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Hierarchical fuzzy modelling of risks in road transportation of dangerous goods taking into account the influence of the human factor

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Abstract. The aim of the study was to develop a hierarchical fuzzy model for assessing the risks of road transportation of dangerous goods, taking into account the influence of the human factor to increase the accuracy and informativeness of decision-making in the field of transport security. The study employed a systematic approach, analysis and synthesis, expert assessment, comparative analysis, and fuzzy modelling based on the Mamdani algorithm, implemented in MATLAB, to assess human factor risks. The research resulted in the development of a hierarchical fuzzy framework for evaluating risks associated with the road transportation of dangerous goods. A key focus of the model is the assessment of human factors based on three input variables: the driver's health status, their experience in transporting dangerous goods (measured in tonne-kilometres), and the duration of accident-free operation. The fuzzy model, implemented using the Mamdani algorithm, includes 27 fuzzy logic rules and has demonstrated stable behaviour even under varying input parameters. Testing the model on four real drivers produced scores reflecting the quality of the human factor, ranging from 28.5 to 62.6 points. These scores indicate the model's sensitivity to individual personnel characteristics. An integrated assessment of overall risk is generated through a two-level aggregation of results from sub-models, allowing the system to adapt to different transportation scenarios. This model can be effectively incorporated as a critical component of a logistics operator's Decision Support System for dynamic risk analysis prior to each transport operation

Keywords: decision support system; expert evaluation; accident-free experience; membership function; logistics safety

Introduction

Transporting dangerous goods by road is one of the riskiest aspects of logistics. Accidents during such transportation can have severe consequences for human life, property, and the environment. Traditional risk assessment methods rely largely on deterministic or stochastic models, which fail to consider the complex interactions among various risk factors, including regulatory, logistical, physical, and human elements. Furthermore, these methods are less effective when dealing with incomplete, unclear, or subjective data. This is particularly crucial when evaluating human factors, such as a driver's health, fatigue, or experience in handling dangerous goods. Despite the

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growing interest in using fuzzy logic and multicriteria approaches to address these issues, this area remains underdeveloped. Therefore, there is a need to create a hierarchical fuzzy model that considers the influence of the human factor as a key source of risk in the transportation of dangerous goods by road. This model should offer a more accurate and flexible risk assessment by processing both quantitative and qualitative data, ultimately making the decision-making process in safe logistics more efficient.

An analysis of the literature published in scientific journals reveals a growing interest among the scientific community in risk assessment in logistics, particularly regarding the influence of human factors. Modern research increasingly employs approaches such as fuzzy logic, multi-criteria analysis, and machine learning to model situations where personnel behaviour, condition, or errors are critical. Significant attention is devoted to various aspects, including driver fatigue, instruction violations, underestimation of risks in warehouse or transportation operations, and the effects of psychological stress on the quality of logistics procedures. N. Vojinović *et al.* (2021) considered the results of the latest trends in the development of fuzzy modelling for assessing the activities of road transport companies engaged in the transportation of dangerous goods: the method of improved fuzzy step-by-step analysis of weighting coefficients; the method of decision-making by multiple criteria (MCDM Method); the method of finding an alternative to rough measurement and ranking based on a compromise solution (R-MARCOS – "Rough Measurement Alternatives and Ranking according to the Compromise Solution" method). As a result of the fuzzy modelling, the authors obtained rating scores for 11 companies that operate in the service market.

S. Benchkovska *et al.* (2020) introduced an innovative method for risk assessment that emphasises the role of "human errors". The main idea behind this method is to evaluate and model the human factor as a primary cause of road traffic accidents. To quantify the parameter relating to the human factor, fuzzy logic techniques are utilised. This model calculates the probability of a road accident occurring during the transportation of hazardous goods. This new approach to risk assessment considers various factors, including how the human element influences the likelihood of accidents, and recognises the diversity of the different segments that comprise the overall route for transporting dangerous cargo. The method is valuable for assessing risk variability and accounts for the human factor on both planned and existing routes. It also takes into consideration the classification of road sections, categorisation of hazardous materials, and the potential impact of various scenarios and risks on transportation safety. A comparative analysis of risk models for transporting dangerous goods by rail may be useful for examining similar models for road transportation, particularly in fuzzy risk modelling (Benchkovska *et al.*, 2020). T.D. Milošević *et al.* (2021) discussed the development of a fuzzy Mamdani model designed to assess the quality of routes used for the transportation of dangerous goods by road. The evaluation of these routes is based on five specific criteria. Each input variable is represented by three membership functions, while the output variable is determined through five membership functions. The rules within the fuzzy logic system are created using the Aggregation of Weighted Preconditions (ATPP) method, which helps build a knowledge base grounded in expert experience and intuitive reasoning. Given the number of input variables and their respective membership functions, a total of 243 rules has been defined. To establish the weights for the membership functions, three experts from the Ministry of Defence were consulted, and the weight values were determined using the Full Consistency Method (FUCOM). B. Matić *et al.* (2022) developed a fuzzy model of road infrastructure based on multicriteria analysis. The determination of weighting coefficients for evaluation criteria in fuzzy models is discussed in a paper by Ž. Stević *et al.* (2022) in the field of applied mathematics.

