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Interdependency patterns of potential seaport risk factors in relation to supply chain disruption in Indonesia

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Abstract

As an integral part of the global supply chain network, Indonesian supply chain entities should understand conditional seaport risk factors that could lead to seaport threats that affect supply chain continuity. This study aims to provide a procedure for evaluating the interdependencies, implications, and correlations among various seaport risk factors for supply chain threats, specifically by investigating current practices in the developed economic region of Indonesian seaport operations. The study uses a rough set method to solve feature selection problems and multivariate analysis of variance to assess the correlation between dependent and independent variables. We find 39 conditional seaport risk factors that are potentially influenced by about 21 dependent factors related to seaport-fulcrum supply chain entities. Furthermore, threats from the planning process, infrastructure, seaport service process, distribution process, financial costs of nuclear enterprises and security existed and affluent highest potential risk in Indonesia.

Keywords: Seaport risk factors, Interdependency risk analysis, Rule rough set theory, Genetic algorithm, Association rule mining

Introduction

In the context of global economic integration, seaports are key components of wider transportation systems, both within and between countries. Otherwise, the competitive position of seaport depends more on their role in the supply chain. Modern seaport organisations have thus become an important node in the globally integrated supply chain. In addition, their role has changed from transport or distribution centres to integrated logistics service centres. As an intersection of the global mobility chain of goods and people, ports have become a critical part of effectively and efficiently assessing and managing seaport-centric supply chain risks (Loh et al. 2017), protecting people and the environment, and maintaining quality and performance. For instance, issues such as the giant ship blocking the Suez Canal due to high winds in 2021, and the pandemic-related ship backlog in Southern California resulted in severe shipment delays and significant financial losses (Notteboom et al. 2021).

Disruptive events at seaports affect various stakeholders and dimensions of the seaport supply chain. Identifying seaport risks involves understanding threats to the supply chain from disruptive events. Correctly identifying these risks contributes to the logistics industry by increasing seaport resilience and ensuring business sustainability. According to Shu et al. (2017), supply chain disruption risk carriers can be classified into two main types: macro-carriers and micro-carriers. Macro-carriers are mainly environmental, demand, and financial risks that cover events, market, and foreign exchange risks. Microcarriers can be divided into overt and covert carriers, and primarily concern internal risks such as with capital, cost, quality, technology, and information. Overt carriers include capital, information, and logistics, while covert carriers pertain to the bullwhip effect (Lee et al. 1997), financial leverage effect and the domino effect, among many others. Therefore, the risk assessment needs to include various elements related to the maritime industry and its supply chain system.

Some disruption-management activities that seaport enterprises conduct considerably influence seaport operators in Indonesian seaports and can be involved in supply chain disruption. According to statistics from the Inspectorate General Ministry of Transportation of the Republic of Indonesia (2014–2018), a total of 9,755 disruption management actions have occurred. Furthermore, cargo distribution imbalances, such as those due to infrastructure availability, shipping patterns, and the supply and demand of maritime transport, including port connectivity, between the western (developed economic region) and eastern (developing economic region) parts of Indonesia create challenges related to supply chain risk disruption, reduce the satisfaction level of seaport operation, and increase high logistics costs and price disparity between the two regions (Do. Bagus and Hanaoka 2022a). Moreover, these shipping costs affect the gross regional domestic product per capita in some developing economies due to the above-mentioned disparity.

Assessing the significance of seaports toward supply chain continuity in the past increases awareness of conditional risks and concerns to maintain its resilience. Therefore, the seaport-fulcrum supply chain risk proposed by Do. Bagus and Hanaoka (2022b) is defined as all activities of conditional seaport risk factors that have the potential to threaten the supply chain continuity. Although various studies (Esteban et al. 2020; Jiang et al. 2018; Dewi and Purnamasari 2021; Loh et al. 2017; Morris 2020; Weng et al. 2020) have attempted to explain such a phenomenon, few studies have been conducted to describe interdependence patterns (degree) among conditional seaport risk factors and identify the potential risks of these correlations. Therefore, the purpose of this study is to provide a procedure for evaluating the interdependence, implications, and associations among various seaport risk factors for supply chain threats by analysing current practices of Indonesian seaport operations in the developed economic region.

To reduce uncertainty and address the large number of risk factors in the dataset, this study employs the Rough Set Based Genetic Algorithm (RSGA) to examine the patterns between conditional seaport risk factors. Furthermore, an output of the rough set generates the core attribute set, which is independent of the multiple reduction attribute set, taking into account the calculation of the degree of dependency of the rough set (Pawlak 1991). The RSGA is then useful to separate the seaport risk factors into two categories—core (independent variables) and non-core (dependent variables) attributes—based on their degree of dependence on the rough set. Furthermore, the separation is assessed using a multivariate analysis of variance (MANOVA) to generate model interactions for both attributes. The purpose of the MANOVA is to test whether the vector of means of the seaport risk variables for observations of two or more groups are from the same sampling distribution. As a result, MANOVA is used to analyse the interaction between certain dependent variables and numerous predictors, and then to determine whether the interactions are significant for a linear combination of variables or for each variable separately. Accordingly, the regression risk model is used as the predictive model for seaport-fulcrum supply chain risks. Finally, the association rule learning is calculated according to the rough set model to explain the extent to which the degree of interdependence affects the implication degree of implication of the conditional seaport risk factors. This comparison can provide insight into the potential conditional seaport risk factors that can disrupt supply chain continuity.

Literature review

The seaport is not only for the transfer of goods, containers or people from one mode of transport to another, but it is also the place to add value and generate benefits to the supply chain activities (Do Bagus and Hanaoka 2022a). The passage of a commodity through a seaport may be the most basic service provided to the end customer (i.e., importer and exporter) of the supply chain (Hossain et al. 2020). Due to the involvement of interconnected structural and infrastructural nodes that form a framework supporting the functionality of the global supply chain system, seaports often experience a disruptive event that consequently reduces the performance of the supply chain network itself (Do Bagus and Hanaoka 2022b; Loh et al. 2017; Hossain et al. 2020). For example, catastrophic maritime accidents have severe social and economic impacts on the sustainability of this system (Akyuz 2015; Celik et al. 2010; Heij et al. 2011). These impacts have been dramatically demonstrated in events such as the Amoco Cadiz oil tanker spill, which spilled 230,000 tonnes of crude oil and had a severe negative impact on local tourism-related businesses (Wang et al. 2021), and ground-shaking and soil liquefaction from earthquakes (e.g. Port-au-Prince, Haiti, 2010; Maule, Chile, 2010; Tohoku, Japan, 2011; Samara, Costa Rica, 2012; Kaikoura, New Zealand, 2016), which resulted in severe damage to seaport structures (Conca et al. 2020). Furthermore, Mokhtari et al. (2012) argue that these infrastructure systems can affect a country's cost structure, industrial competitiveness and living standards. Thus, potential disruptions can trigger a domino effect that affects the performance of the entire supply chain system, including the overall well-being of society.

Seaports are often located in densely populated areas with operational activities (e.g., loading and unloading), to support economic activities in regional and national development (Notteboom et al. 2021). The economic function of a seaport, according to Gross (1990), is to increase the producer and consumer surplus of those who generate the exports and those who ultimately consume the imports that pass through it. The management of a seaport is therefore complex, as it requires the consideration and active monitoring of various operations and the concerns of all the actors in the supply chain. Overall, seaports play a crucial role in various commercial activities; however, they are highly complex systems that require a large number of employees due to the widespread use of personnel and technological equipment (Nevins et al.

