Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P1657-cd

Towards the Risk Assessment Framework Conceptualization Using Fuzzy Logic for Last-Mile Cargo Drones.

Ievgen Medvediev

Department of Hydromechanics and Ship Design, Gdansk University of Technology, Poland.
Department of Railway and Road Transport, Lift and Care Systems, Volodymyr Dahl East Ukrainian National University, Ukraine E-mail: ievgen.medvediev@pg.edu.pl

Dmitriy Muzylyov

Department of Transport Technologies and Logistics, State Biotechnological University, Ukraine. E-mail: murza_1@ukr.net

Jakub Montewka

Department of Hydromechanics and Ship Design, Gdansk University of Technology, Poland. E-mail: jakub.montewka@pg.edu.pl

The use of autonomous and controlled drones for last-mile delivery of small cargo is rapidly advancing due to improvements in technology, artificial intelligence, and an increase in their cargo capacity. The application of drones to improve public services and meet transportation needs in today's world is an undeniable possibility. However, despite the clear benefits of using drones for last-mile delivery, there are potential risks, both known and new, that could lead to disruptions in the goods delivery. Hence, there is a necessity to design a method that will consider the impact of various risks on drone delivery sustainability at a significantly improved standard. Due to the diverse hazards nature associated with operating the aforementioned systems, it can be argued that to address these hazards and ensure sustainable delivery, it is essential to develop a flexible model using relevant approaches such as fuzzy logic or neural network modeling. Unlike probabilistic models, fuzzy logic does not necessitate extensive data. Additionally, an initial data sample on delivery risks posed by drones can be gathered through expert opinions. This research marks the initial phase in designing a fuzzy model for assessing risks in delivery systems using both autonomous and controlled drones by fuzzy logic. The study identified the key risks that primarily impact the drone deliveries' sustainability due to the expert survey. The risks were categorized into four groups: human factor; technical hardware issues; software failure; and weather conditions. Participants can help to identify the two most significant risk factors for each group. This information was used to determine the inputs for the logical-linguistic model. The fuzzy model defines five evaluation levels of supply sustainability. The key benefit is recommendations about the feasibility of drone use for last-mile delivery under specific conditions.

Keywords: Transportation, hazard, human factor, technical hardware issues, software failure, weather conditions, unmanned aerial vehicle, autonomous vehicle, controlled vehicle, logico-linguistic model.

1. Introduction

Drones are increasingly popular for delivering small shipments, especially for last-mile logistics (Garg et al., 2023; Jazairy et al., 2024). They can be human-controlled or autonomous, but identifying potential hazards during route planning remains a major challenge **P1** (Kitjacharoenchai and Lee, 2018; Kalinichenko et al., 2023). Improving hazard prediction is vital for enhancing the reliability of drone logistics operations.

Previous studies have shown that the risks associated with the last mile of delivery differ from those encountered during the initial stage of the route (Tu and Piramuthu, 2023). The problem **P2** of reliability of drone usage requires careful and detailed examination. Assessing risks during the final stages of delivery significantly enhances the stability of the entire supply chain (Mismar et al., 2022).

Some studies have examined hazards and risks in drone delivery (Huang, 2023). However, current risk assessment methods fail to proactively address these hazards, impacting supply planning. Such impact of risks to the drone delivery system can be explained through key aspects:

- Delays in the cargo delivery at the last mile.
- Route disruptions caused by unforeseen weather conditions.
- Unexpected twists in the drone's flight plan.
- Erroneous drone delivery.
- Emergency loss of communication with both autonomous and controlled drones.
- Software failures.
- Technical breakdowns of the drone.
- Unintentional release of cargo from the load-handling device during flight.

This brief overview highlights potential negative consequences of various risks associated with drone usage in supply chains. Weighting factors are needed to evaluate the impact of these risks, but studies are lacking/ This fact is justified by work (Deepu and Ravi, 2023). Challenges from swarm drones must also be considered (Shreeraj et al., 2024). Additional solutions for drone-related issues in flexible production systems are discussed (Deja et al., 2019; Sutak et al., 2019). The absence of universal methods for assessing these risks undermines the stability of cargo supply chains, especially in the last mile.