S.A. Beczkowska & I. Grabarek (2021) discussed the key role of the human factor in ensuring safety during the transportation of dangerous goods. The authors examine common staff errors, the causes of safety violations, and how the psychological and physical well-being of employees can influence risk levels. They placed particular emphasis on the need to consider behavioural and organisational aspects when evaluating threats in transportation processes. The article highlights the significance of a systematic approach to enhancing safety, which includes training, monitoring, and management of human factors. The article by T. Panchyshyn *et al.* (2024) presented an analysis of international experience in investing in human capital development. The authors explore the key trends and effective strategies of states and corporations to improve the quality of education, training and innovation activity of employees. Particular attention is paid to the role of investment in the formation of a competitive economy in the context of digital transformation. The article by K.M. Bozhko *et al.* (2024a) presented a method for assessing the effectiveness of investments in the human capital of an enterprise using fuzzy modelling based on linear and logarithmic scales of input data. In another article by K. Bozhko *et al.* (2024b) considered an approach to evaluating start-up projects from the investor's perspective based on fuzzy models. They proposed the use of variable evaluation criteria to take into account the uncertainty and subjectivity of investment decisions. Thus, a review of the literature indicated the relevance of applying fuzzy modelling to assess the risks associated with the transport of dangerous goods by road, which encourages the author to continue research in this direction.

Despite the existence of some studies on risk modelling in the transportation of dangerous goods, several important aspects remain underdeveloped. First, there is no holistic hierarchical model that would simultaneously cover all key groups of risk factors – regulatory, logistical, physical, and human – in a single fuzzy environment. Secondly, the human factor, despite its critical role in accidents, is often considered in a fragmented manner or without taking into account the interrelationships with other risk groups. There is also a lack of models that would allow quantitative assessment of the human factor based on variables of the driver's health, experience, and behavioural characteristics in dynamic transportation conditions. Additionally, the challenge of adapting input linguistic or fuzzy data to a formalised multi-level evaluation structure is still relevant, complicating the practical application of these models within logistics information systems. Most existing approaches also lack a mechanism for comparative analysis based on qualitative criteria, which would allow for ranking routes or carriers through an integrated risk assessment. Therefore, the development of a hierarchical fuzzy model that includes a comprehensive assessment of the human factor as a separate module remains essential and inadequately addressed in current scientific and applied research. This article aimed to design and substantiate a hierarchical fuzzy model for assessing risks in the road transportation of dangerous goods, with particular emphasis on integrating the human factor into a comprehensive risk assessment framework. The objectives of the study included the formalisation of key risk factor groups, the development of a fuzzy model for evaluating the human factor, the construction of a hierarchical structure of the integrated risk model, and the validation of its applicability using empirical data to support managerial decision-making in the transportation of dangerous goods.

