Risk Evaluation of “Not-In-My-Back-Yard” Conflict Potential in Facilities Group: A Case Study of Chemical Park in Xuwei New District, China

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Received: 12 December 2019; Accepted: 23 March 2020; Published: 30 March 2020

Abstract: The social risk of chemical industry park projects attracts much attention, as they are perceived to yield strong environmental risks. This paper systematically evaluates the social risk of Xuwei Chemical Park in China, which was investigated as an example to guide the risk control strategy of conflict in industrial facilities for developing countries. The results show that residents and government departments have a resistance to the risks of the project as a stronger sense of group risk perception (the value is 7 × 10−6) compared with the basic value of 7 × 10−5. By contrast, the low value of group risk perception was evaluated in an enterprise group (7 × 10−4), indicating that the risks of petrochemical projects are often accepted. The expert group’s risk perception regarding petrochemical projects is consistent with the basic value. This is a very interesting finding indicating that the greater the experience, the more the support for petrochemical projects. The knowledge and information from education or experience improve the judgment of the risk of the facility, which increases the individual’s rational assessment comprehension of risk. Moreover, factors that are significantly related to residents’ attitudes are information cognitive factors (trust in information publicity and petrochemical project understanding), and project influencing factors (project planning rationality, quality of life improvement, and economic development satisfaction). Among them, the degree of trust in information disclosure has the highest degree of influence, followed by the level of education, while the satisfaction with economic development has the lowest degree of influence. Therefore, improving the trust of residents in the information disclosure of petrochemical projects should be the core of the government’s risk control policy.

Keywords: environmental risk; chemical park project; social risk; fuzzy comprehensive evaluation method; probit model

1. Introduction

In the growth of global economy, the petrochemical industry plays an important role. Despite this, the influence of the petrochemical industry on environmental and human health has attracted much attention for decades, as many pollutants were discharged from the process of petrochemical production. For instance, oil production increases CO2 emissions significantly from the first to sixth quantiles, with a greater effect at the lowest quantile and a weaker effect at the highest quantile [1]. Chen reported CO2 and NOx emission from flue gas in a petrochemical plant and indicated the essential requirement of pollution reduction [2]. For human health risk, Aghadadashi studied the spatial structure of sedimentary total Polycyclic Aromatic Hydrocarbons(PAHs) and revealed its potential cancer risks [3]. Shaygan examined the prevalence of chronic pain among workers of several petrochemical and petroleum refinery plants for its predictive role of psycho-familial variables (depression, work-family conflict, and job stress) in causing chronic pain when controlling for
demographic and occupational factors [4]. This led to a great concern regarding the risk of pollution and eco-system damage from the petrochemical industry.

Based on the risk of the petrochemical industry, a public opposition to its construction within a certain range of its own residence occurs. This phenomenon is defined as a “not in my back yard” (NIMBY) conflict. It is proposed that this conflict is usually activated when a high environmental risk project is recognized by the public. For instance, Signorino indicated that proximity to industrial pollution sources influences risk perception and assimilates risk perception profiles of populations in the risk perception profiles of populations residing in the neighborhood of two petrochemical enterprises [5]. Tortosa-Edo showed the corroboration of the direct and indirect effects of personal environmental values on the variables that make up the trust in companies–heuristic-systematic theory (HSM) of information processing–risk perception sequence [6]. Therefore, much effort has been made to reduce the NIMBY conflict. Zhiqiang Geng et al. proposed a novel data envelopment analysis (DEA) model based on the affinity propagation (AP) clustering algorithm (AP-DEA), which is efficient in terms of energy saving and carbon emission reduction of a petrochemical industry [7]. Nicolletti studied how petroleum companies can adapt to climate change using social learning approaches [8]. In 2019, Choi found that the petrochemical industry exhibits 63.5% emission trading scheme (ETS) performance, on average, showing a huge potential for improvement in the sustainable governance of the Korean petrochemical industry [9]. Thus, it is proposed that decreasing the environmental and health risks, combined with increasing the public benefits, are usually the common risk reduction strategies.

Recently, the increase in petrochemical production with the continuous increase in the demand for chemicals led to the construction of chemical parks that usually include a group of petrochemical industries [10]. This resulted in a strong NIMBY conflict as a result of the increase in risk perception of environmental pollution and health hazards [11]. The conflict led to social risk, which had a negative effect on social stability. Therefore, it is necessary to evaluate the risk of chemical parks to the public and its corresponding control strategy.

Herein, this paper aims to study the social risks caused by chemical park projects with high environmental risks by taking Xuwei New District as an example. On the basis of identifying the environmental risks existing in chemical projects, from the perspective of risk perception, the social population is assessed based on the social risk perception caused by the project’s environmental risks, and the social risks of the projects are analyzed. Finally, according to the conclusion of the social risk control research, advice and guidance are provided for the government’s risk control policy.

2. Literature Review

2.1. Social Risk Assessment

Risk perception theory is the basic theory of social risk assessment. The World Health Organization (WHO) has provided a guide for risk assessment, which demonstrates that the assessment of risk perception should be considered as a fundamental instrument for creating proper risk communication plans that sustain the implementation of risk-management and territorial remediation strategies [12]. The theory reveals that risk conflict mainly stems from the difference of risk perceptions between different subjects. This difference is an important driving factor for the formation of group events. Zhang studied the risk of lane-change behaviors in multilane urban expressway off-ramp areas [13]. Yu et al. explored the impact of risk programs on risk perceptions of nearby residents in 2018 [14]. The results showed that residents’ age, gender, education level, and environmental awareness were significantly correlated with their risk perception. This reasoning could be followed by adverse environmental, social, and economic effects that could threaten the sustainable development of urban spaces. Based on risk perception and project environmental risk perspectives, Lefley studied the relationship between risk occurrence probability and the possible impact on risk management when an accident does occur [15]. By analyzing the changes in residents’ risk perceptions in risk-disaster accidents, Chiang suggested that residents’ risk perceptions should be incorporated into risk communication to promote residents’ adaptive actions in accidents [16].
Zhu et al. studied the key factors of people’s anti-nuclear behavior intentions [17]. The results indicate that people’s behavior intentions are driven by risk perception, which cannot be stimulated by systematic processing. This usually results in an inverse U-relationship between perceived knowledge and behavior intention against facility construction.

The quantitative risk assessment method is based on the quantitative assessment of the risk of high-risk environmental projects to evaluate the social acceptability of the risks associated with accidents. Thus, risk assessment is a concrete method for measuring risk perception and a tool to reveal the potential values of risk in real situations. The assessment method is widely used in the quantitative assessment of risks in various chemical industries and other areas [11,12]. Wang et al. proposed a new dynamic quantitative risk assessment method to analyze the operational performance of chemical processes, and to estimate the probability of the occurrence of risk events by monitoring multiple key variables [18]. Recently, Gholipour et al. used quantitative microbial risk assessment (QMRA) to analyze Listeria infections for workers and farmers [19]. Aliléche et al. studied the domino-effect quantitative analysis method applied to the chemical park scenario, which provided an overview, comparison, and discussion of the current regulations of the domino effect [20]. Based on the domino effect, Cozzani et al. reported a quantitative risk assessment of accidents caused by process equipment fires and explosion damage in the chemical industry [21]. Markowski and Kotynia incorporated the “bowtie” model into the analytic hierarchy analysis method to achieve the quantitation of the risk, and optimized the safety measures for specific accident scenarios through optimization of the model’s construction [22]. Fabbrocino used quantitative analysis to study the chemical plant accident hazard caused by seismic risk and gave countermeasures [23]. In 2016, Valencia-Barragán et al. quantitatively analyzed the potential impacts of chemical park accidents on people inside and outside the industry, and conducted a risk analysis of insiders and personnel leaving the factory [24].

