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Analysis and Empirical Study of Factors Influencing Urban Residents' Acceptance of Routine Drone Deliveries

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Abstract: The usage of drone delivery couriers has multiple benefits over conventional methods, and it is expected to play a big role in the development of urban intelligent logistics. Many courier companies are currently attempting to deliver express delivery using drones in the hopes that this new type of tool used for delivery tasks will become the norm as soon as possible. However, most urban residents are currently unwilling to accept the use of drones to deliver express delivery as normal. This study aims to find out the reasons for the low acceptance of the normalization of drone delivery by urban residents and formulate a more reasonable management plan for drone delivery so that the normalization of drone delivery can be realized as soon as possible. A research questionnaire was scientifically formulated which received effective feedback from 231 urban residents in Jinjiang District, Chengdu City. A binary logistic model was used to determine the factors that can significantly influence the acceptance of residents. In addition, the fuzzy interpretive structural model(Fuzzy-ISM) was used to find out the logical relationship between the subfactors inherent to these influencing factors. It was concluded that when the infrastructure is adequate, increasing public awareness and education, enhancing the emergency plan, lowering delivery costs, enhancing delivery efficiency and network coverage, and bolstering the level of safety management can significantly raise resident acceptance of unmanned aerial vehicle(UAV) delivery. Given the positional characteristics of the subfactors in the interpretive structural model(ISM) and matrices impacts croises-multiplication appliance classemen(MICMAC) in this study, we should first make sure that the drone delivery activities can be carried out in a safe and sustainable environment with all the necessary equipment, instead of focusing on increasing the residents' acceptance right away, in the future work of regularized drone urban delivery has not yet started the construction phase. There should be more effort put into building the links that will enable acceptance to be improved with higher efficiency, which will be helpful to the early realization of the normalization of drone urban delivery if there is already a certain construction foundation in the case where the drone delivery environment is up to standard and hardware conditions are abundant.

Keywords: drone delivery; acceptance; binary logistic; Fuzzy-ISM; management construction path

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1. Introduction

Nowadays, express delivery volume worldwide is increasing daily due to the e-commerce sector's explosive growth. Customers are demanding delivery methods that are more effective, safe, and affordable, and current logistics service providers are aggressively pursuing these goals [1]. At present, most academic research and real-world operations focus on the optimization of traditional transport distribution routes and the improvement of existing management modes. Overall, the effectiveness produced by these methods has been somewhat limited in recent years [2] since traditional transport modes are generally fixed in stone and can only be optimized at a micro level. Therefore, if logistics service providers wish to achieve more effective breakthroughs in improving distribution operations than they have in the past, they may have to seek a new distribution method in the future. Compared with traditional express delivery methods, in urban logistics, drones can break through the limitations of time, space, and geography due to technological breakthroughs, and realize the automation, unmanned delivery, and information of express delivery to solve some problems in resource allocation and traffic congestion of current urban logistics. Thus, it can improve the delivery efficiency and service quality of express delivery to ease the contradiction between express demand and express service capacity.

With the continuous development of artificial intelligence, automation, and other technologies, the efficient execution of military, security, patrol, logistics, and other tasks by drones will gradually become the norm [3]. This kind of distribution has untapped potential in the eyes of logistics service providers. Due to the continuous updating and maturity of UAV-related technologies, UAVs in logistics applications have gradually demonstrated unique performance advantages such as their low cost, environmental protection, and energy saving properties [4,5], and studies in the field of medical supplies, emergency supplies, and part of the conventional supplies distribution have shown that the use of UAVs for supplies distribution can effectively overcome the impact of the terrain environment on logistics activities, and based on combining scientific algorithms, to a certain extent can save the cost of labor, transportation, storage and other aspects of the logistics process [6–9]. As a result, many logistics organizations have made an effort during the past few years to conduct drone logistics pilots. In the United States, Amazon.com has suggested the Prime Air initiative, which aims to provide drone couriers with quicker and more convenient logistics and distribution services. In China, one of the biggest e-commerce platforms, Jingdong, has also established the Jingdong Drone Flight Base and begun to deploy drones in Jiangxi, Sichuan, Hunan, and other locations, and demonstrated success in express delivery. SF, a pioneering company in China's express delivery market, has also implemented the SF High-End Logistics Drone Manufacturing Base Project, demonstrating the viability of the current drone technology by safely operating its drones in Jiangxi, western Sichuan, Jinshan, Shanghai, the Great Bay Area, and numerous other locations for nearly one million frames [10,11]. Since the majority of drones used for distribution around the world are still in the experimental stages or have only being flown on a planned basis in more extreme environments, the Research and Development Perspectives is more inclined to improve drone reliability and optimize their distribution routes, which is to put them into daily distribution tasks safely and efficiently as soon as possible and to minimize the logistics costs associated through this new vehicle [12]. While drone research and development technology are advancing, the development of drone loading and unloading, ground transfer, airspace docking, and other related supporting facilities is still in its infancy. As a result, a mature drone distribution network cannot be formed, and little effort has been put into creating the drone logistics industry's "soft environment". The public has grown somewhat wary of adopting this new type of carrier for delivery tasks due to the ongoing influence of news about delivery trials and other tasks by drones [13,14]. While the drone delivery process requires the transmission of both personal information and goods, it is a new and rapidly evolving field of technology, so its corresponding targeted regulatory laws are comparatively lacking, while there is also concern that drone logistics activities will harm public safety, invade people's privacy, and result in other undesirable phenomena. In addition, the public is worried about the potential impact of drones on employment, which has led to opposition to the use of drones for daily express delivery work in some cities and nations [15]. Even for drone delivery, there is considerable opposition. The concept that the logistics sector intends to exploit this new kind of vehicle to widen its development route is not supported by this situation. Drone logistics is filling a void in the aviation logistics sector and is a crucial step in releasing the low-altitude field's resources to build a complete three-dimensional transportation network. The widespread promotion of drones, however, cannot be supported by the lower level of popular approval. It is critical to allay urban residents' current concerns about using new delivery tools and increase their acceptance of this effort if we want to launch extensive drone delivery trials soon or make future delivery missions using drones in cities the norm.

A high percentage of residents living in cities with larger overall sizes and higher population densities have low acceptance of drones for delivery activities [16]. To more clearly explore the root causes of urban residents' concerns about drones for delivery, this study will take the residents of the Jinjiang District of Chengdu City, a city with a high degree of population modernization and a high density in China, as the research object. Based on the characteristics of empirical research, after combining the academic questionnaire survey on relevant topics for urban residents, the authors use statistical methods and systematic analysis means to analyze the data obtained, to determine the influencing factors and their inherent logical relationships that lead to the low acceptance of drones by current residents in the normalized distribution of the city, and to obtain the path of the management construction of the drones when they carry out the distribution operation in the urban area, to provide a certain theoretical solution for the management of drones when they are employed in normal distribution tasks in the future.

2. Literature Review

Unmanned aircraft technology, also known as UAV technology, is a broad term that encompasses unmanned aircraft systems, unmanned aircraft engineering, and other related applications [17,18]. UAV technology is widely employed in many different industries, including photography, surveying and mapping, and engineering operations. The application scenarios for UAV technology are now being expanded regularly. Drone operations, etc. have become a research direction in various industries and can be used in situations where people cannot reach or where labor costs are extremely high, effectively improving operational efficiency and reducing operational costs. To contribute to the realization of the normalization of urban drone delivery, the main scenario of this study is based on the analysis of the users' influence factors on the normalization of the use of drone delivery in the city. This study also examines the acceptance of the application of drone technology in logistics and distribution.

Urban logistics mainly refers to the logistics that serve the city [19,20], realizing the flow, concentration, or dispersion of goods in the city, covering a variety of modes and system systems. Urban logistics emphasizes the point-to-point movement of commodities, which can be expressed in one of two ways: either by using logistics companies to express the form of realization or by hiring specialized personnel to express the directional movement of goods. There is another approach to implementing this type of logistics, though, and it makes use of drone technology. To support the promotion of the use of urban drone delivery technology, this study examines the intersection of urban logistics and drone delivery. The elements of the problem and their subfactors are examined in-depth from the perspective of residents' acceptance of drones in normalized urban delivery.

The feeling that different types of customer needs have been met to a certain extent is referred to as consumer acceptance [21]. It will directly affect the development of the product or service. This study mainly focuses on users' acceptance of the normalization of urban drone delivery and analyzes the major factors influencing users' acceptance of the normalization of urban drone delivery. By studying these factors, we hope to encourage the normalization of urban drone delivery.

Theoretically, the use of drones for cargo transportation can reduce logistics costs and carbon emissions compared to traditional transportation methods [22,23]. Some academics have focused their research on how to use intelligent algorithms to improve drone efficiency, reduce distribution costs, and reduce environmental impact. For example, Jeon et al. [24] used Mixed Integer Linear Programming (MILP) and other heuristic algorithms to successfully reduce the number of empty flights of logistics UAVs in a logistics UAV test on Jeju Island, which in turn increased the UAV utilization rate. Hu et al. [25] discovered that using new logistics delivery methods with iterative heuristic algorithms could effectively increase the flight distance of drones in logistics processes during drone delivery experiments on the island. Choudhury et al. [26] proposed a phased approach to developing algorithms that shorten UAV flight time, save UAV flight miles through existing ground transportation networks, and thus improve UAV efficiency. Hassija et al. [27] increased UAV flight time through a cost-optimal UAV charging schedule algorithm, which in turn achieves increased UAV efficiency. These studies have theoretically proved the feasibility of using drones for material distribution, and its logistics optimization effect compared with the existing traditional distribution methods, has a higher distribution efficiency and can save more logistics costs. However, these conclusions are reached through experimental flights or simulations, if in the future the city regularizes drone courier delivery, there may be a deviation between theoretical and actual results due to the complexity and variability of the environment and the differences in the way of management of the drone distribution [12].

Given the characteristics of the current network structure of urban logistics and the awareness of the widespread use of drones by urban residents, some scholars have conducted a significant number of social surveys and trials to make the use of drones in urban logistics the norm as soon as possible in the future. However, they have discovered that the use of drones in urban logistics at this stage faces a significant number of challenges. Merkert [15] found that at this stage, urban Australians prefer postal delivery to drone delivery, unless it offers significant speed and cost advantages. In a study by Park et al. [27], it was found that drones were inefficient compared to other modes of transport when delivering to multiple destinations in the same area, and that only by effectively addressing this problem will it be possible to transform the means of delivery from cars to drones from an economic point of view for future drone urban delivery. Ren et al. [28] found that, in addition to the risks that drones may pose to residents for technical reasons, the loud noise generated by their rotating blades is off-putting to urban dwellers, and people are very concerned about the invasion of their privacy by videos taken by drone-based cameras. Grote et al. [29] found that a lack of regulation on the use of drones around the world may lead to further problems, which may make it difficult for people to accept the use of drones in logistics activities on a large scale if the problem is not well addressed. Kellermann et al. [30] claim that industrial drones may be camouflaged by unscrupulous elements and utilized for terrorist attacks and illegal activities, which will cause locals to be concerned about drones for daily deliveries to some level. According to the findings of these studies, to achieve the normalization of drone delivery, in addition to the need for further reform and innovation in drone technology, it is necessary to strengthen the management of drone applications, achieve increased drone efficiency from a management standpoint, and improve urban residents' acceptance of the widespread use of drones.