To address the hazards of operating these systems, a flexible model is essential. Approaches like fuzzy logic (Medvediev et al., 2020) and neural networks (Muzylyov et al., 2021) can be used. Fuzzy logic, unlike probabilistic models, requires less extensive data (Muzylyov et al., 2024), but it necessitates defining initial data ranges (Aqlan and Lam, 2015). These values can be provided directly by researchers (Janjua et al., 2021) or gathered through expert surveys (Mostafa et al., 2021). That's why, it is crucial to development of a fuzzy (logical-linguistic) model involves key stages: data fuzzification; selecting the type of membership function; justifying a fuzzy inference model; designing inference rules; modeling using MATLAB; clarifying membership function weights; and defuzzification of results (Hezam et al., 2022; Zhang et al., 2021; Luscinski and Ivanov, 2020).

Currently, few systematic models are using fuzzy logic to assess risks associated with drone deliveries, highlighting the need for a proposed model to resolve this gap, P3. The study has applied fuzzy logic in an intelligent decision support system for this purpose (Kovač et al., 2021). Also, fuzzy logic has proven effective in various fields, including risk assessment in Human-Road-Environment-Vehicle Systems (Medvediev et al., 2024a), supply chain risk management (Medvediev et al., 2024b), determining safe parameters for inland waterways, and evaluating customs delays (Medvediev et al., 2024d). The fuzzy models are also used to quickly assess drone capabilities and communicate technical risks.

2. Framework and methodology of the study

The study purpose is to design a new method for proactive risk assessments for autonomous and controlled drones by fuzzy logic. The purpose can be successfully achieved by solving the problems **P1**, **P2**, and **P3** in the approaches **A1**-**A5** listed in Table 1.

Table 1. Key problems of the study and approaches to solve them.

Key problem	Approach
P1Currently, there's no widely accepted framework for identifying risks in last-mile goods delivery with autonomous and controlled systems.	**A1** a semantic analysis in a literature review focused to risks of drones using **A2** an expert survey aimed at identifying these risks
P2. The issues regarding the stability of the last-mile cargo delivery system using drones stem from improper risk assessment.	**A3** defines the fuzzy nature of the initial data **A4** using Simulink to model the fuzzy framework.
P3. Lack of a flexible (intelligent) decision support system for last-mile delivery using autonomous and controlled systems	**A5** ddevelopment of intelligent decision support modules using a fuzzy model for proactive risk assessments.

2.1. *Definition of the level of advisability for drone*

The definition of the level of advisability for drone (L_{ad}) use is expressed as the impact of uncertainty on purpose. The key direction of the study is to find the pattern between quality drone use and risk factors for their use due to various hazards: human factors, technical hardware issues, software failure, and weather (environment) conditions. Therefore, the level of advisability for drone use can be formulated as the following equation (see Eq. (1)):

$$RF(H_{hum}; H_{hw}; H_{sw}; H_{ec}) = L_{ad} \in [0;1] \quad (1)$$

RF – risk factors due to various hazards at drone use; H_{hum} - human factors; H_{hw} - technical hardware issues; H_{sw} - software failure; H_{ec} – weather (environment) conditions.

2.2. *Framework*

This study focuses on a framework conceptualizing a fuzzy model to assess risks in drone delivery systems, incorporating both autonomous and controlled drones. Key risks affecting sustainability will be identified through an expert survey and categorized into four groups: human factors, technical hardware issues, software failures, and weather (environment) conditions. Participants will select the two most significant risks from each group, which will inform the inputs for the logical-linguistic model. The fuzzy model will ultimately define five evaluation levels of supply sustainability. The research framework is depicted in Fig. 1.