In the evaluation of the social risk of the petrochemical project in Xujing New District, this paper establishes a risk perception evaluation index system by using the analytic hierarchy process, and uses the fuzzy comprehensive evaluation method to measure the risk perception value of different groups and society to analyze the social risks of the project.

### 2.2. Social Risk Control

The social amplification theory of risk is an important theory of social risk research. The theory holds that the relationship between risk and risk events is linked by risk signals, and that the risk signals control the scope and role of risks through reinforcement and weakening [25]. In 2018, Fellenor examined the social amplification of risk on Twitter [26]. Jagiello and Hills explored the effects of message dissemination on risk amplification and risk communication, which indicated that the more widely messages spread, the more negative statements were contained in the message [27]. The increase in perceived risk and the generation of negative information are closely related to the amount of information received. Moreover, re-exposure to the initial information is ineffective for reducing prejudice. Wirz et al. used the risk framework to study the role of social media responsibility and risk perception in risk amplification, which pointed out the importance of multilingual approaches in risk communication [28]. In 2002, using the risk amplification effect model, Frewer et al. analyzed the collection of attitude data before, during, and after the increased reporting of the risks of genetically modified food in the United Kingdom (spring 1999). It has been demonstrated that people’s risk perceptions increase and decrease in line with what might be expected upon examination of the amplification and attenuation mechanisms integral to the framework [29]. It was concluded that the social amplification of risk frameworks is a useful framework for beginning to explain the potential impact of a risk event on risk perceptions, particularly if that risk events are presented to the public as a new hazard occurring in a crisis context. By studying the uncertainty and instability of risk message propagation through the diffusion chain, Mehdi et al. provided the quantitative analysis of risk-aware social amplification to help policymakers with the better prediction and management of public insights into emerging threats [30].
Risk control is an attempt to establish a risk control mechanism as a way to prevent risks and is based on the analysis of risk triggers. An open information environment, as well as high variability and uncertainty are necessary parts of the vacancy of an active distributed network (ADN) risk control system. In 2018, Wang and Ieee applied a cyber physical system (CPS) into ADN risk control. In the formulation of the risk prevention and control system, the main risk control measures are enterprise risk control, personnel risk control, park risk control, and government risk control [31]. For instance, the risk prevention and control system, anti-control system, and supervision system of chemical park enterprises can provide corresponding suggestions and improve the safe production capacity of enterprises. In order to improve the ability of emergency management for storage areas of dangerous chemicals, a framework for a risk management technical system for flammable and explosive dangerous chemicals was proposed [32]. Using the dynamic risk management system, it can effectively achieve the goal of dynamic supervision, risk identification, and real-time monitoring, as well as assisting the emergency decision-making of dangerous chemicals in the whole life cycle.

Under this circumstance, the government should guide its own branches, the media, experts, and enterprises to conduct risk supervision and risk information judgment to build an efficient chemical park from the perspectives of risk participants. In the formulation of government risk control policies, it is recommended that residents’ risk attitudes be influenced through the control of different risk signals, such as media and experts, to improve residents’ support for petrochemical projects.

2.3. Literature Review of Model Application

2.3.1. Fuzzy Comprehensive Evaluation Method

The fuzzy comprehensive evaluation method is based on the fuzzy set theory and the principle of maximum membership degree. The fuzzy set is used to effectively quantify the evaluation target. This method is widely used to solve the complex problem of multi-factor decision-making [33]. The analysis is used to determine the membership degree of each layer of indicators in the indicator set based on the set of indicators [34].

In 2014, Shi et al. obtained the best emergency treatment technical solution immediately after a chemical pollution accident occurred in the planning database [35]. Based on the group decision-making improved fuzzy comprehensive evaluation method, the technical evaluation index system was established. An example analysis was carried out with an aniline pollution accident. The sustained casing pressure (SCP) threatened the wellbore safety significantly. Considering the serious SCP situation in the gas field in the southwest of China, Dezhi established a SCP risk evaluation model based on the fuzzy comprehensive evaluation method [36].

The social risk assessment of the chemical park project studied in this paper is a multi-index level problem. In the social risk assessment, the fuzzy comprehensive evaluation method is used to study the social risk perception of different social groups, and the risk perception value of different groups is calculated comprehensively. The social total risk perception value is used for determining the social risk of the project.

2.3.2. Probit Model

In the research of social risks, many scholars have chosen to apply econometric models, statistical analysis models, and other methods to both assess risks and prevent accidents [37]. The Probit model is also used as a discrete selection model for the analysis and prediction of risk accidents [38].

In view of the potential accident risks brought by technical operations to the process industry, Crăciu et al. studied the impact of thermal radiation on the population and used different probit functions to carry out personal risk calculations. By comparing the case findings, different uses were applied in estimating the consequences. Based on an ordered probit model, the risk degree model of bridge damage caused by the collision of disabled ships was established and applied to analyze the risk degree of bridge damage [39]. Ma and Jie aimed to understand four types of vehicle ownership
within a household, including the automobile, motorcycle, electric bicycle, and human-powered bicycle [40]. The study presented a cross-sectional multivariate ordered probit model with a composite marginal likelihood estimation approach, which accommodated the effects of explanatory variables and captured the dependence among the propensity of households for vehicle ownership. To ensure that people can safely evacuate during chemical release, James determined the maximum safe shelter time by using the probit model and provided a link between expected response probability and group exposure to specific risk events [41].

In order to effectively control the risk of petrochemical projects in chemical parks, this paper takes the residents’ group participating in the group event as the research subject of risk control, so as to analyze the factors affecting residents’ risk attitudes using the probit model. We also select key factors to formulate risk control policies.

3. Social Risk Assessment of the Xuwei Petrochemical Project

3.1. Xuwei New District

Xuwei New District (ND) is located in the southeast of Lianyungang city. The petrochemical industry is one of the key port development industries in Xuwei. The construction of a large petrochemical industrial base in Xuwei is an important part of Jiangsu’s petrochemical industry layout adjustment. The development of the petrochemical industry is based on the integration of refining, ethylene, and aromatics, supplemented by diversified raw materials processing, featuring clean energy, organic raw materials, and synthetic materials that feature new chemical materials and fine chemicals. A large-scale refining and chemical integration form a multi-product chain and multi-product cluster. The construction of the petrochemical industry along the Yangtze River, promoted industrial adjustment and upgrading, and played a major role in meeting the demand for petrochemical products and raw materials in the Yangtze River Delta region, as well as in the central and western regions. A number of companies have officially entered the production and operation stage, including Jiangsu Honggang Petrochemical Co, Ltd., and Lianyungang Hongyang Thermal Power Co, Ltd. Xuwei ND includes three administrative villages (Zhangtiao, Dongbanshan, and Xianghe) and four communities (Yuejin, Chengwei, Banqiao, and Gaowei) with a population of 16,000.

3.2. Construction of Social Risk Assessment Model

The social risk assessment of the petrochemical project is based on the risk perception perspective, examining the social risks caused by the project’s environmental risks, and establishing the social risk assessment model to analyze the social risks of the project. According to the figure 1 showed in the following text, the social risk assessment model consists of three parts: (1) the basic theory—risk perception theory, and the setting of the risk perception base value; (2) the social risk perception evaluation index system; and (3) the social risk perception assessment. The analysis process divides the entire social population into residents, Groups, expert groups, government departments, and enterprise groups are the subjects in the fuzzy comprehensive evaluation method; the risk perception value of each group is calculated, along with the total social risk perception value.

