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Safety Risk Factors of Urban Logistics Drone Delivery in the Context of the Low-Altitude Economy

Yuanyuan Zhang*, Xianglong Li, Nuoning Zheng, Yuxin Xue

College of Transportation and Civil Engineering, Fujian Agriculture and Forestry University, 350108 Fuzhou, China

* Correspondence: Yuanyuan Zhang (zhangyy@fafu.edu.cn)

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Abstract: This study analyzes the safety risk transmission mechanism in urban logistics drone last-mile delivery within the policy-driven low-altitude economy. To address the limitations of traditional risk identification methods, which rely heavily on accident data, this research integrates the Fuzzy Decision Analysis Laboratory Method (Fuzzy-DEMATEL),Interpretive Structural Modeling (ISM), and the Matrix of Cross-Impact Multiplication (MICMAC) to construct a three-dimensional analytical framework based on causal relationships, structural hierarchy, and attribute classification.First, Fuzzy-DEMATEL is employed to quantify the strength of causal relationships among risk factors. Next, ISM is used to deconstruct the multi-level hierarchical network and identify fundamental causes within the risk system. Finally, MICMAC is applied to calculate the dependencies and driving forces of each influencing factor, helping prioritize risk governance measures. The research findings indicate that: (1) The safety risk system of urban logistics drones for last-mile delivery exhibits a "dual-core driven – multi-loop coupled" characteristic. Equipment failures act as the physical carriers of systemic failures, while the root-cause risks stem from institutional factors such as inadequate pre-service training and violations of laws and regulations. (2) The risk hierarchy follows a pyramid-shaped transmission path, with risks propagating from the root layer to the surface in successive layers. Open airspace serves as an accelerator, transforming environmental disturbances into institutional defects, which in turn lead to technical failures. (3) The dependency attributes of each factor indicate the priority order for risk prevention and control: management leverage points serve as the strategic control core, the environment-technology interaction network is central to joint prevention, standardized processes solidify basic operations, and systemic risk levels are reduced.

Keywords: Low-altitude economy; Urban logistics drones; Last-mile delivery; Safety risks

1 Introduction

The continuous expansion of e-commerce and growing consumer demand for instant delivery have placed urban last-mile logistics systems under multifaceted pressures concerning cost, efficiency, and reliability. Against this backdrop, logistics drones have emerged as a pivotal technological pathway for transforming last-mile delivery models, leveraging their exceptional flexibility, significant marginal cost advantages, and operational reliability. Notably, 2024 witnessed the inaugural inclusion of the "low-altitude economy" in the Chinese Government Work Report, elevating it to the level of national strategy and providing robust policy support for the standardized and commercial application of drone logistics.

However, it is crucial to recognize that urban last-mile drone delivery does not constitute a simple extension of traditional general aviation scenarios; instead, it represents an emerging domain characterized by high complexity and multiple constraints [1]. Compared to rural or open airspace, urban environments exhibit distinct features such as high building density, concentrated populations, complex airspace structures, and significant electromagnetic interference (EMI). High-rise building clusters not only induce navigation signal attenuation and urban canyon effects but also generate complex aerodynamic disturbances, including turbulence and wind shear. Densely populated areas demand extremely high fault tolerance for operational safety. Furthermore, the presence of various restricted flight zones (RFZs), altitude limitation areas, and dynamic airspace restrictions within cities substantially increases the complexity of path planning.

Regarding communication and information security, drone systems face potential threats from cyberattacks, including unauthorized access, control hijacking, and system manipulation, leading to safety risks or data breaches. The dense distribution of Wi-Fi, 4G/5G base stations, and other wireless devices creates a strong-interference, highly dynamic electromagnetic ecosystem, posing severe challenges to drone communication links and control stabilitys [2–5]. Finally, governmental regulatory bodies, as key stakeholders, must establish regulations to ensure safe and controlled airspace operations—such as defining permissible flight zones, altitude restrictions, and rules for sensitive areas. Nevertheless, international standards specifically tailored for low-altitude logistics drone delivery scenarios remain absent, and regulatory policies across nations persist in a fragmented exploratory stage, further exacerbating uncertainties in the standardized development of this field. Precisely because of these multifaceted challenges faced by logistics drones performing last-mile tasks in urban environments, safety risks have emerged as the core bottleneck constraining their large-scale deployment and applications [6, 7].

Existing research primarily focuses on identifying logistics drone risks, assessing risk probability and severity, proposing risk control/mitigation measures, or exploring their macroscopic feasibility within the logistics sector. However, studies systematically identifying the coupling relationships, interaction pathways, and hierarchical structures among multiple risk factors in urban last-mile delivery remain insufficient. There is a particular lack of integrated analytical frameworks capable of simultaneously addressing factor fuzziness, causal relationships, and structural hierarchies, hindering the formulation of risk governance and tiered intervention strategies.

To address these research gaps, this study focuses on the safety risk system of logistics drones in urban last-mile delivery. We propose a novel three-dimensional integrated analytical framework combining fuzzy DEMATEL, ISM, and Matrice d'Impacts Croisés-Multiplication Appliquée à un Classement (MICMAC). This framework aims to:

(1) Systematically identify key risk factors and quantify their interdependencies;

(2) Unveil the hierarchical structure and multi-level cascading relationships among risk factors;

(3) Identify fundamental factors with high driving power and surface-level factors with high dependence within the system;

(4) Construct tiered intervention pathways tailored to risks at different levels.

This research provides theoretical foundations and decision-making support for achieving the safe, controllable, and large-scale integration of urban logistics drones.

2 Literature Review

In recent years, the rapid expansion of drones deployed for last-mile delivery has garnered significant attention due to their potential to revolutionize the logistics industry. However, frequent occurrences of in-flight incidents have heightened public skepticism regarding their operational safety, which has emerged as a critical bottleneck restricting further industry development. As a result, safety issues associated with drones have progressively become a major focus of research [8–11].

Early studies in the field of urban logistics drone safety risks primarily focused on the preliminary identification and static assessment of safety risks. For example, Tubis et al. [12] conducted a systematic review of 257 publications and developed an eight-dimensional risk framework covering areas such as surveillance, logistics, and cybersecurity. This framework provided a theoretical benchmark for identifying the safety risk factor system in urban logistics drones. Further refining the risk classification system for last-mile delivery scenarios, Tu and Piramuthu [11] proposed a three-dimensional framework encompassing "code risk, object risk, and signal risk," addressing the gap in traditional risk identification regarding the coupling mechanisms between privacy breaches and signal security. Fehling and Saraceni [13] employed the Analytic Hierarchy Process (AHP) to evaluate the technical and legal factors influencing drone delivery in Germany through pairwise comparisons. Although these studies laid the foundation for risk understanding, their evaluation frameworks were often generalized, lacking targeted analysis of the complexities of urban terminal environments and the specific characteristics of electric multirotor drones. Moreover, they struggled to reveal the dynamic coupling mechanisms among multiple factors. Betti Sorbelli [14] conducted a comprehensive systematic review integrating 12 dimensions, including ethics, sustainability, and safety risks, revealing an imbalanced research landscape characterized by a "strong technology-driven focus but weak scenario adaptation." Addressing this issue, Zhu et al. [8] innovatively applied a network analysis model to deconstruct the public's risk perception topology of drone delivery. They found that property damage from malfunctions and privacy violations formed a coupled cluster through strong connections. Their simulation experiments demonstrated that interventions targeting central nodes provided a precise, cognition-structure-based targeting strategy for risk communication. This finding confirms the existence of dynamic feedback between technical failure risks and social acceptance in last-mile delivery scenarios, necessitating structural interventions to break negative cycles. Furthermore, the study by Maeng et al. [15] was the first to indicate that the core challenge of drone safety has shifted from purely technical failures to "human-machine-environment" coupled risks.