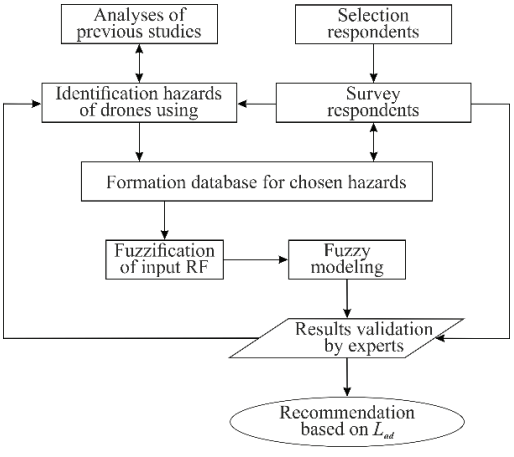

Fig. 1. Framework of the study.

2.3. Research methodology

2.3.1. *Brief description of potential hazards for each group of risk factors*

In the initial stage of the study, it is important to identify the hazards associated with each group. A preliminary list of hazards for each group will be presented on Figures (see Fig. 2-Fig. 5).

In the first group, we can identify risks related to human factors, specifically hazards arising from the drone operator's lack experience with either a specific model of drone or its controlling software. These hazards heighten the risk of damage to the drone due to improper handling or incorrect understanding of the drone's dynamic and maneuvering characteristics. Moreover, if the drone operator has lacks information about the route—such as obstacles, tall buildings, power lines, and other potential hazards—this can lead to delivery issues. Additionally, the operator's emotional and psychophysiological state must be stable. It is important to remember that the drone is not a toy; operators should not take any liberties during cargo transportation or deviate from the flight plan and safety guidelines. *In addition, an Adverse Mental State has a significant impact on the productivity of a human-controlled system (Grindley et al., 2024; Schmitz-Hübsch et al., 2024).* Furthermore, if the operator experiences a decline in physical health, such as a fever, their ability to maintain control over the transport and ensure stability may be compromised.

The main hazards associated with the first group of risk factors (Human factors) are depicted in Figure 2

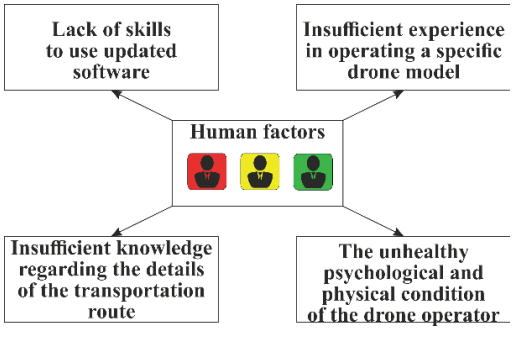

Fig. 2. Potential key Human factors arising risk.

In many instances, human errors arise from inadequate preparation. This often happens when a drone pilot lacks sufficient flight hours, particularly in densely populated urban areas

where last-mile deliveries are made (Nwaogu et al., 2024). Another common error on a global scale is related to the incorrect design of the delivery route (Bruni et al., 2023).

A critical factor affecting the cargo supply chain sustainability when using drones is the technical reliability of the drone itself. The drone state can change during delivery due to various issues, such as damage from collisions with obstacles or failures caused by overload (not adhering to the drone's operating conditions). Particular attention should be given to the load/unload gripper, as subpar equipment can lead to the risk of cargo loss during transportation. This could compromise a fundamental logistical principle: cargo must be delivered in its original quality and quantity. The study aims to test the reliability of cargo fastening on a drone under various weight loads.

The potential hazards for the "Technical hardware issues" group are depicted in Figure 3.

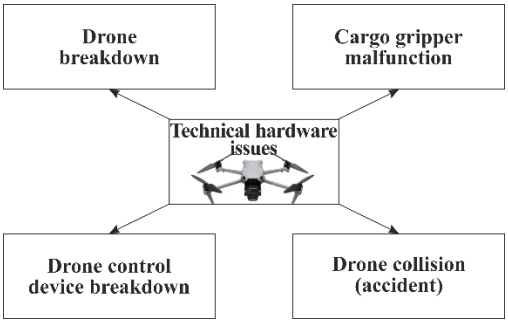

Fig. 3. Potential key technical hardware issues arising risk.