Materials and Methods

The research materials comprised regulatory and legal acts and specialised regulations in the field of road transport of dangerous goods, academic publications on transport risk assessment, and results of pilot testing of a fuzzy model based on data from four drivers. The study employed a systematic approach, as well as methods of analysis and synthesis, expert assessment, fuzzy modelling, and comparative analysis. Fuzzy logic was used to formalise dependencies between human factor parameters, and the model was constructed using the Mamdani algorithm. The feasibility of applying this algorithm was determined by a combination of factors, including its effectiveness under conditions of a small sample size and its suitability for supporting management decision-making with limited input data. In addition, the Mamdani algorithm is widely implemented in the MATLAB package, which enables the rapid development and adjustment of fuzzy models through a graphical interface. It has been traditionally used in fuzzy risk assessment models, where excessive precision is not required, whereas efficiency in decision-making is prioritised. The model was based on the hypothesis of a normal distribution of input data. The input data were empirical and obtained from annual reports of Ukrainian motor transport enterprises. The study examined the human factor assessment module of a two-level hierarchical risk model for the transport of dangerous goods by road. In the basic fuzzy model, only the driver was considered as the main agent in the process, without including other transport participants such as logistics specialists, mechanics, system administrators, or freight forwarders. The Human Factor model contained three input variables – Health, Volume, and Safetime – and one output variable, Hum, which reflected an integrated score of the human factor quality. The Health variable characterised the driver's state of health and was assessed on a ten-point scale based on expert medical evaluation. The Volume variable reflected accumulated experience in transporting dangerous goods and was measured in millions of tonne-kilometres. The Safetime variable characterised the duration of continuous accident-free driving before the journey. Gaussian membership functions were applied to the input variables, while triangular membership functions were used for the output variable; the knowledge base of the model contained 27 fuzzy logic rules. In the human factor submodel, all weighting coefficients were set equal to 1. The procedure for forming the base of 27 fuzzy inference rules was carried out by the authors acting as experts. Additional information was obtained through oral surveys of managers of motor transport enterprises. The ranges of variables were defined as follows: Health $\in$ [1; 10], Volume $\in$ [0; 1], Safetime $\in$ [0; 1,000], Hum $\in$ [0; 100]. If actual values exceeded the defined limits during modelling, boundary values were applied. The parameters of the membership functions were determined using the MATLAB environment during the development of the fuzzy model in interactive mode:

- for input Health $\sigma = 1.529$; average membership values were 1; 5.5; 10;
- for input Volume $\sigma = 0.17$; average membership values were 0; 0.5; 1;
- for input Safetime $\sigma = 152.9$; average membership values were 100; 550; 1,000;
- for output Hum, vertex coordinates were 0; 50; 100 points.

The assessment of drivers' health status was conducted by a qualified medical professional using a ten-point scale in accordance with the ethical principles set forth in the Declaration of Helsinki of the World Medical Association (WMA, 2024), ensuring confidentiality of personal data and obtaining informed consent from all participants. Input data for model validation were generated for four drivers based on pre-trip medical checks, transported cargo volume, and accident-free driving records. Model validation was performed using functional testing in the Fuzzy Designer MATLAB environment, with average input values: Health = 5 points, Volume = 0.5 million tkm, Safetime = 550 hours. The MATLAB environment was used for modelling and processing results, including implementation of model structure, membership functions, rule base, and defuzzification procedure.

Results and Discussion

The preliminary analysis indicates that all possible risk factors for the transportation of dangerous goods by road can be grouped into common features: regulatory; logistical; physical. Regulatory features include a set of legal rules and regulations governing the transportation of dangerous goods, as well as the degree of compliance with their requirements by the carrier. Logistical factors include coordinating the complexity of the route with the regulations, continuous online monitoring of its progress, and optimising the schedule for the busiest sections. Physical features include material factors of the driver-vehicle-environment system: readiness of the vehicle for the transportation of dangerous goods; quality of the road surface; meteorological and air pollution conditions. All three groups of factors have a certain impact on the human factor. The human factor provides feedback to other groups of risk factors. For example, the optimal route logistics from the driver's point of view is one that will provide him with sufficient rest without reducing his salary. Structuring the risk factors into groups leads to a hierarchical fuzzy model with two levels, the first of which contains four fuzzy models for each group, and the second level contains a model with four inputs and the results of the evaluations performed by the first level models. The output of the second-level model provides a score for the total risk of dangerous goods transportation. Thus, fuzzy risk modelling uses a set of five models on the full set of factors M:

$$M = Reg \cup Log \cup Ph \cup Hum, \quad (1)$$

where Reg – regulatory factors (regulations); Log – logistics factors; Hum – human factor.

The human factor is considered. For the basic fuzzy model, only the driver is taken into account as the main subject of the process, while other participants (logistics specialists, mechanics, system administrators, freight forwarders, etc.) are not considered. For the integrated assessment of the human factor, three main parameters are selected:

- driver's health condition – Health;
- experience: the volume of dangerous goods transportation over the entire driver's career – Volume;
- period of continuous trouble-free operation on the day of transportation – Safetime.

The block diagram of the two-level fuzzy risk model for the transportation of dangerous goods by road is shown in Figure 1.