Since drones cannot respond to emergencies promptly as human pilots can during flight, robust autonomous flight systems and safety control systems must be in place to ensure that drones can safely travel from takeoff to landing. At the present stage, the management of drones in countries all over the world is mostly limited to the restriction of the scope of drone activities (i.e., the requirement for drones to fly in a certain airspace), and the lack of effective management of drone application [31]. The lack of regulation has created great psychological concern about the use of this newfangled tool for social production. Cracknell AP [32] suggested that legislation on drone activities must be enacted as soon as possible to ensure that the lives and property of residents are not damaged by the massive use of drones. Menda et al. [33] argued that the operators of large drones for all types of industry must receive strict training and education and be informed of the relevant laws to avoid legal disputes and safety accidents arising from the work of professional drone operators. Khan et al. [34] analyzed the acceptance of drone delivery in Pakistan and found that residents of developing countries are concerned about the exposure of personal information in drone delivery, and the team called for the issue of privacy exposure to be effectively addressed in future drone operations. Sliusar et al. [35] argue that the current research on drone technology has far outstripped the research on drone management, that the management tools have failed to keep up with the technological upgrade, that more attention should be paid to the construction of the soft power of drones at this stage.

This will allow for more targeted monitoring and legislation on the use of drones in such operations and maximize public acceptance of such operations. Lundin [36] pointed out that the use of drones to carry out operations should not be limited to the management of the aircraft, but should also take into account the nature of the current operations, operators, etc., to develop a comprehensive professional management program, which will enable more targeted supervision and legislation related to drone operations, to maximize the public's of the use of drones to carry out operations.

In the research exploring how to use drones to make the distribution work more efficient, in addition to strengthening the way of technological upgrading, some scholars try to use comprehensive management tools to maximize the utilization rate of drone distribution. Gunaratne et al. [16], in their study on the distribution problem in low- and middle-income countries, found that utilizing a heterogeneous (i.e., trucks combined with drones) solution can be a more efficient way of accomplishing low-income country distribution tasks at the current stage than utilizing only drones for distribution. Kuru et al. [37] point out that the biggest economic problem with drones for distribution is that they are mostly empty during the return journey, which greatly wastes capacity, and suggest that cargo staging areas can be deployed in a scientifically optimized manner by region to reduce resource wastage due to empty loads. Perera et al. [38] proposed a new economic order lot model based on the nature of UAV work and the characteristics of local logistics warehouses, which can ensure that a certain number of UAVs can complete the regional distribution tasks within the specified working time. Goncharenko et al. [39] found through experiments that regularly carry out the necessary maintenance on mission UAVs, in addition to improving the service life of UAVs, can to a certain extent improve the efficiency of UAVs and reduce carbon emissions. Hossain et al. [40] found that, depending on the distance of the mission, using multi-stage UAV delivery (i.e., multiple UAVs arranged to relay the mission over a certain distance of the delivery route) has little impact on mission effectiveness but can significantly improve UAV usage time and result in cost savings.

Currently, there have been some studies on the acceptance of drone usage in urban areas. This paper has collected the latest relevant research literature from the past five years and compiled it into Table 1.

This body of literature demonstrates that much research is still being conducted on the topic of urban acceptance of the usage of drone logistics. Most of the literature only briefly describes the problems faced by urban drone delivery, generalizes the various factors affecting urban drone delivery, and tries to solve the problems by improving drone technology and optimizing drone delivery paths, and lacks analysis of the factors affecting the acceptance of urban drone delivery by residents as well as its inherent logical relationship, and there is no systematic and quantitative research. Based on these studies, this paper will investigate, analyze, and summarize further. It will first break down the major issues into five categories of research scope. Next, it will analyze the problem's constituent parts using survey data, determine the main issue factors based on an analysis of their significance, look into their intrinsic subfactors, and offer recommendations based on these subfactors. The study's identification of the management construction path can serve as a guide for policymakers as they develop policies, while also helping logistics providers prioritize their services to enhance customer satisfaction and minimize labor and resource waste. It will first break down the major issues into five categories of research scope. Next, it will analyze the problem's constituent parts using survey data, determine the main issue factors based on an analysis of their significance, look into their intrinsic subfactors, and offer recommendations based on these subfactors. The study's identification of the management construction path can serve as a guide for policymakers as they develop policies, while also helping logistics providers prioritize their services to enhance customer satisfaction and minimize labor and resource waste.

Table 1. Recent studies on the acceptance of the use of drones in urban logistics within the last five years.

Research Topic	Author	Published	Sample Size	Research Methodology	Key Findings
Public acceptance of the use of drones for logistics: The state of play and moving towards more informed debate [41]	Smith, A., Dickinson, J. E., Marsden, G., Cherrett, T., Oakey, A., & Grote, M.	2023/2	300	Online Survey	Residents have positive attitudes toward drone urban logistics and focus on the environmental benefits of drone logistics
Implementing mitigations for improving societal acceptance of urban air mobility [42]	Çetin, E., Cano, A., Deransy, R., Tres, S., & Barrado, C.	2022/1	Offline seminars	Observations, interviews, literature review	The concerns of the population about drones, which have already been responded to in several public surveys, are presented, along with several proposed measures
Attitudes towards Urban Air Mobility for E-Commerce Deliveries: An Exploratory Survey Comparing European Regions [43]	Silva, A. T., Duarte, S. P., Melo, S., Witkowska-Konieczny, A., Giannuzzi, M., & Lobo, A.	2023/6	925	Questionnaire, Cluster analysis	Different regions may have different attitudes towards drone delivery due to cultural differences, but overall attitudes are positive
Public acceptance of drone applications in a highly urbanized environment [44]	Tan, L. K. L., Lim, B. C., Park, G., Low, K. H., & Yeo, V. C. S.	2021/1	1050	Knowledge testing, KAP modeling	The public is positive about the use of drones, but the public still has more concerns
Consumer acceptance of delivery drones in urban areas [34]	Khan, R., Tausif, S., & Javed Malik, A.	2018/9	307	Quantitative analyses	Pakistan region sees privacy as a top issue related to unmanned delivery

3. Method

3.1. Research Steps

To shed light on the efficient management techniques that drones can adopt for urban delivery in the future and to comprehend the actual perceptions of urban residents towards this means of delivery at this stage, this paper will concentrate on the current acceptance of drone delivery activities by urban residents. First, based on the model paradigm, combined with relevant topic literature retrieval, research, and other empirical preliminary work, a set of scientific questionnaires that can effectively carry out statistical analysis of residents' acceptance was designed. After a large number of questionnaires were delivered to residents of target cities and effectively recovered, regression analysis of data was carried out using the binary logistic method. The factors that can effectively affect the current urban residents' acceptance of UAV express delivery activities were determined, and then the fuzzy interpretive structural model (Fuzzy-ISM) was used to deeply analyze the internal logical relationship of the subfactors of those factors related to the construction of UAV logistics. In addition, the impact of these factors on residents' acceptance from a deeper perspective was explored. This research lays a theoretical foundation for the final determination of the construction path of future urban drone delivery work.

3.2. Current Analysis of Residents' Acceptance of Drones in Regular Urban Delivery

In this paper, urban residents' acceptance of the normalization of drone delivery may be influenced by several factors mentioned earlier. However, ultimately, residents' evaluation of these factors will directly determine whether they accept the normalization of drone delivery. Therefore, we can regard this problem as a typical binary decision-making problem, i.e., the residents' attitudes may have only two endpoints: acceptance or non-acceptance. General studies frequently employ the Markov method, algebraic approach ordered binary decision diagrams, and other methods for analysis to address the binary decision problem. Given the design of the questionnaire and the volume of valid data obtained during the research for this work, using extremely complex methods for analysis may greatly increase the waste of mathematical power and make it impossible to achieve reliable conclusions. When paired with the binary logistic regression method, which can accurately predict whether an event will occur or not, and with comparatively simple calculation procedures, the final effective data volume of this study can meet the method's calculation volume requirements. Considering the complexity of the social phenomenon, this study also takes into account the various factors that may be connected to urban residents' current acceptance of the normalization of drone deliveries for express delivery. As a result, we may use the foundations of these two logics to create a model [45,46] that is generally quite self-consistent in logic, which will show the degree of influence of each factor on the acceptance more intuitively and provide a reference for subsequent in-depth analysis and scientific decision-making.

3.2.1. Model Construction

Based on logistic regression, a crucial instrument for probability estimation and classification prediction, binary logistic regression is a popular technique in statistical modeling analysis. It is frequently applied to forecast the likelihood of a "success-failure" occurrence. It is used to forecast categorically whether an event will occur or not on a "success-failure" issue. It is a technique that can aid with frequency variable prediction. It is a technique for forecasting the likelihood that a test taker will succeed or fail, or that they would respond to a question on the test with a yes or no answer. Numerous academic studies and business sectors, including marketing and analysis, investment analysis, financial risk analysis, etc., frequently employ this methodology.

It is possible to make predictions with tiny sample sizes that are yet large enough to be studied efficiently by using binary logistic regression models to find the optimal parameters to fit the model. Compared to previous complex classification procedures, the solution is more effective, the model computes more quickly, and it allows for the evaluation of several elements' concurrent impacts.

In the analysis of the study of urban residents' acceptance of drone delivery as the norm delivery method, the indicator of whether residents currently accept the use of drone delivery as the norm delivery method is set as the dependent variable, numbered D, under the properties of the binary logistic model [47,48]. D has a value of 1 if residents currently accept, and 0 if residents do not. The resulting binary logistic regression equation in this study is calculated as follows:

$$\mathrm{LogitP} = \ln(\mathrm{P}/1 - \mathrm{P}) = \beta_0 + \beta_1 \mathrm{A}_1 + \beta_2 \mathrm{A}_2 + \ldots + \beta_n \mathrm{A}_n + \varepsilon \quad (1)$$

In Equation (1), P is the probability that the current acceptance of routine delivery by drones by urban residents is acceptance, i.e., the probability of D = 1 occurrence. β_0 is the regression coefficient of the independent variable, β_n is positive, indicating that the nth factor has a positive effect on acceptance, and β_n is negative, indicating that the nth factor hurts acceptance. A_n indicates the nth independent variable affecting acceptance and ε is the random error. Two basic assumptions are made for the model in terms of the nature of the dependent variable and the equations constructed:

Hypothesis 1. *Urban residents' acceptance of drone delivery routinization varies. Individual characteristics (e.g., gender, education, age, lifestyle habits), monthly delivery volume, and other regularization factors are likely to influence whether residents choose to receive deliveries using drones in the future.*

Hypothesis 2. *In this study, the main factors affecting the acceptance of residents range from individual characteristics of urban residents, habits of accessing couriers, evaluation of traditional courier delivery modes, knowledge of existing drone technology, and various perceptions of future drone technology.*

As a result of combining prior analysis and field research, the survey variables/questionnaire design content of residents' opinions on drone delivery in urban areas in this study were identified, as indicated in Table 2.