The third group of hazards considers potential failures in software and drone sensors, which can lead to significant challenges when delivering cargo during the last mile. The reliability of drone control is also influenced by the software patch's version. A common issue is that the updated version of the drone control program may perform worse than the previous one. Additionally, urban environments are often saturated with various communication devices and electronics, resulting in an increased background level of electromagnetic radiation. This, in turn, can degrade the quality of communication with the drone, especially as the distance from the operator increases.

The identified hazards associated with the "Software failure" group are depicted in Figure 4.

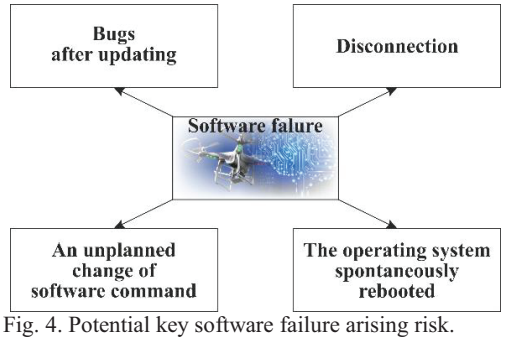

Fig. 4. Potential key software failure arising risk.

The fourth group of factors pertains to weather conditions. While drones offer significant advantages for last-mile deliveries, they also have a considerable drawback: their performance is highly dependent on weather conditions.

Wind can impact the drone's speed and may necessitate adjustments to its flight path. Additionally, rain or snow can reduce the drone's flight performance. Heavy cloud cover or fog can limit the drone's operational capabilities, increasing the risk of collisions with obstacles such as pillars, buildings, or trees, which could result in the loss of cargo. Figure 5 presents an estimated set of hazards associated with the "Weather Conditions" factor.

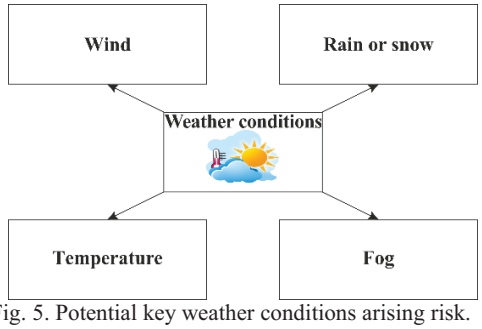

Fig. 5. Potential key weather conditions arising risk.

2.3.2. *Methods utilized in the study*

The following methods are anticipated here:

- Expert Survey: Identify significant hazards for each group to inform input factors for the logical-linguistic model.
- Fuzzy Logic: Develop a risk model.

- Simulink: Use this tool to assemble the model and run simulations to evaluate variation in Lad.
- Mathematical Statistics: Calculate errors for validating the logical-linguistic model.
- Decision-Making Theory: Design modules for an intelligent support system to enable flexible decisions during drone operations.
- Field Drone Testing: Understand risk factors related to "Weather Conditions" and "Human Factors."

2.4. *Outlining the main steps of semantic analysis to recognize the primary hazards of drones.*

This stage of theoretical research will allow for the identification of potential hazards associated with using drones in both autonomous and controlled systems for last-mile cargo delivery. The hazards will be categorized through semantic analysis, focusing on common risks that are characteristic of both managed and autonomous systems. Additionally, we will highlight unique hazards specific to each delivery system utilized in the last mile.

Semantic analysis helps to eliminate non-relevant literature, enabling a more accurate identification of potential hazards. The primary objective is identifying the various hazards associated with drone operations, particularly in goods delivery. This approach allows for the hazard classification into four groups of risk factors, which can then be used to prioritize the most significant hazards.