Phase Two of the research primarily focused on assessing the likelihood of risk occurrence and evaluating the severity of risk consequences. Representative achievements include economic loss models that integrate impact kinetic energy and population density distribution, as well as casualty probability algorithms that incorporate trajectories of airframe disintegration. Such models provide quantitative targets for risk control strategies. Among these, Bayesian Networks (BN) have gradually become a mainstream tool for dynamic risk analysis due to their dual capability in event logic modeling and probabilistic reasoning. For example, Liu and Shen [16] focused on biological sample transportation scenarios and quantified the coupled risks of cold chain temperature control failure and hazardous material leakage. Li and Nie [17] developed an ISM-BN hybrid model for collision accidents, confirming that propulsion system failures and electromagnetic interference are core causative factors. Han et al. [18], from the perspective of failure mechanisms, demonstrated that battery power anomalies and propeller fractures are common vulnerabilities in crash accidents. These studies collectively form a key consensus: the reliability of the propulsion system is the common root cause of multiple types of operational risks in logistics drones. Notably, Ren and Chen [19] innovatively introduced a third-party risk perspective and constructed a three-dimensional grid-based risk index model. By quantifying the weighted composite of injury risk (potential casualties from crashes) and noise risk, they expanded the dimensions of risk assessment. Allouch et al. [20] proposed a qualitative safety analysis method combining ISO 12100 and ISO 13849 standards with a quantitative analysis framework based on Bayesian Networks. This approach systematically identified internal and external risk sources faced by drones in internet-connected environments and validated the feasibility and effectiveness of the hybrid method in drone delivery applications through case studies. This research further emphasized the necessity of multi-factor coupled risk analysis and provided methodological support for scenario-specific risk assessment. Hannan et al. [21], from an operational perspective, confirmed that environmental interference is a core constraint affecting the reliability of identity authentication in drone delivery systems.

In the third phase, research has primarily centered on determining risk acceptability and developing frameworks for risk control and mitigation. For instance, Shao [22] empirically demonstrated in Taiwan that within a layered UTM (Unmanned Traffic Management) architecture, population density-based ELS (Equivalent Level of Safety) calculations combined with real-time trajectory adjustments could reduce delivery risks in suburban areas below acceptable levels. This offers a technical template for scalable applications in high-density urban environments. Zhang [23] proposed a blockchain-based distributed security enhancement solution, moving beyond the traditional centralized risk management model of UTM. Additionally, Alsawy et al. [24] addressed the lack of automated safety assessment during parcel delivery by introducing a lightweight image processing framework. By integrating monocular camera and GPS data, they achieved end-to-end real-time safety assurance—from static safety assessment to dynamic risk monitoring of drop zones. An analysis of these studies on logistics drone risks reveals that while existing research has identified risk sources, probabilities, severity levels, and proposed corresponding control measures, practitioners still struggle to pinpoint root causes and assess cascading effects among risks. Moreover, evaluating the operational risks of urban logistics drones must begin with an analysis of mission profiles and operational scenarios [25]. As emphasized by Han et al. [25], urban logistics drones typically operate at altitudes of 70–150 meters over densely populated areas. Therefore, task attributes, operational environments, and drone models serve as essential prerequisites for assessing ground collision risks and formulating targeted mitigation strategies. Consequently, establishing a systematic framework capable of identifying and analyzing safety risks specific to last-mile delivery scenarios and drone types is critical for promoting the widespread adoption of this technology [6].

In summary, current research exhibits the following limitations:

(1) Lack of Scenario-Specific and Drone-Specific Analysis: Most safety risk studies focus on logistics drones as a whole or broad operational contexts. There is a notable scarcity of refined safety risk research targeting high-density, highly dynamic urban last-mile delivery environments—particularly for electric multirotor drones, which dominate such scenarios. Urban-specific challenges, including building canyon effects, frequent take-off and landing cycles, high population density, and complex electromagnetic environments, as well as the unique characteristics of electric multirotor drones in terms of infrastructure and mechanical design, require urgent and targeted investigation.

(2) Overreliance on Data-Intensive Models: Mainstream research on key risk factors heavily depends on Bayesian Network (BN) models to identify critical risks. However, parameter learning in BN models necessitates large volumes of complete accident data. Given the relatively short history of commercial operations for urban last-mile delivery drones—especially electric multirotor models—the available safety incident databases remain far from comprehensive. Consequently, the robustness of existing BN-based findings derived from limited data is questionable, underscoring the need for cross-validation and supplementation through integration with other methodologies.

(3) Inadequate Systemic and Hierarchical Risk Analysis: Urban last-mile drone safety constitutes a highly coupled complex system. Current evaluations predominantly focus on calculating probabilities or consequences of isolated risk events (e.g., collisions or crashes) and conducting risk ranking, while neglecting the analysis of causal interactions and hierarchical structures among key factors that constitute the entire risk system. This significantly limits the ability of managers to accurately trace risk evolution pathways, identify critical leverage points, and implement efficient interventions from a systemic perspective.

To address these gaps, this study integrates the strengths of three modelling approaches: The DEMATEL model, which quantitatively expresses causal relationships among factors within the system; The ISM approach, which stratifies risk factors into surface, intermediate, and fundamental levels to construct a multi-level hierarchical structure and clarify risk transmission paths; The MICMAC method classifies factors based on their attributes and clarifies interrelationships and control priorities within the system [26–28].

By combining these methodologies, this paper constructs a three-dimensional analytical framework—"causality-structural hierarchy-attribute classification"—focused on electric multirotor logistics drones in urban last-mile delivery scenarios. A safety risk factor indicator system is established based on literature review and official regulations. The core of this research lies in developing a fuzzy DEMATEL-ISM-MICMAC hybrid model to deeply investigate the coupling relationships, causal connections, and relative importance of various risk factors; clarify their interaction pathways; and reveal critical regulatory nodes within the system. This provides a theoretical foundation for subsequent decision-making in safety risk prevention and control.

3 Construction of a Risk Influence Factor System

Given that urban logistics drone technology is still in its infancy of development, there is a relative lack of comprehensive case studies on safe delivery accidents. This study primarily extracted safety risk influence factors from relevant literature and current national and industry standards and regulations. Through systematic searches in the databases of the China National Knowledge Infrastructure (CNKI), Google Scholar, and Web of Science (WoS), a total of 114 valid samples from the literature were screened using keywords such as "logistics drone delivery", "drone delivery risks", "drone delivery", "drone deliver risk", "UAV delivery", "drone logistics", and "multicopter risk". Based on this, references to national regulations and industry standards were identified, such as the "Interim Regulations on the Management of Unmanned Aerial Vehicle Flights", "Specifications for the Establishment of Logistics Flight Routes for Light and Small Unmanned Aerial Vehicles in Urban Scenarios", "Technical Requirements for Logistics Electric Multicopter Unmanned Aerial Vehicle (Light and Small) Systems in Urban Scenarios", "Technical Requirements for Takeoff and Landing Sites of Electric Vertical Takeoff and Landing Aircraft (eVTOL)", "Operational Standards for Drone Logistics Delivery", and the "Guidelines for the Trial Operation Certification of Civil Light and Small Unmanned Aerial Vehicle Logistics Delivery". A comprehensive analysis method was employed to systematically analyze and construct a system of safety risk factor indicators for urban logistics drone last-mile delivery from four core dimensions: personnel, equipment, environment, and management. Through a systematic review of global academic literature and industry policies and regulations, a preliminary set of risk factors affecting the safety of urban logistics drone last-mile delivery has been identified in Table 1. This approach ensured the comprehensiveness and credibility of the risk factor identification process, thus laying a solid theoretical foundation for subsequent expert evaluation.