3.2.2. Data Sources

In terms of the existing supporting conditions needed for drones to develop distribution activities in cities, large cities with a higher level of development and a larger population may have a better chance of adopting this technology to begin regular distribution activities sooner [49]. In terms of city layout and population distribution, Chengdu, China, has a well-developed infrastructure, a sizable city volume, a high population density, and a vast logistics network. In 2017, the first large-scale UAV feeder logistics transit project in China also landed in Chengdu. Therefore, this study chose to take the residents of Chengdu as the subject of the study. Given that urban residents in Chengdu may be more familiar with drone delivery-related activities than residents in other areas, and that the data obtained can more effectively reflect urban residents' attitudes toward accepting drone delivery, this study was conducted with urban residents in Jinjiang District, where drone delivery activities were carried out during the COVID-19 pandemic. After scientifically formulating the questionnaire for this study, the questionnaire was randomly distributed to residents of Jinjiang District, which is the most modernized district in Chengdu, and to residents of Taisheng Road, a community in Jinjiang District where drone delivery activities had been carried out, who went to the Qibao station to pick up goods during the peak period of the pickup period from 3 February to 7 February 2023, and the questionnaires were effectively collected as the raw data for the analysis of the residents' acceptance of drone delivery in the present study. It was used to identify the influencing factors related to the construction of drones with high impact. To maximize the validity of the questionnaire data, this study used offline distribution of the questionnaires and on-site collection of the questionnaires. Panelists met face-to-face with participants to answer as many concerns and questions as possible so that participants could accurately fill in the most desired option for each question. Considering that the sample size requirement of the binary logistic method is generally 10–15 times the number of independent variables [48], too much or too little data may cause bias in the analysis results, after consulting with statistical experts, the sample size required for this study was controlled by the team in the range of 200–300. In order to obtain valid questionnaires with 10–15 times the number of dependent variables and to ensure that the recovery rate of the questionnaires is above 80%, 50 questionnaires were distributed to each of the 5 sites in the test area, all questionnaires were filled out voluntarily and without any compensation by the site personnel, and 19 invalid questionnaires, such as those that were not filled out completely and those that were filled out with too many items were sorted out and sifted, and 231 valid questionnaires were returned (with an effective rate of 92.4%, which meets the range of sample size required by the binary logistic model). Furthermore, the data obtained could more accurately reflect urban residents' attitudes toward drone delivery of express delivery than those in regions that had not received related activities because the region had handled tasks relating to drone delivery of living materials during the prevention and control of the COVID-19 pandemic. In addition, the data analysis of the acceptance of regular drone delivery in the city, and the conclusions of the analysis of the binary logistic model are presented (the methodology and findings of the analysis are detailed in Section 4).

Table 2. Design of residents' survey variables/questionnaire design for drone delivery couriers in urban areas.

No.	Variable	Variable Definition	Variable Type	Remark
A1	Gender	0 = Male, 1 = Female	Nominal Variable	Basic information about the investigator
A2	Age	1 = 18–30 years old, 2 = 31–45 years old, 3 = 46–60 years old	Ordered variable	
A3	Education background	1 = Junior high school and below, 2 = High school, 3 = University, 4 = Masters and above	Ordered variable	
A4	Does using drones in your life or your job?	0 = no, 1 = yes	Nominal Variable	
A5	Monthly delivery volume	1 = many, 2 = fair, 3 = few/none	Ordered variable	Surveyors' evaluation of current express delivery
A6	Daily online product packaging specifications	1 = small, 2 = average, 3 = large	Ordered variable	
A7	Current distribution speed	1 = fast, 2 = moderate, 3 = slow	Ordered variable	
A8	Current Express Fee	1 = high, 2 = moderate, 3 = slow	Ordered variable	
A9	Is the current courier activity regarded as safe?	0 = no, 1 = yes	Nominal Variable	
A10	Is the perception that delivering by drone creates more safety issues?	0 = no, 1 = yes	Nominal Variable	Surveyors' evaluation of drone delivery
A11	Are you worried that delivery by drone cannot be accurately delivered to the designated location?	0 = no, 1 = yes	Nominal Variable	
A12	Are there concerns about additional legal risks associated with delivering with drones?	0 = no, 1 = yes	Nominal Variable	
A13	Whether the region can effectively regulate drones?	0 = no, 1 = yes	Nominal Variable	
A14	Do you mind the noise generated by the drone flight?	0 = no, 1 = yes	Nominal Variable	
A15	Whether the current drone delivery technology is considered immature?	0 = no, 1 = yes	Nominal Variable	
A16	Whether you think drone delivery is good for the environment?	0 = no, 1 = yes	Nominal Variable	
A17	Whether you think the adoption of drone delivery will reduce logistics costs?	0 = no, 1 = yes	Nominal Variable	
A18	Whether you think the adoption of drone delivery will speed up delivery efficiency?	0 = no, 1 = yes	Nominal Variable	
A19	Where do you most want drones to deliver to?	1 = home, 2 = express post, 3 = other	Nominal Variable	
A20	The most acceptable model of logistics drone?	1 = Fixed-wing aircraft, 2 = Multi-rotor aircraft, 3 = Vertical take-off and landing fixed-wing aircraft, 4 = Other	Nominal Variable	
D	Is it acceptable to use drones to deliver fast reads in urban areas regularly at the moment?	0 = no, 1 = yes	Nominal Variable	Surveyors' acceptance of drone delivery activities in urban areas (dependent variable)

3.3. Analysis of Intrinsic Subfactors of Factors That Have a Significant Impact on the Construction of Drone Logistics

To better develop urban drone logistics management strategies, taking into account the subfactors that exist within each variable and the specific relationships between them, it is necessary to examine the logical relationships between these independent variables. The binary logistic analysis allows for visualizing which key independent variables have a significant impact on the dependent variable, but since the underlying model does not allow for any possible interactions between the respective variables, in this study, after identifying the pertinent subfactors, the fuzzy explanatory structural model approach [50,51] will be used to further analyze the subfactors inherent in the factors related to the construction of drone logistics after identifying the relevant subfactors.

3.3.1. Model Construction

The traditional Interpretative Structural Modeling Method (ISM method), which was first proposed by John N. Warfield [52] in 1976 when he revealed the complexity problem, has now become one of the most widely used methods in system analysis after decades of intensive development. Traditional ISM is essentially a structural modeling technique that uses the mathematical logic underlying the existence of the research object. Through scientific topological operations on its conceptual system, traditional ISM eventually forms a highly streamlined and hierarchically directed topological diagram. The analyst can use the final topology diagram to determine the relevant order and overall focus of work in dealing with the existing problem of the research object and to find the optimal solution from a global perspective. However, the subjective judgment of the modeler may lead to inaccuracies [53,54]. It cannot, however, accurately indicate how strongly two objects are associated. The basic ISM lacks effective quantitative analysis to reflect the strength of the association between the objects; therefore, to address the issue of analyzing the strength of the association, it is necessary to further improve the basic ISM by the quantitative characteristics of ISM combined with other quantitative research methods, to further improve the model's accuracy, which may be hampered by subjective judgment. This study will combine the Delphi method to conduct thorough research and judgment on the influencing conditions, forming a fuzzy-ISM method to circumvent the result errors caused by individual subjective judgment errors as much as possible. The general procedure steps of this method are shown in Figure 1 to help explain how it works.

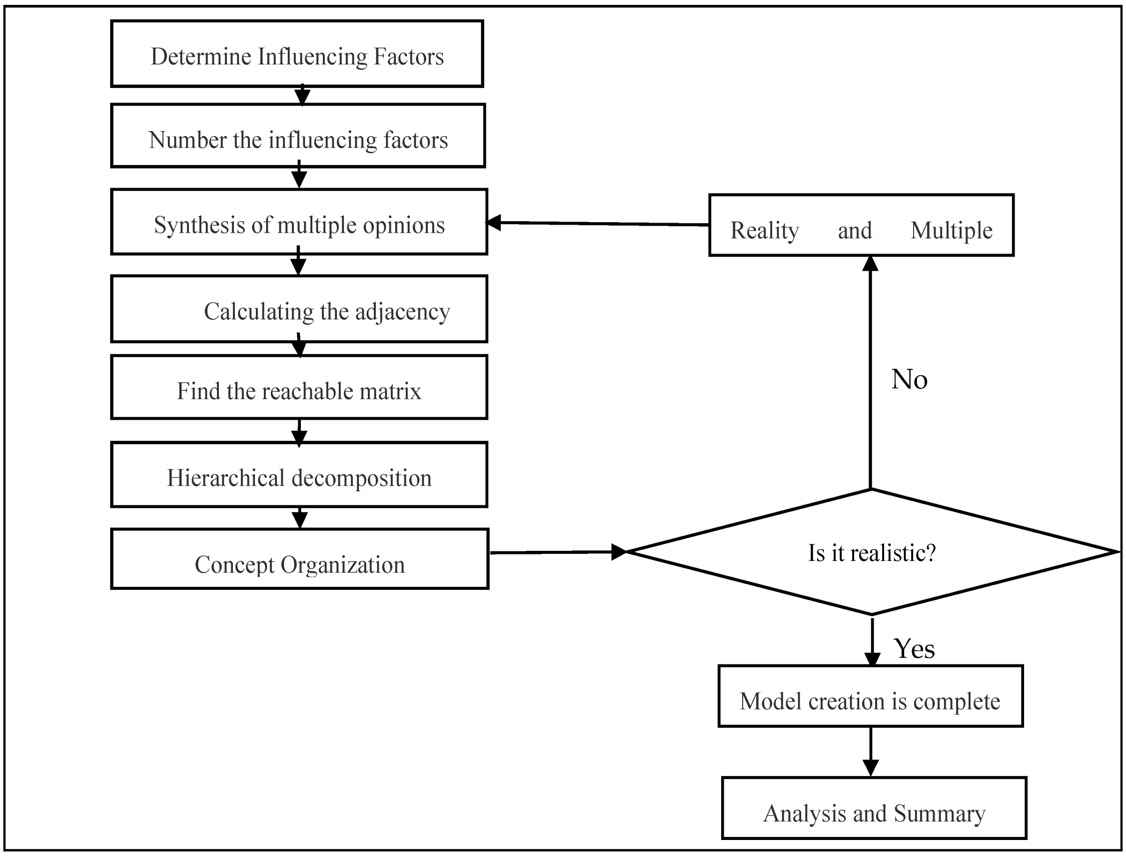

Figure 1. Fuzzy ISM general procedure.

Based on traditional ISM, the errors that may occur in the construction of a single evaluation adjacency matrix can be avoided through fuzzy mathematical processing of numerous evaluation data, and the basic idea is to utilize the precision unique to mathematical means to quantitatively describe and model the fuzzy concepts, phenomena, and logical relationships that may exist in the research object. The fuzzy content is identified as an appropriate mathematical indicator to increase the quantitative nature of the research method. At this stage of research, the fuzzy mathematical method can be used for judgment, speculation, decision-making, evaluation, etc., and applies to the development of research in several fields. It is a method of effective integration of multiple viewpoints using mathematical logic, and in previous studies, the use of Fuzzy-ISM methods for effective research on decision-making in supply chain management and business management has been relatively mature [55,56], and the modeling idea of these studies is to build a fuzzy evaluation by synthesizing the correlation strength data viewpoints between many influencing factors of the research object, establishing a fuzzy evaluation, to get comprehensive evaluation data that combine multiple viewpoints in mathematical logic, and use this comprehensive data to scientifically analyze the research object to draw a final effective conclusion.

This research is based on the theoretical steps of Fuzzy-ISM. Following the data collecting, processing, adjacency matrix, and reachable matrix solving processes, the final ISM is constructed, at which point the final logical relationships between the subfactors have been obtained and will be the basis for the conclusions of this study.

3.3.2. Data Sources

After reviewing the relevant literature and consulting with experts in drones and logistics, the team identified intrinsic subfactors for factors related to the construction of UAV logistics that have a large impact effect on the existence of the effect, then distributed the inter-factor interrelationship opinion request form to 21 professors of transportation and logistics related research directions at some universities located in Chengdu, on 10 February 2023, with complete instructions on the subfactor connotations and filling requirements. After the questionnaires were all retrieved validly on 17 February 2023, the analysis was carried out according to standard procedures, and the final ISM model was obtained (see Section 4 for the analysis process and results).