3.2.1. Risk Perception Base Value

Chemical accident management requires studies estimating the potential scale of chemical accidents’ effects, their unpredictability, and the uncertainties of their consequences for environmental risk assessment [42–44]. The risk value of chemical accidents was evaluated by the natural mortality rate, which served as the benchmark for risk assessment [45]. At the end of 2017, China’s total population was 139.08 million and the population mortality rate was 0.711%. The conservative estimate of the natural mortality rate of the population was 0.7%. Since the death risk of residents is increased through the potential emissions of the chemical industries, an annual mortality rate of 1% was taken as the basic value. Therefore, the perceived risk base value of the project was $7 \times 10^{-5}$. 
3.2.2. Risk Perception Assessment Indicator System

It can be seen from figure 2, in the social risk assessment model, the social risk perception assessment index system consists of three layers, the first of which is the overall goal (level one indicator layer A), which is the degree of social risk perception. The second level indicator layer (layer B) includes three effects: the factors affecting the environmental risk characteristics of the project, personal influence factors, and social influence factors. The third-level indicator layer (layer C) is the evaluation index included in each influencing factor.

In the assessment system, the environmental risk characteristics of the project include health risks, accident risks, pollution risks, and safety risks. The personal influence factors were selected including basic personal characteristics, such as occupation, age, and education, as well as risk-aware factors, such as risk willingness, risk experience, and risk education. Social influence factors include government supervision level, government assistance, chemical park information disclosure, chemical park accident emergency rescue capability, and media credibility.

3.2.3. Group Risk Perception Calculation

As the influence degree of various factors on different groups’ risk perception is complex and uncertain, the fuzzy comprehensive evaluation method is an effective method to solve these uncertainties [46]. This method was used to quantitatively evaluate the risk perception of different groups. The assessment for the level of risk perception was set to five levels, namely $V_1$ (strong) to $V_5$ (weak). According to the weight calculation step of the fuzzy comprehensive evaluation method, the
evaluation of the bottom layer index was carried out, followed by the calculation of the target layer weight [47]. The specific calculation was as follows [48].

(1) Building a multi-level evaluation set.

Suppose \( A \) contains the set of all factors of the first level indicator (target layer), \( U_A = (U_{B1}, U_{B2}, U_{B3}) \), and the single factor set corresponding to layer \( B \) is: \( U_{B1} = (C_1, ..., C_4) \), \( U_{B2} = (C_5, ..., C_{10}) \), \( U_{B3} = (C_{11}, ..., C_{15}) \). The evaluation set of risk influencing factors \( C \) is a collection of all possible evaluation results of the evaluation object. The evaluation set is defined as \( U_C = V_C = (v_{c1}, v_{c2}, ..., v_{cn}) \), where \( v_i \) represents a possible risk-aware evaluation result.

(2) Determining the weights of indicators at all levels.

Assuming that the weight value of each factor of the second-level indicator \( U_B \) is \( \omega_i \), the weight set is \( W_{B1} = (\omega_{C1}, ..., \omega_{C4}) \), \( W_{B2} = (\omega_{C5}, ..., \omega_{C10}) \), \( W_{B3} = (\omega_{C11}, ..., \omega_{C15}) \). The weight set of the target layer \( A \) layer is \( W_A = (\omega_1, \omega_2, \omega_3) \). The weight determination of the risk-aware influence factor was determined by the collected data according to the weight calculation principle of the analytic hierarchy process [49]. According to the opinions of experts who participated in the environmental impact assessment hearing of the overall development plan of the Lianyungang Petrochemical Industrial Base and the weight calculation principle of the above analytic hierarchy process, the weight values of risk-aware factors were obtained. It can be seen that the second-level indicator weight sets are:

\[
W_{B1} = (0.467, 0.278, 0.160, 0.095) \\
W_{B2} = (0.094, 0.093, 0.238, 0.112, 0.200, 0.263) \\
W_{B3} = (0.187, 0.230, 0.167, 0.322, 0.094)
\]

The weight set of the target layer \( A \) is: \( W_A = (0.509, 0.179, 0.312) \)

(3) Single factor membership.

The rating of the individual factors of the three-level indicator evaluation set \( U_C \) was analyzed by collecting data from the risk perception questionnaire of the respondents. The evaluation result for the risk perception degree for each sample was combined with the normalization method to calculate the proportion of each index being evaluated at different levels. The membership value of the index for the five evaluation levels was able to be determined, and the maximum membership degree principle could be inferred for a single risk perception level of each different factor of the sample. Moreover, according to the membership value of the three-level indicator, the membership degree matrix of each level factor included in the second layer \( B \) can be further obtained: \( V_{Bi} = \begin{pmatrix} v_{c11} & \cdots & v_{cm1} \\ \vdots & \ddots & \vdots \\ v_{c1n} & \cdots & v_{cmn} \end{pmatrix} \), \( i = 1, 2, 3 \)

(4) Fuzzy evaluation set of each indicator.

The fuzzy comprehensive evaluation set of each evaluation index layer can be calculated in the following way: First, the membership degree matrix of the various factors included in \( B \) is \( V_{B1}, V_{B2}, V_{B3} \), and in the second-level fuzzy evaluation set, the weight set is \( W_{B1} = (\omega_{C1}, ..., \omega_{C4}) \), \( W_{B2} = (\omega_{C5}, ..., \omega_{C10}) \), \( W_{B3} = (\omega_{C11}, ..., \omega_{C15}) \). Then, the formula based on the indicator fuzzy evaluation set can be calculated:

\[
B_i = W_{Bi} \times V_{Bi}, \quad i = 1, 2, 3
\]

A two-level fuzzy evaluation set for the factors affecting the environmental risk characteristics of the project can be expressed as:
where

\[ P(i) = P(a) \times \alpha \]  

(3)

The fuzzy assessment set of personal factors and social factors are evaluated in the same way with a fuzzy evaluation set of the first-level indicators.

(5) Risk perception value synthesis calculation.

The calculation formula based on the risk perception value can be expressed as:

\[ P(i) = P(a) \times \alpha \]  

(3)

where \( P(i) \) is the risk perception value, \( P(a) \) is the risk perception base value of \( 7 \times 10^{-5} \), \( \alpha \) is the risk perception degree coefficient, and the risk perception degree according to the fuzzy comprehensive evaluation method corresponds to the selected coefficient (Table 2). As shown in Table 1, the risk perception value is small as the degree of risk perception is weak, which indicates that the group can accept more risks. If the degree of risk perception were strong, the group would have a risk-resisting mood.

**Table 1** Risk perception degree coefficient and perceived value.

| Risk Perception | Stronger | Strong | Normal | Weak  | Weaker |
|-----------------|----------|--------|--------|-------|--------|
| Risk perception coefficient | 0.01 | 0.1 | 1 | 10 | 100 |
| Risk perception value | \( 7 \times 10^{-7} \) | \( 7 \times 10^{-6} \) | \( 7 \times 10^{-5} \) | \( 7 \times 10^{-4} \) | \( 7 \times 10^{-3} \) |

**Table 2.** Single factor membership and evaluation level of each factor.

| Risk factor membership assessment | Single Factor Membership | Evaluation Level |
|-----------------------------------|--------------------------|------------------|
| Project environment characteristics | Health risk \( C_1 \) | \( V_1 \) | \( V_2 \) | \( V_3 \) | \( V_4 \) | \( V_5 \) |
| | Accident risk \( C_2 \) | 0.212 | 0.420 | 0.231 | 0.086 | 0.051 |
| | Pollution risk \( C_3 \) | 0.223 | 0.416 | 0.342 | 0.018 | 0.001 |
| | Security risk \( C_4 \) | 0.076 | 0.052 | 0.345 | 0.327 | 0.200 |
| | Career \( C_5 \) | 0.041 | 0.368 | 0.227 | 0.234 | 0.134 |
| | Age \( C_6 \) | 0.030 | 0.024 | 0.621 | 0.113 | 0.212 |
| | Education \( C_7 \) | 0.050 | 0.057 | 0.574 | 0.202 | 0.117 |
| | Accept the risk willingness \( C_8 \) | 0.001 | 0.227 | 0.442 | 0.320 | 0.010 |
| | Risk experience \( C_9 \) | 0.010 | 0.531 | 0.337 | 0.112 | 0.010 |
| | Risk Education \( C_{10} \) | 0.045 | 0.112 | 0.531 | 0.212 | 0.100 |
| Personal influence factor \( B_1 \) | Government supervision level \( C_{11} \) | 0.050 | 0.621 | 0.212 | 0.117 | 0.020 |
| | Government assistance support capacity \( C_{12} \) | 0.015 | 0.312 | 0.527 | 0.116 | 0.030 |
| | Chemical Park Information Disclosure \( C_{13} \) | 0.010 | 0.114 | 0.312 | 0.447 | 0.117 |
| | Chemical Park Accident Emergency Rescue Capability \( C_{14} \) | 0.212 | 0.628 | 0.117 | 0.023 | 0.020 |
| Social influence factor \( B_3 \) | Media credibility \( C_{15} \) | 0.050 | 0.062 | 0.515 | 0.213 | 0.160 |