1998). Thus, all stakeholders of supply chain entities play equally important roles. For example, port state control is carried out by port state authorities to ensure that foreign vessels comply with safety requirements and pollution regulations. If serious deficiencies are found, the ship is detained and ordered to rectify the deficiencies before its departure (Wang et al. 2021). Do Bagus and Hanaoka (2022b) investigated the obligations of seaport organisations such as seaport management, seaport operators, and seaport users in relation to seaport-fulcrum supply chain risk disruptions. Pileggi et al. (2020) also provided a stakeholder analysis carried out by the port authority, which revealed that the communication asymmetry between stakeholders was responsible for the disruption of seaport operational continuity and contributed to the other conditional seaport risk factors.

In general, an interdependency between two or more entities/factors is a correlation dependency between them. In recent decades, many studies have focused on the risk analysis of interdependencies between the critical infrastructure as a centre and other entities or factors. For example, Mota et al. (2016) investigated the impact of cascading failures in complex infrastructure systems that clearly affect the whole transport system, including its supply chain network. Understanding other risk factors, such as the mutual risk events between natural disasters and emergency risk planning, high logistics costs and price disparities, or other seaport disruptions with economic impacts, is as important as critical infrastructure correlation (Do Bagus and Hanaoka 2022b). In addition, Adiliya (2019) addressed the issue of high logistics cost and price disparity in Indonesian seaport operations. Amin et al. (2021) found that shipping costs are detrimental to per capita gross regional domestic product in some developing countries due to the above-mentioned disparity. While some of the developed regions in Indonesia are still struggling with dwell time, inefficient maritime security inspections at sea reduce the productivity of ships, leading to fees and contract cancellations, and increasing voyage costs (Do Bagus and Hanaoka 2022a; Dewi and Purnamasari 2021; Zaman et al. 2015; Komarudin et al. 2017). Amin et al. (2021) showed that the lower demand for containers due imbalance of cargo throughput in the developing regions of Indonesia leads to higher sea transport costs and maritime logistics and reduces port performance. Loh et al. (2017) revealed that the mismatch communication among stakeholders may be responsible for port strikes. They further stated that such an event can result in the inability to fulfil orders, breach of contractual obligations, negative impact on manufacturing, retail, and food industries, and delayed, duplicated or lost shipments of supplies, delayed shipments to customers, and inventory build-up.

The literature review above shows that seaports are increasingly integrated into the continuity of the supply chain, and therefore disruptive events originating from seaport can affect these entities. However, many supply chain risk identification and assessment models emphasise seaport infrastructure in terms of interdependency. Therefore, further research is likely to be needed to elucidate the interdependence between conditional seaport risk factors and supply chain concerns, as well as their potential risks in terms of stakeholder preferences. Limited research has been conducted explaining the above phenomena of interdependence. Therefore, this study fills the research gap by providing an interdependency risk factor analysis of stakeholder preferences regarding risk management in seaport using the case study in Indonesia seaport.

Materials and methods

Survey data and procedures

This empirical study investigated the roles of supply chain entities to understand their patterns of interdependency. Thus, to collect primary data from seaport-fulcrum supply chain organisations in Indonesia, we used a stratified random sampling technique (Slovin's formula) to invite 750 respondents to participate in an online questionnaire survey and face-to-face interviews with some top-level managers. The survey began in January and ended in August 2021. The design of the questionnaire was such that the definition of each dimensional threat factor and conditional seaport risk factor was clearly stated before the questions. Moreover, the definition of the scale in the subsequent Sect. Selection of dimensional threats and risk attributes is also explained before the questions and is shown in Appendix A.

The seaport-fulcrum supply chain stakeholders in Indonesia were divided into three major entities that substantially influence supply chain concerns, according to Do. Bagus and Hanaoka (2022b). The seaport manager works for a government agency or government-owned company. The seaport operator is in control of the seaport firm's operating procedures, which includes containers and non-containerised commodities, such as automobiles, liquids, and dry bulk items. Finally, the seaport users are stakeholders that collaborate with seaport operators and have a direct interest in the goods moved via seaports. As a result, the seaport users targeted include cargo owners, freight forwarders, ship owners, and ship management businesses. Three stratum samples comprising 10% of seaport managers, 30% of seaport operators, and 60% of seaport users, were collected as primary data from seaport-fulcrum supply chain entities in Indonesia.

Referring to Shipping Law Number 17 of 2008, the Port Authority in Indonesia has outwardly returned the authority to manage state land and business activities at the port to a government agency under the Ministry of Transportation, replacing the state-owned enterprise [Perseroan Terbatas (PT)]. Pelindo (Persero) acted as an operator and regulator at the port prior to the enactment of the decree but only as an operator after. Thus, the Port Authority of Indonesia's seaport consists of two entities: a harbour master as the regulator and PT. Pelindo as the port operator. Hence, in this study, the seaport manager is the harbour master, whereas the seaport operator is a state-owned enterprise. Furthermore, seaport users such as PT. Temas Shipping and Kalla Lines are included in this study. The distribution of questionnaire feedback from seaport-fulcrum supply chain stakeholders is shown in Fig. 1. As noted, the number in the graph indicates the number of experts who filled out the questionnaire completely.

A total of 153 data units (20% estimated response rate) were collected from seaport-fulcrum supply chain stakeholders, which is in line with the planned collection target of 150 data units. The respondents comprised 10.5% seaport managers, 42.5% seaport operators, and 47.0% seaport users. The gender composition of the sample was 69.3% male and 30.7% female. More than half of the respondents (56.9%) had over 10 years of experience, followed by those with 5–10 years of experience (39.2%). This study's procedure began with examining the potential of supply chain disruption as a threat dimension and then generated conditional risk factors rated on a five-level ordinal scale, which indicated the risk implications for supply chain continuity.

Fig. 1 The number of responses questionnaire per region

To create the proposed model, an initial test of primary data was deployed first to verify the reliability of the dataset after collection. In total, 153 responses were tested. Based on Cronbach's alpha, the dataset was determined to be reliable, with 88.2% as an input for the RSGA. Next, a decisional factor was developed to assess this term and determine the impact of seaport disruption on seaport-fulcrum supply chain risk. This approach adapts a rough set model to find the central dependency in several attributes through a questionnaire survey, according to Do Bagus and Hanaoka (2022b). The algorithm generates a reduction attribute set that helps obtain a core attribute set. The core attribute set is crucial for understanding the centre of the seaport-focal supply chain risk tendency.

Selection of dimensional threats and risk attributes

We mainly identified dimensional threats and seaport risk attributes from accident reports found in the literature. The dimensional threats defined as potential risks from the seaport operation, whether direct or indirect, that have a significant impact to disrupt the continuity of the supply chain. Accordingly, 61 risk attributes divided by 10 dimensional threats were identified as the result of an extensive examination of the relevant literature (e.g. Jiang et al. 2018; Loh et al. 2017; John et al. 2014; and Kavirathna et al. 2018) and discussions with some experts. Thus, we categorised the 10 dimensional threats in Table 1, which were sourced from 61 conditional seaport risks according to the four abovementioned studies. We then identified several indices to capture the different perspectives of domain experts. However, the dimensional threats as latent variables have different conditional seaport risk factors as seaport risk criteria. Thus, we created this threat categorisation to represent the degree/level of reaction to the danger in terms of ports monitoring, as well as to describe the breadth of measures that may be taken. Furthermore, the 61 conditional seaport risk factors are divided by the 10 dimensional threats, as indexed and labelled in Table 1 (Do. Bagus and Hanaoka 2022b).