The expected outcome of research task **T1** is to identify the main hazards associated with each type of drone: autonomous and controlled.

2.5. *Survey of experts to identify potential hazards*

Justification for the target segment of respondents participating in the hazard identification survey involves segmenting respondents by age, gender, experience with drones, and other relevant factors. *It is planned that 20 drone users in Ukraine and Poland will be selected as experts. Age group from 21-60 years, taking into account working age and in compliance with gender policy*. Tailored questionnaires will be compiled for each target audience based on these criteria. A mathematical justification will be provided for the number of respondents selected from each target group.

The survey will be conducted among the identified target groups. The results will be analyzed to assess the consistency of expert opinions by calculating Kendall's concordance coefficient. This analysis will help identify a set of significant hazards for each of the four risk groups (human factors, technical hardware issues, software failures, and weather conditions).

In this research task, we plan to conduct field tests using a drone due to the next step of the study. This approach will help us better understand the risks involved, particularly focusing on the "weather conditions" and "human factor" risk groups. The results from our tests will be compared with expert opinions to finalize the identification of key hazards related to the delivery of goods. These findings will be used to develop a fuzzy model.

The expected outcome of research task T2 is to justify the key hazards for inputting into a fuzzy model.

2.6. *Preparing database and Conceptualization of future fuzzy model*

Preparation of the database for the proposed fuzzy model, including the fuzzification (approach – **A3**). The next step in the study involves determining the primary range of values for each identified risk factor based on. A second expert survey will be conducted to verify the accuracy of the selected values. The quality of responses will be assessed using a Likert scale. This approach will help identify whether adjustments are necessary for the initial range of specific risk factors. Following this, the corrected data for fuzzification will be prepared.

The range of hazards will assess change values associated with weather conditions and human factors through drone field tests. Additionally, other risks and their variations will be evaluated using flight simulation by special software purchased in the research. This approach will enable us to compare field test results with expert opinions and better understand the range of hazard changes needed for fuzzification and input into a fuzzy model.

The rationale for selecting the types of membership functions (triangular and trapezoidal). Fuzzification is based on the chosen

membership functions. Formulating a mathematical conclusion using the fuzzy Mamdani inference. The fuzzification process transforms precision values into fuzzy linguistic values, which are categorized as minimal, average, and maximum. Due to the defuzzification method based on the centroid approach, the output parameter (level of drone usage) also has the same three levels as the input parameters.

Developing an experimental plan that addresses all potential risk situations. Designing logical rules for each experiment case per the plan for conducting a full-factor experiment.

When developing a conceptual framework for a fuzzy model, it is essential to consider the following features: each group undergoes risk modeling using a distinct logical-linguistic model; each fuzzy model has two inputs, corresponding to the number of key selected hazards for research task (**T2**); three levels of variation characterize each hazard; all fuzzy models are configured in MATLAB.

The generic conceptualization for fuzzy modeling is depicted in Figure 6.

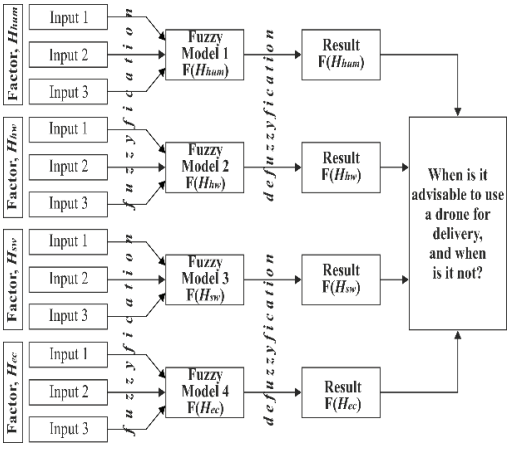

Fig. 6. Generic conceptualization for fuzzy modeling.