3.2.4. Social Total Risk Perception Calculation

According to the fuzzy comprehensive evaluation method and the principle of maximum membership degree, the risk perception results of each group were analyzed. The risk perception value \( P(i) \), \( i = 1, 2, 3, 4 \) of each group was obtained by the risk perception calculation formula. The total risk perception value \( P \) of society was then calculated using the following equation:

\[ P = P(i) \times W = P(1) \times \omega_1 + P(2) \times \omega_2 + P(3) \times \omega_3 + P(4) \times \omega_4 \]  

(4)

where \( W = (\omega_1, \omega_2, \omega_2, \omega_4) \) is the weight value of each group.
3.3. Social Risk Perception Assessment

3.3.1. Survey and Data Sources

Document research was conducted on four groups, taking residents as an example. Data collection was conducted by issuing a public participation questionnaire. The participants of this survey were residents living within 10 km of the boundary of the petrochemical base. We carried out the survey in seven regions in Xuwei, and on average, 76 samples were conducted in each. The residents living in these regions included farmers, industry workers, and people who attained both fundamental and elite education. The questionnaire was distributed by means of direct investigation and entrusting units. A total of 532 questionnaires were distributed and 516 questionnaires were collected, of which 500 were valid questionnaires. The effective recovery rate was 94.1%. The content of the questionnaire design consisted of the risk assessment factors that were selected at different evaluation levels of residents’ risk perception assessments.

3.3.2. Social Risk Perception Assessment of Resident Groups

The data collected by the questionnaire were analyzed to obtain each factor’s membership degree as well as the evaluation grade result for the individual factors of risk perception, which in turn influence the factors of the resident group.

According to the fuzzy comprehensive evaluation method and the principle of maximum membership degree, the residents' judgment on the risk perception factors was further analyzed. Among the project’s characteristic risk factors, residents’ risks perceptions of health risks, accident risks, and safety risks were relatively strong (0.420, 0.416, and 0.368, respectively). This highlighted that the health risks in the park are important factors affecting the health of residents. The outbreak of accidents is a risk that has the potential to directly lead to residents’ panic and affect social stability. Similarly, security risks can trigger the outbreak of panic in residents’ groups. This indicates that residents’ risk perception of these three factors is strong. The risk of pollution may involve more ecological and environmental impacts. It takes a long time for pollution to accumulate to a level at which it has a significant impact on the environment. Accordingly, residents’ perception of pollution risks is at a normal level (0.345). Among the personal influence factors, the risk experience is relatively strong for residents’ risk perception (0.531), because the residents are more sensitive to the risk and the resistance to the equipment will be stronger after the risk accident.

According to the calculation formula of the fuzzy evaluation set of the second-level index, and according to the fuzzy comprehensive evaluation of the maximum membership degree, the maximum membership degree of $B_1$ is 0.355, and the evaluation grade is $V_2$, indicating that the residents’ perceptions of the project’s environmental risk characteristics is strong. The degree of $B_2$ is at a normal level. The results of this indicator demonstrate that the impact of personal characteristics on residents’ risk perception is at a normal level.

The fuzzy matrix based on the first-level indexes obtained above constitutes the evaluation matrix $V_B$ of the target layer. The fuzzy matrix of the target layer is obtained by calculation, $A = [0.170 \ 0.342 \ 0.317 \ 0.149 \ 0.071]$. According to the maximum criterion of fuzzy comprehensive rating membership, the residents’ groups have a strong level of environmental risk perception of the petrochemical project. According to the calculation formula for residents’ risk perception value, the perceived value of the resident group is $7 \times 10^{-5}$, which indicates that the resident group has a strong sense of risk of the petrochemical project, and that residents have a resistance to risk.

In the same way, the perceived value of the expert group is $7 \times 10^{-5}$, which demonstrates that the risk perception level of the expert group for the petrochemical project is normal. This indicates that experts rely more than residents on professional risk analysis for petrochemical projects via knowledge and professional ability to assess the risks of the project itself and the combined impact on society. The risk perception value of the government department is $7 \times 10^{-6}$, indicating that the government’s risk perception level for the petrochemical project is at a relatively high level. The risk perception value of the enterprise groups is $7 \times 10^{-4}$, indicating that the enterprise group’s risk
perception of the Xuwei Petrochemical Project is weak, and the enterprise can accept more risks. It shows that enterprises are willing to accept greater risks and have a lesser degree of risk perception when they grasp the maximization of their own information and corporate interests.

3.3.3. Total Social Risk Perception

Based on the analysis of the expert questionnaire, the multi-level structure weights of the residents, expert groups, government departments, and enterprise groups were determined (Equations (4)). The total social risk perception value is about $7.252 \times 10^{-4}$, which is the result of the standard value of acceptable social risk perception. After the group risk perception and social risk perception are obtained, the results can be used as a reference for the planning of the park project. The risk of the petrochemical project should not exceed the standard value acceptable for a certain group and society.

4. Social Risk Control of Petrochemical Project in Xuwei

4.1. Social Risk Control Model Construction

Risk control research along with the largest risk-aware group is divided into three parts, namely: the confirmation of risk control research subjects; the selection of risk control factors and the degree of influence; and the design of risk control policies.

4.2. Survey Object and Data Source

The survey scope of the social risk control investigation was streets, villages, enterprises, and institutions within the scope of evaluation of petrochemical bases. The design of the questionnaire was divided into three aspects: (1) basic personal characteristics, including gender, age, education level, occupation, etc.; (2) information on cognitive factors, including environmental quality satisfaction, petrochemical project understanding, and information disclosure trust; and (3) project influencing factors, including project planning rationality, quality of life improvement, economic development satisfaction, etc. You can see the results in Table3. and see more details in Section 3.3.1.

4.3. Variable Setting

The residents’ attitudes were set as the dependent variable $Y$, which was measured by the support rate of the measurement model. In the selection of the independent variable $X$, the key independent variables of this paper were set as information cognitive factors and project influencing factors according to our previous survey results of risk attitude evaluation of waste incineration plant with the model hypothesis [50]. Among them, information cognitive factors include environmental quality satisfaction, petrochemical project understanding, and information disclosure trust. Project influencing factors include project planning rationality, quality of life improvement, and economic development satisfaction.

