zadeh [62] introduced the traditional fuzzy set theory and defined the degree of membership as a real value μ, where $0 \leqslant \mu \leqslant 1$, and non-membership is a complement of membership $(1 - \mu)$. This membership expression helped to handle vagueness and uncertainty [63]. However, representing non-membership as a complement of the membership causes a limitation in expressing all the information where the decision maker's hesitation is ignored during the decision-making process. The principle of intuitionistic fuzzy sets (IFSs), as an extension to Zadeh's fuzzy set, can consider membership and non-membership degrees with hesitation index simultaneously [64][65]. Therefore, the IFSs theory is widely used because it can represent ineluctably imprecise or not utterly reliable judgments [66]. Furthermore, affirmation, negation and hesitation can be expressed well in IFSs with the help of membership definitions. The consistency of IF preference relations and experts' opinions collected from these preference relations has an important role in providing accurate decision results in group decision-making (GDM) [67]. Thus, FDOSM is extended into intuitionistic-FDOSM to evaluate and select the DAS systems. Thus, the ninth and last question is '**What is the novelty and contributions of the present study**?'.

The presented study can support the industrial community by a novel benchmarking methodology to choose the best DAS. The study contributions can be summarised in the following points:

1. This study fills the gap of DAS comparison by identifying the affective criteria and dataset.

2. This study develops a new formulation of the MCDM method called intuitionistic-FDOSM to determine the significant effect of each DAS, avoiding the hesitation and uncertainty concerning the DAS's dataset behaviour.
3. This study made a decision matrix (DM) based on the crossover of the 'DAS systems', '15 multiple evaluation criteria, including seven sub-criteria for "comprehensive complexity assessment" purpose and eight sub-criteria for "Design and implementation" purpose'.
4. This study developed a novel methodology for evaluating DAS criteria and benchmarking DAS systems on the basis of formulated DM for the driver behaviour field and can overcome predefined fourth issues.

2. Proposed Benchmarking Methodology

This section presents a detailed description and an overview of the methodology for producing a benchmarking solution for DASs. The benchmarking process is implemented using the FDOSM extension (intuitionistic FDOSM). Section 2.1 presents the first phase that identifies the criteria for the DAS evaluation, the dataset and the proposed DM for formulating the selecting process. The outcome of the first phase is utilised for the second phase. Section 2.2 illustrates the second phase, which introduces the stages of the extended FDOSM used in benchmarking the DASs. Figure 2 provides a map of the methodology in benchmarking the DAS based on the proposed FDOSM extension.

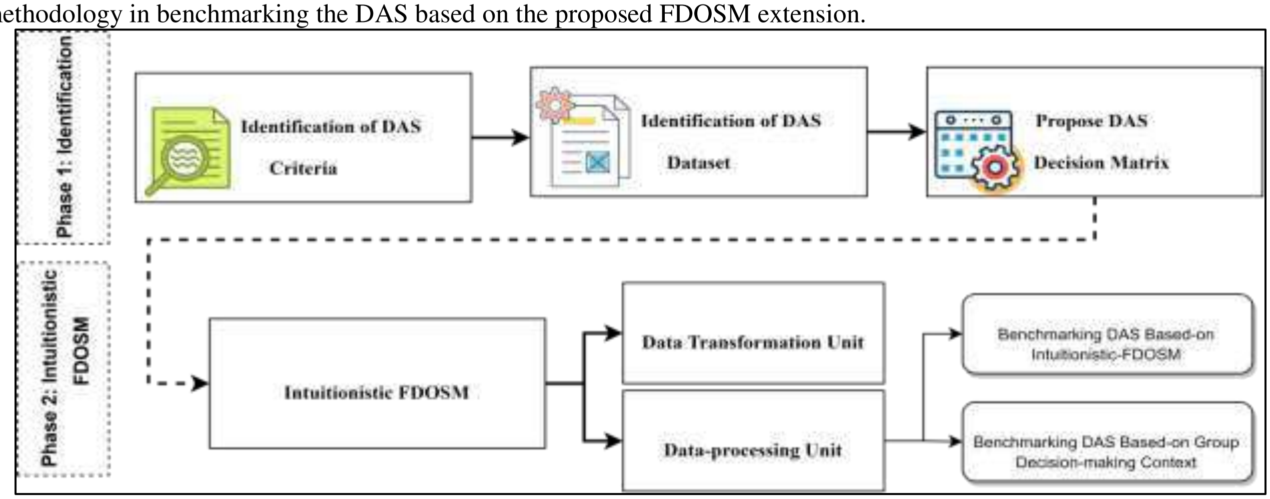

Figure 2 Benchmarking Methodology

The values of each criterion resulting from the output of the evaluated DAS priorities were inserted into the DM to start with the benchmarking DAS prioritise solution. This DM's subjective evaluation values were proposed by authors in [43] to evaluate the current proposed DASs in the literature. This DM is also considered as input in a proposed intuitionistic FDOSM. Thus, each DAS method can be benchmarked based on 15 evaluation criteria.

2.1 Phase 1: Identification

Three essential stages have been presented in this phase. First, DASs' criteria and their description were defined and identified. Second, the DASs' dataset and the alternatives depending on the identified criteria were presented. Third, the examined subjective criteria, dataset and alternatives were utilised in the formulation DM used in the evaluation and benchmarking of the DAS method configuration.

2.1.1 Identification of DAS Criteria

The affected criteria were derived from the previous study [43]. The two main set criteria are 'comprehensive complexity assessment', which includes seven sub-criteria, and 'design and implementation', which includes eight sub-criteria. These two sets are highly affected by the design of DAS when implantation is caused by industrial communities. Further descriptions for all DAS criteria are presented the Table 1.

Table 1 Criteria Description and Types of DAS

No.	Main criteria	Sub Criteria	Criteria description
1	Comprehensive Complexity Assessment	Sophisticated Equipment	This criterion refers to the sensor/device composition of embedded materials and or active/passive materials. That is, GPS devices represent simple sensors that are easy to implement, and lidar and radar are adequate devices that require special design customisation for data acquisition/interfacing and processing.
2		Availability of Components	This criterion refers to the ease of acquiring or the need to order and/or customise a special design. For example, most of the devices/sensors used in NDS experiments are sophisticated devices and not off the shelf that can be acquired easily at any time.
3		Longitudinal and Lateral	This criterion illustrates DAS's ability to collect longitudinal and/or lateral data using instrumented cars.
4		Design and Programming	These procedures should be performed when sophisticated devices must be integrated into the DAS design. Adding more electronic boards/sensors to a DAS system requires more time to program/interface these devices (i.e. not plug and play).
5		Operation and Maintenance	Routine procedures should be performed on a large DAS to ensure that sophisticated sensors/boards components are working properly. If they fail, then replacing them is not economical.
6		Equipment Reliability	If the electronic components of DAS are expensive/sophisticated, then the DAS is mostly reliable. Otherwise, using unreliable components is not cost-efficient (e.g. off-the-shelf components have low reliability compared with sophisticated ones).
7		Implementation Cost	This criterion refers to the cost of wiring/adjustment and modification performed on a car's body to house DAS components. These modifications increase implementation cost, and DAS that requires a low level of maintenance on a car's body must be designed. In the end, cost-efficiency is evaluated subjectively depending on the DAS design layout and provided features.
8	Design and Implementation	Cost-efficiency	This criterion indicates/describes the level of cost-efficiency of currently proposed/implemented DAS. For example, if DAS consists of lidar/radar, GPS and CAN bus data collection devices, then the system exhibits low cost-efficiency.
9		DAS Size	This criterion describes the size of the architecture of the proposed DAS in the literature. The assessment value considers the number of electronic elements of DAS.
10		Power Consumption	This criterion estimates the power level required by DAS to operate fully.
11		Latency	This criterion is the time between cause and effect (i.e. the time that elapses when DAS starts measuring the environment until the outcome is delivered to the user).
12		Information Size	This criterion represents the amount of raw data that DAS can collect.
13		Information Diversity	This criterion represents the variety of raw data that DAS can collect, similar to the data collected from radar/lidar, GPS and/or CAN bus.
14		Computational Complexity	This criterion represents the difficulty in processing the amount of collected raw data. This criterion differs when processing the raw data collected from lidar or radar.
15		DAS Complexity Level	This criterion assesses the overall level of complication in the current proposed/implemented DAS in the literature based on the preceding criteria. For example, if the DAS system consists of GPS and CAN bus, then it possesses a low complexity level.