4. Descriptive Analysis

4.1. Binary Logistic Analysis of Resident Acceptance

4.1.1. Data Characterisation

Table 3 displays an overview of the study's validly recovered data. According to the preliminary survey data, 81 respondents—representing 35.03 percent of the valid surveys—temporarily reject the normalization of drone delivery in urban areas. This finding is consistent with the findings of previous studies [13,15,29], and the proportion of each component of other statistical indicators in the independent variable that are unrelated to drone delivery is also roughly in line with reality. According to the results of the statistical indicators related to drone delivery in the independent variables, the respondents generally believe that using drones for routine delivery tasks will cause many negative impacts. At the same time, a rather strange phenomenon emerged: the number of researchers who believed that drones could significantly improve the delivery environment but were more advantageous to the growth of the logistics industry was not obvious, specifically: 121 people, accounting for only 52.38% of the total survey, thought that delivery by drones could be accurately delivered to the designated location; 141 people, accounting for only 52.38% of the total survey, thought that delivery by drones could be accurately delivered to the designated location. This contradicts research and publications that claim drones can significantly help with the logistical "last mile" problem [3]. In the data analysis that follows, this study will also start a further scientific investigation into the origins of this occurrence.

Table 3. Statistical Results of Resident Acceptance Data.

Variable Number	Variable Definition	Count	Percentage
A1	0	102	0.4416
	1	129	0.5584
A2	1	114	0.4935
	2	55	0.2381
	3	62	0.2684
A3	1	31	0.1342
	2	111	0.4805
	3	72	0.3117
	4	17	0.0736
A4	0	201	0.8701
	1	30	0.1299
A5	1	54	0.2338
	2	126	0.5455
	3	51	0.2208
A6	1	100	0.4329
	2	94	0.4069
	3	37	0.1602
A7	1	55	0.2381
	2	142	0.6147
	3	34	0.1472
A8	1	37	0.1602
	2	151	0.6537
	3	43	0.1861
A9	0	200	0.8658
	1	31	0.1342
A10	0	52	0.2251
	1	179	0.7749
A11	0	110	0.4762
	1	121	0.5238
A12	0	68	0.2944
	1	163	0.7056
A13	0	132	0.5714
	1	99	0.4286
A14	0	38	0.1645
	1	193	0.8355
A15	0	61	0.2641
	1	170	0.7359
A16	0	110	0.4762
	1	121	0.5238
A17	0	90	0.3896
	1	141	0.6104
A18	0	29	0.1255
	1	202	0.8745
A19	1	83	0.3593
	2	128	0.5541
	3	20	0.0866
A20	1	49	0.2121
	2	89	0.3853
	3	89	0.3853
	4	4	0.0173
D	0	150	0.6494
	1	81	0.3506

4.1.2. Binary Logistic Conclusion Analysis

In this study, the data obtained were used to conduct a binary logistic regression analysis using SPSS. The all-in method was used to analyze the factors influencing the current residents' acceptance of the normalization of drones in urban delivery, and the calculated results are shown in Table 3. With a Hosmer –Lemeshaw significance coefficient of 0.361 (greater than 0.05), a model chi-square value of 8.78, an Omnibus significance of less than 0.05, a model Cox–Snell R-squared value of 0.593, a Negoco R-squared value of 0.816, and a model −2 log-likelihood value of 91.642, the regression model corresponding to Table 4 is in a good fit state and can be used for the following analysis.

Table 4. Regression results for dependent variable D.

Variable Number	B	S.E.	Wald	df	Sig.	Exp(B)
A1	−0.815	0.630	1.673	1	0.196	0.443
A2	0.276	0.560	0.242	1	0.622	1.318
A3	0.056	0.433	0.017	1	0.896	1.058
A4	−3.487	1.179	8.744	1	0.003	0.031
A5	−0.045	0.430	0.011	1	0.917	0.956
A6	−2.697	0.712	14.350	1	0.000	0.067
A7	−2.228	0.726	9.410	1	0.002	0.108
A8	−2.294	0.738	9.666	1	0.002	0.101
A9	0.080	0.817	0.010	1	0.922	1.083
A10	−3.148	0.912	11.923	1	0.001	0.043
A11	−3.754	0.945	15.766	1	0.000	0.023
A12	−3.954	0.929	18.111	1	0.000	0.019
A13	3.906	0.918	18.084	1	0.000	49.683
A14	−4.370	1.170	13.962	1	0.000	0.013
A15	−2.544	0.906	7.893	1	0.005	0.079
A16	2.324	0.855	7.380	1	0.007	10.214
A17	2.296	0.878	6.845	1	0.009	9.936
A18	6.279	1.627	14.891	1	0.000	533.510
A19	0.654	0.527	1.543	1	0.214	1.924
A20	−0.161	0.420	0.146	1	0.702	0.852
Constant term C	13.694	5.239	6.833	1	0.009	885,781.973

From the regression results in Table 4, the factors with Sig. values less than 0.05 can significantly influence the acceptance of current residents, which are: whether they are exposed to drones in their life/work, the packaging specifications of products purchased online, the current delivery speed, the current delivery fee, whether they believe that delivery by drones will cause more safety problems, whether they are concerned that delivery by drones will not be able to deliver accurately to the designated location, whether they are concerned that delivery by drone will create more legal risks, whether the drone can be effectively regulated in the region where it is located, whether they mind the noise of drone flights, whether they think that the current drone delivery technology is immature, whether they think that drone delivery is conducive to protecting the environment, whether they think that the use of drone delivery will reduce the cost of logistics, and whether they think that the use of drone delivery will speed up the efficiency of delivery. According to the binary logistic model properties [50], if new methods can be explored to make residents' evaluation of the above factors improve in the future, this could theoretically lead to an increase in residents' acceptance of the normalization of drone delivery in cities. In the next section, based on the results of this part of the analysis, we will continue to carry out more in-depth research to determine the path that should be followed in the construction of the future management of drone courier delivery.

4.1.3. Analysis of the Causes of Doubtful Statistics

As discussed in the previous section, some of the data analyzed in the study from a proportional perspective led to conclusions that contradict the prevailing view in the existing literature and research that drones can significantly solve the logistics "last mile" problem. According to the research team, this occurrence might be directly tied to the surveyor's personal traits, courier habits, and assessment of current courier delivery. To determine whether there is any evidence to support the conjecture, this study will continue to use the three dubious values (A11, A16, and A17) as the dependent variables and the nine factors relating to the surveyor's characteristics, the surveyor's courier habits, and the evaluation of current courier delivery as the independent variables. The distribution will also continue to be based on a binary logistic regression. The distribution of regression results for the three questionable value-derived models after the SPSS all-entry method is shown in Tables 5–7. Among them, the Hosmer–Lemeshaw significance coefficient for the regression model corresponding to Table 5 is 0.788 (greater than 0.05), the model chi-square value of 4.714, the Omnibus significance is less than 0.05, the model Cox-Snell R-square value of 0.089, Negoco R-square of 0.119, −2 log-likelihood value of 298.101. Table 6 corresponds to the regression model Hosmer–Lemeshaw The significance coefficient is 0.168 (greater than 0.05), the model chi-squared value is 11.636, the Omnibus significance is less than 0.05, and the model Cox–Snell R-squared value is 0.085, Negoelko R-squared is 0.113, and −2 log likelihood value is 299.201. Table 7 corresponds to the regression model Hosmer–Lemeshaw significance coefficient is 0.514 (greater than 0.05), the model chi-squared value of 7.211, the Omnibus significance is less than 0.05, the model Cox–Snell R-squared value of 0.155, Negoco R-squared of 0.211, −2 log-likelihood value of 269.894. From these data, these three derived models' data fit well, and consider that one can try to use these three derived models and related data to explain the causes of the strange phenomenon mentioned before.

In the regression results in Table 5, the factors with Sig. values less than 0.05 were age, exposure to drones in life or work, and packaging specifications of products purchased online daily. The factors with Sig. values less than 0.05 in the regression results in Table 6 are age and whether life or work is exposed to drones. In the regression results in Table 7, the factors with Sig. values less than 0.05 are age, education, package size of daily online product purchases, and current delivery speed. Combining these three results, the two surveyors' evaluation factors of the current express delivery, namely the packaging specifications of daily online products and the current delivery speed, are influenced by consumer intentions, and the market environment, which are very difficult to change from the point of view of improving the logistics management methods of drones. The other influential factors of basic information about the surveyor have one thing in common: they all reflect the surveyor's experience with drones. According to the statistics, it does seem that the data is less suspect the more drone surveying expertise the surveyor has. It is expected that a significant portion of respondents is uninformed about recent advancements in drone technology, which accounts for the values' dubious reliability. Therefore, our team thinks that in the future, by stepping up efforts to educate the public about drone expertise and inform residents about drone activities, the misjudgment of residents about drone developments can be effectively improved. Our team also thinks that this outlier will vanish when survey respondents are very familiar with drone developments and drone activities.

Table 5. Regression results of questionable value A11.

Variable Number	B	S.E.	Wald	df	Sig.	Exp(B)
A1	0.200	0.286	0.489	1	0.484	1.221
A2	−0.562	0.198	8.071	1	0.004	0.570
A3	−0.103	0.194	0.283	1	0.595	0.902
A4	−1.178	0.443	7.087	1	0.008	0.308
A5	−0.028	0.215	0.017	1	0.895	0.972
A6	−0.489	0.206	5.604	1	0.018	0.613
A7	−0.103	0.241	0.181	1	0.670	0.903
A8	−0.282	0.248	1.300	1	0.254	0.754
A9	0.674	0.427	2.488	1	0.115	1.961
Constant term C	2.950	1.168	6.379	1	0.012	19.112

Table 6. Regression results of questioned values A16.

Variable Number	B	S.E.	Wald	df	Sig.	Exp(B)
A1	−0.174	0.285	0.373	1	0.542	0.840
A2	0.521	0.198	6.908	1	0.009	1.683
A3	−0.168	0.195	0.739	1	0.390	0.846
A4	1.502	0.490	9.385	1	0.002	4.490
A5	−0.073	0.214	0.118	1	0.731	0.929
A6	0.309	0.203	2.300	1	0.129	1.361
A7	0.255	0.242	1.111	1	0.292	1.290
A8	0.330	0.250	1.746	1	0.186	1.391
A9	−0.322	0.417	0.597	1	0.440	0.725
Constant term C	−2.004	1.164	2.963	1	0.085	0.135

Table 7. Regression results of questionable value A17.

Variable Number	B	S.E.	Wald	df	Sig.	Exp(B)
A1	0.093	0.304	0.094	1	0.759	1.098
A2	0.865	0.222	15.144	1	0.000	2.375
A3	0.613	0.217	7.944	1	0.005	1.845
A4	−0.223	0.440	0.256	1	0.613	0.800
A5	−0.094	0.231	0.164	1	0.685	0.910
A6	0.586	0.222	6.967	1	0.008	1.796
A7	0.556	0.261	4.557	1	0.033	1.744
A8	0.348	0.269	1.673	1	0.196	1.416
A9	−0.308	0.454	0.460	1	0.497	0.735
Constant term C	−4.991	1.296	14.843	1	0.000	0.007

4.2. Subfactor ISM Analysis

4.2.1. Determination of Subfactors to Be Studied

By using binary logistic model analysis, we were able to pinpoint the variables that directly influence how readily residents currently accept the normalization of drone delivery in urban areas. Theoretically, all that is required to increase residents' acceptance of the normalization of urban drone delivery is an improvement in their perception of these variables. To determine whether there is a deeper logical connection between these indicators, as well as to use scientific methods to determine the priority and focus of future UAV urban distribution construction. Subfactors for the underlying mechanisms of these factors were identified, and the results are shown in Figure 2 while these subfactors are numbered and succinctly described for the convenience of subsequent research (Table 8). This was done based on the previous descriptive analysis, the team's prior research experience, and literature references [3,10,13,27,57–59].

4.2.2. Data Processing

As there may be some direct or indirect influence between the above subfactors, the fuzzy-ISM approach described in Section 3 can effectively determine the interrelationship between these subfactors. The Fuzzy-ISM established by multi-expert scoring can largely avoid the problems of over-subjectivity in individual evaluation; at the same time, the use of certain mathematical methods to combine the scores of multiple experts makes the constructed model highly accurate and logical, without the need to repeatedly adjust the final model as in the traditional ISM method [51].