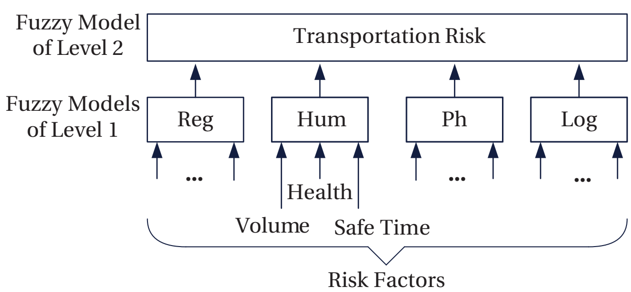

Figure 1. Two-level fuzzy risk model for road transportation of dangerous goods

Note: Reg – regulations; Hum – human factor; Ph – physical environmental influences; Log – logistics

Source: created by the authors

At the first level of the fuzzy model, the following parameters were identified: Reg (regulations), Hum (human factor), Ph (physical environmental influences), and Log (logistics). The human factor assessment module represented one of the principal components of the first-level model and reflected the influence of driver-related characteristics on overall risk formation. The second level is a fuzzy risk assessment. Within the scope of this study, consideration was limited to the fuzzy model of the human factor in the road transportation of dangerous goods. For all three input factors of the model, corresponding values and evaluation scales were defined within the adopted methodological framework. Experience in the transportation of dangerous goods was measured in million tonne-kilometres of transported cargo (million tkm). The accident-free driving record was measured in hours spent behind the wheel. The ranges for all three input variables were subsequently defined: Health ∈ [1; 10], Volume ∈ [0; 1], Safetime ∈ [0; 1,000], Hum ∈ [0; 100]. If the range limits of any of the functions are exceeded, the modelling saves its limit value. The Hum output function has a 100-point rating scale Hum [0; 100]. The section of the four-dimensional surface along the Safetime coordinate has the shape of a surface with a convex shape, which indicates the monotonicity of the output function (Fig. 2).

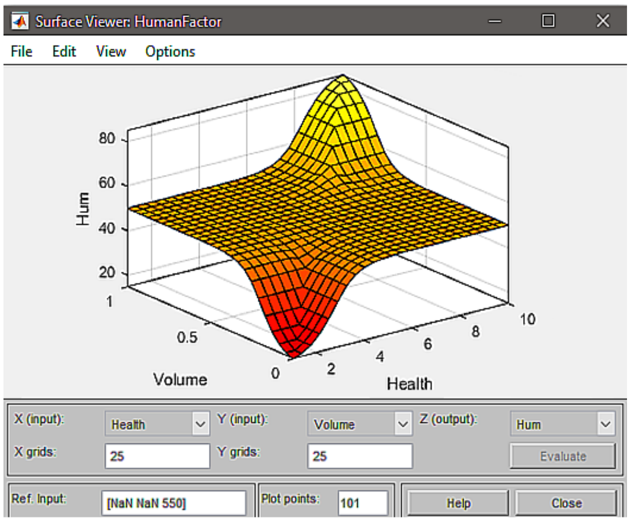

Figure 2. Decision surface for the human factor fuzzy model in coordinates "Health – Volume"

Source: created by the authors

Figure 2 illustrates a cross-section of the decision surface for the HumanFactor fuzzy model, with Safetime fixed at 550 hours. The plotted relationship demonstrates the variation of the integral human factor assessment (Hum) under the influence of two input variables: Health and Volume. The non-linear surface indicates that improvements in driver health parameters and accumulated transport experience correlate with an increase in the overall assessment. This confirms the model's capacity to account for the synergistic, rather than isolated, influence of input parameters on the final result. Model effectiveness is verified via the "Rules" option within the "View" menu of the MATLAB Fuzzy Designer module. Initially, the model adopts average values for all input parameters:

- health: 5 points;
- experience: 500,000 tonne-kilometres of dangerous goods transported;
- uninterrupted period of accident-free transport prior to the start of the expedition: 550 hours.

The result of modelling under such conditions is 50 points of human factor quality (Fig. 3). The higher the score, the lower the risk for transportation. In a comparative analysis (rating) of carriers, the highest level in the quality scale will be occupied by those agents with the highest score.

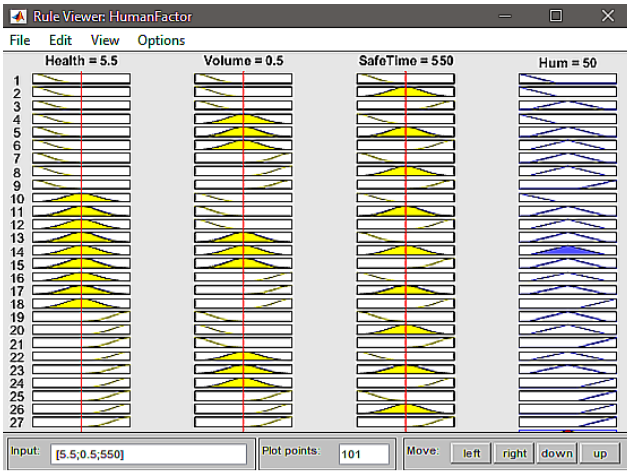

Figure 3. Unclear assessment of the human factor (score equal to 50 points)
Source: created by the authors