In general, evaluation criteria can be categorised into two types: benefit criteria and cost criteria. Benefit criterion means that a bigger value is more valuable, whereas cost criteria are just the opposite [45]. Thus, all criteria towards these beneficial and cost categories should be identified before providing the development solutions phase. Table 1 presents and defines the 15 sub-criteria. According to the descriptions of these criteria and based on the benefit and cost concept, 5 criteria belong to the beneficial type, and 10 criteria belong to the cost type. The benefit criteria are the availability of longitudinal and lateral components, equipment reliability, information size and information diversity. The cost criteria are sophisticated equipment, design and programming, operation and maintenance, implementation cost, cost-efficiency, DAS size, power consumption, latency, computational complexity and DAS complexity level. Accordingly, the required dataset must be identified based on these criteria types. The next section presents the dataset description and identification.

2.1.2 Identification of DAS Dataset

We based our study on the subjective dataset of DASs. The analysis shed light on the feasibility of DAS design in terms of the above-identified criteria (Table 1). Several assessment criteria were proposed with subjective evaluation values in [43]. The fourteen selected DASs that were proposed to be used in a car-following context in microscopic studies and not the naturalistic ones. However, this section presents DASs to be placed in the benchmarked process. Thus, out of 39 DASs, only 14 DASs are selected to prove the concept of DAS benchmarking using in this study. These are numbered accordingly from DAS#1 to DAS#14, as presented in the dataset in Table 2.

Table 2 DASs Dataset

Ref.	Alternatives	Comprehensive Complexity Assessment							Design and Implementation							
		Sophistication Level	Off the shelf component	Longitudinal & Lateral Data	Design and Programming	O/P	Equipment Reliability	Implementation Cost	Cost Efficient Level	DAS Size	Power Consumption	Latency	Information Size	Information Diversity	Computational Complexity	DAS Complexity Level
[28]	DAS#1	L	Yes	Yes	L	L	L	L	H	S	L	L	M	H	L	L
[15]	DAS#2	H	No	Yes	L	L	H	H	L	B	H	M	B	H	H	H
[68]	DAS#3	VH	No	No	H	L	H	H	L	B	VH	H	VB	H	VH	H
[16]	DAS#4	H	No	Yes	H	H	H	H	L	M	H	M	B	H	H	H
[69]	DAS#5	H	No	No	NA	L	H	H	L	B	H	M	B	H	H	H
[25]	DAS#6	M	Yes	No	M	L	H	H	L	S	M	L	S	L	L	L
[17]	DAS#7	H	No	Yes	H	M	H	M	H	B	H	H	B	H	H	H
[27]	DAS#8	M	No	Yes	L	L	H	M	M	M	M	L	B	H	H	M
[23]	DAS#9	H	No	Yes	H	L	H	M	H	B	H	M	B	H	H	H
[70]	DAS#10	H	No	Yes	H	M	H	H	L	VB	VH	H	VB	H	H	VH
[18]	DAS#11	H	No	Yes	H	H	H	H	L	M	M	M	B	H	H	H
[71]	DAS#12	H	No	No	H	M	H	M	M	B	H	M	M	M	H	H
[20]	DAS#13	H	No	Yes	H	H	H	H	L	B	M	M	B	H	H	H
[21]	DAS#14	VH	No	No	H	H	H	H	VL	B	H	M	B	H	H	H
Remarks: H= High, VH= Very High, L= Low, VL= Very Low, B= Big, M= Medium, VB= Very Big, S= Small																

Table 2 shows that conflict and trade-off are obvious among these criteria because increasing in one value of criterion may decrease/increase other criteria values. Considering one criterion only and not the effect of other criteria on the system performance is a problem in the evaluation process. For example, if the sophisticated level criterion increases, then the cost-efficiency criterion decreases, and the complexity level increases. If the latency criterion is high, the complexity and cost-efficiency values decrease. If the DAS equipment reliability is low, then the complexity level is low, and the system poses a high cost-efficiency value. Therefore, a trade-off occurs among the cost-efficiency criteria when compared with the complexity criteria. The best DAS cannot be selected unless a criteria trade-off can be overcome. To this end, a new proposed DM presented in the next section can deal with these considerations.

2.1.3 Formulated DAS DM

This section presents the proposal of DASs' evaluation and benchmarking DM. The DM-based approach can give guidance on prioritisation for all available DASs. To select the best available DAS in terms of cost-efficiency and less complexity, a new DM should be proposed to point out the procedure of selection. The intersection between 'DASs' and 'DAS Criteria' is the proposed DM, as shown in Table 3.

Table 3 Formulated DM

Alternative Methods	Comprehensive Complexity Assessment							Design and Implementation							
	C1=Sophistication Level	**C2=Off the shelf component**	**C3=Longitudinal & Lateral Data**	**C4=Design and Programming**	**C5=O/P**	**C6=Equipment Reliability**	**C7=Implementation Cost**	**C8=Cost Efficient Level**	**C9=DAS Size**	**C10=Power Consumption**	**C11=Latency**	**C12=Information Size**	**C13=Information Diversity**	**C14=Computational Complexity**	**C15=DAS Complexity Level**
DAS1	C1/DAS1	C2/DAS1	C3/DAS1	C4/DAS1	C5/DAS1	C6/DAS1	C7/DAS1	C8/DAS1	C9/DAS1	C10/DAS1	C11/DAS1	C12/DAS1	C13/DAS1	C14/DAS1	C15/DAS1
DAS2	C1/DAS2	C2/DAS2	C3/DAS2	C4/DAS2	C5/DAS2	C6/DAS2	C7/DAS2	C8/DAS2	C9/DAS2	C10/DAS2	C11/DAS2	C12/DAS2	C13/DAS2	C14/DAS2	C15/DAS2
DAS3	C1/DAS3	C2/DAS3	C3/DAS3	C4/DAS3	C5/DAS3	C6/DAS3	C7/DAS3	C8/DAS3	C9/DAS3	C10/DAS3	C11/DAS3	C12/DAS3	C13/DAS3	C14/DAS3	C15/DAS3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
DAS14	C1/DAS14	C2/DAS14	C3/DAS14	C4/DAS14	C5/DAS14	C6/DAS14	C7/DAS14	C8/DAS14	C9/DAS14	C10/DAS14	C11/DAS14	C12/DAS14	C13/DAS14	C14/DAS14	C15/DAS14

The formulation of the above DM is projected to provide the proper decision with the accurate DAS to ensure and improve the driving experience and obtain the required dataset when designing and implementing an accurate DAS for the industry. However, selecting the best available DAS is difficult when the subjective evaluation has multiple criteria because some criteria cannot be measured without a clear methodology for the metrics of evaluation. Furthermore, previous work [43] showed that the current available DAS lacks a clear and valid method of evaluation and benchmarking. The evaluation and benchmarking of DASs are regarded as complex multi-attribute decision problems. In this situation, each DAS is considered as an alternative for the decision-maker considering multiple evaluation perspectives. According to the problems of selecting the best DAS mentioned in the introduction part, the new extended decision-making method (intuitionistic FDOSM) considered a substantial approach to decrease problem complexity.

2.2 Phase 2: Formulated Intuitionistic FDOSM

This phase presents the stages of FDOSM used in benchmarking the DAS priorities (see Figure 3). Section 2.2.1 provides the first stage of the FDOSM, which is the data transformation unit. Section 2.2.2 presents the second stage of the extended FDOSM into intuitionistic FDOSM, which is data processing.