The rating scale issued to the experts this time was divided into five options, indicating the extent to which a factor was evaluated against the comparison factors. After the rating scale was collected the evaluation text was converted into numerical scoring values and the criteria are shown in Table 9. A weighted average of the collected data was obtained based on the data characteristics and a primary matrix was generated using MATLAB as shown in Table 10, with the values in the table indicating the weighted average of the degree of influence that the corresponding vertical factor had on the horizontal factor.

After obtaining the primary matrix, the ISM model properties and fuzzy mathematical principles are combined to find the correlation strength matrix, which is transformed into the following formula:

$$C_{ij} = C_{ij}/(C_{i.} + C_{j.} - C_{ij}) \tag{2}$$

where G_{ij} is the i-th row and j-th column factor in the correlation strength matrix, C_{ij} is the i-th row and j-th column factor in the initial matrix, $C_{i.}$ is the sum of the values of the i-th row factors in the initial matrix and $C_{j.}$ is the sum of the values of the j-th column factors in the initial matrix. The association strength matrix data generated using MATLAB is shown in Table 11.

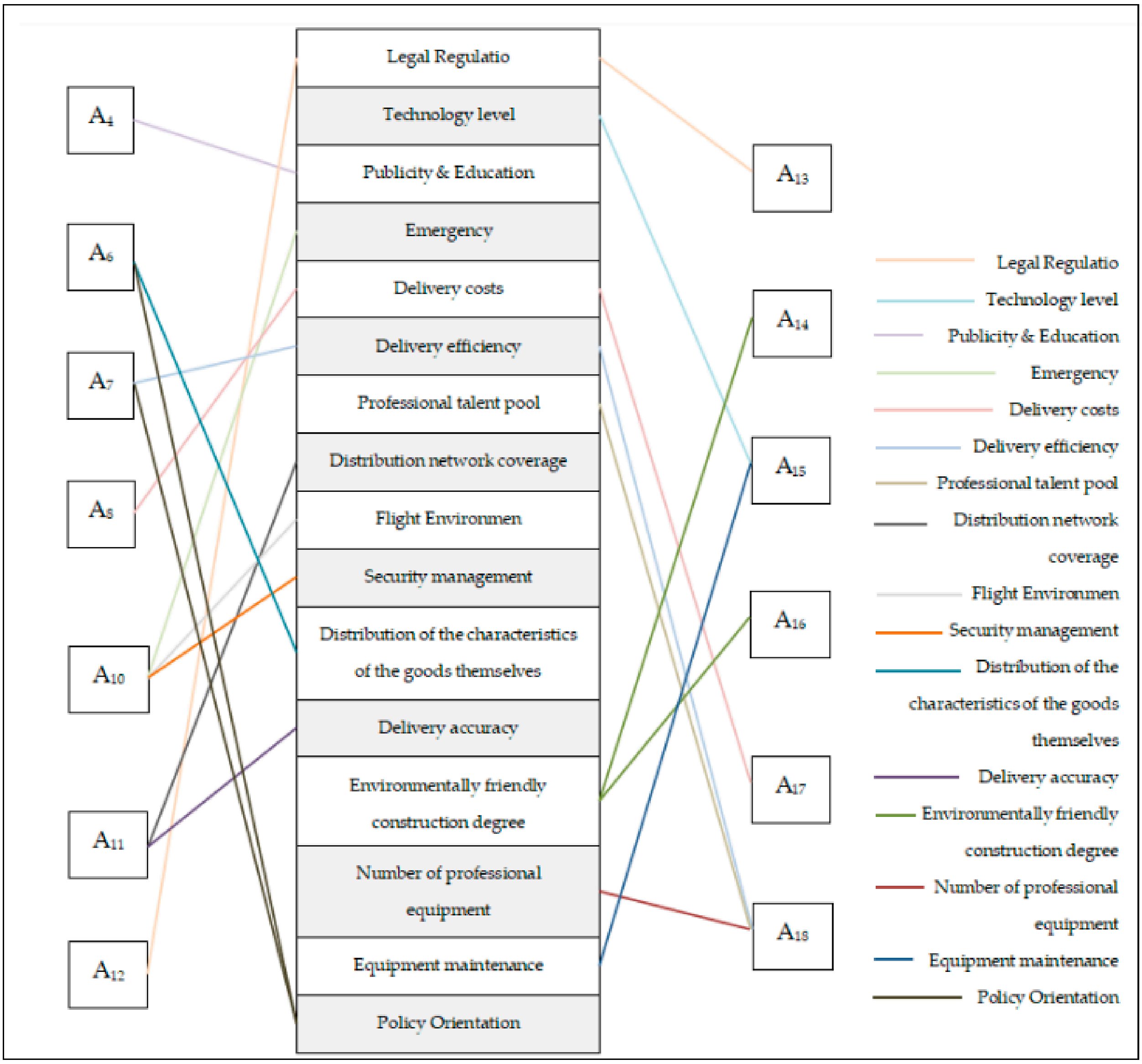

Figure 2. Correspondence diagram between influencing factors and intrinsic mechanism.

Table 8. Table of subfactor numbers and brief descriptions.

Number	Subfactor Name	Brief Description of Content
I1	Legal Regulation	The status and strength of local laws regulating drone activities
I2	Technology level	The technical level of drones for distribution
I3	Publicity & Education	Daily efforts to popularize and promote the science of drone activities to residents
I4	Emergency Preparedness	Emergency response capabilities in the event of an emergency or unforeseen situation
I5	Distribution costs	Costs incurred when delivering drones
I6	Distribution efficiency	The efficiency of drones for delivery
I7	Professional talent pool	Number of personnel owned by logistics companies who can operate and manage drones for distribution activities
I8	Distribution network coverage	UAV delivery coverage area
I9	Flight Environment	Airspace and surrounding built environment, etc.
I10	Security management level	Logistics companies implement all the ways to manage drone safety
I11	Distribution of the characteristics of the goods themselves	Is the cargo convenient for drones to deliver?
I12	Delivery accuracy	The error between the location of the drone dropping cargo and the receiving point
I13	Environmentally friendly construction degree	The extent to which drone logistics activities support environmental protection
I14	Number of professional equipment	The amount of drone equipment owned by logistics companies that can perform distribution activities
I15	Equipment maintenance efforts	Logistics company's efforts in routine maintenance and repair of drones
I16	Policy Orientation	Policy support for drone logistics activities

Table 9. Criteria for evaluating the degree of impact of subfactors.

Degree Option	No or Weak Effect	Low Impact	Moderate Impact	High Impact	Deep IMPACT
Point value	0	0.25	0.5	0.75	1

Table 10. Subfactor ISM analysis primary matrix data table (C).

Factor Number	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15	I16
I1	0	0.083333333	0.69047619	0.095238095	0.095238095	0.821428571	0.095238095	0.69047619	0.130952381	0.726190476	0.095238095	0.214285714	0.75	0.095238095	0.154761905	0.214285714
I2	0.107142857	0	0.761904762	0.738095238	0.75	0.773809524	0.119047619	0.75	0.154761905	0.738095238	0.083333333	0.857142857	0.738095238	0.107142857	0.095238095	0.083333333
I3	0.023809524	0.023809524	0	0.083333333	0.107142857	0.107142857	0.047619048	0.095238095	0.083333333	0.095238095	0.083333333	0.095238095	0.107142857	0.095238095	0.083333333	0.071428571
I4	0.023809524	0.035714286	0.047619048	0	0.095238095	0.071428571	0.05952381	0.071428571	0.071428571	0.738095238	0.071428571	0.071428571	0.119047619	0.071428571	0.083333333	0.095238095
I5	0.011904762	0.035714286	0.05952381	0.071428571	0	0.833333333	0.095238095	0.773809524	0.083333333	0.083333333	0.107142857	0.119047619	0.095238095	0.05952381	0.095238095	0.05952381
I6	0.011904762	0.035714286	0.047619048	0.095238095	0.761904762	0	0.071428571	0.071428571	0.071428571	0.095238095	0.083333333	0.107142857	0.107142857	0.095238095	0.083333333	0.095238095
I7	0.023809524	0.011904762	0.071428571	0.083333333	0.797619048	0.845238095	0	0.107142857	0.083333333	0.738095238	0.05952381	0.071428571	0.083333333	0.107142857	0.107142857	0.107142857
I8	0.011904762	0.071428571	0.095238095	0.773809524	0.761904762	0.845238095	0.05952381	0	0.083333333	0.083333333	0.095238095	0.083333333	0.107142857	0.107142857	0.107142857	0.083333333
I9	0.023809524	0.05952381	0.047619048	0.702380952	0.785714286	0.845238095	0.05952381	0.797619048	0	0.095238095	0.095238095	0.107142857	0.119047619	0.75	0.714285714	0.071428571
I10	0.047619048	0.05952381	0.035714286	0.654761905	0.083333333	0.083333333	0.095238095	0.05952381	0.05952381	0	0.083333333	0.05952381	0.107142857	0.107142857	0.083333333	0.05952381
I11	0.023809524	0.05952381	0.011904762	0.083333333	0.738095238	0.869047619	0.071428571	0.80952381	0.083333333	0.071428571	0	0.773809524	0.095238095	0.107142857	0.05952381	0.071428571
I12	0.023809524	0.035714286	0.05952381	0.071428571	0.785714286	0.80952381	0.083333333	0.05952381	0.107142857	0.107142857	0.083333333	0	0.083333333	0.071428571	0.702380952	0.095238095
I13	0.011904762	0.023809524	0.095238095	0.05952381	0.726190476	0.095238095	0.083333333	0.083333333	0.071428571	0.071428571	0.083333333	0.095238095	0	0.095238095	0.095238095	0.083333333
I14	0.023809524	0.011904762	0.095238095	0.738095238	0.797619048	0.857142857	0.05952381	0.726190476	0.071428571	0.05952381	0.107142857	0.107142857	0.107142857	0	0.107142857	0.107142857
I15	0.023809524	0.071428571	0.083333333	0.095238095	0.726190476	0.833333333	0.095238095	0.702380952	0.095238095	0.797619048	0.071428571	0.678571429	0.083333333	0.095238095	0	0.071428571
I16	0.05952381	0.05952381	0.761904762	0.071428571	0.071428571	0.095238095	0.083333333	0.083333333	0.702380952	0.095238095	0.095238095	0.107142857	0.095238095	0.095238095	0.095238095	0

Table 11. Subfactor association strength matrix data table (G).