Each attribute is coded and assigned to the appropriate numerical value as follows: (1) 'highest level' indicates loss of ability to perform operations and/or meet customer requirements; (2) 'high level' indicates temporarily interrupting or stopping normal operations and/or delivery of goods and/or services to customers; (3) 'medium level' indicates postponement in force of regular operations, plans and schedules, and/or

Table 1 Seaport-fulcrum supply chain risk factors

Dimensional threats	Index A_i	Conditional risk attributes	Index a_{ij}
Planning process threats	A_1	Lack of seaport-enterprise strategic risk	a_{11}
		Lack of berth risk planning	a_{12}
		Lack of supply chain strategic risk planning	a_{13}
		Lack of ship risk planning	a_{14}
		Lack of handling process risk planning	a_{15}
		Lack of storage risk planning	a_{16}
		Lack of transfer risk planning	a_{17}
		Lack of distribution risk planning	a_{18}
		Deficiency of berth allocation risk planning	a_{19}
Infrastructure threats	A_2	Port equipment breakdown	a_{21}
		Inadequate port cargo handling equipment	a_{22}
		Occupational accidents	a_{23}
		Power outages	a_{24}
		Breakdown of vessel traffic management system	a_{25}
		Breakdown of port information system	a_{26}
		Collisions in the waterway	a_{27}
Seaport service process threats	A_3	Congestion in the waterway	a_{31}
		Congestion within terminals	a_{32}
		Congestion at hinterland transfer	a_{33}
		Less services calling at port	a_{34}
		Fewer ship visits	a_{35}
		Less load factors in captive cargo	a_{36}
		Shortage of facilities or equipment	a_{37}
		Shortage of port capacity	a_{38}
		Shortage of IT and advanced technology	a_{39}
Distribution process threats	A_4	Less timeliness of port departure and entry	a_{41}
		Low punctuality of delivery goods	a_{42}
		Less timeliness of port customs clearance	a_{43}
		Bad defect condition of goods	a_{44}
		Low deviation time	a_{45}
		Low efficiency of navigational services	a_{46}
		Long time in feeder link	a_{47}
		Less quality of logistics company	a_{48}
Relationship process threats	A_5	Lack of member coordination	a_{51}
		Member exit mechanism	a_{52}
		Port labour strikes	a_{53}
		Less motivation of member interest distribution mechanism	a_{54}
		Member information asymmetry	a_{55}
Nuclear-enterprise financial threats	A_6	Low revenue	a_{61}
		High debt	a_{62}
		Low-efficiency operation	a_{63}
		Low growth development	a_{64}
		Less cash flow	a_{65}
		Less growth of domestic and international macroeconomic operation	a_{66}
Monetary threats	A_7	Less efficient deviation cost s	a_{71}
		Less efficient port cost s	a_{72}
		Less efficient costs in feeder link	a_{73}

Table 1 (continued)

Dimensional threats	Index A_i	Conditional risk attributes	Index a_{ij}
Location threats	A_8	Short sailing time to other hub ports	a_{81}
		Less accessibility of hub ports	a_{82}
		Long connectivity of feeder markets	a_{83}
Security threats	A_9	International trade war	a_{91}
		War or terrorist attacks	a_{92}
		Stowaway	a_{93}
		Smuggling	a_{94}
		Trafficking	a_{95}
		Exchange rates	a_{96}
Environmental threats	A_{10}	Earthquake frequency	a_{101}
		Pandemic/epidemic occurrence	a_{102}
		Typhoon frequency	a_{103}
		Increasing sea-level at the seaport	a_{104}
		Increasing sedimentary level at the seaport	a_{105}
Decisional factors	D	Implication of seaport risk to the potential threats of supply chain continuity	

additional conveyance of products and/or services to customers; (4) 'low level' indicates deviation in transportation plans, costs, common operations, timetables, quality, and/or additional measures of conveyed merchandise (products) and/or services to customers; and (5) 'lowest level' indicates operations that remain unaffected or only experience a negligible effect.

Rough set for attribute reduction problem

Rough set theory can effectively address the complexity and uncertainty of the seaport-fulcrum supply chain risk. However, support is needed when dealing with several seaport risks and nondeterministic polynomial-hard problems in the combinatorial optimisation of the dataset. Therefore, we followed the RSGA according to Do. Bagus and Hanaoka (2022b), which was designed to obtain the reduction attributes and solve the combination problem between seaport risk and its threats to the supply chain with minimal data processing. The algorithm was built in Matlab and operated 50 times to obtain the reduction and intersection of whole reduction attributes, called core attributes, which contained the independent attributes to be examined using a MANOVA.

Given a decision table as a quadruple (4-tuples) $IS = \{U, A, V_a, f\}$, where $U = \{x_1, x_2, \ldots, x_q\}$ is a finite set of objects (universe); $A = \{a_1, a_2, \ldots, a_j\}$ is a finite set of features, consisting of conditional and decision attributes denoted $A = C \cup D$, where $D = \{d_1, d_2, \ldots, d_j\}$, $C \neq \emptyset$, and $D \neq \emptyset$; V_a is the value set of attribute a, where $V = 1, 2, \ldots, 5$ indicates the highest to lowest evaluations; and $V = \cup_{a \in A} V_a$; and f: $U \times A \rightarrow V$ is a total function such that $f(x,a) \in V_a$ for each $a \in A$, and $x \in U$ is called the information function.

The indiscernibility relation (I_B), which is an equivalence relation, aims to reduce the geometric increase in the possible risk alternative and determine the elementary sets, connection, and functional form. For instance, some objects in U (e.g. x_1 and x_2) can hardly be distinguished in an available set of attributes. Hence, let be B in A. This definition is called an *indiscernibility relation* I_B for every $b \subset B$. Any set of all indiscernible objects is called an elementary set because it represents the smallest discernible groups of decision-makers, and such a set forms a basic granule of knowledge about the seaport-fulcrum supply chain risk factors.

Moreover, the rule induction technique in the proposed model hinges on a pair of crisp sets, known as the positive region ($\underline{B}(X) = \bigcup_{x \in U, I_B(x) \subseteq X} I_B(x)$) and negative region ($\overline{B}(X) = \bigcup_{x \in X} I_B(x)$). Elements $\underline{B}(X)$ are all and only those objects $x \in U$ certainly belonging to the equivalence classes generated by indiscernibility relation I_B contained in X. The elements of $\overline{B}(X)$ are all and only those objects $x \in U$ belonging to the equivalence classes generated by indiscernibility relation I_B containing at least one object x belonging to X. Table 2 shows the parameters, indices, and decision variables.

The following formula was used for fitness design to obtain the attribute reduction set:

$$\min F_B = p_1 k_B + p_2\left(\frac{|C| - |B|}{|C|}\right) + p_3 \overline{S}_B \tag{1}$$

subject to:

$$k_B = \frac{|POS_B(D)|}{|U|}, 0 \leq k_B \leq 1 \tag{2}$$

$$\sum_{i=1}^{n} \overline{S}_B = \frac{|POS_C(D)| - \left|POS_{(B-a_i)}(D)\right|}{|U|} = 1, \overline{S}_B > 0 \tag{3}$$