Table 1. Safety risk factors for urban logistics drone delivery

Number	Secondary Indicator	Explanation of Influencing Factors
A1	Lack of Maintenance	Ground maintenance personnel need to repair and maintain components such as batteries, arms, propellers, motors, and ultrasonic systems.
A2	Low level of operational skills	The professional competence of urban logistics drone operators and transportation managers directly affects the safety and efficiency of the entire transportation process.
A3	Pre-flight inspection missing	Before takeoff, ground staff for urban logistics drones must conduct pre-flight checks, weather checks, and cargo-loading checks in accordance with the flight manual established by the operating company.
A4	Cyber attack	Unauthorized individuals can impersonate legitimate participants and engage in malicious activities when assuming false identities. Attackers may mimic valid drones, control stations, or users, subsequently hijacking drones to execute deviant flight paths, modify flight plans, or perform other malicious operations. Such actions exploit system vulnerabilities, compromising the performance of delivery operations.
A5	Power system failure	Failures in power equipment such as batteries, motors, speed controllers, and rotors can cause urban logistics drones to lose power.

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Number	Secondary Indicator	Explanation of Influencing Factors
A6	Communication/navigation system failure	Including remote controls, data transmission/image transmission modules, etc., to achieve human-machine interaction and data transmission. Drones use 4G networks and radio communication technology to transmit data to ground control centers and self-service parcel lockers, sending real-time geographic coordinates and status information, and receiving instructions from the control center.
A7*	Safety system failure	Urban logistics drones need to be equipped with safety devices such as parachutes, cameras, airbags, laser radars, sensors, and obstacle avoidance equipment to ensure that they can land safely in the event of an emergency.
A8	Ground control system failure	The operator's commands are transmitted to the drone via the ground system, enabling the drone to perform the corresponding operations. The information and data collected by the drone (flight status, energy status, cargo status, flight path weather conditions, etc.) are transmitted to the ground system and displayed and stored on the ground system's display or smart terminal.
A9	Flight control system failure	The flight control system ensures flight safety and stability. Failure or malfunction may result in loss of control, crash, or deviation from the planned flight path.
A10	Urban obstacles	High-rise buildings and natural terrain in urban environments can affect the risk of drone collisions. When drones encounter such obstacles, they need to adjust their heading or altitude to fly around them. During the fly-around process, drone collisions or even multiple drone collisions are likely to occur.
A11	Adverse weather conditions	Low-altitude wind shear, heavy rainfall, low clouds, thunderstorms, and other adverse weather conditions can easily affect drone operations in the air, interfering with drone flight paths and causing drones to veer off course.
A12	Electromagnetic interference	During flight, interference from various electronic devices or electromagnetic fields, such as radio signals, radar waves, high-voltage lines, urban Wi-Fi, 5G base stations, high-voltage cables, and other dense electromagnetic sources, may cause communication link interruptions or navigation signal distortion, thereby causing the drone's control system to lose its stable flight capability.
A13	Bird flight interference	The large number, diverse species, and random flight patterns of birds flying at low altitudes in cities pose significant uncertainty in terms of collision risk.
A14	Insufficient pre-service training	Operating companies' lack of systematic safety education and training for drone operators and carriers may lead to operational errors and equipment damage.
A15	Unreasonable route designation	Air route planning includes the design and planning of flight plans, such as air routes, approach and departure routes, takeoff and landing points, and safety separation standards. If logistics route planning is improperly set up, it may lead to temporary uncontrollable situations for drones, increasing the risk of accidents.
A16	Inadequate contingency plans	Carriers need to develop contingency plans for situations that may arise during the operation of logistics drones (such as drone crashes, emergency landings, hijackings, loss of control links, and illegal interference with ground control stations). If contingency plans are inadequate, it may be difficult for logistics drones to fly and land safely.
A17	Violation of relevant laws and regulations	If an operating company fails to submit the application for review, it may violate relevant laws and regulations, potentially leading to unauthorized flights and causing safety incidents.

4 Research Methods

As a carrier for low-altitude logistics, urban logistics drones have a complex system and multiple influencing factors that are interrelated and causal in nature, making it difficult for traditional quantitative methods to effectively characterize their internal mechanisms. To address this, this paper adopts an integrated system analysis framework combining Fuzzy-DEMATEL, ISM, and MICMAC (as shown in Figure 1) to systematically assess the safety risk factors influencing urban logistics drone last-mile delivery, revealing their complex interactions and hierarchical structure. Specifically: first, Fuzzy-DEMATEL is combined with fuzzy theory to mitigate the ambiguity and subjectivity in expert evaluations [29], identifying and quantifying causal relationships between factors. Second, ISM is applied to construct a hierarchical structure model, clarifying the transmission pathways of factors from root causes to surface phenomena. Finally, MICMAC analysis is used to cluster factors into four groups—autonomous, dependent, interdependent, and independent—based on the dependency of driving forces. This methodological framework ensures a thorough analysis of risk factors, providing support for optimizing safety management decisions. Given that the large-scale commercial application of urban logistics drones in last-mile delivery is still in its early stages, obtaining detailed and publicly available real-world accident data remains challenging, which consequently limits the use of purely data-driven models—such as Bayesian Networks—for in-depth analysis. However, the fuzzy DEMATEL-ISM-MICMAC integrated framework based on expert knowledge, as employed in this study, offers an effective methodological response to such "data-poor" complex system problems. Its strength lies in its ability to deeply extract and structure the tacit knowledge of domain experts, thereby revealing the internal structure and interaction mechanisms among system elements during the early research phase when extensive statistical data are lacking.

Although experimental data are scarce, this study constructs a multi-tiered, structured risk analysis model by integrating authoritative literature, regulatory guidelines, and rigorously screened evaluations from seasoned experts. The value of this model lies not in providing precise probabilistic predictions, but in systematically clarifying key driving factors, transmission paths, and hierarchical relationships within a complex risk network—offering prioritized insights and theoretical understanding for risk management. Future research may empirically validate and dynamically update the conclusions of this model as more industry data become available.