Factor Number	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15	I16
I1	0	0.015021459	0.095551895	0.010269576	0.007359706	0.06359447	0.015779093	0.068075117	0.019332162	0.082321188	0.015473888	0.025862069	0.107142857	0.013769363	0.020733652	0.035087719
I2	0.014876033	0	0.084099869	0.070056497	0.052852349	0.052041633	0.015037594	0.062562066	0.017881706	0.068888889	0.010324484	0.089775561	0.082777036	0.012162162	0.01010101	0.010233918
I3	0.01459854	0.012820513	0	0.015053763	0.011673152	0.010843373	0.020408163	0.01362862	0.027131783	0.016701461	0.034482759	0.020460358	0.027522936	0.030075188	0.022012579	0.028571429
I4	0.011049724	0.015075377	0.01025641	0	0.009803922	0.006841505	0.020920502	0.009478673	0.01980198	0.132196162	0.024193548	0.013729977	0.027027027	0.019230769	0.019337017	0.031746032
I5	0.003937008	0.011070111	0.010845987	0.010309278	0	0.079096045	0.025974026	0.100619195	0.018716578	0.011744966	0.028391167	0.01980198	0.018018018	0.012987013	0.018475751	0.01529052
I6	0.005235602	0.014423077	0.010025063	0.015473888	0.083224967	0	0.024291498	0.009345794	0.019230769	0.015037594	0.02734375	0.020316027	0.023684211	0.02507837	0.018867925	0.030651341
I7	0.006389776	0.003003003	0.011538462	0.010920437	0.075365579	0.075211864	0	0.011811024	0.016129032	0.103161398	0.01312336	0.010544815	0.013861386	0.020408163	0.018292683	0.023498695
I8	0.003125	0.017964072	0.015267176	0.110356537	0.071269488	0.074736842	0.013262599	0	0.015909091	0.010574018	0.020833333	0.012195122	0.017681729	0.020134228	0.018072289	0.017902813
I9	0.004175365	0.01010101	0.005813953	0.078145695	0.0625	0.063963964	0.009310987	0.077011494	0	0.009744214	0.014705882	0.012295082	0.01497006	0.113924051	0.098846787	0.010869565
I10	0.022857143	0.025906736	0.007751938	0.120350109	0.008610086	0.008027523	0.034482759	0.007936508	0.016666667	0	0.028806584	0.011520737	0.024523161	0.029508197	0.019553073	0.019920319
I11	0.005464481	0.013089005	0.001730104	0.010086455	0.065469905	0.073366834	0.014184397	0.08994709	0.014373717	0.008450704	0	0.115452931	0.014362657	0.018218623	0.009107468	0.013667426
I12	0.00660066	0.009345794	0.009784736	0.009493671	0.075	0.072572038	0.019498607	0.006613757	0.021327014	0.013975155	0.01897019	0	0.014141414	0.013824885	0.136574074	0.021390374
I13	0.005376344	0.009803922	0.020512821	0.009708738	0.079530639	0.009101251	0.029045643	0.011006289	0.019543974	0.011342155	0.027888446	0.018223235	0	0.025477707	0.021917808	0.027237354
I14	0.005405405	0.002564103	0.013913043	0.096423017	0.070824524	0.072	0.011682243	0.079530639	0.012195122	0.006993007	0.020737327	0.014446228	0.016071429	0	0.016393443	0.020454545
I15	0.004807692	0.013921114	0.011254019	0.01076716	0.061122244	0.066793893	0.016985138	0.072392638	0.014925373	0.095851216	0.01242236	0.09178744	0.011513158	0.014678899	0	0.012269939
I16	0.020080321	0.018656716	0.159600998	0.010327022	0.006749156	0.00845666	0.022727273	0.009957326	0.183800623	0.013468013	0.025236593	0.017821782	0.018058691	0.020997375	0.018518519	0

4.2.3. Determining the Model Adjacency Matrix

To facilitate the subsequent data analysis and ISM model-building work, after obtaining the correlation strength matrix by judging the correlation strength matrix value, the relationship between the set threshold value can be converted into the basic multi-order matrix model as shown in the traditional ISM. Through communication with experts and empirical judgment, the threshold value of 0.045 was chosen (considering the existence of small errors in the analysis process or causing misjudgment of some of the influential degree factors, a value slightly below the theoretical median was chosen), and the formula for conversion to the adjacency matrix was:

$$L_{ij} = \begin{cases} 1, \ G_{ij} \geq 0.045 \\ 0, \ G_{ij} < 0.045 \end{cases} \tag{3}$$

where L_{ij} is the value of the factor in row i and column j of the adjacency matrix. At this point, MATLAB was used to calculate the adjacency matrix for this study that could be used directly for subsequent ISM modeling:

$$L = \begin{array}{cc} & \begin{array}{cccccccccccccccc} I_1 & I_2 & I_3 & I_4 & I_5 & I_6 & I_7 & I_8 & I_9 & I_{10} & I_{11} & I_{12} & I_{13} & I_{14} & I_{15} & I_{16} \end{array} \\ \begin{array}{c} I_1 \\ I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \\ I_7 \\ I_8 \\ I_9 \\ I_{10} \\ I_{11} \\ I_{12} \\ I_{13} \\ I_{14} \\ I_{15} \\ I_{16} \end{array} & \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

4.2.4. Building the Model Reachability Matrix

Based on the properties of Boolean matrix operations on the adjacency matrix L and the unit matrix I (this study is of order 16) to perform several power operations, when satisfied $D = (L + I)^n = (L + I)^{n+1} \neq (L + I)^{n-1}$ to stop the calculation, at this time to find the reachable matrix D. In the numerical meaning of the reachable matrix, element 1 indicates that there is a strong logical relationship between the factors have reachable path; element 0 indicates that there is no strong logical connection between the two factors. Due to the complexity of the operation process and the large amount of data, MATLAB was used to program the calculation to ensure the accuracy of the results, and the reachable matrix of this study was obtained after four power operations.

$$
D = \begin{array}{cc}
 & \begin{matrix} I_1 & I_2 & I_3 & I_4 & I_5 & I_6 & I_7 & I_8 & I_9 & I_{10} & I_{11} & I_{12} & I_{13} & I_{14} & I_{15} & I_{16} \end{matrix} \\
\begin{matrix} I_1 \\ I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \\ I_7 \\ I_8 \\ I_9 \\ I_{10} \\ I_{11} \\ I_{12} \\ I_{13} \\ I_{14} \\ I_{15} \\ I_{16} \end{matrix} &
\begin{bmatrix}
1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1
\end{bmatrix}
\end{array}
$$

4.2.5. Hierarchical Decomposition and Determination of the Multi-Level Conclusion of the Structure Chart

The hierarchy of the reachable matrix provides a more systematic and intuitive understanding of the logical relationships that exist between the subfactors. The set of subfactors influenced by Ii in the reachable matrix forms the reachable set P = (Ii), and the set of subfactors influencing Ii forms the prior set Q = (Ii); the intersection of the reachable set and the prior set is performed, and the top subfactor is Ii when P = (Ii) = P(Ii)∩Q(Ii); a new reachable matrix can be formed by crossing out the row in which it is located; the above hierarchical decomposition steps can be repeated several times to divide the final model into layers and their corresponding subfactors. Repeating the above decomposition steps several times, the final model can be divided into different levels and their corresponding subfactors. The results of the hierarchical decomposition (from top to bottom) are shown in Table 12.

Table 12. Hierarchical decomposition results.

Number of Layers	Presence of Subfactors
First layer	I_3,I_4,I_{10}
Second layer	I_5,I_6,I_8
Third layer	I_7,I_{12},I_{13},I_{14},I_{15}
Fifth layer	I_1,I_2,I_9,I_{11}
Sixth layer	I_{16}

The multi-level structure of the ISM is shown in Figure 3, which is based on the interactions between subfactors and other subfactors at each level. In addition, to further study the system, a multiplicative analysis of the number of subfactors influenced in the reachable matrix was performed to make a coordinate distribution of the subfactor cross-influence matrix multiplicative method (MICMAC), as shown in Figure 4.

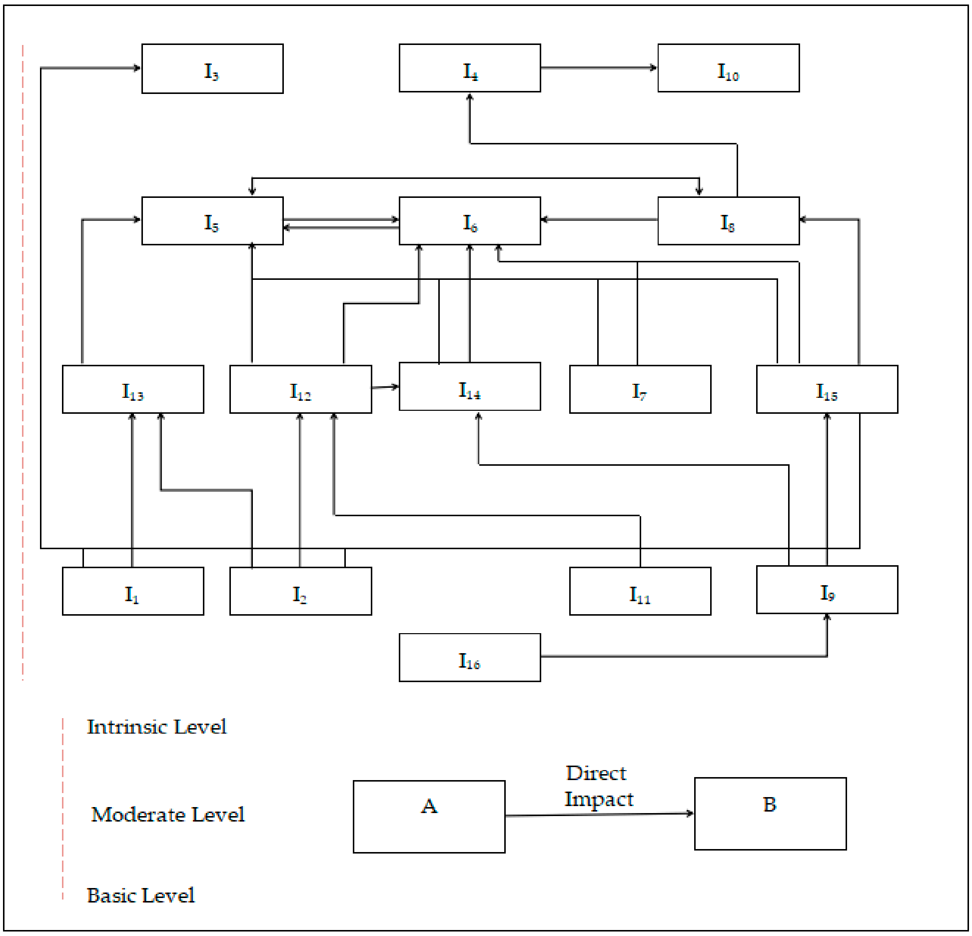

Figure 3. ISM multi-level conclusion structure diagram.

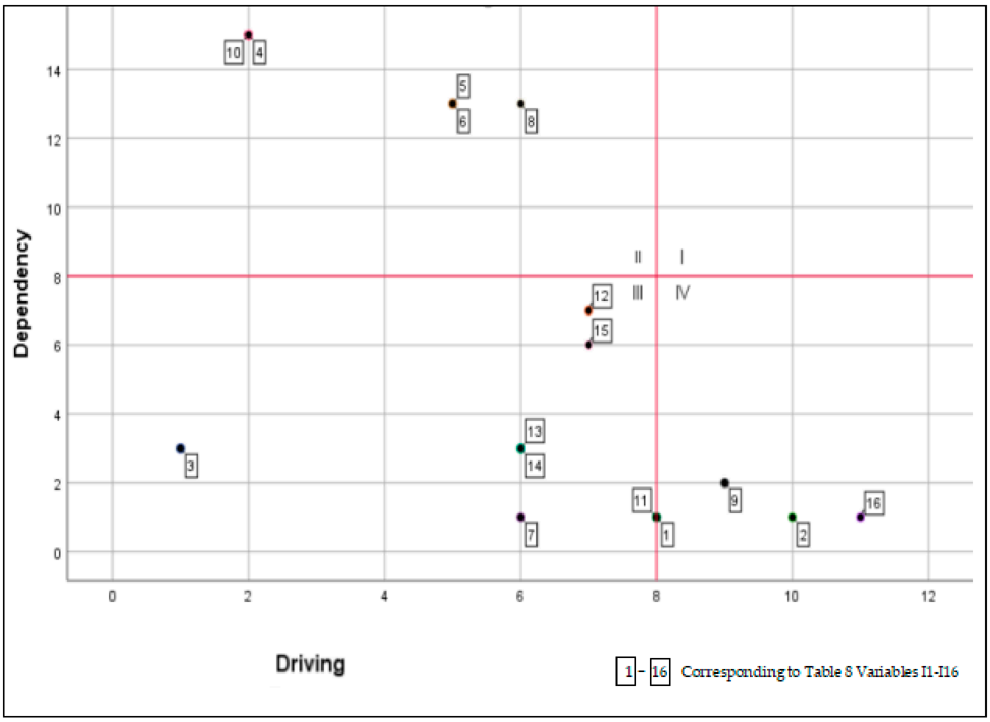

Figure 4. Distribution of MICMAC coordinates.