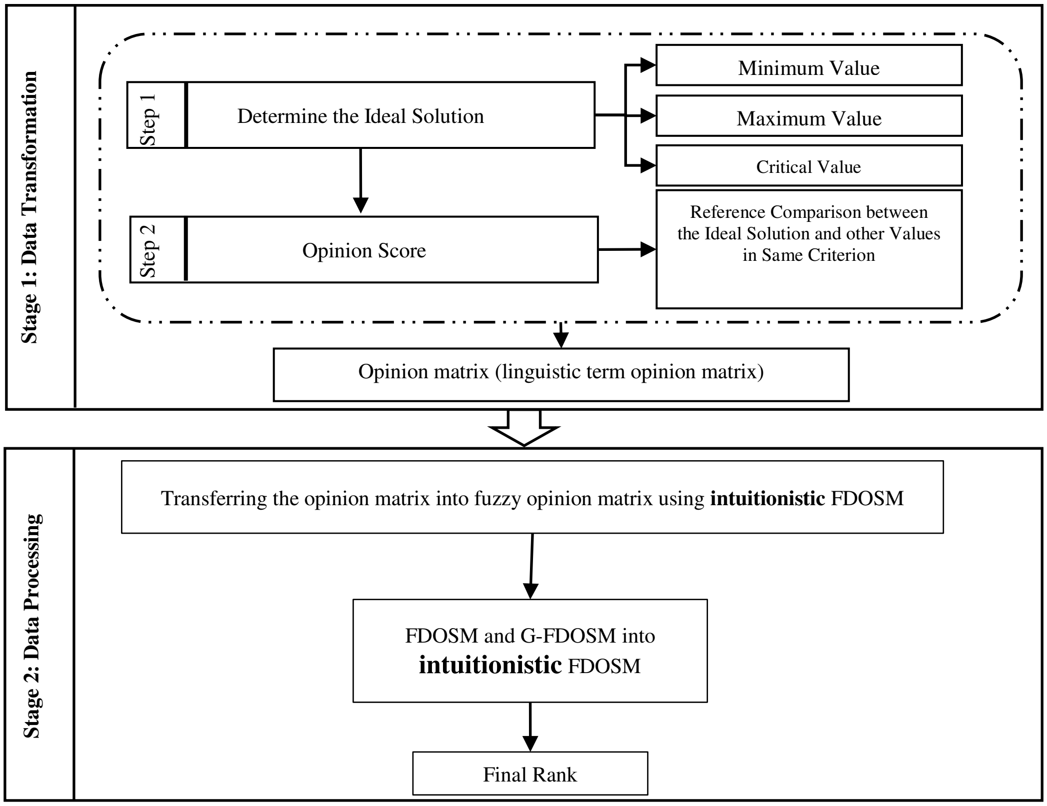

Figure 3 Intuitionistic FDOSM Stages

2.2.1 Stage 1: Data Transformation Unit

According to Reference [60], the transformation of the DM into an opinion matrix is achieved on the basis of the following steps.

Step 1:

The ideal solution of each sub-criterion used in the benchmarking of the DAS (i.e. DAS size, power consumption, latency, information size, information diversity, computational complexity and DAS complexity level, implementation cost and cost-efficiency) is selected. Therefore, the ideal solution is defined as follows:

$$A^* = \left\{\left[\left(\max_i v_{ij} \,\middle|\, j \in J\right), \left(\min_i v_{ij} \,\middle|\, j \in J\right), (Op_{ij} \in I.J) | i = 1.2.3. \dots .m\right]\right\}, \qquad (1)$$

where max is the ideal value with benefit criteria (i.e. off the shelf component and equipment reliability), min is the ideal solution for cost criteria (i.e. sophistication level, design and programming and implementation cost), and $Op_{ij}$is the critical value when the ideal value lies between the max and min. Thus, the critical value is determined by the decision-maker. However, in this research, no criteria is needed to determine the ideal solution by using the critical value.

Step 2:

Reference comparison between the ideal solution and other values per criterion is used in benchmarking the DAS methods. Five scales are used in comparing the linguistic terms of no difference, slight difference, difference, big difference and huge difference. The ideal solution selection step is followed by comparing the ideal solution with the value of alternatives in the same criterion, as in Equation 2.

$$Op_{Lang} = \left\{\left(\left(\tilde{v}_{ij} \otimes v_{ij} \,\middle|\, j \in J\right). \,\middle|\, i = 1.2.3. \dots .m\right)\right\}, \qquad (2)$$

where ⊗ represents the reference comparison between the ideal solution and the value of alternatives in the same criterion. The final output of this block refers to the linguistic term opinion matrix that is ready to be transformed into fuzzy numbers using the intuitionistic fuzzy number, as in Equation 3.

$$Op\_Lang = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} op_{11} & \cdots & op_{1n} \\ \vdots & \ddots & \vdots \\ op_{m1} & \cdots & op_{mn} \end{bmatrix} \quad (3)$$

2.2.2 Stage 2: Data-processing Unit

The opinion matrix refers to the output of the transformation unit. The final block begins by converting the opinion matrix into a fuzzy opinion DM via the application of the intuitionistic fuzzy number, as shown in Table 4. In [59], the authors used the triangular membership and arithmetic mean to aggregate with direct aggregation with a single decision-maker and GDM. Thus, the present study extends FDOSM into intuitionistic FDOSM to evaluate and benchmark the DAS priorities with individual and group contexts.

2.2.2.1 Benchmarking DAS based on intuitionistic FDOSM

This study applied direct aggregation with intuitionistic FDOSM to evaluate and benchmark the DAS. To achieve this goal, two steps are presented and described as follows.

Step 1: Application of Intuitionistic Fuzzy Theory

Definition 1: Let *X* be the universal set:

i) A set $\widetilde{A} = \{x, m_{\tilde{A}}(x) | x \in X\}$ is called a fuzzy set of *X*, where $m_{\tilde{A}}(x): X \to [0,1]$ is membership function that, for all $x \in X, m_{\tilde{A}}(x)$ expresses the degree of membership of element x in $\tilde{A}$.

ii) A set $\widetilde{A} = \{x, m_{\tilde{A}}(x), n_{\tilde{A}}(x) | x \in X\}$ is called IFS of *X*, where $m_{\tilde{A}}(x), n_{\tilde{A}}(x)$ are membership function and non-membership function, respectively. Thus, $0 \le m_{\tilde{A}}(x) + n_{\tilde{A}}(x) \le 1, \forall x \in X$.

Table 4 Conversion of the linguistic terms into IFSs [72]

Linguistic terms	Intuitionistic fuzzy number	
No difference (NO.D)	0.90	0.05
Slight difference (S.D)	0.75	0.20
Difference (DI)	0.50	0.40
Big difference (B.D)	0.25	0.60
Huge difference (H.D)	0.10	0.80

Step 2:

The resulting values from the previous step for each alternative are aggregated. Once the fuzzy DM is accomplished, the aggregation process is applied to determine the best alternative. The following equation presents the aggregation operator.

$$\left(1 - \prod_{j=1}^{n}\left(1 - \mu_{\beta_{\sigma(j)}}\right), \prod_{j=1}^{n} v_{\beta_{\sigma(j)}}\right) \quad (4)$$

Step 3:

The defuzzification step is reported in Equation (5):

$$s(\alpha) = \mu\alpha - v\alpha, \quad (5)$$

where $\mu\alpha$ is the membership and $v\alpha$ is the non-membership.

The DAS has the highest score corresponding to the best-ranking order.