Table 2 Symbols used in the reduction model

Sets and indices	
U	Set of observations, indexed by $x \in U$
A	Set of risk factors related to the threats, indexed by $a_{ij} \in A$ for all attributes
C	Set of conditional seaport risk factors, indexed by $a_{ij} \in C_j$
D	A decisional variable, indexed by $a_{ij} \notin D_j$
V_a	Set of risk magnitude {1, 2, 3,…,h} indexed by f(x,a) $\in V_a$
I_B or B	Set of indiscernible relation, indexed by $(x_1, x_2) \in I_B$
I	Number of threat factors
J	Number of conditional risk factors
L	Number of observations
Parameters	
K	Dependency degree
S	Importance degree
p_1	Classification ability
p_2	Reduction rate
p_3	Correction factor
Variables	
k_B	Dependency degree for each indiscernible relation $a_i \in I_B$
F_B	Attribute reduction set
$\overline{S}$	Weight indicator

$$X = \left\{x \in B : x_1(u_j) \neq x_2(u_j)\right\} forj = 1, 2, \ldots, n \quad (4)$$

$$p_1 = -5, p_2 = -2, p_3 = 1\} k < k_B \quad (5)$$

The objective function depicts the total weighted (importance degree) change in the overall indiscernibility relation of the conditional seaport risk for various changes in the seaport risk factors. In the constraint of Eq. 2, the basic approximation law of rough set theory (degree of dependence) is indicated. In addition, the dependence between the risk attributes can be defined as follows. First, if D and C are subsets of A, D will depend on C to degree K $(0 \le k \le 1)$, denoted by $C \Rightarrow {}_k D$, and if $k = \gamma(C, D)$. Second, if $K = 1$, D depends entirely on C; if $K < 1$, D depends partially (in K) on C. These concepts of dependence are discussed in relation to the seaport risk factors in the datasets. Therefore, the degree of dependence for any positive regions in constraint (5) should not exceed the degree of dependence in the indiscernibility relation. Meanwhile, to maintain the convergence speed and achieve the global optimum, while preserving the knowledge in the dataset, we follow a preliminary step from Do. Bagus and Hanaoka (2022b) to determine the pre-classification model as a significance attribute, where the conditional attribute subset is $I_B \subset C \ \forall \ a_i \in I_B$, and the significance of I_B is defined in the constraint of Eq. 3. This completes the basic concept of the RSGA and indicates the removal of redundant attributes or remaining dependent attributes. The final output of RSGA was the core set of attributes that were independent, while the remaining conditional attributes were grouped as dependent. Each independent and dependent variable was tested with the MANOVA.

MANOVA procedures

After the RSGA, we separated the conditional seaport risk variables into independent and dependent variables. Both were analysed using a MANOVA, and the procedures are shown in Fig. 2. In this study, MANOVAs were used in two circumstances. First, we wanted to check some associated dependent variables from the seaport risk features in the single test to this collection of variables rather than multiple individual tests. Second, we aimed to investigate how independent factors impact certain response patterns of dependent variables. In this case, we used an equivalent of contrast codes on the dependent variables to test hypotheses regarding how the independent factors differentially predict the dependent variables.

The MANOVA was performed using IBM SPSS. The categorical data from the subjective preferences of seaport stakeholders shown in Table 1 were transformed into continuous data using a successive interval method (Mosier 1940; Edwards and Thurstone 1952). For the MANOVA, we performed a statistical test in a single attempt and checked whether it retained the characteristics of the dependent and the independent variables. If there was insignificance from the first attempt, we changed the original variables to other variables until we obtained significance for all features. In this way, we were able to predict the risk of supply chain disruption for the seaport fulcrum using the multiple regression function generated. The flowchart of the method is presented in Fig. 2.

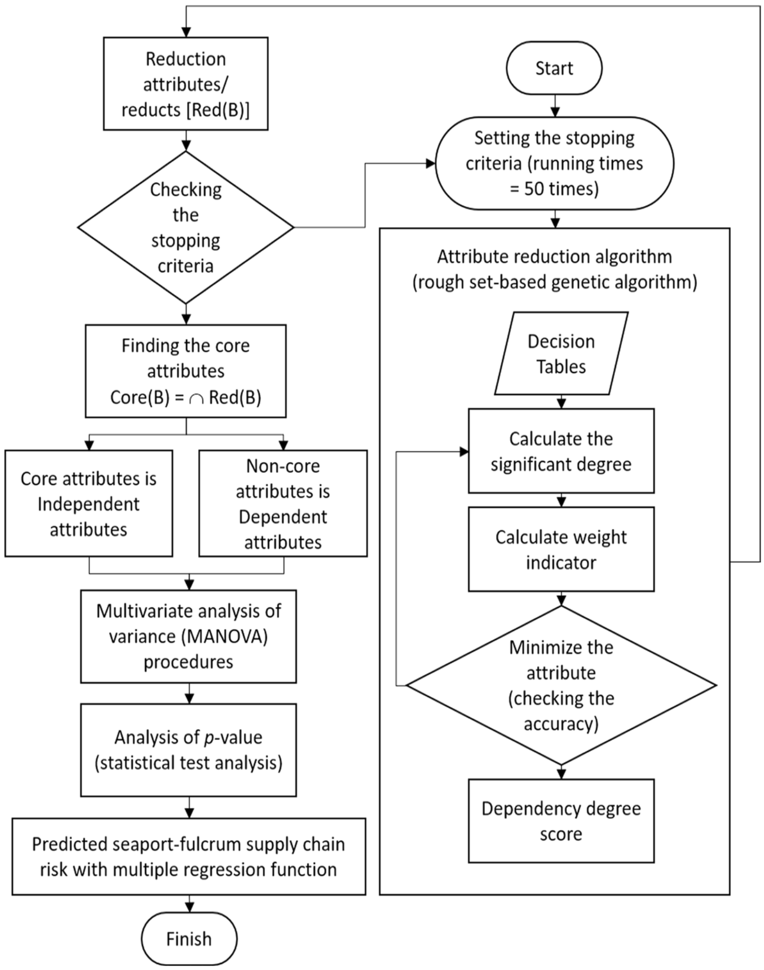

Fig. 2 Flowchart of the method

Rule induction of the rough set for the potential risk analysis

To analyse the potential risks for seaport-fulcrum supply chain disruption, we used rule induction according to Do. Bagus and Hanaoka (2022b). Our basic assumption is that the datasets are presented as decision tables. As mentioned in Sect. Rough set for attribute reduction problem, the set of all cases is denoted by U, $U=\{1, 2, 3, \ldots, 153\}$, and the conditional seaport risk factors (features) are divided to denote conditional attributes (C_j) and decisional attributes (D_j). For attribute a and case x, $a(x)$ denotes the value of attribute a for case x. Hence, it can be generated as an equivalence relation using the rough set presented in Sect.Rough set for attribute reduction problem

The elementary sets of the equivalence relation are based on partition $\{d\}$, which are referred to as concepts. Each concept contains five different risk levels according to Sect. Selection of dimensional threats and risk attributes. The set of all equivalence classes $[x]_B$ is a partition of U denoted by B^*. Thus, the definition of rule r is expressed as follows:

$$(c_1, v_1)\&(c_2, v_2)\&\ldots\&(c_i, v_5) \rightarrow (d, w) \tag{6}$$

where c_1, c_2,..., c_i are distinct attributes, d is a decision, v_1, v_2, ..., v_5 are respective attributes values, and w is decision values.

A case (object) x is covered by a rule r if and only if any attribute value pairs of r are satisfied by the corresponding value of x. By this definition, we can determine some domains of the conditional seaport risk level (range of value) from both attributes respectively:

$$V_C = \cup_{c_i \in C} V_{c_i} \text{for conditional attributes} \tag{7}$$

$$V_D = \cup_{d_j \in D} V_{d_j} \text{for decisional attributes} \tag{8}$$

Based on Eqs. 6–8, we can obtain a foundation to determine a decision protocol. We consider the frequency of risk level in the simplicity of the analysis. Then, we can compute the decision protocol according to the risk level as follows:$V_{c_i}^1 \to V_{d_j}^1$ for the decision protocol highest risk, $V_{c_i}^2 \to V_{d_j}^2$ for the decision protocol high risk, $V_{c_i}^3 \to V_{d_j}^3$ for the decision protocol medium risk,$V_{c_i}^4 \to V_{d_j}^4$ for the decision protocol low risk, and $V_{c_i}^5 \to V_{d_j}^5$ for the decision protocol lowest risk.