3. Results and discussions

The expected outcome according to the research framework for evaluating the level of advisability for drone use includes the following type of assessment, as depicted in Figure 7. As an example, we show in this study how the assessment approach for "Human factors" described in chapter 2 (subsection 2.3.1) would look like

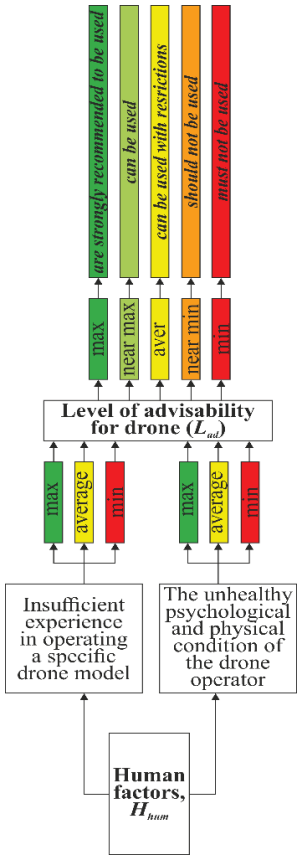

Fig. 7. Fuzzy model for "Human factors".

The modeling results will be evaluated using metrics like SME or RMSE. The logical-linguistic model will undergo face, content, and predictive validity verification, and limitations will be outlined. Expected outcomes include a system to evaluate drone feasibility based on four groups of hazards identified by experts, represented by the equation (see Eq. (2)).

$$if\ L_{ad} = \begin{cases} \text{min} \\ \text{near min} \\ \text{aver} \\ \text{near max} \\ \text{max} \end{cases} \quad then\ drones \begin{cases} must\ not\ be\ used \\ should\ not\ be\ used \\ can\ be\ used\ with\ restrictions \\ can\ be\ used \\ are\ strongly\ recommended\ to\ be\ used \end{cases} \tag{2}$$

Determine the weighting factor for each risk, which will impact the sustainability and reliability of delivery, particularly in the last mile. Justify the functionality of each module in the intelligent decision support system designed for proactive risk assessment when using drones for last-mile deliveries. Prepare the decision-

making system for digitalization, followed by the development of software.

The concept of intelligent decision-making support system is depicted in Figure 8.

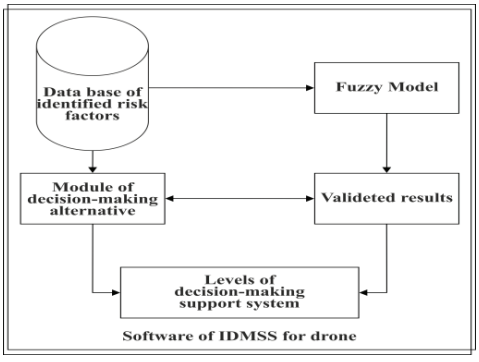

Fig. 8. Conceptualization of the of the intelligent decision-making support system (IDMSS).

The design IDMSS main outcome is the establishment of clear ranges of variation based on identified patterns among the input values of the risk factors for each group of hazards. This method will serve as a simple tool for finding answers to the questions: "When is it advisable to use a drone for delivery, and when is it not?"

4. Conclusion

This paper presents a conceptualization and research framework for level of advisability for drone use, accounting for experts' knowledge and fuzzy logic as modeling techniques.

The proposed concept for identifying risks in last-mile drone deliveries allows us to pinpoint key risk factors from four groups (human factors, technical hardware issues, software failures, and weather (environment) conditions). This assessment helps identify hazards in the proactive manner that could impede delivery efficiency. By focusing on these risk factors, we can assist drone pilots or adjust autonomous delivery algorithms, ultimately improving last-mile supply chain sustainability.

This approach will support the creation of an intelligent decision support system for last-mile cargo delivery and software for risk simulations prior to actual deliveries. Additionally, the fuzzy model can be applied to drone manufacturers during production to integrate potential risks into technical parameters based on expert surveys and field test results.