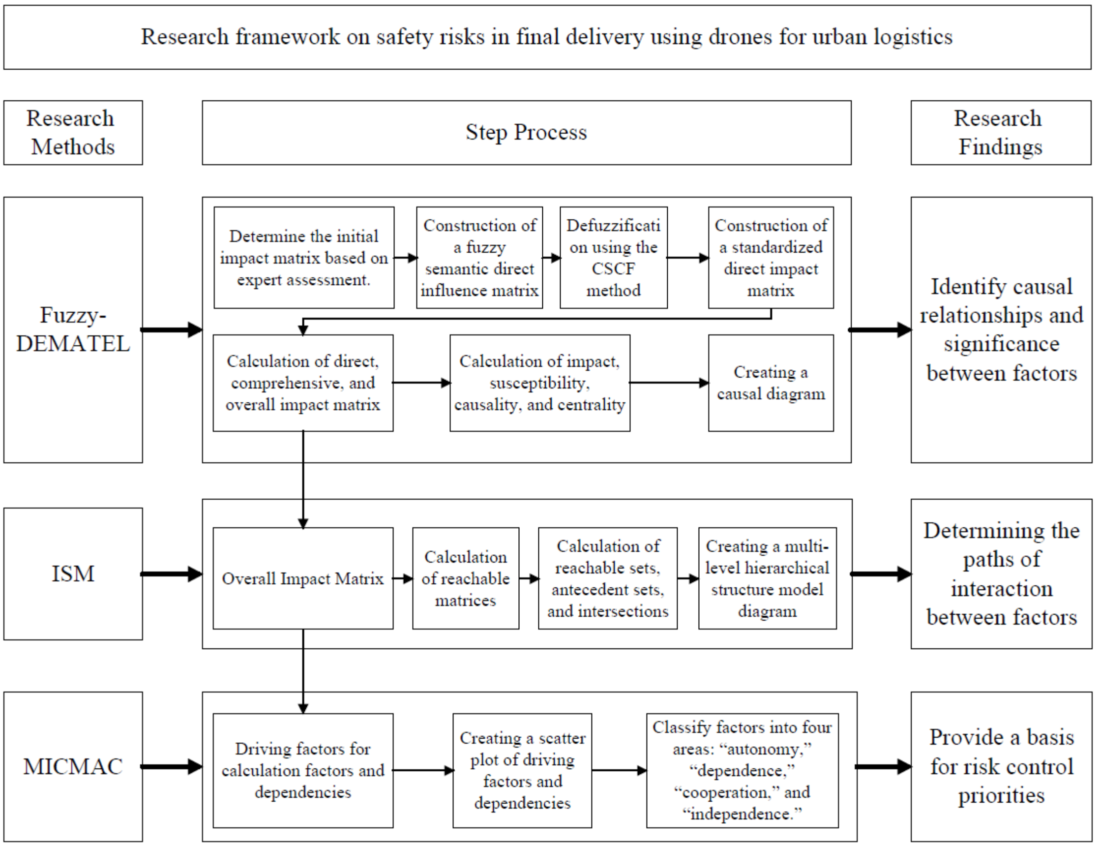

Figure 1. Research framework diagram

4.1 Fuzzy-DEMATEL Model

The DEMATEL method is a methodology proposed by American scholars Gabus and Fontela for addressing complex problems [30]. This method utilizes the logical relationships and direct influence matrices among the elements within a system to calculate the influence and affectedness of each element on others, thereby determining the causality and centrality of each element, and establishing the causal relationships between elements and their respective positions within the system. The specific calculation steps are as follows:

(1) Obtain the initial direct influence matrix. Five logistics experts and industry practitioners from both academic and industrial sectors were invited to pairwise score the 17 influencing factors. The experts rated the relationships between factors using a five-level scale: "0" for no influence, "1" for weak influence, "2" for moderate influence, "3" for strong influence, and "4" for very strong influence, thereby determining the direct influence levels between different factors and forming the initial direct influence matrix. The basic information of the experts is presented in Table 2.

Table 2. Basic information of experts

Expert	Academia/Industry	Professional Experience	Specialized Domains
E1	Academia	$>$ 3 year	Master's Degree
E2	Academia	$>$ 3 year	Master's Degree
E3	Academia	$>$ 5 year	Associate Professor
E4	Industry	$>$ 5 year	Drone operator
E5	Industry	$>$ 7 year	Logistics Operations Manager

(2) Establish a clear direct impact matrix. Use the Converting the Fuzzy Data into Crisp Scores (CFCS) method to defuzzify the fuzzy semantic direct impact matrix and obtain the defuzzified clear direct impact matrix [31]. The fuzzy semantics conversion table is presented in Table 3.

Table 3. Expert evaluation and triangular fuzzy number conversion table

Expert Evaluation	Impact Value	Triangular Fuzzy Number
No impact	0	(0, 0, 0.25)
Weaker impact	1	(0, 0.25, 0.5)
Moderate impact	2	(0.25, 0.5, 0.75)
strong influence	3	(0.5, 0.75, 1.0)
Extremely strong influence	4	(0.75, 1.0, 1.0)

The specific steps are as follows:
Standardization

$$xl_{ij}^{k} = \frac{l_{ij}^{k} - \min l_{ij}^{k}}{\Delta_{\min}^{\max}} \tag{1}$$

$$xm_{ij}^{k} = \frac{m_{ij}^{k} - \min l_{ij}^{k}}{\Delta_{\min}^{\max}} \tag{2}$$

$$xr_{ij}^{k} = \frac{r_{ij}^{k} - \min l_{ij}^{k}}{\Delta_{\min}^{\max}} \tag{3}$$

Among them $\Delta_{\min}^{\max} = \mathrm{maxi}_{\mathrm{ij}}^{\mathrm{k}} - \mathrm{minl}_{\mathrm{ij}}^{\mathrm{k}}$.
Calculate the standardized values for the left and right sides:

$$xls_{ij}^{k} = \frac{xm_{ij}^{k}}{1 + xm_{ij}^{k} - xl_{ij}^{k}} \tag{4}$$

$$xrs_{ij}^{k} = \frac{xr_{ij}^{k}}{1 + xr_{ij}^{k} - xm_{ij}^{k}} \tag{5}$$

Calculate the total standardized value:

$$x_{ij}^{k} = \frac{\left[xls_{ij}^{k}\left(1 - xls_{ij}^{k}\right) + xrs_{ij}^{k} xrs_{ij}^{k}\right]}{\left[1 - xls_{ij}^{k} + xrs_{ij}^{k}\right]} \tag{6}$$

Calculate the defuzzification value of the k expert evaluation:

$$z_{ij}^{k} = \min l_{ij}^{k} + x_{ij}^{k} \Delta_{\min}^{\max} \tag{7}$$

Based on the evaluations of various experts, a clear and direct impact matrix was obtained after defuzzification:

$$z_{ij} = \frac{1}{p}\left(z_{ij}^{1} + z_{ij}^{2} + \cdots + z_{ij}^{p}\right) \tag{8}$$

(3) Establish a normalized direct impact matrix. Normalize the direct impact matrix obtained using formula (10). That is, sum each row of the matrix, take the maximum value, divide all elements in the matrix by the maximum value, and obtain the normalized impact matrix.

$$B = \frac{z_{ij}}{\max\left(\sum_{j=1}^{n} z_{ij}\right)} \tag{9}$$

(4) Construct a comprehensive impact matrix. Continuously multiply the normalized direct impact matrix and add the results to represent the increased indirect impact between factors. The formula I is the unit matrix.

$$T = \left(B + B^{2} + \cdots + B^{k}\right) = \sum_{k=1}^{\infty} B^{k} = B(I - B)^{-1} \tag{10}$$

(5) Calculate the influence degree, affected degree, centrality, causality, and weight of each element. The influence degree refers to the sum of each row in the comprehensive influence matrix, representing the comprehensive influence value of each row element on all other elements. The affected degree refers to the sum of each column in the matrix, representing the comprehensive influence value of each column element on all other elements. Centrality indicates the position of a factor within the evaluation system and the magnitude of its role. The centrality of a factor is the sum of its influence and affectedness. Causality is obtained by subtracting the influence of a factor from its affectedness. Normalizing the centrality yields the weight of the indicator.

$$D_i = \sum_{j=1}^{n} x_{ij}, (i = 1, 2, n) \tag{11}$$

$$C_i = \sum_{j=1}^{n} x_{ji}, (i = 1, 2, n) \tag{12}$$

$$M_i = D_i + C_i \tag{13}$$

$$R_i = D_i - C_i \tag{14}$$

$$W_i = \frac{M_i}{\sum_{j=1}^{n} M_j} \tag{15}$$

(6) Draw a cause-and-effect diagram. Mark the positions of each influencing factor with centrality as the x-axis and causality as the y-axis, and draw a cause-and-effect diagram.

4.2 ISM Model

The Explanatory Structural Model (ISM) is a structured method. The essence of the ISM model lies in refining complex systems through a hierarchical structure, thereby facilitating the identification of key points [32]. This method can divide the safety risk factors of urban logistics drone last-mile delivery into surface, intermediate, and bottom layers, forming a multi-level hierarchical structure that provides a layered perspective for risk management. The specific calculation steps are as follows:

(1) Determine the overall influence matrix H. The overall influence matrix H is the sum of the comprehensive influence matrix and the n-order unit matrix I.

$$H = T + I \tag{16}$$

(2) Calculate the reachability matrix F. The key to establishing the reachability matrix is to determine the threshold value. Different values of λ will form different hierarchical models. If the influence of a factor is greater

than λ, then that factor can directly influence another factor. Conversely, if the influence of a factor on another factor is less than λ, then that factor has no direct influence on the other factor. The calculation formula is as follows:

$$\mathbf{F}_{ij} = \begin{cases} 1 & \mathrm{h}_{ij} \geq \lambda(i,j=1,2,19) \\ 0 & \mathrm{h}_{ij} < \lambda(i,j=1,2,19) \end{cases} \tag{17}$$

(3) Calculate the reachable set, antecedent set, and intersection. The reachable set consists of factors corresponding to columns with a value of 1 in each row, indicating the set of all factors that can be reached from that factor. The antecedent set consists of factors corresponding to rows with a value of 1 in each column, indicating the set of all factors that can reach that factor. Then calculate the intersection and perform factor stratification to obtain the reachable set, antecedent set, and intersection.