The above assumptions are useful for computing degrees of interdependency (*coverage factors*) and implication (*certainty factors*). According to Do. Bagus and Hanaoka (2022b), *certainty* represents the conditional probability that deficiency itemset D will occur under the condition that deficiency itemset C occurs, which means the frequency of occurrence is found in the dataset as defined below. If the certainty is equal to 1, itemset C implicates itemset D, while if the certainty is between 0–1, an itemset C is dependent on the others to implicate itemset D. While *coverage* is defined as the ratio of the conditional probability of the occurrence of antecedent C and that of consequent D to the probability of the occurrence of antecedent C, as expressed below. Coverage can be used explain a decision class. Both degrees are denoted as follows:

$$cer_x(C;D) = \frac{|C(x) \cap D(x)|}{|C(x)|} = \frac{Supp_x(V_{c_i}^h \to V_{d_j}^h)}{|C(x)|} \tag{9}$$

$$cov_x(C;D) = \frac{|C(x) \cap D(x)|}{|D(x)|} = \frac{Supp_x(V_{c_i}^h \to V_{d_j}^h)}{|D(x)|} \tag{10}$$

Evaluation of influencing factors

Evaluation of attribute reduction

Indexing the set is a crucial construction related to the reasonability and quality of the comprehensive evaluation. This step is necessary to determine the weight of the parameters, which can sometimes lead to a multiple attribute decision problem. In line with the seaport-fulcrum supply chain risk in Table 1, the index construction is described in Sect. Rough set for attribute reduction problem Following the reduction algorithm, the reduction sets were generated as shown in Appendix B. A core set containing the predictors for the MANOVA was then defined as an intersection of the reduction set shown in Appendix C. The core set contains the central tendency of the seaport risk factors as shown in Table 3. In addition, to analyze the convergence performance of the algorithm, we record the changes in the optimal individual and average fitness values in the iterative process for each reduction attribute set based on the discriminability matrix, as shown in Fig. 3. While the termination setup of RSGA is to reach 200 generations to

Table 3 MANOVA results for between-subject effects

First attempt				**Second attempt**			
Dependent atts	**Sig. test (*p* value)**	**Independent atts**	**Sig. test (*p* value)**	**Dependent atts**	**Sig. test (*p* value)**	**Independent atts**	**Sig. test (*p* value)**
a_{11}	0.000	a_{14}	0.012	a_{11}	0.000	a_{14}	0.003
a_{12}	0.000	a_{15}	0.000	a_{12}	0.000	a_{15}	0.000
a_{13}	0.000	a_{16}	0.004	a_{13}	0.000	a_{16}	0.001
a_{17}	0.000	a_{18}	0.010	a_{17}	0.000	a_{18}	0.006
a_{19}	0.000	a_{25}	0.000	a_{19}	0.000	a_{25}	0.000
a_{21}	0.000	a_{26}	0.000	a_{21}	0.000	a_{26}	0.000
a_{22}	0.000	**a_{31}**	**0.185**	a_{22}	0.000	a_{33}	0.000
a_{23}	0.000	a_{33}	0.001	a_{23}	0.000	a_{34}	0.035
a_{24}	0.000	a_{34}	0.016	a_{24}	0.000	a_{38}	0.018
a_{27}	0.000	a_{38}	0.027	a_{27}	0.000	a_{39}	0.000
a_{32}	0.000	a_{39}	0.000	a_{31}	0.001	a_{42}	0.009
a_{35}	0.000	a_{42}	0.009	a_{32}	0.000	a_{43}	0.000
a_{36}	0.000	a_{43}	0.000	a_{35}	0.000	a_{54}	0.000
a_{37}	0.000	a_{54}	0.000	a_{36}	0.000	a_{61}	0.000
a_{41}	0.000	a_{61}	0.000	a_{37}	0.000	a_{73}	0.000
a_{44}	**0.146**	**a_{64}**	**0.051**	a_{41}	0.000	a_{91}	0.003
a_{45}	0.001	a_{73}	0.000	a_{45}	0.000	a_{95}	0.000
a_{46}	0.000	**a_{81}**	**0.621**	a_{46}	0.000	a_{101}	0.000
a_{47}	0.001	a_{91}	0.008	a_{47}	0.000	a_{102}	0.001
a_{48}	0.000	**a_{94}**	**0.513**	a_{48}	0.000	a_{104}	0.004
a_{51}	0.000	a_{95}	0.014	a_{51}	0.000	a_{105}	0.016
a_{52}	0.000	a_{101}	0.000	a_{52}	0.000	21 variables in total	
a_{53}	0.000	a_{102}	0.001	a_{53}	0.000		
a_{55}	0.000	a_{105}	0.006	a_{55}	0.000		
a_{62}	0.007	24 variables in total		a_{62}	0.000		
a_{63}	0.000			a_{63}	0.000		
a_{65}	0.000			a_{64}	0.000		
a_{66}	0.000			a_{65}	0.000		
a_{71}	0.000			a_{66}	0.000		
a_{72}	0.000			a_{71}	0.000		
a_{82}	0.007			a_{72}	0.000		
a_{83}	0.000			a_{81}	0.040		
a_{92}	0.000			a_{82}	0.004		
a_{93}	0.000			a_{83}	0.000		
a_{96}	0.031			a_{92}	0.000		
a_{103}	0.000			a_{93}	0.000		
a_{104}	0.112			a_{94}	0.000		
37 variables in total				a_{96}	0.007		
				a_{103}	0.000		
				39 variables in total			