2.2.2.2 Benchmarking DAS based on the GDM Context

Given the variation in DAS ranking between decision-makers, aggregate choices made by separate evaluators are important for the convergence of benchmarking performance. Thus, this study used community decision-making to incorporate all decision-makers benchmarking to accomplish a final priority DAS benchmark. In the above scenarios of benchmarking DAS, this analysis expanded the optimal configuration of the decision-maker into collective decision-making. Therefore, the community decision-making process was reached by aggregating the fuzzy opinion matrices of the experts into the following equation:

$$Group\ intuitionistic\ - FDOSM = \oplus \quad S^*, \tag{6}$$

where $\oplus$ is the arithmetic mean and S^* is the Final score for each expert.

The detailed steps of pseudocode for the intuitionistic FDOSM to evaluate and benchmark the DASs system are presented below.

```
Pseudocode: Intuitionistic FDOSM for evaluating and benchmarking DASs
Step 1: Formulated DAS DM:
        identify C[i]              // C is the set of the identified affected criteria of DAS.
        identify DASs[j]   // DASs are the set of 14 selected DASs.
        DM [i,j] ← intersect (C, DASs) // Formulated DAS DM
Step 2: Formulate the intuitionistic-FDOSM:
        DM [i,j]  ← DASs Dataset
        Initialise OM [i,j]  // Empty Opinion Matrix
Step 2.1: Data Transformation
        J  ←  length (C)
        m  ←  length (DASs)
        For j in {1..J}
        For i in {1..m}
         A*[j] ← max{C[i,j]} | min{C[i,j]}    // Select the ideal solution A*_j of each sub-criterion, where max is the ideal
                                                value with benefit criteria and min is the ideal solution for cost criteria as
                                                in Eq. (1)
           OM [i,j]  ← A*[j] ⊗ C[i,j]}         // Reference comparison between the ideal solution and other values per
                                                criterion using Likert scale values as in Eq. (2)
           ~OM [i,j] ← OM [i,j]                // Transform the linguistic term OM into fuzzy OM (~OM) using the intuitionistic
                                                fuzzy number as in Eq. (3)
          endfor
        endfor
Step 2.2: Data Processing
        J  ←  length (C)
        m  ←  length (DASs)
        n  ←  Number of Experts
        For x in {1..n}
          For i in {1..m}
            For j in {1..J}
            I~ND^x [μ_j, v_j] ← (1 − ∏_{j=1}^{J}(1 − μ_~OM[i,j]), ∏_{j=1}^{J} v_~OM[i,j])  // Implement direct aggregation on fuzzy OM (~OM)
                                                                                           for each expert (I~ND) as in Eq. (4)
            S^x[j] ← I~ND^x [μ_j] - I~ND^x [v_j]                                          // Compute the score (S) for each alternative (i.e.
                                                                                           DAS) per expert as in Eq. (5)
            endfor
          endfor
         GS[i] ← ⊕S^x[i]                                   // Compute the grouped decision-making score (GS)
                                                            using the arithmetic mean of the score (S) of each
                                                            alternative (i.e. DAS) overall experts as in Eq. (6)

        Endfor
```

This intuitionistic FDOSM for evaluating and benchmarking DASs was implemented. The results are presented in the following section.

3. Results and Discussion

This section presents the results and discussion on the benchmarking DASs based on individual and GDM contexts. Section 3.1 presents the results of benchmarking the opinion matrix for three experts in linguistics and its fuzzy conversion. Section 3.2 explains and elaborates the results of benchmarking based on the individual decision-making context. Section 3.3 presents the application of group decision making (GDM) to individual decision-making results to obtain the final benchmarking DAS systems results.

3.1. Results of the Benchmarking Opinion Matrix and Benchmarking Fuzzy Opinion Matrix

This section reports the opinion matrix and fuzzy opinion matrix used in the benchmarking DASs. By using the five scales, three decision-makers are giving their opinion to convert the DM into the opinion matrix. Table 5 presents the opinion matrix of the first decision-maker. The opinion matrices of other DMs are reported in Table A1 and A2 in the Appendix.

Table 5 Opinion DM of the First Decision Maker

Alternatives		Comprehensive Complexity Assessment							Design and Implementation							
		C1=Sophistication Level	**C2=Off the shelf component**	**C3=Longitudinal & Lateral Data**	**C4=Design and Programming**	**C5=O/P**	**C6=Equipment Reliability**	**C7=Implementation Cost**	**C8=Cost Efficient Level**	**C9=DAS Size**	**C10=Power Consumption**	**C11=Latency**	**C12=Information Size**	**C13=Information Diversity**	**C14=Computational Complexity**	**C15=DAS Complexity Level**
[28]	DAS#1	S.D	NO.D	NO.D	NO.D	NO.D	DI	NO.D	B.D	NO.D	NO.D	NO.D	DI	DI	NO.D	NO.D
[15]	DAS#2	B.D	DI	NO.D	B.D	H.D	B.D	B.D	NO.D	S.D	DI	DI	B.D	DI	B.D	B.D
[68]	DAS#3	DI	NO.D	DI	DI	NO.D	B.D	B.D	NO.D	NO.D	S.D	NO.D	NO.D	H.D	NO.D	NO.D
[16]	DAS#4	B.D	DI	NO.D	B.D	S.D	B.D	DI	B.D	DI	DI	B.D	B.D	DI	B.D	B.D
[69]	DAS#5	B.D	DI	NO.D	B.D	NO.D	B.D	DI	B.D	DI	DI	DI	B.D	DI	B.D	B.D
[25]	DAS#6	B.D	DI	NO.D	B.D	H.D	B.D	B.D	NO.D	S.D	S.D	DI	B.D	DI	B.D	B.D
[17]	DAS#7	B.D	DI	NO.D	B.D	H.D	B.D	B.D	NO.D	DI	S.D	DI	B.D	DI	B.D	B.D
[27]	DAS#8	S.D	NO.D	DI	NO.D	NO.D	NO.D	NO.D	H.D	NO.D	NO.D	DI	NO.D	H.D	NO.D	NO.D
[23]	DAS#9	S.D	NO.D	NO.D	NO.D	NO.D	NO.D	NO.D	B.D	NO.D	S.D	DI	NO.D	H.D	DI	NO.D
[70]	DAS#10	S.D	NO.D	DI	NO.D	NO.D	DI	NO.D	H.D	NO.D	NO.D	NO.D	NO.D	H.D	NO.D	NO.D
[18]	DAS#11	NO.D	NO.D	NO.D	NO.D	NO.D	DI	NO.D	H.D	NO.D	NO.D	DI	DI	B.D	NO.D	DI
[71]	DAS#12	DI	DI	DI	DI	NO.D	B.D	NO.D	DI	NO.D	NO.D	NO.D	DI	H.D	DI	NO.D
[20]	DAS#13	B.D	DI	NO.D	B.D	H.D	B.D	B.D	NO.D	B.D	H.D	B.D	H.D	NO.D	H.D	H.D
[21]	DAS#14	DI	DI	DI	DI	S.D	B.D	DI	DI	S.D	S.D	NO.D	DI	H.D	NO.D	DI
Remarks: NO.D= No difference, S.D= Slight difference, DI= Difference, B.D= Big difference, H.D= Huge difference																

Using Eq. 1, the DMs calculated the ideal solution according to one of the most required criteria from their perspective (i.e. cost coefficient level and sophisticated level) and complexity criteria. Depending on linguistic terms, the opinion matrix is designed to compare the ideal solution with numbers from the same criterion but a different alternative. The creation of the opinion matrix by comparing the ideal solution with other values per criterion or each alternative uses the linguistic terms. Furthermore, a fuzzy opinion matrix is obtained by transforming the opinion matrices of each decision-maker. Tables B1, B2 and B3 in Appendix A illustrates the fuzzy opinion matrix of each expert or decision-maker. Furthermore, intuitionistic FDOSM is implemented on the fuzzy opinion matrices to acquire the comparisons among DASs. The next section presents the results of the individual decision-making context.

3.2. Benchmarking Results Based on the Individual Decision-Making Context

The results of the benchmarking of the DAS based on the individual decision-making context for the three decision-makers are reported below (see Table 6).