(4) Draw a multi-level hierarchical structure model diagram. Based on the results of the hierarchical division of influencing factors, combined with the influence relationships indicated in the reachability matrix, draw a hierarchical structure diagram of influencing factors.

4.3 MICMAC Model

(1) Calculate the driving force torque dependency. Calculate the driving force and dependency based on the reachability matrix F. The driving force represents the degree of influence of a factor on other factors, while the dependency represents the degree to which a factor is influenced by other factors.

$$\begin{aligned} Q_i &= \sum_{i=1}^{n} \mathrm{F}_{ij} \\ Y_i &= \sum_{j=1}^{n} \mathrm{F}_{ij} \end{aligned} \tag{18}$$

(2) Draw a driving force-dependence diagram. Based on the driving force and dependence values, draw a driving force-dependence diagram with the driving force as the horizontal axis and the dependence as the vertical axis. Each factor corresponds to a point in the coordinate system, and its specific coordinates reflect its correlation, dividing the factors into autonomous clusters (I), dependent clusters (II), connected clusters (III), and independent clusters (IV).

5 Analysis of Results

5.1 Identification of Key Risk Factors

Expert evaluation scores were used to obtain their judgments on the interrelationships between factors affecting the safety of urban logistics drone last-mile delivery. The results are shown in Table 4.

A causal relationship diagram was drawn based on the data in Table 4, as shown in Figure 2.

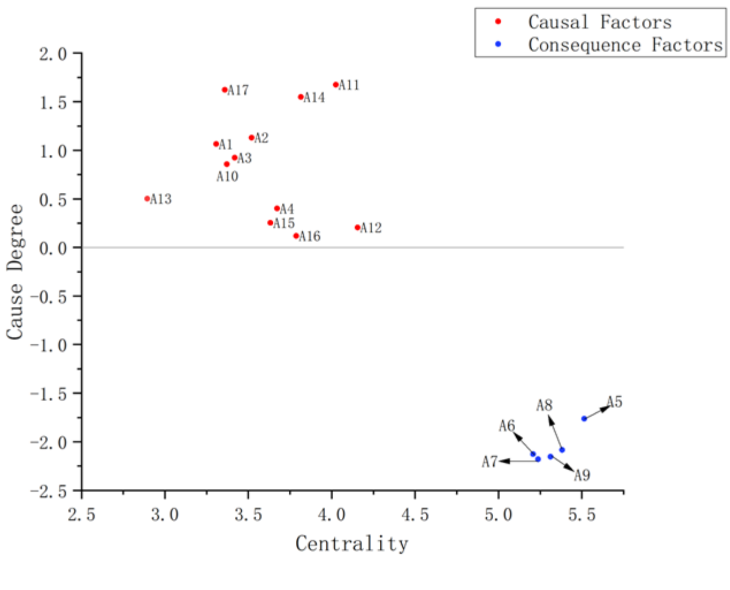

Figure 2. Causal relationship diagram of factors affecting the safety risks of urban logistics drone last-mile delivery

Table 4. Influence, affectedness, centrality, causality, and indicator weighting

Influencing Factors	Influence (D)	Degree of Influence (C)	Centrality (M)	Causality (R)	Weighting (W)	Centroid Sorting
A1	2.186	1.121	3.307	1.065	0.048	14
A2	2.325	1.195	3.52	1.13	0.051	12
A3	2.171	1.247	3.418	0.924	0.049	13
A4	2.037	1.635	3.672	0.402	0.053	10
A5	1.876	3.638	5.514	-1.762	0.079	1
A6	1.54	3.667	5.207	-2.127	0.075	4
A7	1.529	3.708	5.237	-2.179	0.075	4
A8	1.649	3.732	5.381	-2.083	0.077	2
A9	1.579	3.733	5.312	-2.154	0.076	3
A10	2.114	1.257	3.371	0.857	0.048	14
A11	2.85	1.175	4.025	1.675	0.058	7
A12	2.18	1.975	4.155	0.205	0.06	6
A13	1.698	1.196	2.894	0.502	0.042	17
A14	2.682	1.133	3.815	1.549	0.055	8
A15	1.943	1.689	3.632	0.254	0.052	11
A16	1.953	1.834	3.787	0.119	0.054	9
A17	2.491	0.868	3.359	1.623	0.048	14

The causal relationships between influencing factors can be quantified through cause measurement analysis: the higher the cause degree, the stronger the association of the factor. A positive cause degree indicates that the factor is a causal factor, while a negative value indicates that it is a result factor. Result factors are the comprehensive manifestation of the effects of causal factors. The state of result factors changes with alterations in the structural functions of causal factors, thereby leading to the complex dynamic evolution of safety risks. Based on the DEMATEL model's quantitative analysis, the influencing factors are categorized into 12 causal factors and 5 result factors. Among these, A11 (adverse weather conditions), A17 (violation of relevant laws and regulations), A14 (insufficient pre-service training), A2 (low operational technical proficiency), A1 (inadequate maintenance and inspection), A3 (lack of pre-flight checks), A10 (urban obstacles), A13 (bird flight interference), A4 (cyberattacks), A15 (unreasonable flight path design), A12 (electromagnetic signal interference), and A16 (inadequate emergency response plans) are the causal factors. The outcome factors include A5 (power system failure), A8 (ground control system failure), A6 (communication and navigation system failure), A9 (flight control system failure), and A7 (safety system failure).

Quantitative analysis based on the DEMATEL model indicates that the safety risks associated with urban logistics drone last-mile delivery exhibit a hierarchical structure characterized by "management-driven, equipment-constrained" factors. Regulations and pre-employment training, with high cause degrees ($R_v > 1.5$), are identified as the fundamental root causes of the system; Although power system failures have the highest centrality ($M_v > 5.3$), they are strongly constrained by other factors ($R_v < -1.7$), making them a key influencing factor in the system. However, their causality values are all significantly negative ($R_a \leq -2.127$), revealing that equipment failure factors (A5–A9) are passive carriers of environmental pressure and management defects; Conversely, low centrality factors such as A11 adverse weather ($R_a = 1.675$) and A17 regulatory violations ($R_a = 1.623$) exhibit strong causality characteristics, forming core risk sources.

This centrality-causality inversion phenomenon primarily stems from the equipment-management duality breakdown mechanism in urban logistics drone safety risks: At the engineering level, the flight duration of logistics drones operated by many logistics companies today is primarily between 30 and 60 minutes. As delivery tasks increase, this inevitably leads to higher workloads. Insufficient battery technology and the high frequency of urban last-mile logistics delivery tasks can cause drones to suddenly run out of power during operations, resulting in flight interruptions or even crashes. This is primarily due to the current constraints of battery technology in the industry [33]. This defect is amplified in short-term, high-power consumption urban last-mile logistics scenarios, ultimately causing the power systems of electric multi-rotor logistics drones to become physical carriers of systemic failure during high-frequency commercial operations. At the management level, despite the rapid development of low-altitude aircraft technology and related industries, many countries worldwide have not yet established clear regulatory frameworks to permit civil drones into their airspace [34]. Furthermore, if aviation authorities fail to implement rigorous safety design inspections for operational drones, it will be difficult to ensure that they meet stringent safety standards in practical operations. This may result in insufficient reliability of equipment performance, ultimately hindering the enhancement of industry norms and safety levels [35].The underlying contradiction may stem from the acceleration paradox in the context of the low-altitude economy, where the structural imbalance between "strong policy drivers, technological overload, and weak institutional constraints" is highly likely to trigger a chain reaction and exponential amplification of systemic risks in densely populated urban environments with complex airspace. This also highlights the need for a coordinated governance approach combining institutional constraints (to suppress the root causes of risks A14/A17) and redundant safeguards (to block the transmission chain of risks A5–A9) to mitigate the triple coupling risks of "environment–management–equipment."