4.4. Probit Model Construction

The constructed Probit regression model was used to measure the probability of residents supporting the construction of petrochemical projects, and then to assess the main influencing factors of residents’ attitudes. The Probit regression model is expressed as:

$$Y_i^* = \alpha + \beta X_i + \mu$$ (5)

where $X_i$ is the independent variable vector, which refers to the basic personal eigenvector ($X_1$), information cognitive factor vector ($X_2$), and project influence factor vector ($X_3$). $Y_i^*$ is the explanatory variable, indicating whether the residents support the petrochemical project construction, $\mu$ is the random interference term and it obeys the standard positive distribution. When $Y_i = 1$, the probability that the residents support the project construction can be expressed as:
\[ P(Y_i = 1 | X_i = x) = P(Y_i > 0 | x) = P[\mu > -(\alpha + \beta x) | x] \\
= 1 - P[\mu \leq -(\alpha + \beta x) | x] = 1 - \Phi[-(\alpha + \beta x)] \\
= \Phi(\alpha + \beta x) \]

The analyzed variables are then incorporated into the above equation to obtain the following formula:

\[ P(Y_i = 1 | X_i) = \Phi(\alpha_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \mu) \\
= \Phi(\alpha_0 + \beta_{11} x_{11} + \beta_{12} x_{12} + \beta_{13} x_{13} + \beta_{14} x_{14} + \beta_{21} x_{21} \\
+ \beta_{22} x_{22} + \beta_{23} x_{23} + \beta_{31} x_{31} + \beta_{32} x_{32} + \beta_{33} x_{33} + \mu) \]

According to the influencing factors of residents’ attitudes summarized above, \( x_{11} \) represents the first independent variable under the basic personal eigenvector, namely the resident’s gender, \( x_{12} \) is the age, \( x_{13} \) is the education level, and \( x_{14} \) is the occupation; \( x_{21} \) is the first independent variable under the information cognition factor of the environmental quality satisfaction, \( x_{22} \) is the degree of petrochemical project understanding, and \( x_{23} \) is the degree of trust in information publicity; \( x_{31} \) is the first independent variable under the project influencing factors—the project planning rationality, \( x_{32} \) is the degree of quality of life improvement, and \( x_{33} \) is the degree of economic development satisfaction.

4.5. Model Analysis Results

The probit regression model was used to analyze the influencing factors affecting residents’ attitudes. The results are shown in Table 4. In the regression results of the model, the factors affecting the basic personal characteristics are not significantly related, except for the significant degree of cultural levels and residents’ attitudes. Among the information cognitive factors, petrochemical project understanding, trust in information publicity, and residents’ attitudes are significant. Further relevant factors are project planning rationality, quality of life improvement, and economic development satisfaction, which are significant factors affecting residents’ attitudes.

| Variable                              | Number of People | Proportion (%) |
|---------------------------------------|------------------|----------------|
| Environmental quality satisfaction    |                  |                |
| Very satisfied                        | 141              | 28.2           |
| Satisfied                             | 312              | 62.4           |
| Not satisfied                         | 47               | 9.4            |
| understanding                         | 242              | 48.4           |
| Information cognition factor          |                  |                |
| Petrochemical project understanding   |                  |                |
| Know a little                         | 172              | 34.4           |
| Do not understand                    | 86               | 17.2           |
| Trust                                | 298              | 59.6           |
| Distrust                              | 46               | 9.2            |
| Information disclosure trust          |                  |                |
| Does not matter                      | 156              | 31.2           |
| Distrust                              | 46               | 9.2            |
| Project planning rationality          |                  |                |
| More reasonable                      | 168              | 33.6           |
| Reasonable                           | 314              | 62.8           |
| Unreasonable                         | 18               | 3.6            |
| Increase                              | 344              | 68.8           |
| Quality of life improvement          |                  |                |
| No effect                             | 122              | 24.4           |
| Reduce                               | 34               | 6.8            |
| Advantageous                         | 441              | 88.2           |
| Economic development satisfaction     |                  |                |
| No effect                             | 52               | 10.4           |
| Unfavorable                          | 7                | 1.4            |
| Attitude towards the petrochemical project |      |                |
| Support                              | 442              | 88.4           |
| Oppose                               | 58               | 11.6           |

**Table 4.** Model generalized linear regression results.

| Variables                         | Probit Model | Logistic Model |
|-----------------------------------|--------------|----------------|
| Basic personal characteristics    | Gender       | −0.0643        | −0.0900        |
In the average marginal effect of the probit model (Table 5), in terms of information cognitive factors, the more comprehensive the interviewee’s information cognition, the more support they had for the petrochemical project construction. This is embodied in the following two aspects: the resident’s understanding of the petrochemical project can increase the project support rate by 5% for each level of increase; the resident’s confidence in the project’s information publicity rises by one level, which indicates that the probability of residents supporting the project is 18% higher than the probability of residents opposing the projects. This shows that the higher the trust in information disclosure and the higher the understanding of petrochemical projects, the more inclined residents are to support the construction of the project. This means that the government can understand and support the project construction when the residents fully understand and trust the petrochemical project.

For project impact factors, it is considered that the more reasonable the project planning, the greater the improvement in the quality of life, the higher the satisfaction with the economic development, and the more positive the attitudes of the supporters towards the project. Among them, given the other variables, project planning rationality, quality of life improvement, and economic

### Table 5. Average marginal effect of the probit model.

| Factor                        | Mean   | dy/dx  | Std.Err. | z       | P > |z| | 95% Conf. | Interval |
|-------------------------------|--------|--------|----------|---------|-----|---|------------|----------|
| Gender                        | 0.514  | -0.0143| 0.0328   | -0.440  | 0.6620| |0.0786| 0.0499 |
| Age                           | 1.248  | -0.0109| 0.0226   | -0.480  | 0.6310| |0.0552| 0.0335 |
| Educational level             | 1.982  | 0.1215 | 0.0182   | 6.670   | 0.0000| |0.0858| 0.1573 |
| Career                        | 2.304  | 0.0109 | 0.0106   | 1.020   | 0.3060| |0.0100| 0.0317 |
| Environmental quality         | 1.070  | 0.0336 | 0.0283   | 1.190   | 0.2350| |0.0218| 0.0890 |
| satisfaction                  | 1.128  | 0.0496 | 0.0406   | 1.220   | 0.0220| |0.0300| 0.1291 |
| Petrochemical project         | 1.044  | 0.1811 | 0.0367   | 4.940   | 0.0000| |0.1092| 0.2531 |
| understanding                | 1.052  | 0.0990 | 0.0426   | 2.3300  | 0.0200| |0.1824| 0.0155 |
| Information disclosure trust  | 1.020  | 0.0923 | 0.0444   | 2.0800  | 0.0380| |0.0053| 0.1793 |
| Project planning rationality  | 0.944  | 0.1488 | 0.0412   | 3.610   | 0.0000| |0.2297| 0.0680 |
| Quality of life improvement   |        |        |          |         |      |   |           |          |
| Economic development          |        |        |          |         |      |   |           |          |
| satisfaction                  |        |        |          |         |      |   |           |          |

Number of Obs: 500.
development satisfaction increased by 10%, 9%, and 15% for each level of increase in residents’ project support rate, respectively.

Given the other variables, among the personal factors, as the level of education increased, the support rate for the project increased by 12%. The results show that people with higher levels of education are more likely to support petrochemical projects, which may be related to the extent to which they receive information. In order to improve the situation of information asymmetry, the higher the education level of residents, the more actively they can understand various information, and hence rational judgment is improved.

The analysis shows that there was no significant correlation between the personal factors of residents’ gender, occupation, and age and residents’ attitudes. Within the personal factors, the higher the level of education, the more support for the petrochemical project, which may be related to the extent to which residents receive information. The judgment on the risk of the facility increased with a higher the level of education. This is attributed to greater knowledge and the ability to understand information, which increase the individual’s rational assessment. Factors significantly related to residents’ attitudes are information cognitive factors and project influencing factors. Information cognitive factors include trust in information publicity and petrochemical project understanding, while environmental quality satisfaction has no significant correlation with residents’ attitudes. Moreover, the most influential factors affecting residents’ attitudes are trust in information publicity followed by the education level. The economic development satisfaction factor has the lowest effect on the attitude to the project.