4.2.6. Model Interpretation

Based on the ISM analysis method [50], combined with the ISM multi-level concluded structure diagram and MICMAC coordinate diagram, the subfactors at the fourth and fifth levels possess strong drive and very low dependence, proving that these subfactors are the basis for building up the evaluation of urban residents' acceptance of the current normality of using drones for delivery, however, a single increase in the construction of this subfactor will not significantly increase the acceptance of drone delivery by the population in the future. To make the residents' acceptance reach a certain level, strict legal regulation, improved technology, precise determination of the delivery goods' characteristics, maintenance of the flying environment, and improved policy guidance must be established. From the position of these subfactors in the two figures, due to their low dependence on the influence of the underlying characteristics of the ISM [50], the level of construction of this part of the subfactor cannot be significantly re-enhanced in the case of the completion of a certain scale of construction, but these subfactors are the basis that constrains the formation of the acceptance of the residents and must be carefully implemented in any stage of the delivery carried out by the UAV, the only thing that can be considered in this part is to explore new methods to save construction costs while ensuring that the construction effect is not compromised.

The subfactors located in the third tier are all in Zone III of the MICMAC coordinates and exhibit low dependence and low drive, proving that these subfactors are difficult to construct, but improving them is the most effective way to increase residents' acceptance of drones in urban delivery. The subfactors in this tier show the characteristics of expanding construction efforts but failing to enhance residents' acceptance more efficiently they are also the basis for the construction of the entire drone delivery activities. The construction of this tier of subfactors must be planned scientifically and rationally to ensure that the construction of this part of subfactors can achieve optimal cost performance. For this part of the subfactor, it is recommended that after scientific and effective planning, the construction should be focused on the initial stage of urban logistics construction, and in the future daily distribution work, it is only necessary to ensure that it can operate effectively under a certain scale.

Among the subfactors in the first and second tiers, all of them are located in the MICMAC coordinate II area except for awareness education, which has a low-driven, high-dependence characteristic. The subfactor of publicity and education is located in the first tier but possesses low-driven and low-dependence characteristics, which is caused by the difficulty of short-term operation of this subfactor, the high investment, and slow effect [60], and also the characteristics of the MICMAC model further confirm the previous speculation on the causes of doubtful data, which require long-term construction to make the population aware that the use of drone delivery is effective. For other subfactors, it is required to build a lot after all basic activities and construction of UAV delivery are ready. How to control the cost, speed up the distribution speed, enhance the distribution area, and ensure the safety of the activity are considered in other studies as the primary problems of the current reform of the UAV distribution method [15,16]. For this part, this study argues that after all preparations for drone logistics activities are effectively completed, the focus should be on building the subfactors of these two levels, and only if the construction of these two subfactors can be effectively improved can the acceptance of drones in urban delivery by residents be significantly increased.

5. Discussion

Through the analysis in the earlier chapters, this study was able to identify the key variables that can have a significant influence on the current shifts in urban residents' acceptance of drone delivery and the logical relationships between the subfactors that exist between these variables. Concerning the results of these empirical analyses, effective suggestions for the future conduct of drone logistics construction can be provided for a series of management construction paths. From a general perspective, to improve residents' acceptance of drones for normalizing delivery activities in cities, focus on upgrading subfactors with high dependency characteristics based on completion of drone delivery construction, overall improvements must be made in terms of increasing publicity, improving delivery speed, reducing delivery fees, ensuring delivery safety, improving delivery accuracy, strengthening supervision, improving technology, and reducing noise, etc. However, considering that there are certain direct or indirect links between some of the constraints internally, to ensure the best results of future construction and management work, it is necessary to identify the intrinsic subfactors of these influencing factors and clarify their logical relationships, to determine the priority level of future work and the best practice for improving the acceptance of residents. As a result, through the empirical analysis in the previous section, for areas at different stages of construction, this study considers that two main types of work can be carried out.

For countries or regions that have not yet started to build drone delivery systems and facilities: it is not urgent to immediately make this new type of activity acceptable to all residents but should formulate relevant promotion policies before construction, and plan for regulation, equipment, and task environment to ensure that future drone normalized delivery activities can be developed in an orderly and sustainable environment with sufficient hardware support at the time of delivery, to gradually improve the residents' acceptance of drones in the city's normalized delivery, we have made solid construction and preparation work.

For countries or regions that already have some construction: Because of the special nature of drone logistics work, no country or region has yet been able to normalize drone express delivery, and all those in the pilot phase of drone delivery or short-term use of drones for special delivery activities are in this state of construction [61]. Through a large number of drone transportation experiments, this part of the world has gradually perfected the technical aspects of using drones for distribution and has theoretically confirmed the feasibility of using drones for distribution in the local area. According to the characteristics of this stage, this part of the region should focus on the test results back to the optimization of the operating environment, improve the current urban drone supervision and flying environment, and other aspects of improvement, to ensure that the future into the normal work phase can have good environmental support. The purpose of a large number of trials is to apply drones to daily delivery work as early as possible. The analysis of this study also points out that strengthening publicity and education, emergency plans, safety management level, improving delivery efficiency and logistics network area, and reducing delivery rates are the key practices to improve residents' acceptance of drones in the normalization of urban delivery. Meanwhile, the absolute low cost and absolute high efficiency have been confirmed in other studies as the main reasons why residents would choose to use drones for delivery. Safety issues arising from drone applications have also been identified as a key factor in residents' resistance to large numbers of drone operations [11–14]. In future in-depth experiments in areas at this stage, more surveys can be used to understand the real thoughts of residents in the test routes, to make timely improvements to existing problems and to supplement positive publicity, and to re-explore new methods and routes of transportation to reduce logistics rates and strengthen safety management, all of which can theoretically effectively improve the acceptance of residents.

6. Conclusions

The goal of this study was to investigate the fundamental causes of the low acceptability, to develop a focused and effective strategy to allay urban residents' existing fears about the use of drones for courier service, and to broaden public acceptance of this novel activity. A questionnaire survey of residents in Jinjiang District, Chengdu City, was conducted and a binary logistic model was used to identify the factors that can influence changes in residents' acceptance. The Fuzzy-ISM method was employed to find out the logical relationships between the subfactors inherent in these influencing factors. Significant factors affecting residents' acceptance of the normalization of urban drone delivery and the logical relationships between subfactors of these factors including publicity, delivery speed, and courier costs were found, and accordingly, the basic paths to improve the current acceptance of the normalization of urban drone delivery by residents were identified and continued to propose two management and construction ideas that should be carried out in response to the different levels of construction. This paper's relevance comes from its capacity to help governments decide what management policies should be implemented regarding drones, such as the need to develop and implement drone flight regulations and safety standards, to make sure that drone operations are coordinated with and safe for other air traffic and crowd activities, and to make sure that drone delivery activities are in line with the overall urban planning and sustainable development goals. This paper will also help relevant companies prioritize the enhancement of their logistical services, which can contribute to the early normalization of urban drone delivery activities.

Although this study gives an executable management approach for UAV logistics construction under different construction states through empirical research methods, there are still some shortcomings in this study that need to be further improved in future research. First of all, due to time and manpower limitations on the part of the investigation team, the research for this paper is only based on one region, Jinjiang District. There is no investigation or research on other, more advanced regions with dense populations or other places of a similar nature, and there may be bias in the recommendations and policies made for those other regions. Second, this paper uses the Fuzzy-ISM method to determine the inter-logical relationships between the subfactors of the influence acceptance factors, but because some of the subfactors are subject to multiple influencing factors at the same time, this study has not yet found a suitable method to determine the strength of association between subfactors of the same level to determine the priority of the same level of implementation (initially, the fuzzy evaluation method was considered to be used again for in-depth analysis, but the connection between factors and influencing factors is too complex, and the conclusions obtained using this method may produce large errors with the data of binary logistic analysis, and the use of this method was finally abandoned). We can expand current studies to solve the aforementioned flaws in future studies. To make the most use of time and resources, online questions can be introduced first. We advise performing comparative research at various levels in various regional and geographic contexts, such as comparing how well-liked employing drones for delivery is in urban vs. suburban locations. To achieve a more exact implementation path and guarantee that benefits are maximized, future research should pick more suitable methodologies to determine the strength of correlation between elements at the same level. Future research can explore the single factor for achieving the best effect of acceptance in depth separately and determine the actual improvement method.