5.2 Construction of a Hierarchical Model of Influencing Factors

The overall influence matrix H is determined according to Eq. (16). The threshold in the DEMATEL analysis is determined by repeated testing [9]. After multiple tests, this paper takes and obtains the reachable matrix according to Eq. (17), as shown in Table 5. The hierarchical structure of the influencing factors is divided according to the reachable matrix, and the results are shown in Table 6.

Based on the above hierarchical structure and reachability matrix, a multi-level hierarchical structure diagram of the safety risk factors affecting urban logistics drone last-mile delivery is drawn in Figure 3.

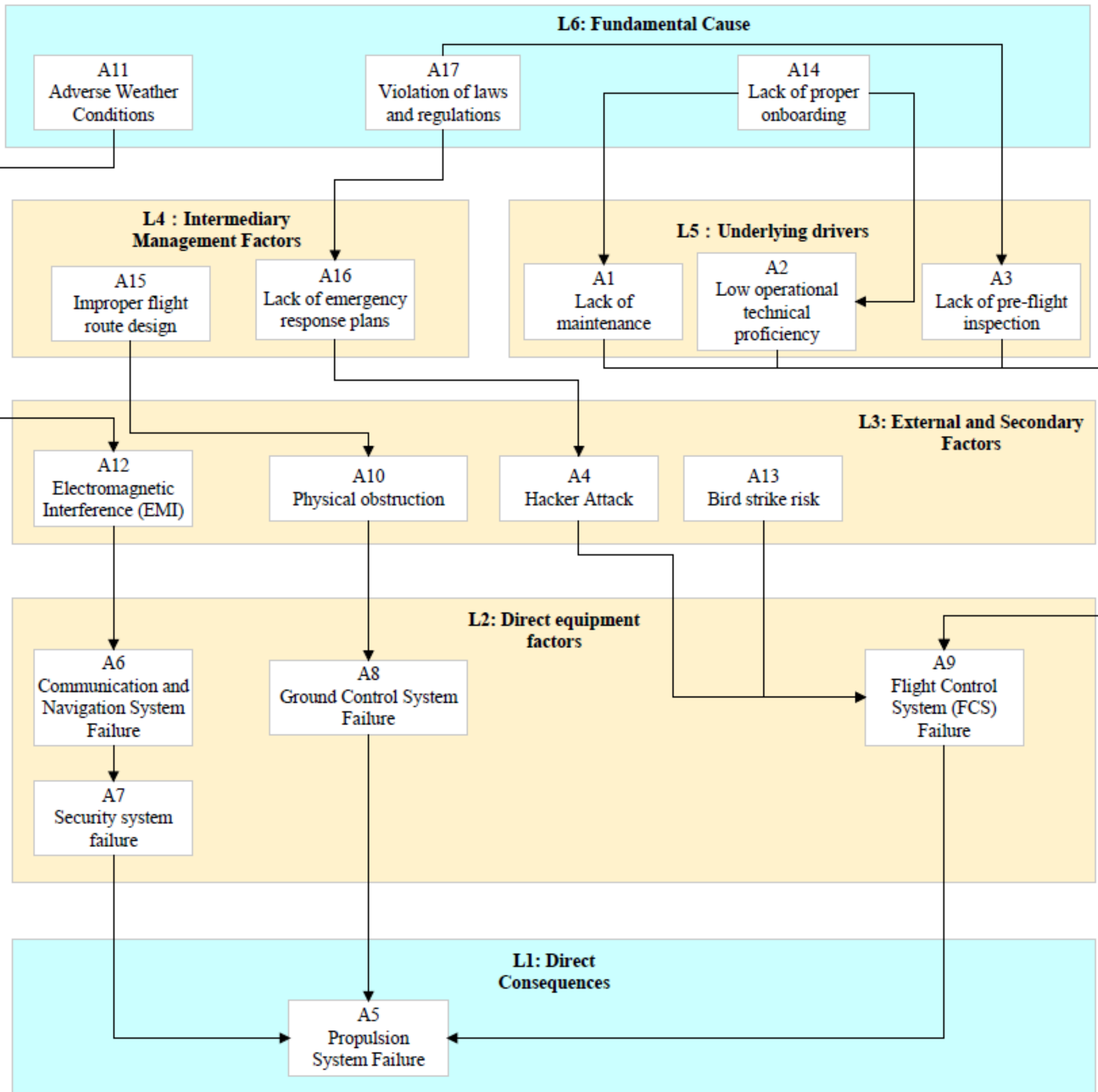

Figure 3. Multi-level hierarchical structure diagram of safety risk factors for urban logistics drone last-mile delivery

The ISM model categorizes the safety risk factors of urban logistics drone last-mile delivery into surface, intermediate, and underlying layers, thus forming a multi-level hierarchical structure that provides a layered perspective for risk management. Through hierarchical topological analysis, it is evident that risk factors exhibit a pyramid-shaped hierarchical isolation structure (L1–L6) and a fundamental-to-surface transmission pathway of "Management Deficiencies (L5/L6) $\rightarrow$ External Interference (L3) $\rightarrow$ Equipment Malfunction (L2) $\rightarrow$ System Failure (L1)". The fundamental layer of L6 includes two factors: violations of relevant laws and regulations in the management dimension and insufficient pre-employment training. This result aligns with the previous DEMATEL analysis, as these factors influence other layers through both direct and indirect transmission effects. The intermediate layers (L2–L5) include ten risk factors: low operational technical proficiency, adverse weather conditions, inadequate maintenance and inspection, missing pre-flight checks, urban obstacles, unreasonable flight route design, missing emergency response plans, cyberattacks, electromagnetic signal interference, and bird flight interference. Although these factors may not directly cause accidents, their complex relationships transmit safety risks generated by fundamental-level factors to surface-level factors, thus leading to insufficient overall system safety and placing the system in a vulnerable state prone to accidents. The surface layer of L1 includes equipment-related factors such as power system failure, communication and navigation failure, safety system failure, ground control system failure, and flight control system failure.

Owing to stringent regulatory controls on drone operations in China, which aim to ensure airspace security, the number of enterprises qualified for drone logistics delivery remains limited. Each operation requires pre-approval of key parameters such as airspace, time, and flight range. However, the application process for drone operation permits involves seven procedures, including national security review, radio frequency approval, and airspace use filing. Similar to the FAA's case-by-case airspace risk assessment approach, the absence of a standardized fast-track channel results in a routine approval time of 120–180 days for Beyond Visual Line of Sight (BVLOS) operations [36].This protracted approval process incentivizes companies—pressed by operational efficiency demands—to bypass or simplify reporting procedures. Such potential regulatory avoidance leads to flight activities operating outside effective oversight [37], directly giving rise to technical-level vulnerabilities including inadequate maintenance, operational errors, and inspection oversights. These deficiencies further amplify management risks such as flawed route planning and insufficient emergency preparedness. Under external disturbances, including adverse weather, electromagnetic interference, and cyber attacks, these weaknesses can trigger direct equipment failures such as communication/navigation malfunctions and flight control breakdowns. Ultimately, these subsystem-level failures become concentrated points of risk exposure, leading to safety incidents in logistics drone operations.