The result shown in Figure 3 indicates that, for Health = 5.5 points, Volume = 0.5 million tkm and Safetime = 550 hours, the fuzzy HumanFactor model produces an output value of Hum = 50 points. This corresponds to the average level of human factor assessment and confirms the model's consistency for an average combination of input characteristics. The highest human factor quality score in this fuzzy model is 85.4 points, and the lowest is 14.6 points. Low risk has a range from 85.4 to 68.9 points; medium risk has a range from 68.8 to 41.8 points; high risk has a range from 41.7 to 14.6 points. The specificity of fuzzy modelling is that it does not provide hard boundary estimates, since the values are formed on the basis of membership functions that reflect the degree of membership in linguistic terms, rather than clear boundaries. If the user of a fuzzy expert system needs exactly the boundary scores (0 and 100 points), then it is necessary to stretch the range of the output function in both directions or apply normalisation of the results after defuzzification. This will allow the model to be adapted to the requirements of a specific application task, for example, for comparison with traditional rating scales. Determining the threshold value for decision-making is the prerogative of the user of the expert system based on a fuzzy model, that is, the manager or responsible person of the transport enterprise. The fuzzy model of the human factor was tested at the premises of ALA-TRUCK Ltd (Kyiv) between 1 June 2025 and 10 June 2025. Four drivers (D1-D4) with documented experience in the transport of dangerous goods took part in the pilot testing. The sample included adult drivers with a valid driving licence for the relevant category, existing experience in the transport of dangerous goods, and a complete set of input data for modelling. The grounds for exclusion were the absence of voluntary consent to participate, the absence of confirmed experience in the relevant transport operations, incomplete input data, and medical contraindications to the performance of professional duties at the time of assessment. A general practitioner with nine years of professional experience assessed the Health indicator. This specialist was responsible for conducting pre-trip health checks on drivers at the company. He carried out the initial medical assessment of the drivers' condition on a 10-point scale, with the results subsequently used in a fuzzy model. The Volume and Safetime indicators were derived from drivers' work data documented by ALA-TRUCK Ltd. Table 1 shows the values of the human risk factor components for four drivers (D1, D2, D3, D4).

Table 1. Values of human risk factor components for drivers

No.	Name	Health, balls	Volume, TKM	Safe time, hours
1	D1	9	0	80
2	D2	7	0.1	150
3	D3	5	0.5	300
4	D4	8	1	220

Source: created by the authors

Table 1 presents the initial values of the three human risk factor components for four drivers, which were used as input data for the HumanFactor fuzzy model. A comparison of the indicators reveals variations in drivers' individual characteristics, including health status, the volume of dangerous goods transported, and accident-free driving records. Driver D1 has the highest health rating, but lacks experience in transporting dangerous goods and has the lowest Safe Time value. Driver D4, conversely, combines a high level of health with the highest transport volume, whilst D3 has average or moderate values across all three indicators. The data presented in the table serve as the basis for further fuzzy evaluation of the human factor and for a comparative ranking of drivers. The results of the fuzzy human risk factor assessment for four drivers are shown in Figures 4-7.

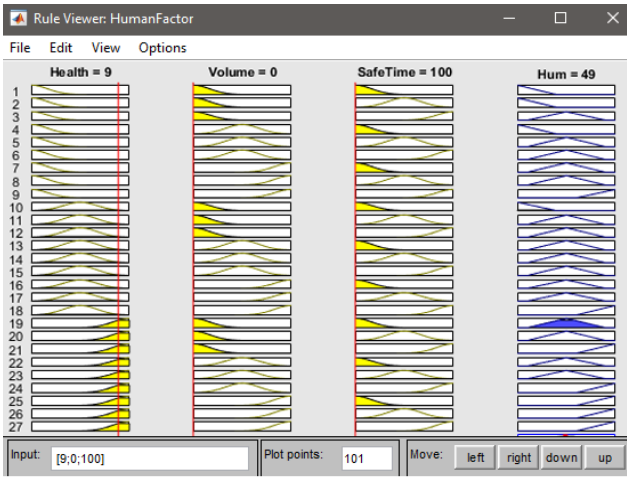

Figure 4. Unclear assessment
of the human risk factor (D1 received 49 points)
Source: created by the authors