5. Discussion

5.1. Risk Perception Differences between Various Groups

There are many factors that can impact on risk perception. In 2019, Ul-Abdin and Zainwritten investigated various attributes of users’ formation of risk perception [51]. The results suggested that risk formation among users evolves around tangible and non-tangible attributes. The spectrum of risk perception was developed, which visualizes risk evolution by considering various attributes. Different groups have different risk perceptions of the chemical Park. Residents’ groups are more aware of risks and have a resistance to risk. This is because residents have a general knowledge of the risks of chemical projects, and there are few intellectual and scientific considerations. The factors affecting risk estimates and tolerance among persons were closely associated with judged benefits of the hazard source, acceptance or denial of vulnerability, judgments of exposure voluntariness, and environmental attitudes [52]. If the health risks, accident risks, and safety risks are very serious, this leads to risk perception being stronger and to a reduction in risk acceptance. According to the analysis results, the residents’ groups have a resistance to the risk of petrochemical projects, which is the largest risk source group of all social groups. Residents are also the participants of group events. Therefore, in subsequent research on social risk control, the resident group will be taken as the research subject of risk control, and the risk control will be analyzed.

The risk perception level of the expert group on the project is at a normal level. This is because the experts have comprehensive information on chemical projects and the risk assessment is more scientific and reasonable due to the accumulation of their own professional knowledge [53]. In terms of risk perception, it relies on more comprehensive risk project information, risk education, and personal experience [14]. The risk assessment will comprehensively consider the influencing factors of the accident risk characteristics and objectively evaluate the risks.

When government departments conduct risk management, the information asymmetry relies more on the judgment of experts. The decision-making also considers more political achievements. However, for accident risks, the government shows a tendency to avoid risks. For government departments, health risk accidents, chemical accidents, security risks, and media transmission will lead to a passive situation. At this time, there will be a strong risk perception. In most cases of risk management, the government’s own interests will become an important decision-making factor for risk perception.
Enterprise groups are less aware of the risks of the project and can accept greater risks. Under the comprehensive risk information, enterprises have a comprehensive understanding of the project’s environmental risks. Despite this, they have a risk-aware weak decision-making cognition that is willing to accept more risks as a result of economic interests. Among the risk-aware factors, the frequent appearance of project accident risks and the occurrence of major accidents will result in resistance to risks [54].

5.2. The Risk Control of the Residents’ Attitudes

The evaluation of the risk control was taken to represent the residents’ attitudes to the petrochemical project (support/objection), which is considered as the criterion for judging whether or not to participate in the group event. In 2017, Huan investigated the status of knowledge, attitudes, and behaviors with regard to schistosomiasis control among rural residents in the Wanjiang River region after a flood, so as to provide a reference for targeted health education [55]. The conclusion was that targeted health education should be strengthened to decrease the risk of schistosomiasis transmission. Hong developed an extended technology acceptance model (TAM) to explain residents’ intention to adopt green labeled residential buildings (GLRBs), and examined it in a survey conducted in Tianjin City, China [56]. The results showed that subjective knowledge about GLRBs, social trust in organizations responsible for GLRBs, perceived usefulness of GLRBs, attitude towards GLRBs, and general environmental attitude measured by the new ecological paradigm (NEP) scale are the significant psychological determinants of the intention to adopt GLRBs. According to the analysis results, educational level, information cognitive factors, and project influencing factors are significantly related to the residents’ attitudes. In the present study, the information cognitive factors included the residents’ trust in information publicity and their petrochemical project understanding. The project influencing factors included project planning rationality and quality of life improvement, as well as economic development satisfaction. The degree of information publicity had the highest degree of influence on residents’ attitudes, followed by the level of education, and the satisfaction with economic development had the lowest degree of influence. Improving the level of trust in residents through information disclosure is the core of the government’s risk control policy. In the design and formulation of risk control policies, it is recommended that the government protect the nature of the information that residents receive through the information disclosure of enterprises and governments, as well as the guidance of media and experts. This is proposed to improve the information trust in residents, and to improve the support and understanding for chemical projects.

5.3. Risk Control Policy

In order to effectively prevent social risks and maintain social stability, the government should assume a key role in risk control. Li et al. studied soil pollution, summarizing the existing law, action plan, regulations, and risk control rules regarding soil pollution prevention in China [57]. In 2015, Zhao established ultra high voltage (UHV) power transmission construction projects, which seek to improve the risk control level and the sustainable development of UHV power transmission construction projects [58]. Ioannou investigated uncertainties present during the operation of offshore wind (OW) energy assets with a view of informing risk control policies for hedging of the incurring losses [59]. As a risk regulator, the government needs to supervise and guide the risks for participants, namely residents, media, experts, and enterprises. As the main source of risk concerns, residents are the main subject of government risk control. The government needs to protect residents’ safety risks and health benefits from the perspective of the residents. Through the analyses above, the core of risk control policy formulation is to ensure information transparency and information disclosure to improve residents’ information trust, by requiring that enterprises disclose information, using the information transmission capabilities of expert media, diversifying and expanding residents’ participation, and so on. Therefore, more information needs to be taken into account and information guidance is required in the government’s risk control policy.

The media and experts are connected to enterprises and residents as the mediums for risk information, hence the government needs to guide them to maintain social stability [60]. The
government should pay attention to the role of the media and experts in the transmission of risk information, use the media and experts to disseminate correct risk knowledge, report government and enterprise risk information in a timely manner, and prevent the unwarranted amplification of risks caused by the distortion of risk information [28]. Moreover, social software, such as network channels, is a tool for residents to communicate information. The government needs to promptly intervene to use the official information publicity platform to enable the public to obtain correct risk perception.

In addition, the petrochemical enterprise, as the main body responsible for risks, is an important part of the government’s risk control system and the object of supervision [5]. The government’s supervision of enterprises not only requires the publicity and transparency of enterprise protection information, but also needs to comprehensively formulate risk control policies from both internal and external levels. Internal risk control includes the application of advanced facilities, implementation of cleaner production, improvement of emergency response capabilities, emphasis on diversification of information disclosure, and awareness of corporate social responsibility; external risk control includes policies and regulations, reward and punishment mechanisms, and regulatory measures. In short, in the formulation of the government’s risk control policy, it is necessary to coordinate the relationship between various risk factors in order to truly control the social risks.

6. Conclusions

This paper outlines a systematic study on the social risks of potential high environmental risk chemical park projects. Social risk assessment shows that different groups have both different perceptions of risk and different factors affecting risk perception. Taking the resident group as an example, the resident group has a general knowledge of the risks of chemical projects, and there are few intellectual and scientific considerations. According to the residents’ social risk perception value ($7 \times 10^{-6}$), it can be seen that the residents’ groups have a strong sense of risk of petrochemical projects and a strong resistance to risk. The risk perception level of the expert group for the petrochemical project is normal. The government’s risk perception value ($7 \times 10^{-6}$) shows that the government’s risk perception of the project is at a relatively high level, and that there is resistance to the project risk. Furthermore, according to the social risk perception value of the project ($7 \times 10^{-5}$), it is indicated that the enterprise group is weakly aware of the risk of the project and can accept more risks. Finally, the total social risk perception value of the petrochemical project is about $7.252 \times 10^{-4}$, which is the result of the standard value of acceptable social risk perception. Therefore, in order to avoid the social risk of the park project, the risk of a petrochemical project should not exceed a standard value acceptable to a group and society’s total risk perception.