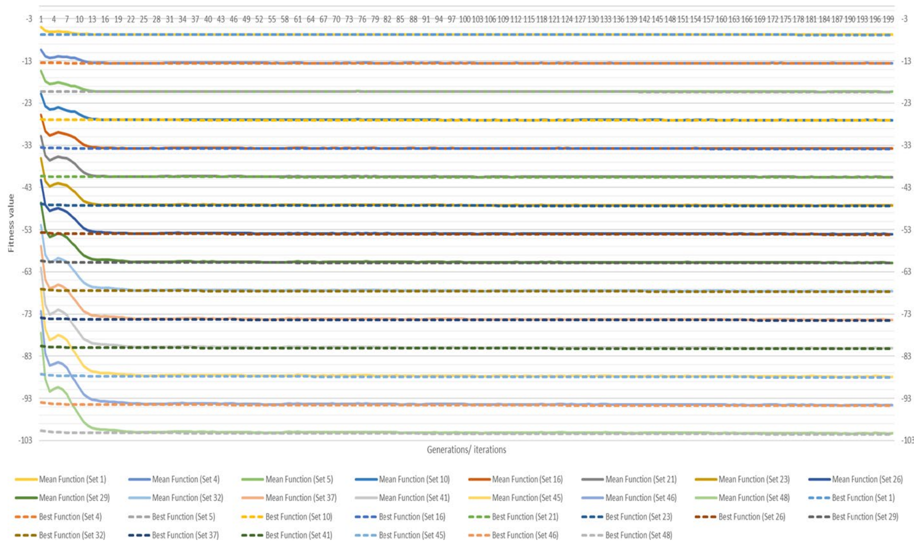

Fig. 3 Optimal and average fitting process

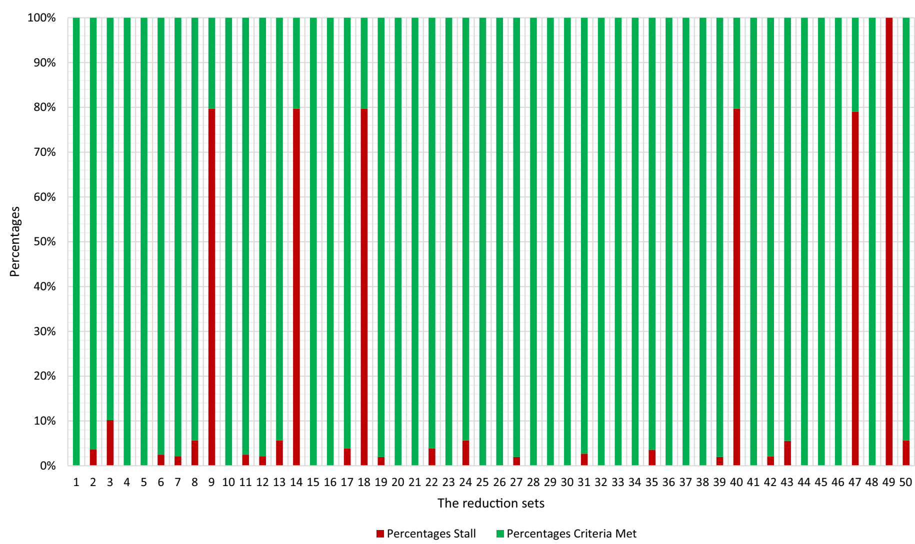

Fig. 4 The percentage of reduction quality according to the stop criteria set

check whether the algorithm has fallen to the local optimum or not. This parameter is called the quality of the reduction attribute sets, shown in Fig. 4. If the iterations stop before reaching the stopping criteria, it is directly related to the percentage of the reduction set itself in Fig. 4.

Evaluation of the MANOVA

We used a two-way MANOVA with an interaction parameter and examined the presence of interaction. The RSGA creates predictor features, while the remaining characteristics serve as dependent factors. Hence, we used a null hypothesis to test the significance of both variables as follows:

H0 The dependent variables from the reduction algorithm have similar matrix correlations (variance–covariance) with the predictor features.

This study uses a significance level (alpha) of 0.05 indicating a 5% risk of concluding that an association exists when there is no actual association. This means if the p value is less than the significance level, it can be concluded that the differences between the means are statistically significant. In the first attempt, we obtained four predictors and two dependent variables that were not statistically significant (p value > 0.05). In the second attempt, the insignificant factors used as independent variables were switched to be dependent variables. However, variable a_{44} (bad defect condition of goods) remained non-significant with a score of 0.202 in the second try. A change is allowed if the significance test is below 5%. Thus, the variable was determined to be ineffective as a classifier and removed from the dataset. In Table 2, the bold indicates that a variable is not significant. Table 3 additionally presents a comparison of various predictor features and predicted factors. The dependent variables differ substantially from the independent variables, as demonstrated by a p value of 0.05 in the statistical test.

Predictive model

Table 4 shows how the 39 conditional seaport risk factors in this investigation depended on 21 predictor features. Hence, the significance levels were used to evaluate the relationship between the variables, and multiple linear regression analysis was used to build the predictive model. Moreover, the empirical equation from the predictive model of the relationships among seaport risk factors based on the distribution of seaport-fulcrum supply chain stakeholders is described in Appendix D, in which the first column shows the dependent variables followed by the intercept and the predictor features. The significance features of the predictors on the dependent variables are shown in Fig. 5.

In Fig. 5, a less efficient deviation cost significantly (a_{73}) contributes to the other 14 dependent seaport risk factors, followed by a shortage of IT and advanced technology (a_{39}) with 12 offshoots to other seaport risk factors. However, the 21 predictors did not significantly influence short sailing time to the other hub port (a_{81}).

Potential conditional seaport risk

The predictive model in Table 4 explains the correlation from the conditional seaport risk factors towards the supply chain disruption. To conduct a better evaluation, we used association rule mining according to Sect. Rule induction of the rough set for the potential risk analysis to find the potential risks in the predictive model. Association rule mining aims to find interesting associations (potential risk) among the features of a large dataset, referring to the parameters in Eqs. 9–10. The discovery of a potential risk that implies a single concept is referred to as an interdimensional association rule, since it contains a single distinct concept with multiple occurrences in the dataset. Therefore, we generated the decision protocol's highest risk to understand the potential risk of seaport-fulcrum supply chain disruption in the dataset.

Attributes of the decision table referring to Sect. Rough set for attribute reduction problem are divided into two disjointed groups. Each object (U) induces a specific decision rule, which is the level of disruption according to Sect. Selection of

Table 4 Predictive model of the planning process threats dimension

R^2	Adjusted R^2	Predictive model
0.50	0.42	$a_{11}=0.11+0.29a_{15}+0.17a_{18}-0.15a_{101}+0.14a_{102}$
0.38	0.28	$a_{12}=0.25+0.22a_{14}+0.19a_{16}-0.20a_{26}$
0.42	0.32	$a_{13}=1.87+0.26a_{15}-0.28a_{25}+0.29a_{26}+0.18a_{33}+0.36a_{39}-0.19a_{54}+0.24a_{73}$
0.41	0.31	$a_{17}=0.67+0.19a_{16}+0.25a_{18}+0.23a_{43}$
0.47	0.39	$a_{19}=0.02+0.20a_{14}+0.105a_{102}$
0.31	0.19	$a_{21}=0.49+0.34a_{25}+0.24a_{91}$
0.38	0.28	$a_{22}=0.27+0.32a_{25}+0.21a_{39}-0.21a_{73}+0.24a_{95}$
0.42	0.33	$a_{23}=1.15+0.31a_{26}-0.28a_{42}+0.24a_{73}+0.22a_{101}$
0.38	0.28	$a_{24}=0.46+0.19a_{25}+0.21a_{26}-0.19a_{39}-0.31a_{42}+0.20a_{101}$
0.47	0.38	$a_{27}=1.71-0.18a_{14}+0.17a_{16}+0.31a_{25}+0.27a_{26}+0.23a_{38}-0.25a_{39}+0.18a_{73}$
0.28	0.16	$a_{31}=1.03-0.22a_{15}+0.18a_{18}+0.23a_{33}-0.21a_{95}$
0.37	0.27	$a_{32}=0.31-0.23a_{33}+0.20a_{38}+0.26a_{39}-0.24a_{43}+0.21a_{101}$
0.32	0.21	$a_{35}=0.52+0.35a_{39}$
0.39	0.29	$a_{36}=0.93-0.18a_{14}+0.22a_{39}+0.32a_{54}+0.29a_{73}-0.21a_{91}-0.23a_{102}$
0.42	0.33	$a_{37}=1.47-0.26a_{15}+0.40a_{16}+0.20a_{26}+0.21a_{38}-0.18a_{54}-0.34a_{95}-0.21a_{104}$
0.35	0.24	$a_{41}=-0.17+0.19a_{18}+0.26a_{42}+0.18a_{54}-0.17a_{102}$
0.31	0.20	$a_{45}=1.57+0.17a_{43}+0.23a_{61}$
0.34	0.23	$a_{46}=0.78+0.25a_{43}+0.28a_{61}$
0.32	0.21	$a_{47}=0.85+0.27a_{34}-0.21a_{95}-0.16a_{104}$
0.34	0.24	$a_{48}=0.88+0.33a_{54}$
0.44	0.35	$a_{51}=0.52+0.20a_{15}-0.21a_{25}+0.22a_{26}+0.21a_{39}+0.22a_{43}+0.22a_{73}$
0.52	0.44	$a_{52}=0.58+0.20a_{18}-0.28a_{33}+0.27a_{34}+0.25a_{54}+0.18a_{61}+0.17a_{91}-0.18a_{95}$
0.34	0.23	$a_{53}=0.32+0.26a_{39}+0.29a_{73}$
0.46	0.38	$a_{55}=0.17+0.19a_{18}+0.24a_{54}+0.25a_{61}+0.22a_{73}$
0.33	0.22	$a_{62}=0.52+0.21a_{16}+0.26a_{61}+0.23a_{73}-0.28a_{104}$
0.43	0.34	$a_{63}=0.56+0.17a_{18}+0.30a_{39}-0.20a_{42}-0.34a_{43}+0.21a_{73}$
0.42	0.33	$a_{64}=-0.36+0.18a_{14}+0.20a_{25}-0.20a_{43}-0.22a_{61}-0.16a_{91}$
0.43	0.34	$a_{65}=0.46+0.19a_{33}+0.32a_{61}$
0.33	0.23	$a_{66}=0.78-0.22a_{38}+0.19a_{42}$
0.48	0.40	$a_{71}=0.46+0.19a_{15}+0.22a_{18}+0.20a_{33}-0.22a_{38}+0.17a_{43}+0.17a_{61}+0.35a_{73}-0.17a_{105}$
0.51	0.43	$a_{72}=-0.26+0.28a_{26}+0.16a_{34}+0.28a_{61}+0.30a_{73}-0.15a_{95}$
0.26	0.14	$a_{82}=1.25-0.21a_{14}+0.22a_{73}$
0.38	0.28	$a_{83}=1.95+0.25a_{15}-0.21a_{16}+0.22a_{26}+0.27a_{39}-0.26a_{42}+0.18a_{73}+0.21a_{104}-0.30a_{105}$
0.43	0.33	$a_{92}=0.37-0.19a_{14}+0.17a_{34}+0.23a_{91}+0.35a_{95}$
0.40	0.31	$a_{93}=0.66+0.18a_{18}+0.32a_{95}+0.28a_{101}-0.18a_{104}+0.23a_{105}$
0.43	0.34	$a_{94}=0.90+0.23a_{15}-0.21a_{16}-0.16a_{33}+0.22a_{38}+0.17a_{43}+0.44a_{95}$
0.25	0.13	$a_{96}=1.14+0.21a_{16}+0.20a_{105}$
0.37	0.27	$a_{103}=1.92+0.18a_{14}+0.24a_{25}+0.20a_{39}$