Table 5. Reachability matrix F

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**	**A13**	**A14**	**A15**	**A16**	**A17**
A1	1	0	0	1	1	1	1	1	1	0	0	1	0	0	1	1	0
A2	1	1	1	1	1	1	1	1	1	0	0	1	0	0	1	1	0
A3	0	1	1	1	1	1	1	1	1	0	0	1	0	0	1	1	0
A4	0	0	0	1	1	1	1	1	1	0	0	1	0	0	0	1	0
A5	0	0	0	0	1	1	1	1	1	0	0	1	0	0	0	1	0
A6	0	0	0	0	1	1	1	1	1	0	0	1	0	0	0	0	0
A7	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0
A8	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0
A9	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0
A10	0	0	0	0	1	1	1	1	1	1	0	1	0	0	1	1	0
A11	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	0
A12	0	0	0	1	1	1	1	1	1	0	0	1	0	0	0	0	0
A13	0	0	0	0	1	1	1	1	1	0	0	0	1	0	0	0	0
A14	1	1	1	1	1	1	1	1	1	0	0	1	0	1	1	1	1
A15	0	0	0	0	1	1	1	1	1	0	0	1	0	0	1	1	0
A16	0	0	0	1	1	1	1	1	1	0	0	1	0	0	1	1	0
A17	1	1	1	1	1	1	1	1	1	0	0	1	0	1	1	1	1

Table 6. Hierarchical division

Influencing Factors	Reachable Set	Preliminary Collection	Intersection
A1	1,4,5,6,7,8,9,12,15,16	1,2,14,17	1
A2	1,2,3,4,5,6,7,8,9,12,15,16	2,3,14,17	2,3
A3	2,3,4,5,6,7,8,9,12,15,16	2,3,14,17	2,3
A4	4,5,6,7,8,9,12,16	1,2,3,4,11,12,14,16,17	4,12,16
A5	5,6,7,8,9,12,16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	5,6,7,8,9,12,16
A6	5,6,7,8,9,12	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	5,6,7,8,9,12
A7	5,6,7,8,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	5,6,7,8,9
A8	5,6,7,8,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	5,6,7,8,9
A9	5,6,7,8,9	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17	5,6,7,8,9
A10	5,6,7,8,9,10,12,15,16	10,11	10
A11	4,5,6,7,8,9,10,11,12,13,15,16	11	11
A12	4,5,6,7,8,9,12	1,2,3,4,5,6,10,11,12,14,15,16,17	4,5,6,12
A13	5,6,7,8,9,13	11,13	13
A14	1,2,3,4,5,6,7,8,9,12,14,15,16,17	14,17	14,17
A15	5,6,7,8,9,12,15,16	1,2,3,10,11,14,15,16,17	15,16
A16	4,5,6,7,8,9,12,15,16	1,2,3,4,5,10,11,14,15,16,17	4,5,15,16
A17	1,2,3,4,5,6,7,8,9,12,14,15,16,17	14,17	14,17

5.3 Determining the Priority of Risk Factor Prevention and Control

Based on the reachability matrix F, calculate the driving force and dependency degree according to Eq. (18). The driving force represents the degree of influence of a factor on other factors, while the dependency degree represents the degree of influence of other factors on a factor. Based on the driving force and dependency degree values, plot a driving force-dependency degree scatter plot with the driving force as the x-axis and the dependency degree as the y-axis, as shown in Figure 4.

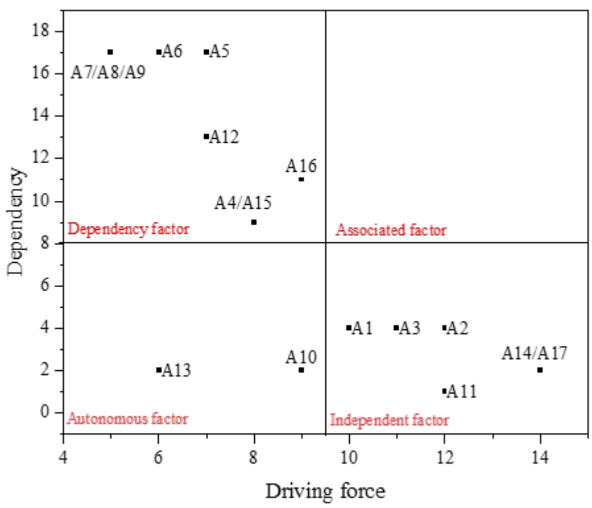

Figure 4. Diving-force-dependency power of factors influencing the scatter plot

The MICMAC model identifies the interrelationships and control priorities among factors within a system by examining the interactions and diffusivity of factors and categorizing them into different types [38]. Based on the MICMAC model's driver-dependency quadrant analysis, urban logistics drone risk factors are divided into four regions: I (autonomous cluster), II (dependent cluster), III (connected cluster), and IV (independent cluster). Autonomous Cluster (Zone I: Low Driving Force/Low Dependency). This zone includes only A13 (Bird Flight Interference). Its dual low characteristics indicate that this factor acts as a system inertia node under logistics operation companies'implementation of flight path avoidance strategies, exhibiting strong independence and a limited disturbance radius. (2) Dependent Cluster (Zone II: Low Driving Force/High Dependency) includes A6 (Communication Failure), A7 (Safety Failure), A8 (Ground Control Failure), and A9 (Flight Control Failure). These factors exhibit high interconnectivity but weak driving force, and are classified as top-level surface factors in the ISM. (3) Connection Cluster (Zone III: High Driving Force/High Dependency) includes A4 (Hacker Attack), A5 (Power Failure), A12 (Electromagnetic Interference), A15 (Route Defect), and A16 (Emergency Shortfall). Its dual-high characteristics make it a risk transmission hub (mid-level in ISM). (4) Independent Cluster (Zone IV: High Driving Force/Low Dependency) involves A14 (Training Deficiencies), A17 (Non-compliance), A11 (Adverse Weather), A2(Operational Inaccuracies), A3 (Inspection Omissions), A1 (Maintenance Negligence), and A10 (Obstacles). Their strong driving force and autonomy characterize systemic root causes (ISM bottom layer).

Based on the MICMAC results for each factor, the following priority order for risk prevention and control is proposed: First, strengthen management pillars by revising the Civil Aviation Law of the People's Republic of China or promoting specialized legislation for drone logistics to establish high-level legal standards, providing a unified basis for industry operations and regulation. Simultaneously, develop specialized regulations covering the entire lifecycle of commercial drones (production, sales, operation, maintenance) to clarify operating license conditions, technical standards for logistics drones, and liability allocation for infringements. Local governments may formulate detailed rules based on regional economic and industry development realities to promote localized development. Strengthen pre-employment training, with unmanned aircraft operators required to obtain licenses in accordance with regulatory authority requirements; those not required to hold licenses must complete training and pass assessments as required by operators. Operators should conduct theoretical and practical training for unmanned aircraft operators based on their duties and capability requirements, establish training curricula and assessment records, and maintain updates. Through regulatory compliance reviews and the restructuring of training systems, control measures A14 and A17 should be implemented to eliminate risk sources at their source; secondly, a dynamic joint defense mechanism should be established. For technical failures, environmental disturbances, and management deficiencies within the interconnected clusters (A4-A6, A9-A16), logistics companies should implement multi-layer encryption and authentication, and equip dedicated anti-interference hardware and active defense systems to enhance cybersecurity and anti-interference capabilities; Integrate with air traffic control systems to obtain real-time civil aviation and no-fly zone information, achieve centimeter-level path avoidance, and deploy millimeter-wave radar and infrared cameras for bird detection, triggering acoustic deterrent devices; install miniature weather stations to monitor wind speed and turbulence in real time, automatically execute pre-set return-to-base/emergency landing procedures during communication interruptions, and utilize offline maps to locate safe zones and respond to extreme scenarios. Finally, standardize routine operations and implement standardized process management for low-motivation factors such as reliance on clusters (A1-A3). Ultimately, through strategic pivot point regulation and multi-node optimization, achieve Pareto-optimal allocation of control resources and reduce the probability of systemic failure.

In summary, the comparison between the MICMAC results and the Fuzzy-DEMATEL-ISM model demonstrates the accuracy and validity of the modeling analysis in this study.