The social risk control research was based on the risk perception judgment conclusion. The risk participation group was further analyzed by the established social risk control research model. The results of the analyses indicated that the individual factors of gender, occupation, and age of residents are not significantly related to residents’ attitudes. Factors that are significantly related to residents’ attitudes are information cognitive factors and project influencing factors. Information cognitive factors include trust in information publicity and petrochemical project understanding. Project impact factors include project planning rationality, quality of life improvement, and economic development satisfaction. The degree of trust in information disclosure has the highest contribution of influence, followed by the level of education; the satisfaction with economic development has lowest degree of influence. Therefore, improving residents’ trust in information disclosure is the key point with regard to government risk control policies. The government’s risk control policy is formulated according to the results of risk control research. As a risk regulator, the government needs to supervise and guide the risks to participants, namely residents, media, experts, and enterprises. Residents, as the main source of risk concerns, are the main subject of government risk control. The government needs to maintain residents’ safety risks and health benefits from the perspective of residents. To improve the residents’ perceptions of the trustworthiness of information disclosure, it is recommended that the government use experts to disclose information. The media has the ability to transmit information, diversify and expand residents’ participation, and improve residents’
knowledge of information to increase residents’ trust in government information disclosure, thereby enhancing residents’ support and understanding of chemical projects.

**Author Contributions:** Conceptualization, Y.N; Methodology, J. Z; Stata and Investigation, J. Z; Writing—Original Draft Preparation, Y. N; Writing—Review and Editing, Y. Z; Supervision, J. Z.”. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work is supported by Shanghai Philosophy and Social Science Planning Project (2016BJB008).

**Acknowledgments:** We appreciate Yanjing Wu in the School of Economics and Zeyuan Liu in the School of Environmental and Chemical Engineering for their data collection.

**Conflicts of Interest:** The authors declare no conflict of interest.

**References**

1. Ike, G.N.; Usman, O.; Sarkodie, S.A. Testing the role of oil production in the environmental Kuznets curve of oil producing countries: New insights from Method of Moments Quantile Regression. *Sci. Total Environ.* 2020, 711, 135208–135208.

2. Chen, T.-L.; Pei, S.-L.; Fan, S.-Y.; Yu, C.-Y.; Chang, C.-L.; Chiang, P.-C. An engineering-environmental-economic-energy assessment for integrated air pollutants reduction, CO2 capture and utilization exemplified by the high-gravity process. *J. Environ. Manag.* 2020, 255, 109870–109878.

3. Aghadadashi, V.; Molaei, S.; Mehedinia, A.; Mohammadi, J.; Moeinaddini, M.; Riyahi Bakhtiari, A. Using GIS, geostatistics and Fuzzy logic to study spatial structure of sedimentary total PAHs and potential eco-risks; An Eastern Persian Gulf case study. *Mar. Pollut. Bull.* 2019, 149, 110489–110501.

4. Shaygan, M.; Yazdanpanah, M. Prevalence and Predicting Factors of Chronic Pain among Workers of Petrochemical and Petroleum Refinery Plants. *Int. J. Occup. Environ. Med.* 2020, 11, 3–14.

5. Signorino, G. Proximity and risk perception. Comparing risk perception ‘profiles’ in two petrochemical areas of Sicily (Augusta and Milazzo). *J. Risk Res.* 2012, 15, 1223–1243.

6. Tortosa-Edo, V.; Lopez-Navarro, M.A.; Llorens-Monzonis, J.; Rodriguez-Artola, R.M. The antecedent role of personal environmental values in the relationships among trust in companies, information processing and risk perception. *J. Risk Res.* 2014, 17, 1019–1035.

7. Geng, Z.; Zeng, R.; Han, Y.; Zhong, Y.; Fu, H. Energy efficiency evaluation and energy saving based on DEA integrated affinity propagation clustering: Case study of complex petrochemical industries. *Energy* 2019, 179, 863–875.

8. Niccoletti, M.; Lutti, N.; Souza, R.; Pagotto, L. Social and organizational learning in the adaptation to the process of climate change: The case of a Brazilian thermoplastic resins and petrochemical company. *J. Clean. Prod.* 2019, 226, 746–758.

9. Choi, Y.; Lee, H.S.; Mastur, A. Are Sustainable Development Policies Really Feasible? Focused on the Petrochemical Industry in Korea. *Sustainability* 2019, 11, 3980–3997.

10. Kolla, G.; Strike, C.; Watson, T.M.; Jairam, J.; Fischer, B.; Bayoumi, A.M. Risk creating and risk reducing: Community perceptions of supervised consumption facilities for illicit drug use. *Health Risk Soc.* 2017, 19, 91–111.

11. Pol, E.; Di Masso, A.; Castrechini, A.; Bonet, M.R.; Vidal, T. Psychological parameters to understand and manage the NIMBY effect. *Eur. Rev. Appl. Psychol. Rev. Eur. Psychol. Appl.* 2006, 56, 43–51.

12. Musmeci, L.; Falleni, F.; Cicero, M.; Carere, M. Environmental Pollution in Augusta-Priolo and Gela. In *WHO Book: “Human Health in Areas with Industrial Contamination”*. 2014; pp. 89–98.

13. Zhang, L.; Wang, S.; Chen, C.; Yang, M.; She, X. Modeling lane-change risk in urban expressway off-ramp area based on naturalistic driving data. *J. Test. Eval.* 2020, 48, doi 10.1520/JTE20190269.

14. Yu, C.-H.; Huang, S.-K.; Qin, P.; Chen, X. Local residents’ risk perceptions in response to shale gas exploitation: Evidence from China. *Energy Policy* 2018, 113, 123–134.

15. Lefley, F. What is Our Perception of Project Risk, and do the Current Theories Truly Reflect Our Pragmatic Interpretation of This Perception? *IEEE Eng. Manag. Rev.* 2018, 46, 65–73.

16. Chiang, Y.-C. Exploring community risk perceptions of climate change—A case study of a flood-prone urban area of Taiwan. *Cities* 2018, 74, 42–51.