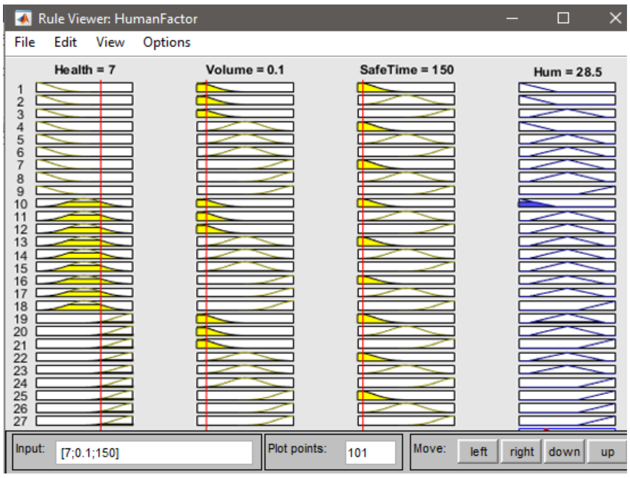

Figure 5. Unclear assessment
of the human risk factor (D2 received 28.5 points)
Source: created by the authors

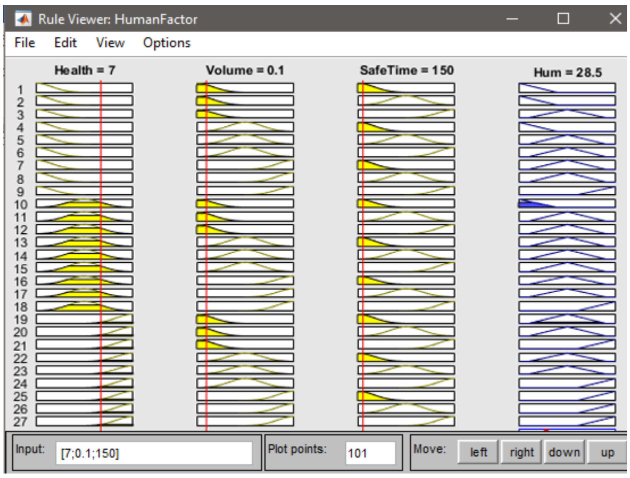

Figure 6. Unclear assessment
of the human risk factor (D3 received 49.5 points)
Source: created by the authors

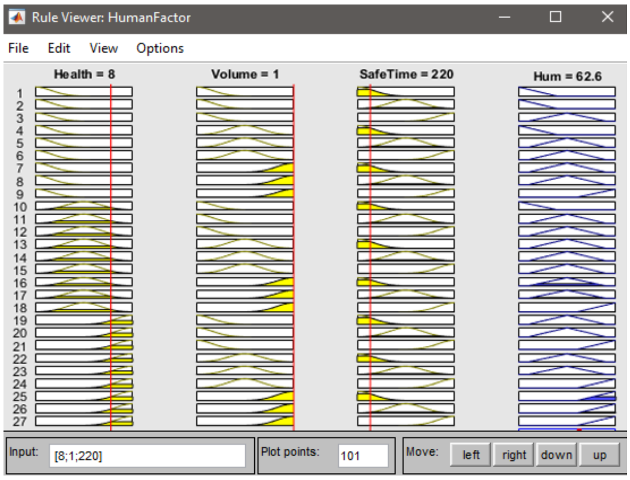

Figure 7. Unclear assessment
of the human risk factor (D4 received 62.6 points)
Source: created by the authors

Figure 4 demonstrates the results obtained for driver D1, for whom the model generated a score of 49 points. This value corresponds to an average human factor rating and indicates a moderate level of risk associated with the influence of human-related factors. Figure 5 presents the assessment results for driver D2, who scored 28.5 points. This value represents a low score on the 100-point scale and indicates an increased level of risk associated with potential human error. Figure 6 illustrates the results obtained for driver D3, for whom the model assigned a score of 49.5 points. Similar to driver D1, this value corresponds to an average human factor rating and reflects a moderate level of risk. Figure 7 presents the assessment results for driver D4, who scored 62.6 points, representing the highest value among the evaluated drivers. This result indicates a relatively low level of risk associated with human-error-related accidents. As follows, Figures 4-7 shows the results of the fuzzy assessment of the human factor for the four drivers. Driver D1 scored 49 points, D2 scored 28.5 points, D3 scored 49.5 points, and D4 scored 62.6 points. The values obtained indicate that drivers D1 and D3 have an average human factor rating, D2 has a low rating, and D4 has the highest rating among the study group, corresponding to the lowest level of risk. The results of fuzzy modelling of the human risk factor for road transportation of dangerous goods are summarised in Table 2.