Table 6 Results of the Individual Decision-Making Context Used in Benchmarking DAS

Alternatives		EXPERT 1		EXPERT 2		EXPERT 3	
		Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**
[28]	DAS#1	0.999999999995312	1	0.999999999998594	1	0.999999999999297	1
[15]	DAS#2	0.999962458009135	10	0.999999934082033	10	0.999999950561524	12
[68]	DAS#3	0.999999999683594	6	0.999999998681641	3	0.999999999752808	4
[16]	DAS#4	0.9998435796846	14	0.999999920898439	12	0.999999990112305	9
[69]	DAS#5	0.999958286720327	12	0.999999956054688	9	0.999999994506836	7
[25]	DAS#6	0.999981228916499	9	0.999999986816406	7	0.999999990112305	9
[17]	DAS#7	0.999962458009135	10	0.999999934082033	10	0.999999975280762	11
[27]	DAS#8	0.999999999989875	2	0.999999983520508	8	0.999999991760254	8
[23]	DAS#9	0.999999999978906	4	0.999999999824219	2	0.999999999934082	2
[70]	DAS#10	0.999999999989875	2	0.999995995487407	13	0.999998498306838	13
[18]	DAS#11	0.999999999915625	5	0.999999996337891	6	0.999999999656677	5
[71]	DAS#12	0.999999989453125	7	0.999999998352051	4	0.999999998764038	6
[20]	DAS#13	0.99989490822694	13	0.999999998168945	5	0.999999999771118	3
[21]	DAS#14	0.99999917602556	8	0.999995995487407	13	0.999998498306838	13

The benchmarking process was implemented according to each decision-maker judgement. The level of evaluation reflected the significance of each criterion from their perspective. The best alternative owns the highest value, whereas the opposite can be said to the least preferred alternative. Table 6 illustrates the outcomes of the extended FDOSM method. The evaluation values of the three experts or DMs are implemented in the benchmarking process of DASs using the extended FDOSM method. The results in Table 6 reveal the best DAS that was proposed for microscopic studies for the car-following context. For example, the three DMs preferred DAS designed by authors in Reference [28] had the following scores: 0.999999999995312, 0.999999999998594 and 0.999999999999297. The worst DAS was designed by authors [16], depending on the opinion of the first decision-maker. The worst DAS for the second and third DMs was designed by authors [70][21]. The differences in the ranking scores of DASs among DMs is broad because it reflects the subjectivity in the evaluation values made by each decision-maker. At this point and according to the above results from the individual decision-making contexts, meeting the industrial community characteristics based on a specific expert and neglecting the others is difficult. Thus, for the aforementioned issue, a GDM process is proposed to solve the ranking variation problem of DASs. The next section illustrates the development of intuitionistic FDOSM in the GDM context.

3.3. Benchmarking Results Based on the GDM Context

GDM is presented to solve the issue of individual decision-making. According to the proposed method, Section (2.2.2.2/Stage 2) and Equation 6, the GDM results of three DMs aggregated based on the arithmetic mean operator. The outcomes illustrate the quality of GDM in DASs benchmarking. Table 7 presents the outcomes of GDM. The best DAS obtained the highest score and vice versa.

Table 7 Group FDOSM Context

Alternatives		Score	Rank
[28]	DAS#1	0.999999999997734	1
[15]	DAS#2	0.999987447550897	11

[68]	DAS#3	0.999999999372681	3
[16]	DAS#4	0.999947830231781	14
[69]	DAS#5	0.99998607909395	12
[25]	DAS#6	0.999993735281737	9
[17]	DAS#7	0.999987455790643	10
[27]	DAS#8	0.999999991756879	6
[23]	DAS#9	0.999999999912402	2
[70]	DAS#10	0.999998164594707	7
[18]	DAS#11	0.999999998636731	4
[71]	DAS#12	0.999999995523071	5
[20]	DAS#13	0.999964968722334	13
[21]	DAS#14	0.999997889939935	8

From Table 7, the best DAS is the one proposed in Reference [28], which has obtained the best rank and best score, which is 0.999999999997734. Most of the benefit criteria in Reference [28] were obtained a high subjective judgment, whereas most cost criteria were obtained a low subjective judgment, as mentioned in Table 2, which are good characteristics to meet industrial requirements. The worst DAS is the one proposed by authors in Reference [16], which has obtained the worst rank and the worst score, which is 0.999947830231781. It can be excluded from the industry perspective. The variances in the ranking scores are affected by the differences in DMs' opinions. Thus, the rank of most DASs is in line when comparing the GDM, improving the role of industrial characteristics, and must be taken into consideration. Furthermore, intuitionistic fuzzy is powerful given the inevitably imprecise and uncertain opinion matrix when converted into fuzzy opinion matrix in the GDM context. This capability gives more accurate results when comparing the final results with the opinion matrix of the GDM context. However, the GDM benchmarking results tends to be accurate, and a validation process can be initiated to test the validity of the outcomes.

4. Validation Results

The validation mechanism of the outcomes of intuitionistic FDOSM is presented and authenticates the GDM benchmarking results of DASs. Numerical authentication was implemented by separating the benchmarked DASs into four groups. This procedure has been deployed by different MCDM studies [73] [74]. The validation outcomes do not alternate with the variation in the number of groups or the number of alternatives in each group [75] [44]. To validate the group benchmarking DASs outcomes, numerous actions are made as follows: (1) The DASs were sorted/ranked based on group decision making results. (2) After arranging, the DASs were divided into four groups. The first and second groups contain three alternatives. The third and fourth groups contain four alternatives. (3) The mean ($\bar{x}$) for each group in GDM outcome is calculated subsequently (see Equation 7).

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (7)$$

The comparison procedure created according to the outcome of the mean in each group. The lowest mean numbers of each group indicate authenticated outcomes because the DMs allocated the lowest linguistic standings to the ideal solution of each criterion, which is the idea of FDOSM. Therefore, the primary group is expected to have the lowest mean to examine result rationality and is tested thereafter with the second, third and fourth groups. The second group's mean outcome should be lowest than or equal to the third and fourth groups but higher than or equal to the first group. The third group's mean outcome should be lower than or equal to the fourth group but higher than or equal to the first and second groups. If the estimations are reliable with the statement, then the outcomes are valid. Table 8 presents the validation results for the group benchmarking results obtained by the proposed intuitionistic FDOSM.

Table 8 Validation of Group Benchmarking Results of DASs

Group no.	DAS	Mean
Group 1	1, 9, 3	1.118518519
Group 2	11, 12, 8	2.007407407

Group 3	10, 14, 6, 7	2.594444444
Group 4	2, 5, 13, 4	2.605555556

As shown in Table 8, given the authentication of the group results of benchmarking DASs found by the proposed intuitionistic FDOSM, the mean of the primary group (i.e. 1.118518519) is lower than that of the other groups (i.e. Group 2 "2.007407407", Group 3 "2.594444444" and Group 4 "2.605555556"). Therefore, the group-extended intuitionistic FDOSM results of the benchmarking DASs are authenticated and used in methodical ordering. In this case, for industrial communities, the validation results provide a clear mechanism for the obtained ranking results, where the accurate designing and implementation of the new DAS can be measured accurately and precisely.

5. Claim and Advantage points

The claim and advantage points of this study can be summarised as follows:

- The acquired results from the novel methodology support the process of industrial communities for ranking and benchmarking the best DAS. The benchmarking process of the best DAS is more affected by the constructed expert opinions formulated for the first time in this study. These results can be attributed to the accumulation of obtained expert opinions of two sets of criteria: seven sub-criteria for 'comprehensive complexity assessment' purpose and eight sub-criteria for 'design and implementation' purpose" as DM. Thus, the figured criteria and the formulated expert opinions should be considered when designing and implementing the next DAS for the advanced driver assistance systems within vehicles.
- An accurate DAS system permits some flexibility while encouraging companies to meet performance goals. However, these goals can be achieved through the presented MCDM methodology, and the intuitionistic FDOSM method is suitable according to our discussion, analyses and ranking and validation results. In this context, an advanced process for selecting the DASs to meet new industrial vehicles use has been described.
- The presented methodology allows carrying out new DAS criteria because being equipped by other researchers or even by the industrial community is necessary when designing and implementing new DASs. Thus, any DAS that does not have sufficient resources or the experimental tests should be detected as useless from industry characteristics perspectives. Especially, particular attention was paid to optimise continuously the DAS system, which would allow the industrial community to increase the specifications of the overall driver assistance systems within vehicles according to its needs.