6 Conclusions and Recommendations

6.1 Conclusions

This paper reviewed literature and official reports on urban logistics drones and analyzed them from four dimensions: personnel, equipment, environment, and management. It established a set of safety risk factors for urban logistics drone last-mile delivery, including one primary indicator and 17 secondary indicators. The paper applied the fuzzy DEMATEL-ISM-MICMAC method to provide logistics operators with a three-dimensional risk factor analysis framework based on "causal relationship structure hierarchical attribute classification". This study revealed three core conclusions through multi-model coupling analysis: (1) The safety risk system for urban logistics drone last-mile delivery exhibited a "dual-core driven–multi-loop coupled" characteristic. System failure is the key risk factor for urban last-mile logistics drone systems, while root-cause driven risks stem from management institutional variables. The underlying mechanism is that policy-driven commercialization acceleration leads to a negative spiral of "management lag" and "technological overload"; (2) The risk hierarchy followed a pyramid-shaped transmission path structure, propagating from the fundamental layer to the surface layer in a rigid transmission mechanism: "management defects → human error → environmental amplification → technological collapse". In this process, open airspace acted as an accelerator, transforming environmental disturbance factors such as electromagnetic interference into accelerators for the transmission of institutional defects to technological failure; and (3) Low-altitude airspace enabled factors to simultaneously serve as both risk sources and transmission media. The driving dependencies of each factor reflect the priority order of risk prevention and control, starting from (i) Taking management as the core of strategic control; (ii) Focusing on the environmental-technical interaction network for joint prevention; and (iii) Standardizing operational procedures to achieve mitigation of systemic risks. This study provided a three-dimensional analytical framework of "causal relationships-structural layering-attribute classification" for urban logistics drone managers and practitioners to determine the severity and root causes of safety risks, thereby promoting the sustainable and safe development of the low-altitude economy.

6.2 Recommendations

6.2.1 Strengthen regulatory and training management as levers to address root-cause risks

Accelerate Specialized Legislation and Standard System Development: It is recommended to add a dedicated chapter on “Commercial Operations of Unmanned Aircraft” in the Interim Regulations on Flight Management of Civil Unmanned Aircraft, or to promote the formulation of the Unmanned Aircraft Logistics Safety Management Regulations to provide a higher-level legal basis for the industry. At this stage, priority should be given to enforcing existing regulations such as the Specific Category Unmanned Aircraft Trial Operation Management Procedures (Trial) stipulated by the Civil Aviation Administration of China and the Technical Requirements for Electric Multi-Rotor Unmanned Aircraft Systems in Urban Logistics Scenarios. A mandatory operational licensing system for logistics drones should be implemented to clarify requirements for operators’ qualifications, aircraft airworthiness certification, and accident liability allocation.

Implement Mandatory and Standardized Pre-Service Training: The strict enforcement of the Civil Unmanned Aircraft Operation Safety Management Rules requires all operators to pass theoretical and practical examinations to obtain corresponding licenses. Operating enterprises should develop and register a comprehensive training syllabus covering daily operations, emergency responses, and maintenance in accordance with the industry standard, Operational Specifications for Unmanned Aircraft Logistics Delivery. Individual training records should be maintained, and simulator platforms should be regularly used for recurrent training and assessments to ensure operators can respond effectively to complex urban environments.

6.2.2 Build an intelligent collaborative defense system integrating "human-machine-environment" to precisely control cascading risks

To ensure secure and reliable urban operations, logistics drones should be equipped with encryption modules supporting national cryptographic algorithms and multi-factor authentication. In compliance with Civil Unmanned Aerial Vehicle System Security Requirements, along with anti-jamming frequency-hopping radios or 4G/5G backup links that undergo rigorous electromagnetic compatibility testing, complex electromagnetic interference could be countered. Additionally, integrating Automatic Dependent Surveillance-Broadcast receivers and cellular signals enables real-time air traffic alerts and coordination with manned aircraft, while Laser Imaging Detection and Ranging or millimeter-wave radar combined with high-precision maps ensures avoidance of centimeter-level static obstacles. Infrared cameras and acoustic-optical devices could be adopted for bird deterrence. Furthermore, drones should feature embedded micro weather sensors to monitor wind and turbulence with autonomous return thresholds. In case of communication or control failure, executing predefined emergency procedures with offline maps and onboard computing could locate safe landing zones and transmit positions via radio beacons to minimize ground risks.

6.2.3 Implement standardized operating procedures (SOP) and institutionalize the management of dependency risks

Implement a full-lifecycle maintenance record system: An electronic maintenance log should be established for each drone. The manufacturer’s maintenance manual should be strictly followed to conduct regular preventive maintenance and replacement of key components, such as the power system and communication modules to eliminate the practice of operating with known faults.

Enforce a pre-flight electronic checklist: Before each mission, operators must complete and submit a digital checklist via a dedicated application, covering items such as battery level, sensor status, and payload security. All data is automatically uploaded to cloud storage in order to ensure the inspection process is non-skippable and fully traceable.

7 Prospect

This study had several limitations. First, the identification of risk factors for last-mile delivery by logistics drones in 17 cities was derived from literature review and specifications of standard. Additional risks may be encountered in real-world operations; therefore, the list of influencing factors is not exhaustive. Due to the relatively short history of commercial operations in drone logistics delivery, there is a lack of real, detailed, and publicly available accident data. The degree of influencing factors was determined based on expert ratings. Although the Fuzzy-DEMATEL model helps mitigate subjective bias, a certain level of subjectivity and uncertainty remains. Future research should involve multiple experts from diverse knowledge domains to enhance the comprehensiveness of the model. Support to obtain more objective data is also required to refine the descriptions of the factors, validate the findings further, and derive more robust conclusions.

Author Contributions

Conceptualization, Y.Y.Z. and X.L.L.; methodology, X.L.L.; validation, X.L.L. and N.N.Z.; formal analysis, X.L.L.; investigation, X.L.L.; data curation, X.L.L., N.N.Z. and Y.X.X.; writing—original draft preparation, X.L.L.;

writing—review and editing, Y.Y.Z.; visualization, X.L.L.; supervision, Y.Y.Z.; project administration, Y.Y.Z.; funding acquisition, Y.Y.Z. All authors have read and agreed to the published version of the manuscript.

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Data Availability

The data used to support the research findings are available from the corresponding author upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

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Nomenclature

l	Lower bound of the triangular fuzzy number
m	Most probable value of the triangular fuzzy number
r	Upper bound of the triangular fuzzy number
I_{ij}^k	Lower bound of the triangular fuzzy number for the k expert's evaluation of the influence of factor i on factor j
m_{ij}^k	Most probable value of the triangular fuzzy number for the k expert's evaluation of the influence of factor i on factor j
r_{ij}^k	Upper bound of the triangular fuzzy number for the k expert's evaluation of the influence of factor i on factor j.
$\Delta_{\min}^{\max}$	Range of the triangular fuzzy numbers.
$xl_{ij}^k, xm_{ij}^k, xr_{ij}^k$	Normalized lower bound, most probable value, and upper bound of the triangular fuzzy number.
xls_{ij}^k, xrs_{ij}^k	Left normalized value and right normalized value.
x_{ij}^k	Total normalized value of the k expert's evaluation.
$\mathrm{z}_{\mathrm{ij}}^{\mathrm{k}}$	Crisp value of the k expert's evaluation
Z_{ij}	Element in the crisp direct influence matrix Z, which is the average of the crisp values from p experts.
Z	Crisp direct influence matrix
B	Normalized direct influence matrix
T	Total-influence matrix
I	Identity matrix
D_i	Degree of influence of factor i
C_i	Degree of being influenced of factor i.
R_j	Cause degree of factor i
M_i	Centrality degree of factor i
W_i	Weight of factor i
H	Overall influence matrix
F	Reachability matrix
F_{ij}	Element of the reachability matrix
λ	Threshold value for determining the direct influence between factors
Q_i	Driving power of factor i
Y_i	Dependence power of factor i

Subscripts

i, j	Index of risk factors $(\mathrm{i}, \mathrm{j} = 1, 2 \ldots, \mathrm{p})$, where n is the total number of factors $(\mathrm{n} = 17$ in this study)
k	Index of experts $(\mathrm{k} = 1, 2 \ldots \mathrm{p})$, where p is the total number of experts $(\mathrm{p} = 5$ in this study $)$