Table 2. Rating assessment
by human risk factor based on fuzzy modelling

No.	Driver	Human factor, score	Place in the ranking
1	D1	49	3
2	D2	28.5	4
3	D3	49.5	2
4	D4	62.6	1

Source: created by the authors

Drivers were assessed based on three criteria: health status, the volume of dangerous goods transported, and accident-free record. The scores achieved through this evaluation allowed for comparative analysis and ranking. According to the results, D4 demonstrated the highest quality regarding human factors, scoring 62.6 points and securing first place in the ranking. D3 followed in second place with a score of 49.5 points, while D2 came in third with 49 points. The lowest score of 28.5 points was recorded by D1, who occupied the last position. This ranking enables the logistics operator or employees of security service to make informed decisions about route assignments and to determine the need for additional monitoring or staff training. To summarise the modelling results, the developed fuzzy model of the human factor demonstrated the ability to classify drivers by risk level based on the combined effects of health parameters, experience in transporting dangerous goods, and accident-free driving history. The scores obtained and the resulting ranking confirmed the model's sensitivity to individual driver characteristics and demonstrated its potential for comparative analysis in the field of transport safety. This provides grounds for considering the HumanFactor model as a functionally suitable component of a two-level hierarchical system for assessing the risks of road transport of dangerous goods.

The results obtained confirm the validity of using fuzzy modelling to assess the risks associated with the road transport of dangerous goods, combining quantitative indicators with expert judgements. This approach is generally consistent with the study by M.M. Aliabadi *et al.* (2024), which consider the human factor as one of the key causes of accidents in the transport of dangerous goods. In particular, in the article by M.M. Aliabadi *et al.* the assessment of human error is combined with artificial intelligence methods and fuzzy inference tools. Unlike studies focusing primarily on transport routes, infrastructure conditions, or individual risk scenarios, as shown in the work of Z. Wang (2018) and M.M. Aliabadi *et al.* (2024), the present study identified the human factor as a separate functional module within a hierarchical assessment system. Z. Wang (2018) proposed a fuzzy model for assessing the transportation routes of dangerous goods, which includes two indicators: a probability indicator and a reliability indicator. The goal of this model is to identify the optimal route schedule that minimises risk while maintaining specific levels of probability and confidence. Research on transport accidents reveals that the human factor is the most significant contributor to the occurrence of these accidents. Therefore, understanding the level of driver unreliability and examining driver behaviour during the transportation of dangerous goods requires thorough investigation. The authors employ fuzzy logic to describe driver actions. In this model, human behaviours are expressed using linguistic terms. The model based on an author's questionnaire and expert research that identified particular features of human behaviour. The output parameter of the model represents the intensity of human error that can lead to accidents. M.M. Aliabadi *et al.* (2024) investigated the identification of human errors and risk assessment during the road transportation of petroleum products. The study proposed the application of the SHERPA method combined with fuzzy modelling techniques. An overview of current research into the challenges arising from the risk assessment of dangerous goods transport is provided in the article by F. Ma *et al.* (2025). An original development of the Fine-Kinne fuzziness risk assessment model, based on the Pythagorean fuzzy set, can be found in work S.R. Satıcı & S. Mete (2024). At that time, M. Gul *et al.* (2022) improved the Fine-Kinne fuzzy model by calculating weighting coefficients for risk factors. The resulting model was tested at petrol stations. V. Tsopa *et al.* (2022) devoted to the multi-factor fuzzy assessment of occupational risks for lorry drivers. S. Vahabzadeh *et al.* (2025) presented the use of fuzzy modelling for assessing risks associated with the transport of dangerous goods and provided a comparative analysis of the Fane-Kinne model and the fuzzy analytic-hierarchical model. T. Luan *et al.* (2024) focused on the application of a fuzzy Bayesian statistical model for risk assessment in the transportation of dangerous goods through road tunnels. A distinctive feature of this approach is the mechanism for compensating for errors caused by insufficient input data. Such compensation is possible through fuzzy data representation and fuzzy inference rules. In doing so, the authors calculated the risks for the network formed by motorways and tunnels and used the monitoring of each transport node to correct the assessment of accident probability in real time.