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References

1. Yang, T.; Wang, W. Logistics network distribution optimization based on vehicle sharing. *Sustainability* **2022**, *14*, 2159. [CrossRef]
2. Davila-Pena, L.R.; Penas, D.; Casas-Méndez, B. A new two-phase heuristic for a problem of food distribution with compartmentalized trucks and trailers. *Int. Trans. Oper. Res.* **2023**, *30*, 1031–1064. [CrossRef]
3. Li, X.; Tupayachi, J.; Sharmin, A.; Ferguson, M.M. Drone-Aided Delivery Methods, Challenge, and the Future: A Methodological Review. *Drones* **2023**, *7*, 191. [CrossRef]
4. Li, Y.; Min, L.; Dandan, J. Application of unmanned aerial vehicles in logistics: A literature review. *Sustainability* **2022**, *14*, 14473. [CrossRef]
5. AlRushood, M.A.; Rahbar, F.; Selim, S.Z.; Dweiri, F. Accelerating Use of Drones and Robotics in Post-Pandemic Project Supply Chain. *Drones* **2023**, *7*, 313. [CrossRef]
6. Zhang, G.; Zhu, N.; Ma, S.; Xia, J. Humanitarian relief network assessment using collaborative truck-and-drone system. *Transp. Res. Part E-Logist. Transp. Rev.* **2021**, *152*, 102417. [CrossRef]
7. Banik, D.; Hossain, N.U.I.; Govindan, K.; Nur, F.; Babski-Reeves, K. A decision support model for selecting unmanned aerial vehicle for medical supplies: Context of COVID-19 pandemic. *Int. J. Logist. Manag.* **2022**, *34*, 473–496. [CrossRef]
8. Hazama, Y.; Iima, H.; Karuno, Y.; Mishima, K. Genetic algorithm for scheduling of parcel delivery by drones. *Adv. Mech. Des. Syst. Manuf.* **2021**, *15*, JAMDSM0069. [CrossRef]
9. Coindreau, M.A.; Gallay, O.; Zufferey, N. Parcel delivery cost minimization with time window constraints using trucks and drones. *Networks* **2021**, *78*, 400–420. [CrossRef]
10. Jung, S.; Kim, H. Analysis of amazon prime air uav delivery service. *J. Knowl. Inf. Technol. Syst.* **2017**, *12*, 253–266.
11. Li, S.; Zhang, H.; Li, Z.; Liu, H. An air route network planning model of logistics UAV terminal distribution in urban low altitude airspace. *Sustainability* **2021**, *13*, 13079. [CrossRef]
12. Chiang, W.C.; Li, Y.; Shang, J.; Urban, T.L. Impact of drone delivery on sustainability and cost: Realizing the UAV potential through vehicle routing optimization. *Appl. Energy* **2019**, *242*, 1164–1175. [CrossRef]
13. Buko, J.; Bulsa, M.; Makowski, A. Spatial Premises and Key Conditions for the Use of UAVs for Delivery of Items on the Example of the Polish Courier and Postal Services Market. *Energies* **2022**, *15*, 1403. [CrossRef]
14. Cohen, A.P.; Shaheen, S.A.; Farrar, E.M. Urban air mobility: History, ecosystem, market potential, and challenges. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 6074–6087. [CrossRef]
15. Merkert, R.; Bliemer, M.C.J.; Fayyaz, M. Consumer preferences for innovative and traditional last-mile parcel delivery. *Int. J. Phys. Distrib. Logist. Manag.* **2022**, *52*, 261–284. [CrossRef]
16. Gunaratne, K.; Thibbotuwawa, A.; Vasegaard, A.E.; Nielsen, P.; Perera, H.N. Unmanned Aerial Vehicle Adaptation to Facilitate Healthcare Supply Chains in Low-Income Countries. *Drones* **2022**, *6*, 321. [CrossRef]
17. Fan, B.; Li, Y.; Zhang, R.; Fu, Q. Review on the technological development and application of UAV systems. *Chin. J. Electron.* **2020**, *29*, 199–207. [CrossRef]
18. Alzahrani, B.; Oubbati, O.S.; Barnawi, A.; Atiquzzaman, M.; Alghazzawi, D. UAV assistance paradigm: State-of-the-art in applications and challenges. *J. Netw. Comput. Appl.* **2020**, *166*, 102706. [CrossRef]
19. Lagorio, A.; Pinto, R.; Golini, R. Research in urban logistics: A systematic literature review. *Int. J. Phys. Distrib. Logist. Manag.* **2016**, *46*, 908–931. [CrossRef]
20. Büyüközkan, G.; Ilıcak, Ö. Smart urban logistics: Literature review and future directions. *Socio-Econ. Plan. Sci.* **2022**, *81*, 101197. [CrossRef]
21. Kähler, S.T.; Abben, T.; Luna-Rodriguez, A.; Tomat, M.; Jacobsen, T. An assessment of the acceptance and aesthetics of UAVs and helicopters through an experiment and a survey. *Technol. Soc.* **2022**, *71*, 102096. [CrossRef]
22. Zubin, I.; van Arem, B.; Wiegmans, B.; van Duin, R. Using drones in the last-mile logistics processes of medical product delivery: A feasibility case study in Rotterdam. In Proceedings of the 99th Annual Meeting TRB, Washington, DC, USA, 12–16 January 2020; pp. 12–16.
23. Jeon, A.; Kang, J.; Choi, B.; Kim, N.; Eun, J.; Cheong, T. Unmanned aerial vehicle last-mile delivery considering backhauls. *IEEE Access* **2021**, *9*, 85017–85033. [CrossRef]
24. Hu, Z.H.; Li, T.; Tian, X.D.; Wei, Y.H. Drone-Based Emergent Distribution of Packages to an Island from a Land Base. *Drones* **2023**, *7*, 218. [CrossRef]
25. Choudhury, S.; Solovey, K.; Kochenderfer, M.J.; Pavone, M. Efficient large-scale multi-drone delivery using transit networks. *J. Artif. Intell. Res.* **2021**, *70*, 757–788. [CrossRef]
26. Hassija, V.; Saxena, V.; Chamola, V. Scheduling drone charging for multi-drone network based on consensus time-stamp and game theory. *Comput. Commun.* **2020**, *149*, 51–61. [CrossRef]
27. Park, J.; Kim, S.; Suh, K. A comparative analysis of the environmental benefits of drone-based delivery services in urban and rural areas. *Sustainability* **2018**, *10*, 888. [CrossRef]
28. Ren, X.; Cheng, C. Model of Third-Party Risk Index for Unmanned Aerial Vehicle Delivery in Urban Environment. *Sustainability* **2020**, *12*, 8318. [CrossRef]
29. Grote, M.; Cherrett, T.; Oakey, A.; Royall, P.G.; Whalley, S.; Dickinson, J. How do dangerous goods regulations apply to uncrewed aerial vehicles transporting medical cargos? *Drones* **2021**, *5*, 38. [CrossRef]

30. Kellermann, R.; Biehle, T.; Fischer, L. Drones for parcel and passenger transportation: A literature review. *Transp. Res. Interdiscip. Perspect.* **2020**, *4*, 100088. [CrossRef]
31. Sah, B.; Gupta, R.; Bani-Hani, D. Analysis of barriers to implement drone logistics. *Int. J. Logist. Res. Appl.* **2021**, *24*, 531–550. [CrossRef]
32. Cracknell, A.P. UAVs: Regulations and law enforcement. *Int. J. Remote Sens.* **2017**, *38*, 3054–3067. [CrossRef]
33. Menda, J.; Hing, J.T.; Ayaz, H.; Shewokis, P.A.; Izzetoglu, K.; Onaral, B.; Oh, P. Optical brain imaging to enhance UAV operator training, evaluation, and interface development. *J. Intell. Robot. Syst.* **2011**, *61*, 423–443. [CrossRef]
34. Khan, R.; Tausif, S.; Javed Malik, A. Consumer acceptance of delivery drones in urban areas. *Int. J. Consum. Stud.* **2019**, *43*, 87–101. [CrossRef]
35. Sliusar, N.; Filkin, T.; Huber-Humer, M.; Ritzkowski, M. Drone technology in municipal solid waste management and landfilling: A comprehensive review. *Waste Manag.* **2022**, *139*, 1–16. [CrossRef]
36. Lundin G, Ö. *Supervision for Drone Flight Safety*; Universite de Toulouse: Toulouse, France, 2020.
37. Kuru, K.; Ansell, D.; Khan, W.; Yetgin, H. Analysis and optimization of unmanned aerial vehicle swarms in logistics: An intelligent delivery platform. *IEEE Access* **2019**, *7*, 15804–15831. [CrossRef]
38. Perera, S.; Dawande, M.; Janakiraman, G.; Mookerjee, V. Retail deliveries by drones: How will logistics networks change? *Prod. Oper. Manag.* **2020**, *29*, 2019–2034. [CrossRef]
39. Goncharenko, A.V. Optimal UAV maintenance periodicity obtained on the multi-optional basis. In Proceedings of the 2017 IEEE 4th International Conference Actual Problems of Unmanned Aerial Vehicles Developments (APUAVD), Kiev, Ukraine, 17–19 October 2017; IEEE: New York, NY, USA, 2017; pp. 65–68.
40. Hossain, N.U.I.; Sakib, N.; Govindan, K. Assessing the performance of unmanned aerial vehicle for logistics and transportation leveraging the Bayesian network approach. *Expert Syst. Appl.* **2022**, *209*, 118301. [CrossRef]
41. Smith, A.; Dickinson, J.E.; Marsden, G.; Cherrett, T.; Oakey, A.; Grote, M. Public acceptance of the use of drones for logistics: The state of play and moving towards more informed debate. *Technol. Soc.* **2022**, *68*, 101883. [CrossRef]
42. Çetin, E.; Cano, A.; Deransy, R.; Tres, S.; Barrado, C. Implementing mitigations for improving societal acceptance of urban air mobility. *Drones* **2022**, *6*, 28. [CrossRef]
43. Silva, A.T.; Duarte, S.P.; Melo, S.; Witkowska-Konieczny, A.; Giannuzzi, M.; Lobo, A. Attitudes towards Urban Air Mobility for E-Commerce Deliveries: An Exploratory Survey Comparing European Regions. *Aerospace* **2023**, *10*, 536. [CrossRef]
44. Tan, L.K.L.; Lim, B.C.; Park, G.; Low, K.H.; Yeo, V. Public acceptance of drone applications in a highly urbanized environment. *Technol. Soc.* **2021**, *64*, 101462. [CrossRef]
45. le Cessie, S.; Van Houwelingen, J.C. Logistic regression for correlated binary data. *J. R. Stat. Soc. Ser. C (Appl. Stat.)* **1994**, *43*, 95–108. [CrossRef]
46. Asenso Barnieh, B.; Jia, L.; Menenti, M.; Jiang, M.; Zhou, J.; Zeng, Y.; Bennour, A. Modeling the underlying drivers of natural vegetation occurrence in west africa with binary logistic regression method. *Sustainability* **2021**, *13*, 4673. [CrossRef]
47. Wu, Y.; Jiang, X.; Kim, J.; Ohno-Machado, L. G rid Binary LO gistic RE gression (GLORE): Building shared models without sharing data. *J. Am. Med. Inform. Assoc.* **2012**, *19*, 758–764. [CrossRef] [PubMed]
48. Zhang, H.; Han, X.; Dai, S. Fire occurrence probability mapping of northeast China with binary logistic regression model. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2013**, *6*, 121–127. [CrossRef]
49. Song, B.D.; Park, K.; Kim, J. Persistent UAV delivery logistics: MILP formulation and efficient heuristic. *Comput. Ind. Eng.* **2018**, *120*, 418–428. [CrossRef]
50. Sindhu, S.; Nehra, V.; Luthra, S. Identification and analysis of barriers in implementation of solar energy in Indian rural sector using integrated ISM and fuzzy MICMAC approach. *Renew. Sustain. Energy Rev.* **2016**, *62*, 70–88. [CrossRef]
51. Bianco, D.; Filho, M.G.; Osiro, L.; Ganga, G.M.D. Unlocking the Relationship Between Lean Leadership Competencies and Industry 4.0 Leadership Competencies: An ISM/Fuzzy MICMAC Approach. *IEEE Trans. Eng. Manag.* **2021**, *99*, 2268–2292. [CrossRef]
52. Han, Y.; Geng, Z.; Zhu, Q.; Lin, X. Energy consumption hierarchical analysis based on interpretative structural model for ethylene production. *Chin. J. Chem. Eng.* **2015**, *23*, 2029–2036. [CrossRef]
53. Jiang, H.; Xiong, W.; Cao, Y. Risk of the maritime supply chain system based on interpretative structural model. *Pol. Marit. Res.* **2017**, *24*, 28–33. [CrossRef]
54. Nasim, S. Total interpretive structural modeling of continuity and change forces in e-government. *J. Enterp. Transform.* **2011**, *1*, 147–168. [CrossRef]
55. Hazelrigg, G.A.; Saari, D.G. Toward a theory of systems engineering. *J. Mech. Des.* **2022**, *144*, 011402. [CrossRef]
56. Ochella, S.; Shafiee, M.; Dinmohammadi, F. Artificial intelligence in prognostics and health management of engineering systems. *Eng. Appl. Artif. Intell.* **2022**, *108*, 104552. [CrossRef]
57. Gorane, S.J.; Kant, R. Modelling the scm enablers: An integrated ism-fuzzy micmac approach. *Asia Pac. J. Mark. Logist.* **2013**, *25*, 263–286. [CrossRef]
58. Ying-Jun, L.; Xian-Heng, R. An empirical analysis on the factor choice of the core competence in Chinese SMEs based on ISM-Fuzzy AHP approach. *Sci. Res. Manag.* **2007**, *24*, 189–198. [CrossRef]
59. Kunze, O. Replicators, ground drones and crowd logistics a vision of urban logistics in the year 2030. *Transp. Res. Procedia* **2016**, *19*, 286–299. [CrossRef]

60. Lafountain, C.; Cohen, K.; Abdallah, S. Use of XFOIL in design of camber-controlled morphing UAVs. *Comput. Appl. Eng. Educ.* **2012**, *20*, 673–680. [CrossRef]
61. Simsek, O.; Tekinalp, O. System Identification and Handling Quality Analysis of a UAV from Flight Test Data. In Proceedings of the AIAA Atmospheric Flight Mechanics Conference, Dallas, TX, USA, 22–26 June 2015; p. 1480.