17. Zhu, W.; Wei, J.; Zhao, D. Anti-nuclear behavioral intentions: The role of perceived knowledge, information processing, and risk perception. *Energy Policy* 2016, 88, 168–177.
18. Wang, H.Z.; Khan, F.; Ahmed, S.; Imtiaz, S. Dynamic quantitative operational risk assessment of chemical processes. *Chem. Eng. Sci.* 2016, 142, 62–78.
19. Gholipour, S.; Nikaeen, M.; Farhadkhani, M.; Nikmanesh, B. Survey of Listeria monocytogenes contamination of various environmental samples and associated health risks. *Food Control* 2020, 108, 6.
20. Alieche, N.; Cozzani, V.; Reniers, G.; Estel, L. Thresholds for domino effects and safety distances in the process industry: A review of approaches and regulations. *Reliab. Eng. Syst. Saf.* 2015, 143, 74–84.
21. Cozzani, V.; Gubinelli, G.; Salzano, E. Escalation thresholds in the assessment of domino accidental events. *J. Hazard. Mater.* 2006, 129, 1–21.
22. Markowski, A.S.; Kotynia, A. “Bow-tie” model in layer of protection analysis. *Process Saf. Environ. Protect.* 2011, 89, 205–213.
23. Fabbrocino, G.; Iervolino, I.; Orlando, F.; Salzano, E. Quantitative risk analysis of oil storage facilities in seismic areas. *J. Hazard. Mater.* 2005, 123, 61–69.
24. Valencia-Barragan, L.; Martinez-Gomez, J.; Maria Ponce-Ortega, J. A quantitative risk analysis for the vegetable oil industry in Mexico. *Clean Technol. Environ. Policy* 2016, 18, 245–256.
25. Zhang, G.; Fan, Y.; Jiang, X.; Fan, W.; Meng, T.; Xu, M. Assessing the impacts of signal coordination on the crash risks of various driving cohorts. *J. Saf. Res.* 2019, 70, 79–87.
26. Fellenor, J.; Barnett, J.; Potter, C.; Urquhart, J.; Mumford, J.D.; Quine, C.P. The social amplification of risk on Twitter: The case of ash dieback disease in the United Kingdom. *J. Risk Res.* 2018, 21, 1163–1183.
27. Jagiello, R.D.; Hills, T.T. Bad News Has Wings: Dread Risk Mediates Social Amplification in Risk Communication. *Risk Anal.* 2018, 38, 2193–2207.
28. Wirz, C.D.; Xenos, M.A.; Brossard, D.; Scheufele, D.; Chung, J.H.; Massarani, L. Rethinking Social Amplification of Risk: Social Media and Zika in Three Languages. *Risk Anal.* 2018, 38, 2599–2624.
29. Frewer, L.J.; Miles, S.; Marsh, R. The media and genetically modified foods: Evidence in support of social amplification of risk. *Risk Anal.* 2002, 22, 701–711.
30. Moussaid, M.; Brighton, H.; Gaismaier, W. The amplification of risk in experimental diffusion chains. *Proc. Natl. Acad. Sci. USA* 2015, 112, 5631–5636.
31. Wang, Y.N. *Risk Control Cyber Physical System for Active Distributed Network*; 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2): Beijing, China, 2018; pp. 1–6.
32. Liu, X.; Li, J.; Li, X. Study of dynamic risk management system for flammable and explosive dangerous chemicals storage area. *J. Loss Prev. Process Ind.* 2017, 49, 983–988.
33. Feng, S.; Xu, L.D. Decision support for fuzzy comprehensive evaluation of urban development. *Fuzzy Sets Syst.* 1999, 105, 1–12.
34. Chen, J.F.; Hsieh, H.N.; Do, Q.H. Evaluating teaching performance based on fuzzy AHP and comprehensive evaluation approach. *Appl. Soft. Comput.* 2015, 28, 100–108.
35. Shi, S.; Cao, J.; Feng, L.; Liang, W.; Zhang, L. Construction of a technique plan repository and evaluation system based on AHP group decision-making for emergency treatment and disposal in chemical pollution accidents. *J. Hazard. Mater.* 2014, 276, 200–206.
36. Zeng, D.; He, Q.; Yu, Z.; Jia, W.; Zhang, S.; Liu, Q. Risk assessment of sustained casing pressure in gas wells based on the fuzzy comprehensive evaluation method. *J. Nat. Gas Sci. Eng.* 2017, 46, 756–763.
37. Xu, X.; Huang, D.; Guo, F. Addressing spatial heterogeneity of injury severity using Bayesian multilevel ordered probit model. *Res. Transp. Econ.* 2019, 100748, doi:10.1016/j.retrec.2019.100748.
38. Antunes, A.; Bonfim, D.; Monteiro, N.; Rodrigues, P.M.M. Forecasting banking crises with dynamic panel probit models. *Int. J. Forecast.* 2018, 34, 249–275.
39. Gan, L.; Zhang, H.; Wen, Y.; Zou, Z. Risk Degree Analysis of Bridge Damage Caused by Collision of Disabled Ships Based on Ordered Probit Model. In Proceedings of the 21st 2011 International Offshore and Polar Engineering Conference (ISOPE), Maui, HI, USA, 19–24 June 2011; pp. 871–875.
40. Ma, J.; Ye, X.; Shi, C. Development of Multivariate Ordered Probit Model to Understand Household Vehicle Ownership Behavior in Xiaoshan District of Hangzhou, China. *Sustainability* 2018, 10, 3660.
41. James, M. Simplified Methods of Using Probit Analysis in Consequence Analysis. *Process Saf. Prog.* 2015, 34, 58–63.
42. Ignatowski, A.J.; Rosenthal, I. The chemical accident risk assessment thesaurus: A tool for analyzing and comparing diverse risk assessment processes and definitions. *Risk Anal.* 2001, 21, 513–532.
43. Albaiges, J. Ecological risk assessment, 2nd edition. *Int. J. Environ. Anal. Chem.* 2008, 88, 601–601.
44. Si, H.; Ji, H.; Zeng, X.H. Quantitative risk assessment model of hazardous chemicals leakage and application. *Saf. Sci.* 2012, 50, 1452–1461.
45. Heo, S.; Kim, M.; Yu, H.; Lee, W.-K.; Sohn, J.R.; Jung, S.-Y.; Moon, K.W.; Byeon, S.H. Chemical accident hazard assessment by spatial analysis of chemical factories and accident records in South Korea. *Int. J. Disaster Risk Reduct.* 2018, 27, 37–47.
46. Liu, Y.H.; Fang, P.P.; Bian, D.D.; Zhang, H.W.; Wang, S.X. Fuzzy comprehensive evaluation for the motion performance of autonomous underwater vehicles. *Ocean Eng.* 2014, 88, 568–577.
47. Chu, W.W.; Li, Y.G.; Liu, C.Q.; Mou, W.P.; Tang, L.M. A manufacturing resource allocation method with knowledge-based fuzzy comprehensive evaluation for aircraft structural parts. *Int. J. Prod. Res.* 2014, 52, 3239–3258.
48. Loh, H.S.; Zhou, Q.J.; Thai, V.V.; Wong, Y.D.; Yuen, K.F. Fuzzy comprehensive evaluation of port-centric supply chain disruption threats. *Ocean Coast. Manag.* 2017, 148, 53–62.
49. Nie, Y.; Wu, Y.; Zhao, J.; Zhou, J.; Chen, X.J.; Maraseni, T.; Qian, G. Is the finer the better for municipal solid waste (MSW) classification in view of recyclable constituents? A comprehensive social, economic and environmental analysis. *Waste Manag.* 2018, 79, 472–480.
50. Nie, Y.; Wu, Y.; Zhao, J.; Zhou, J.; Zhang, Y.; Zhao, J.; Maraseni, T.; Qian, G. Resident risk attitude analysis in the decision-making management of waste incineration construction. *J. Environ. Manag.* 2020, 258, 109946–109962.
51. Ul-Abdin, Z.; De Winne, P.; De Backer, H. Risk-Perception Formation Considering Tangible and Non-Tangible Aspects of Cycling: A Flemish Case Study. *Sustainability* 2019, 11, 6474–6493.
52. Baird, B.N. Tolerance for environmental health risks: The influence of knowledge, benefits, voluntariness, and environmental attitudes. *Risk Anal.* 1986, 6, 425–435.
53. Sjoberg, L. The allegedly simple structure of experts’ risk perception: An urban legend in risk research. *Sci. Technol. Hum. Values* 2002, 27, 443–459.
54. Karpuntsov, M.V. Enterprise risk-resistance. *Actual Probl. Econ.* 2008,81, 71–76.
55. Huan, L.; Ai-Xia, W.; Yuan-Zhen, L.; Ming-Ming, Z. Knowledge, attitude and practice related to schistosomiasis control among rural residents in Wanjing River region after a flood. *Chin. J. Schistosomiasis Cont.* 2017, 29, 219–221.
56. Liu, Y.; Hong, Z.; Zhu, J.; Yan, J.; Qi, J.; Liu, P. Promoting green residential buildings: Residents’ environmental attitude, subjective knowledge, and social trust matter. *Energy Policy* 2018, 112, 152–161.
57. Li, T.; Liu, Y.; Lin, S.; Liu, Y.; Xie, Y. Soil Pollution Management in China: A Brief Introduction. *Sustainability* 2019, 11, 556–571.
58. Zhao, H.; Li, N. Risk Evaluation of a UHV Power Transmission Construction Project Based on a Cloud Model and FCE Method for Sustainability. *Sustainability* 2015, 7, 2885–2914.
59. Ioannou, A.; Angus, A.; Brennan, F. Informing parametric risk control policies for operational uncertainties of offshore wind energy assets. *Ocean Eng.* 2019, 177, 1–11.
60. Rutsaert, P.; Pieniaj, Z.; Regan, A.; McConnon, Á.; Kuttshcreuter, M.; Loes, M.; Lozano, N.; Guzzon, A.; Santare, D.; Verbeke, W. Social media as a useful tool in food risk and benefit communication? A strategic orientation approach. *Food Policy* 2014, 46, 84–93.

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