However, the role of the human factor as a separate subsystem within the model's multi-level architecture is not explored. An important result was that the final assessment proved to be sensitive primarily to the combination of input parameters rather than to any single indicator in isolation. This finding highlighted the complex nature of risk and confirmed the advantages of fuzzy logic in modelling interdependencies between a driver's health, experience, and accident-free driving. In this respect, the proposed model complemented existing research, including the work of V. Tsopa *et al.* (2022), where fuzzy approaches were applied to the ranking of alternatives, route selection, and occupational risk assessment. However, the results of this work should be interpreted with certain limitations in mind. The model covered only a small number of variables and does not include the driver's dynamic psychophysiological characteristics, journey situational factors, or telematics data. Furthermore, the practical accuracy of the study depends on the quality of the membership functions and the rule base, which is a typical limitation of fuzzy models, as indirectly indicated by F. Ma *et al.* (2025). Consequently, hierarchical fuzzy modelling is promising for assessing the safety of road transport of dangerous goods, as it integrates the human factor into a multi-level risk model without sacrificing interpretability or practical value.

Conclusions

The study demonstrated the feasibility of applying fuzzy approaches for expert risk assessment in the road transportation of dangerous goods. These methods effectively handled incomplete, linguistic, and subjective data typical of the transport sector. A two-level multifactor model was developed, aggregating risks into four categories: regulatory, logistical, physical, and human. This approach enabled the calculation of an integrated transportation hazard indicator while maintaining transparency for expert interpretation. A key outcome was the development and validation of the "human factor" model, which was tested using real driver data. The model enabled rapid ranking of personnel according to risk level, taking into account health status, professional experience, and accident-free records. It was established that even minor variations in these parameters significantly affected the overall risk rating, confirming the critical role of the human factor in shaping transportation risk. At the same time, the study covered only one module of the first level of the hierarchy, namely the human factor. The mechanisms for aggregating results at the second level were not implemented at this stage. The proposed model was considered as a foundation for a comprehensive decision support system capable of automatically updating risk assessments before each trip, incorporating dynamic data on the driver, route, and weather conditions. It was anticipated that integration with telematics systems and HR platforms would improve the accuracy of input data and the responsiveness to critical changes. The system could provide dispatchers with visual risk dashboards, automated alerts, and recommendations for route adjustments or driver replacement, thereby enhancing transportation safety. Thus, the developed hierarchical fuzzy model provided a basis for an integrated risk management system in the transportation of dangerous goods and demonstrated strong potential for further automation of decision-making processes. Prospects for further research included expanding the model structure through the incorporation of dynamic indicators, calibration of weighting coefficients, and integration with route optimisation tools to improve the accuracy of risk assessment.

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Conflict of Interest

None.

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Ієрархічне нечітке моделювання ризиків автоперевезень небезпечних вантажів з урахуванням впливу людського фактору

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Анотація. Метою дослідження було розроблення ієрархічної нечіткої моделі для оцінювання ризиків автомобільного перевезення небезпечних вантажів з урахуванням впливу людського фактора, що дозволяє підвищити точність та інформативність прийняття рішень у сфері транспортної безпеки. У дослідженні застосовано системний підхід, методи аналізу і синтезу, експертного оцінювання, порівняльного аналізу, а також нечітке моделювання на основі алгоритму Мамдані, реалізованого в середовищі MATLAB, для оцінювання ризиків, пов'язаних із людським фактором під час автомобільного перевезення небезпечних вантажів. У результаті дослідження було розроблено ієрархічну нечітку модель оцінювання ризиків перевезення небезпечних вантажів автомобільним транспортом. Ключовим елементом моделі є оцінювання людського фактора, що ґрунтується на трьох вхідних змінних: стані здоров'я водія, його досвіді перевезення небезпечних вантажів (вимірюваному в тонно-кілометрах) та тривалості безаварійної роботи. Нечітку модель було реалізовано із застосуванням алгоритму Мамдані; вона включає 27 правил нечіткої логіки. Модель продемонструвала стійку поведінку за умов варіювання вхідних параметрів. Апробація моделі на даних чотирьох реальних водіїв забезпечила отримання оцінок якості людського фактора в діапазоні від 28,5 до 62,6 бала, що свідчить про її чутливість до індивідуальних характеристик персоналу. Інтегральне оцінювання загального ризику формується шляхом дворівневої агрегації результатів підмоделей, що забезпечує адаптацію системи до різних сценаріїв перевезень. Запропонована модель може бути ефективно інтегрована як ключовий компонент системи підтримки прийняття рішень логістичного оператора для динамічного аналізу ризиків перед кожним транспортним рейсом

Ключові слова: система підтримки прийняття рішень; експертне оцінювання; безаварійний стаж; функція належності; безпека логістики