The impact of various weather conditions on the cargo supply chain sustainability requires more in-depth analysis. When identifying the most significant risks, it is essential to rely not only on expert opinions but also on the results of field tests. This study plans to utilize a drone for this purpose. Future field tests will focus on determining the frequency and significance of failures that occur under different weather and climatic conditions during cargo delivery. The initial testing will take place at a safe training ground at Gdańsk Tech, using small consignments. This will help establish patterns and either support or challenge expert opinions to identify the most critical factors affecting cargo delivery.

Acknowledgement

The paper is partially supported by the European Union's Marie Skłodowska-Curie Actions under MSCA4Ukraine funding scheme (project number 1233438, "Systemic, risk-informed decision support system for the definition of boundary conditions for safe inland navigation based on a novel logico-linguistic model".

References

Aqlan, F., & Lam, S. S. (2015). A fuzzy-based integrated framework for supply chain risk assessment. *International Journal of Production Economics 161*, 54-63.

Bruni, M. E., Khodaparasti, S., & Perboli, G. (2023).The drone latency location routing problem under uncertainty. *Transportation Research Part C: Emerging Technologies 156*, 104322.

Deepu, T., & Ravi, V. (2023).A review of literature on implementation and operational dimensions of supply chain digitalization: Framework development and future research directions. *International Journal of Information Management Data Insights 3(1)*, 100156.

Deja, M., Siemiątkowski, M. S., Vosniakos, G., & Maltezos, G. (2019).Opportunities and challenges for exploiting drones in agile manufacturing systems. *Procedia Manufacturing 51*, 527-534.

Garg, V., Niranjan, S., Prybutok, V., Pohlen, T., & Gligor, D. (2023).Drones in Last-mile Delivery: A Systematic Review on Efficiency, Accessibility, and Sustainability. *Transportation Research Part D: Transport and Environment 123*, 103831.

Grindley, B., Phillips, K., Parnell, K. J., Cherrett, T., Scanlan, J., & Plant, K. L. (2024).Over a decade

of UAV incidents: A human factors analysis of causal factors. *Applied Ergonomics 121*, 104355.

Hezam, I.M., Ali, A.M., Sallam, K. et al. (2024).Digital twin and fuzzy framework for supply chain sustainability risk assessment and management in supplier selection. *Sci Rep 14*, 17718

Huang, J. (2023).Risk analysis in last-mile drone delivery. [*Unpublished Bachelor's Degree Programme in Purchasing and Logistics Engineering thesis*]

Janjua, N. K., Nawaz, F., & Prior, D. D. (2021).A fuzzy supply chain risk assessment approach using real-time disruption event data from Twitter. *Enterprise Information Systems 17(4)*.

Jazairy, A., Persson, E., Brho, M., von Haartman, R. and Hilletofth, P. (2025).Drones in last-mile delivery: a systematic literature review from a logistics management perspective. *The International Journal of Logistics Management 36(7)*, 1-62.

Kalinichenko, O. et al. (2023).Determination of Conditions to Provide Transport Logistics Support Service to Aircraft at Aerodromes in Ukraine. In: Arsenyeva, O., Romanova (eds). Smart Technologies in Urban Engineering. STUE 2023. *Lecture Notes in Networks and Systems 807*, Springer, Cham, pp. 390–399.

Kitjacharoenchai, P., & Lee, S. (2018).Vehicle Routing Problem with Drones for Last Mile Delivery. *Procedia Manufacturing 39*, 314-324.

Kovač, M., Tadić, S., Krstić, M., Bouraima, M.B. (2021).Novel Spherical Fuzzy MARCOS Method for Assessment of Drone-Based City Logistics Concepts. *Complexity 2021*, 2374955.

Luscinski, S., Ivanov, V. (2020).A simulation study of industry 4.0 factories based on the ontology on flexibility with using flexsim® software. *Management and Production Engineering Review 11(3)*, 74–83.