6. Conclusion

This study accurately achieved the evaluation and benchmarking of the reliability and efficiency of DASs systems based on the new MCDM method, intuitionistic FDOSM. The proposed novel methodology of this study consists of two phases. The first phase involved the formulation of DAS DM. The second phase included the steps and process of intuitionistic FDOSM. The main contribution of this study is the extension of FDOSM from the traditional fuzzy environment into an intuitionistic fuzzy environment to tackle the hesitation and uncertainty problem adequately. The validation of the results applied statistically using the mean method. Recommendations for future directions are as follows: (1) The FDOSM can extend into a z-number environment. (2) Several fuzzy types, such as interval type-2 hesitant, Neutrosophic and Pythagorean fuzzy set, can be applied to compare the resulted ranks. (3) In the context of the FDOSM to achieve the suitable and optimum one, various Likert scales (e.g. five, seven and nine scales) may be applied and compare the results. (4) For alternative ranking, different defuzzification methods can be employed. (5) The criteria weight in the context of FDOSM is provided implicitly. Integration with other MCDM weighting methods can be suggested to compute the importance of each criterion practically, explicitly and consistently (6) Different weights are often given for the 15 criteria, which further increase the complexity of the task because the other issue associated with criteria importance needs more attention in future direction to support industrial community characteristics in designing and implementing the advanced driver assistance systems within vehicles.

7. References

[1] L. Qi, "Research on intelligent transportation system technologies and applications," in *Proceedings - 2008 Workshop on Power Electronics and Intelligent Transportation System, PEITS 2008*, 2008, pp. 529–531, doi: 10.1109/PEITS.2008.124.

[2] Y. Xie *et al.*, "STM32-based vehicle data acquisition system for Internet-of-Vehicles," in *Proceedings - 16th IEEE/ACIS International Conference on Computer and Information Science, ICIS 2017*, Jun. 2017, pp. 895–898, doi:

10.1109/ICIS.2017.7960119.

[3] H. Li, Y. Kong, and X. Wang, "Design and implementation of a distributed data acquisition function architecture based on DOA/Handle technology," in *MATEC Web of Conferences*, 2021, vol. 336, p. 05018, doi: 10.1051/matecconf/202133605018.

[4] J. Orlovska, F. Novakazi, B. Lars-Ola, M. A. Karlsson, C. Wickman, and R. Söderberg, "Effects of the driving context on the usage of Automated Driver Assistance Systems (ADAS) -Naturalistic Driving Study for ADAS evaluation," *Transp. Res. Interdiscip. Perspect.*, vol. 4, p. 100093, 2020, doi: 10.1016/j.trip.2020.100093.

[5] S. Kaffash, A. T. Nguyen, and J. Zhu, "Big data algorithms and applications in intelligent transportation system: A review and bibliometric analysis," *Int. J. Prod. Econ.*, vol. 231, p. 107868, 2021, doi: 10.1016/j.ijpe.2020.107868.

[6] S. Saharan, S. Bawa, and N. Kumar, "Dynamic pricing techniques for Intelligent Transportation System in smart cities: A systematic review," *Comput. Commun.*, vol. 150, pp. 603–625, 2020, doi: 10.1016/j.comcom.2019.12.003.

[7] Y. Khair, A. Dennai, and Y. Elmir, "A Survey on Cloud-Based Intelligent Transportation System," in *Lecture Notes in Networks and Systems*, 2021, vol. 174, pp. 562–572, doi: 10.1007/978-3-030-63846-7_53.

[8] S. Boyarinov *et al.*, "The CLAS12 Data Acquisition System," *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.*, vol. 966, p. 163698, 2020, doi: 10.1016/j.nima.2020.163698.

[9] A. González, J. L. Olazagoitia, and J. Vinolas, "A low-cost data acquisition system for automobile dynamics applications," *Sensors (Switzerland)*, vol. 18, no. 2, p. 366, 2018, doi: 10.3390/s18020366.

[10] D. Jokić, S. Lubura, V. Rajs, M. Bodić, and H. Šiljak, "Two open solutions for industrial robot control: The case of puma 560," *Electron.*, vol. 9, no. 6, pp. 1–15, 2020, doi: 10.3390/electronics9060972.

[11] A. Kusiak, "Smart manufacturing," *Int. J. Prod. Res.*, vol. 56, no. 1–2, pp. 508–517, Jan. 2018, doi: 10.1080/00207543.2017.1351644.

[12] S. Fanourakis, K. Wang, P. McCarthy, and L. Jiao, "Low-cost data acquisition systems for photovoltaic system monitoring and usage statistics," in *IOP Conference Series: Earth and Environmental Science*, Nov. 2017, vol. 93, no. 1, p. 012048, doi: 10.1088/1755-1315/93/1/012048.

[13] M. Fuentes, M. Vivar, J. M. Burgos, J. Aguilera, and J. A. Vacas, "Design of an accurate, low-cost autonomous data logger for PV system monitoring using Arduino™ that complies with IEC standards," *Sol. Energy Mater. Sol. Cells*, vol. 130, pp. 529–543, Nov. 2014, doi: 10.1016/j.solmat.2014.08.008.

[14] J. Lee, Y. C. Lee, and J. T. Kim, "Migration from the traditional to the smart factory in the die-casting industry: Novel process data acquisition and fault detection based on artificial neural network," *J. Mater. Process. Technol.*, vol. 290, p. 116972, 2021, doi: 10.1016/j.jmatprotec.2020.116972.

[15] M. Zhu, X. Wang, A. Tarko, and S. Fang, "Modeling car-following behavior on urban expressways in Shanghai: A naturalistic driving study," *Transp. Res. Part C Emerg. Technol.*, vol. 93, pp. 425–445, Aug. 2018, doi: 10.1016/j.trc.2018.06.009.

[16] X. Geng, H. Liang, H. Xu, and B. Yu, "Influences of Leading-Vehicle Types and Environmental Conditions on Car-Following Behavior," *IFAC-PapersOnLine*, vol. 49, no. 15, pp. 151–156, 2016, doi: https://doi.org/10.1016/j.ifacol.2016.07.724.

[17] L. Chong, M. M. Abbas, A. Medina Flintsch, and B. Higgs, "A rule-based neural network approach to model driver naturalistic behavior in traffic," *Transp. Res. Part C Emerg. Technol.*, vol. 32, pp. 207–223, Jul. 2013, doi: 10.1016/j.trc.2012.09.011.

[18] N. Arbabzadeh, M. Jafari, M. Jalayer, S. Jiang, and M. Kharbeche, "A hybrid approach for identifying factors affecting driver reaction time using naturalistic driving data," *Transp. Res. Part C Emerg. Technol.*, vol. 100, pp. 107–124, 2019, doi: https://doi.org/10.1016/j.trc.2019.01.016.

[19] M. Brackstone, B. Waterson, and M. McDonald, "Determinants of following headway in congested traffic," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 12, no. 2, pp. 131–142, 2009, doi: 10.1016/j.trf.2008.09.003.

[20] Ó. Mata-Carballeira, J. Gutiérrez-Zaballa, I. Del Campo, and V. Martínez, "An FPGA-Based Neuro-Fuzzy Sensor for Personalized Driving Assistance," *mdpi.com*, 2019, doi: 10.3390/s19184011.