dimensional threats and risk attributes. Furthermore, if a decision rule uniquely determines a decision in terms of conditional seaport risks, the decision rule is certain; otherwise, the decision rule is uncertain (Do Bagus and Hanaoka 2022b). In general, certain decision rules describe positive approximations of decisions in terms of conditional seaport risk factors, whereas uncertain decision rules refer to the boundary regions of decisions. Hence, both definitions lead to two conditional probabilities parameters called the *certainty* coefficient and the *coverage* coefficient.

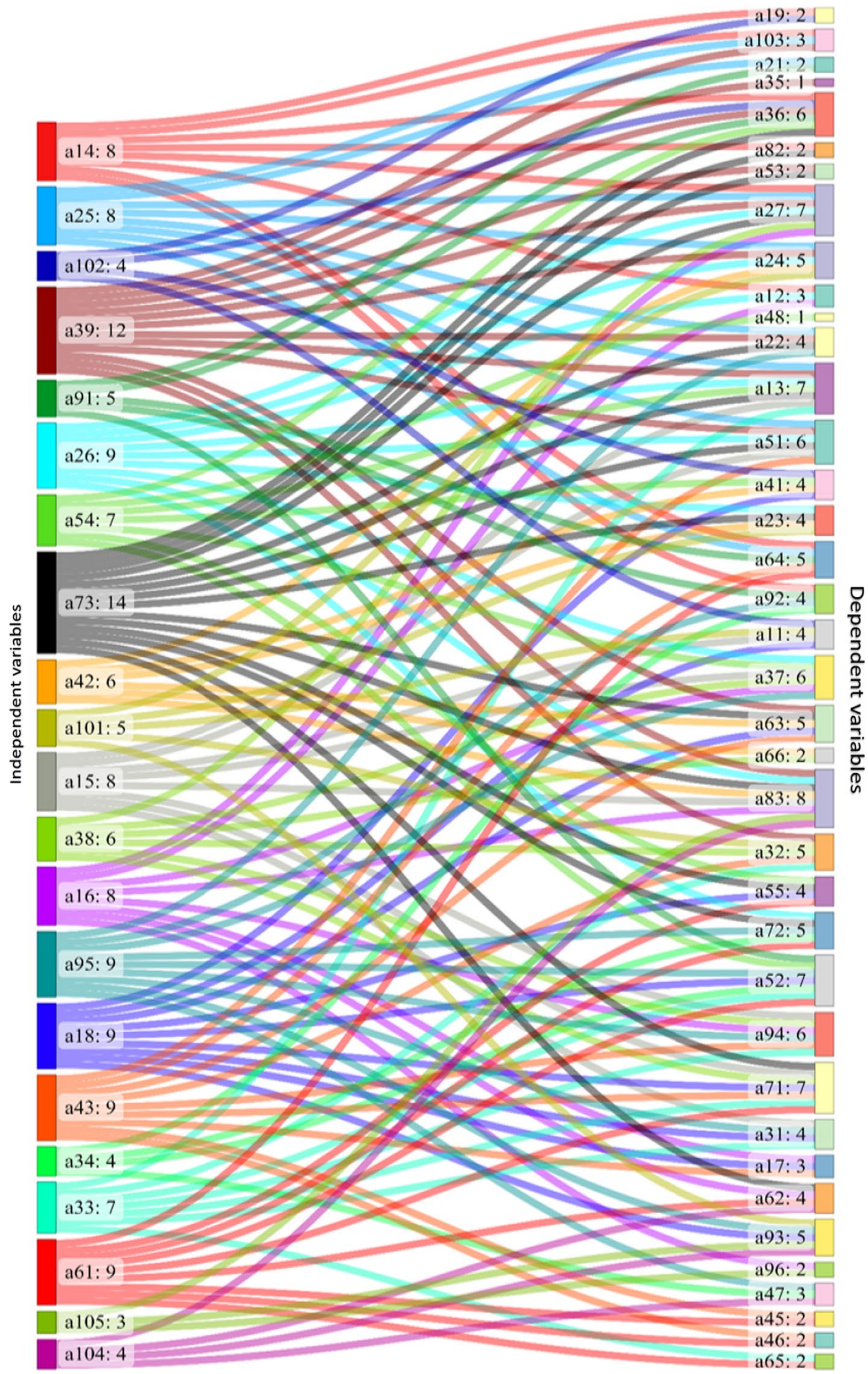

Fig. 5 The significant relationships among independent variables

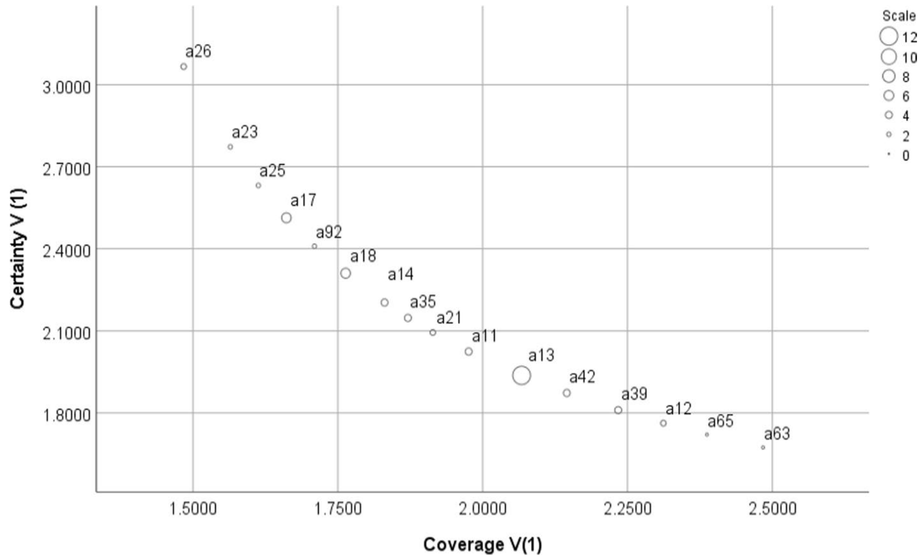

Fig. 6 The highest potential risk of the seaport-fulcrum supply chain risk

The certainty and coverage are compared in the scatter plot in Fig. 6 to provide insight into the implication degree and interdependency degree, referring the decision protocol in the Sect. Rule induction of the rough set for the potential risk analysis. The distribution of the conditional seaport risk factors is provided in Appendix E. Looking at the distribution of seaport risk features, we plotted the position of each feature (marker) that refers to the centroid with hexagonal binning to create a scatter plot between the implication and interdependency degrees using IBM SPSS software. Thus, we obtained the results for potential risks, as shown in Fig. 6.

In Fig. 6, the certainty coefficient expresses the conditional probability of seaport risk factors that an object belongs to the decision class specified by the decision rule, given that it satisfies the condition of the decision protocols in Sect.Rule induction of the rough set for the potential risk analysis Thus, the higher the certainty coefficient, the greater the implication of the conditional seaport risk factors for the specific decision class. Meanwhile, the coverage coefficient provides the conditional probability of consequence (D) for a given decision, which means that the more conditional seaport risk factors (C) are associated with the decision protocols, the more interdependency occurred in the dataset. Thus, both parameters satisfy Bayes' theorem.

Moreover, 15 features are considered to pose the highest potential risk to seaport-fulcrum supply chain continuity. The scale in the legend indicates the correlation referring to the interdependency and implication degrees. Breakdown of port information system (a_{26}) had the highest certainty but the lowest coverage degree, whereas low-efficiency operation (a_{63}) had the lowest certainty but the highest coverage degree. In the middle was lack of supply chain strategic risk planning (a_{13}), which had the highest correlation among the seaport risk features, referring to the decision protocol as the highest risk level.

Discussion of conditional seaport risk factors

The interdependency pattern of this study was identified based on seaport risk features selection with RSGA and an assessment of their variance with a MANOVA. The potential risk was then obtained from each decision protocol of the risk level. Regarding the highest risk in the decision protocol, 15 features are considered to have the highest potential risk level, such as the lack of seaport-enterprise strategic risk (a_{11}); lack of berth risk planning (a_{12}), lack of supply chain strategic risk planning (a_{13}), lack of ship risk planning (a_{14}), lack of transfer risk planning (a_{17}), lack of distribution risk planning (a_{18}), port equipment breakdown (a_{21}), occupational accidents (a_{23}), breakdown of vessel traffic management systems (a_{25}), breakdown of port information systems (a_{26}), number of ship visits (a_{35}), shortage of IT and advanced technology (a_{39}), low punctuality of goods delivery (a_{42}), low-efficiency operations (a_{63}), less cash flow (a_{65}), and war or terrorist attacks (a_{92}). Therefore, the six potential threats are planning process threats (A_1), infrastructure threats (A_2), seaport service process threats (A_3), distribution process threats (A_4), nuclear-enterprise financial threats (A_6), and security threats (A_9), based on their potential risk in rule induction analysis.