Medvediev et al., 2024a. Risk Assessment at Unsignalized Intersections Based on Human-Road-Environment-Vehicle System Applying Fuzzy Logic. In: Ivanov, V., Trojanowska, J., Pavlenko, I., Rauch, E., Piteľ, J. (eds) Advances in Design, Simulation and Manufacturing VII. DSMIE 2024. *Lecture Notes in Mechanical Engineering*. Springer, Cham. pp 437–448.

Medvediev et al., 2024b. A model for agribusiness supply chain risk management using fuzzy logic. Case study: Grain route from Ukraine to Poland. *Transportation Research Part E: Logistics and Transportation Review 190*, 103691.

Medvediev et al., 2024d. Risk Assessment Due to Customs Delays in Supply Chains by Fuzzy Logic. In: Kołowrocki, K. & Dąbrowska, E. (eds) Advances in Reliability, Safety and Security, ESREL2024. Advances in Reliability, Monograph Book Series, Part 4. Jagiellonian University, Cracow, Poland. pp 145–152.

Medvediev Ie., Muzylyov D., Shramenko N., Nosko P., Eliseyev P., Ivanov V. (2020).Design Logical Linguistic Models to Calculate Necessity in Trucks during Agricultural Cargoes Logistics Using Fuzzy Logic. *Acta Logistica 7(3)*, 155-166.

Mismar, H., Shamayleh, A., & Qazi, A. (2022).Prioritizing Risks in Last Mile Delivery: A Bayesian Belief Network Approach. *IEEE Access 10*, 118551-118562.

Mostafa, A.I., Rashed, A.M., Alsherif, Y.A., Enien, Y.N., Kaoud, M., Mohib, A. (2021).Supply Chain Risk Assessment Using Fuzzy Logic. 3rd *Novel Intelligent and Leading Emerging Sciences Conference* (NILES), Giza, Egypt, 2021, pp. 246-251.

Muzylyov, D., Medvediev, I., Pavlenko, O. (2024).Risk factor assessment in agricultural supply chain by fuzzy logic. *IOP Conf. Ser.: Earth Environ. Sci*. *1376*, 012038.

Muzylyov D., Shramenko N., Ivanov V. (2021).Management Decision-Making for Logistics Systems Using a Fuzzy-Neural Simulation. In: Cagáňová D., Horňáková N., Pusca A., Cunha P.F. (eds) *Advances in Industrial Internet of Things, Engineering and Management*. EAI/Springer Innovations in Communication and Computing. Springer, Cham.

Nwaogu, J. M., Yang, Y., Chan, A. P. C., & Wang, X. (2024).Enhancing Drone Operator Competency within the Construction Industry: Assessing Training Needs and Roadmap for Skill Development. *Buildings 14(4)*, 1153.

Schmitz-Hübsch, A., Becker, R., Wirzberger, M. (2024).Emotion-performance relationship in safety-critical human-machine systems. *Computers in Human Behavior Reports 13*, 100364.

Shreeraj, N.K. et al. (2024).Deployment of Swarm Drones for Supply Chain and Logistics. Drone Applications for Industry 5.0, edited by Chandra Singh and Rathishchandra Ramachandra Gatti, *IGI Global*, pp. 176-189.

Sutak, D., Hatala, M., Zajac, J., Radchenko, S., Ivanov, V., Mitalova, Z. (2019).Simulation of Air Flow on the Bodywork Automobile with Direct and Side Load. In: Hamrol, A., Kujawińska, A., Barraza, M. (eds) Advances in Manufacturing II. Manufacturing 2019. *Lecture Notes in Mechanical Engineering*. Springer, Cham.

Tu, Y. J., & Piramuthu, S. (2023).Security and privacy risks in drone-based last mile delivery. *European Journal of Information Systems 33(5)*, 617–630.

Zhang, X. (2021).[Retracted] Enterprise Supply Chain Risk Assessment Based on the Support Vector Machine Algorithm and Fuzzy Model. *Security and Communication Networks 2022(1)*, 3692628.