[21] R. Fu, Z. Li, Q. Sun, and C. Wang, "Human-like car-following model for autonomous vehicles considering the cut-in behavior of other vehicles in mixed traffic," *Accid. Anal. Prev.*, vol. 132, p. 105260, 2019, doi: https://doi.org/10.1016/j.aap.2019.105260.

[22] L. Pariota, G. N. Bifulco, F. Galante, A. Montella, and M. Brackstone, "Longitudinal control behaviour: Analysis and modelling based on experimental surveys in Italy and the UK," *Accid. Anal. Prev.*, vol. 89, pp. 74–87, 2016, doi: https://doi.org/10.1016/j.aap.2016.01.007.

[23] B. Metz, A. Landau, and V. Hargutt, "Frequency and impact of hands-free telephoning while driving – Results from naturalistic driving data," *Transp. Res. Part F Traffic Psychol. Behav.*, vol. 29, pp. 1–13, 2015, doi: https://doi.org/10.1016/j.trf.2014.12.002.

[24] H. Aoki and O. Ozaki, "A study on the method for predicting the driver's car-following tendency," *IFAC Proc. Vol.*, vol. 7, no. PART 1, pp. 319–321, 2013, doi: 10.3182/20130904-4-JP-2042.00017.

[25] A. Kendziorra, P. Wagner, and T. Toledo, "A Stochastic Car Following Model," *Transp. Res. Procedia*, vol. 15, pp. 198–207, 2016, doi: https://doi.org/10.1016/j.trpro.2016.06.017.

[26] G. N. Bifulco, F. Galante, L. Pariota, M. Russo Spena, and P. Del Gais, "Data Collection for Traffic and Drivers' Behaviour Studies: A Large-scale Survey," *Procedia - Soc. Behav. Sci.*, vol. 111, pp. 721–730, 2014, doi: 10.1016/j.sbspro.2014.01.106.

[27] E. Tivesten and M. Dozza, "Driving context influences drivers' decision to engage in visual–manual phone tasks: Evidence from a naturalistic driving study," *J. Safety Res.*, vol. 53, pp. 87–96, 2015, doi: https://doi.org/10.1016/j.jsr.2015.03.010.

[28] P. Wagner, "Analyzing fluctuations in car-following," *Transp. Res. Part B Methodol.*, vol. 46, no. 10, pp. 1384–1392, Dec. 2012,

doi: 10.1016/j.trb.2012.06.007.
[29] H. F. Zhang and W. Kang, "Design of the data acquisition system based on STM32," in *Procedia Computer Science*, Jan. 2013, vol. 17, pp. 222–228, doi: 10.1016/j.procs.2013.05.030.
[30] F. Carena *et al.*, "The ALICE data acquisition system," *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.*, vol. 741, pp. 130–162, Mar. 2014, doi: 10.1016/j.nima.2013.12.015.
[31] R. Abbasi *et al.*, "The IceCube data acquisition system: Signal capture, digitization, and timestamping," *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.*, vol. 601, no. 3, pp. 294–316, Apr. 2009, doi: 10.1016/j.nima.2009.01.001.
[32] H. Rezk, I. Tyukhov, M. Al-Dhaifallah, and A. Tikhonov, "Performance of data acquisition system for monitoring PV system parameters," *Meas. J. Int. Meas. Confed.*, vol. 104, pp. 204–211, Jul. 2017, doi: 10.1016/j.measurement.2017.02.050.
[33] H. Belmili, S. M. Ait Cheikh, M. Haddadi, and C. Larbes, "Design and development of a data acquisition system for photovoltaic modules characterization," *Renew. Energy*, vol. 35, no. 7, pp. 1484–1492, Jul. 2010, doi: 10.1016/j.renene.2010.01.007.
[34] D. Upadhyay and S. Sampalli, "SCADA (Supervisory Control and Data Acquisition) systems: Vulnerability assessment and security recommendations," *Comput. Secur.*, vol. 89, p. 101666, Feb. 2020, doi: 10.1016/j.cose.2019.101666.
[35] J.-S. Lim, "A design of small size sensor data acquisition and transmission system," *J. Converg. Inf. Technol.*, vol. 9, no. 1, pp. 136–141, 2019.
[36] A. B. Garnsworthy *et al.*, "The GRIFFIN data acquisition system," *arXiv*, vol. 853, pp. 85–104, 2017.
[37] R. Palit *et al.*, "A high speed digital data acquisition system for the Indian National Gamma Array at Tata Institute of Fundamental Research," *Nucl. Instruments Methods Phys. Res. Sect. A Accel. Spectrometers, Detect. Assoc. Equip.*, vol. 680, pp. 90–96, 2012.
[38] A. A. Khedkar and R. H. Khade, "High speed FPGA-based data acquisition system," *Microprocess. Microsyst.*, vol. 49, pp. 87–94, 2017, doi: 10.1016/j.micpro.2016.11.006.
[39] N. Erraissi, M. Raoufi, N. Aarich, M. Akhsassi, and A. Bennouna, "Implementation of a low-cost data acquisition system for 'PROPRE. MA' project," *Measurement*, vol. 117, pp. 21–40, 2018.
[40] T. Nguyen, T. H. T. Chan, D. P. Thambiratnam, and L. King, "Development of a cost-effective and flexible vibration DAQ system for long-term continuous structural health monitoring," *Mech. Syst. Signal Process.*, vol. 64–65, pp. 313–324, Dec. 2015, doi: 10.1016/j.ymssp.2015.04.003.
[41] M. Ambrož, "Raspberry Pi as a low-cost data acquisition system for human powered vehicles," *Meas. J. Int. Meas. Confed.*, vol. 100, pp. 7–18, 2017, doi: 10.1016/j.measurement.2016.12.037.
[42] M. Winkelbauer, M. Donabauer, A. Pommer, and R. Jansen, "Naturalistic data on time headway behind motorcycles and other vehicles," *Saf. Sci.*, vol. 119, pp. 162–173, 2019, doi: 10.1016/j.ssci.2019.01.020.
[43] M. Talal, K. N. Ramli, A. A. Zaidan, B. B. Zaidan, and F. Jumaa, "Review on car-following sensor based and data-generation mapping for safety and traffic management and road map toward ITS," *Vehicular Communications*, vol. 25. Elsevier Inc., p. 100280, Oct. 2020, doi: 10.1016/j.vehcom.2020.100280.
[44] K. H. Abdulkareem *et al.*, "A Novel Multi-Perspective Benchmarking Framework for Selecting Image Dehazing Intelligent Algorithms Based on BWM and Group VIKOR Techniques," *Int. J. Inf. Technol. Decis. Mak.*, vol. 19, no. 03, pp. 909–957, 2020, doi: 10.1142/s0219622020500169.
[45] A. S. Albahri, R. A. Hamid, O. S. Albahri, and A. A. Zaidan, "Detection-based prioritisation: Framework of multi-laboratory characteristics for asymptomatic COVID-19 carriers based on integrated Entropy–TOPSIS methods," *Artif. Intell. Med.*, vol. 111, p. 101983, 2021, doi: 10.1016/j.artmed.2020.101983.
[46] A. Mohammed, I. Harris, A. Soroka, and R. Nujoom, "A hybrid MCDM-fuzzy multi-objective programming approach for a G-resilient supply chain network design," *Comput. Ind. Eng.*, vol. 127, pp. 297–312, Jan. 2019, doi: 10.1016/j.cie.2018.09.052.
[47] K. Yang, N. Zhu, C. Chang, D. Wang, S. Yang, and S. Ma, "A methodological concept for phase change material selection based on multi-criteria decision making (MCDM): A case study," *Energy*, vol. 165, pp. 1085–1096, 2018, doi: 10.1016/j.energy.2018.10.022.
[48] Y. Wu, C. Xu, and T. Zhang, "Evaluation of renewable power sources using a fuzzy MCDM based on cumulative prospect theory: A case in China," *Energy*, vol. 147, pp. 1227–1239, 2018, doi: 10.1016/j.energy.2018.01.115.
[49] O. S. Albahri *et al.*, "Fault-Tolerant mHealth Framework in the Context of IoT-Based Real-Time Wearable Health Data Sensors," *IEEE Access*, vol. 7, pp. 50052–50080, 2019, doi: 10.1109/ACCESS.2019.2910411.
[50] B. B. Zaidan and A. A. Zaidan, "Comparative study on the evaluation and benchmarking information hiding approaches based multi-measurement analysis using TOPSIS method with different normalisation, separation and context techniques," *Meas. J. Int. Meas. Confed.*, vol. 117, pp. 277–294, 2018, doi: 10.1016/j.measurement.2017.12.019.
[51] J. Z. Wu and P. J. Tiao, "A validation scheme for intelligent and effective multiple criteria decision-making," *Appl. Soft Comput. J.*, vol. 68, pp. 866–872, 2018, doi: 10.1016/j.asoc.2017.04.054.
[52] Y. Ju and A. Wang, "Emergency alternative evaluation under group decision makers: A method of incorporating DS/AHP with extended TOPSIS," *Expert Syst. Appl.*, vol. 39, no. 1, pp. 1315–1323, 2012, doi: 10.1016/j.eswa.2011.08.012.
[53] Z. Zhang, P. Liu, and Z. Guan, "The evaluation study of human resources based on entropy weight and grey relating TOPSIS method," in *2007 International Conference on Wireless Communications, Networking and Mobile Computing, WiCOM 2007*, 2007, pp. 4423–4426, doi: 10.1109/WICOM.2007.1091.

[54] K. I. Mohammed *et al.*, “Real-Time Remote-Health Monitoring Systems: a Review on Patients Prioritisation for Multiple-Chronic Diseases, Taxonomy Analysis, Concerns and Solution Procedure,” *J. Med. Syst.*, vol. 43, no. 7, p. 223, Jul. 2019, doi: 10.1007/s10916-019-1362-x.

[55] E. M. Almahdi, A. A. Zaidan, B. B. Zaidan, M. A. Alsalem, O. S. Albahri, and A. S. Albahri, “Mobile patient monitoring systems from a benchmarking aspect: Challenges, open issues and recommended solutions,” *J. Med. Syst.*, vol. 43, no. 7, p. 207, 2019.

[56] A. A. Zaidan, B. B. Zaidan, M. A. Alsalem, O. S. Albahri, A. S. Albahri, and M. Y. Qahtan, “Multi-agent learning neural network and Bayesian model for real-time IoT skin detectors: a new evaluation and benchmarking methodology,” *Neural Comput. Appl.*, pp. 1–52, 2019, doi: 10.1007/s00521-019-04325-3.

[57] M. A. Alsalem *et al.*, “Multiclass Benchmarking Framework for Automated Acute Leukaemia Detection and Classification Based on BWM and Group-VIKOR,” *J. Med. Syst.*, vol. 43, no. 7, p. 212, 2019, doi: 10.1007/s10916-019-1338-x.

[58] M. M. Salih, B. B. Zaidan, A. A. Zaidan, and M. A. Ahmed, “Survey on fuzzy TOPSIS state-of-the-art between 2007 and 2017,” *Comput. Oper. Res.*, vol. 104, pp. 207–227, 2019, doi: 10.1016/j.cor.2018.12.019.

[59] M. M. Salih, B. B. Zaidan, and A. A. Zaidan, “Fuzzy decision by opinion score method,” *Appl. Soft Comput. J.*, vol. 96, p. 106595, 2020, doi: 10.1016/j.asoc.2020.106595.

[60] O. S. Albahri *et al.*, “Multidimensional benchmarking of the active queue management methods of network congestion control based on extension of fuzzy decision by opinion score method,” *Int. J. Intell. Syst.*, vol. 36, no. 2, pp. 796–831, 2021, doi: 10.1002/int.22322.

[61] M. M. Salih, O. S. Albahri, A. A. Zaidan, B. B. Zaidan, F. M. Jumaah, and A. S. Albahri, “Benchmarking of AQM methods of network congestion control based on extension of interval type-2 trapezoidal fuzzy decision by opinion score method,” *Telecommun. Syst.*, pp. 1–30, 2021, doi: 10.1007/s11235-021-00773-2.

[62] L. A. Zadeh, “Fuzzy Sets,” *Inf. Control 8*, vol. 353, no. 3, pp. 394–432, 1996, doi: 10.1142/9789814261302_0021.

[63] Z. J. Wang and K. W. Li, “An interval-valued intuitionistic fuzzy multiattribute group decision making framework with incomplete preference over alternatives,” *Expert Syst. Appl.*, vol. 39, no. 18, pp. 13509–13516, 2012, doi: 10.1016/j.eswa.2012.07.007.

[64] K. T. Atanassov, “Intuitionistic fuzzy sets,” *Int. J. Bioautomation*, vol. 20, pp. S1–S6, 2016, doi: 10.1007/978-3-7908-1870-3_1.

[65] A. I. Ban, *Intuitionistic fuzzy measures: Theory and applications*. Physica-Verlag, 2006.

[66] A. Pankowska and M. Wygralak, “General IF-sets with triangular norms and their applications to group decision making,” *Inf. Sci. (Ny).*, vol. 176, no. 18, pp. 2713–2754, 2006, doi: 10.1016/j.ins.2005.11.011.

[67] H. Behret, “Group decision making with intuitionistic fuzzy preference relations,” *Knowledge-Based Syst.*, vol. 70, pp. 33–43, 2014, doi: 10.1016/j.knosys.2014.04.001.

[68] L. Pariota, G. Bifulco, F. Galante, … A. M.-A. A. &, and undefined 2016, “Longitudinal control behaviour: Analysis and modelling based on experimental surveys in Italy and the UK,” *Elsevier*, 2016, doi: 10.1016/j.aap.2016.01.007.

[69] H. Aoki, O. O.-I. P. Volumes, and undefined 2013, “A Study on the Method for Predicting the Driver’s Car-Following Tendency,” *Elsevier*.

[70] G. Bifulco, F. Galante, L. Pariota, … M. S.-…-social and behavioral, and undefined 2014, “Data Collection for Traffic and Drivers’ Behaviour Studies: a large-scale survey,” *Elsevier*.

[71] M. Brackstone, B. Waterson, and M. McDonald, “DETERMINANTS OF FOLLOWING HEADWAY IN CONGESTED TRAFFIC TRANSPORTATION RESEARCH PART F-12(2), 131-142,” *Elsevier*, doi: 10.1016/j.trf.2008.09.003.

[72] M. Li, W. Wei, J. Wang, and X. Qi, “Approach to evaluating accounting informatization based on entropy in intuitionistic fuzzy environment,” *Entropy*, vol. 20, no. 6, p. 476, 2018, doi: 10.3390/e20060476.

[73] N. Kalid *et al.*, “Based on Real Time Remote Health Monitoring Systems: A New Approach for Prioritization ‘Large Scales Data’ Patients with Chronic Heart Diseases Using Body Sensors and Communication Technology,” *J. Med. Syst.*, vol. 42, no. 4, p. 69, Apr. 2018, doi: 10.1007/s10916-018-0916-7.

[74] O. S. Albahri, A. A. Zaidan, B. B. Zaidan, M. Hashim, A. S. Albahri, and M. A. Alsalem, “Real-Time Remote Health-Monitoring Systems in a Medical Centre: A Review of the Provision of Healthcare Services-Based Body Sensor Information, Open Challenges and Methodological Aspects,” *J. Med. Syst.*, vol. 42, no. 9, p. 164, Sep. 2018, doi: 10.1007/s10916-018-1006-6.

[75] K. H. Abdulkareem *et al.*, “A new standardisation and selection framework for real-time image dehazing algorithms from multi-foggy scenes based on fuzzy Delphi and hybrid multi-criteria decision analysis methods,” *Neural Comput. Appl.*, 2020, doi: 10.1007/s00521-020-05020-4.

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