Referring to the decision protocol highest risk ($V^1_{c_i} \rightarrow V^1_{d_j}$), the predictive model generated four responses, including lack of seaport-enterprise strategic risk (a_{11}), lack of berth risk planning (a_{12}), lack of supply chain strategic risk planning (a_{13}), and lack of transfer risk planning (a_{17}), which are related to potential threats in planning process (A_1). Meanwhile, the lack of ship risk planning (a_{14}) and lack of distribution risk planning (a_{18}) are independent variables in Fig. 5 that can explain eight and nine dependent features, respectively. These relationships are depicted in the multiple regression model in Table 3. Our results show that the growing seaport-enterprise strategic risk (a_{11}) significantly increases by 29% for handling process risk (a_{15}), 17% for distribution risk (a_{18}), −15% for earthquake frequency (a_{101}), and 14% for pandemic/epidemic incidence (a_{102}). This is in line with Triantoro's (2020) explanation of the problem of distribution risk that can introduce more uncertainty in the strategic planning of supply chain entities. The main issue is related to the cost of moving trucking containers from the warehouse to the seaport. For example, the average trucking cost in Surabaya is around two million rupiah for an average distance of 68 km, which is half of the total cost spent from warehouse to seaport before being loaded onto a vessel (Subiyanto et al. 2020). This situation also occurs in Makassar, where the trucking charges reach close to two-thirds of the cost spent from warehouse to seaport.

Regarding the potential risk related to infrastructure threats (A_2), port equipment breakdown (a_{21}) and occupational accidents (a_{23}) are the response variables, whereas the breakdown of vessel traffic management systems (a_{25}) and breakdown of port information systems (a_{26}) are predictor variables. Those factors are considered to pose potential threats that could disrupt supply chain continuity in Indonesia. Regarding the response variables, we found that earthquake and typhoon frequency impact the seaport component and occupational accidents. Similarly, Conca (2020) found that the loss of performance of seaport equipment due to an earthquake during a simulation could be significantly attributed to either direct damage or interdependencies (i.e. the domino effect). Furthermore, Notteboom et al. (2021) has shown that typhoon frequency is positively associated with all seaport risks, including jeopardization of seaport infrastructure. For example, the giant ship blocking the Suez Canal due to strong winds, disturbing the vessel traffic management system in 2021, led to severe shipment delays and substantial financial losses. In the Indonesian context, a climate event could clearly induce other risks to Indonesia seaport-fulcrum supply chain operations, such as risk related to seaport operations, shipping voyages, and shipping operations. The force majeure factor causes nine ship accidents per year that mainly affect vessel traffic management systems and IT and advanced technology (Do. Bagus and Hanaoka 2022a).

Considering the congestion in seaport service process threat (A_3), two factors have the highest potential risk for this supply chain issue: number of ship visits (a_{35}) and shortage of IT and advanced technology (a_{39}). Both factors clearly have a linear relationship, in which a one-unit decrease affects the technology shortage (a_{39}) by 35%. However, low punctuality of delivery goods (a_{42}) poses the highest risk that is significantly related to the distribution process threat (A_4). As shown in Fig. 3, the low punctuality of delivery goods (a_{42}) causes a cascade to six conditional seaport risk factors. Such seaport risk factors occurred in Indonesia due to several issues. First, too many agencies are involved in maritime security with no clear division of responsibilities. Second, although most maritime security inspections should be conducted at port, merchant ships are commonly stopped at sea for inspection by maritime security agencies (Dewi et al. 2020). Hence, time loss due to the inspection at sea detrimentally affects ship operations in several ways, including by reducing the ship's productivity. Furthermore, Do. Bagus and Hanaoka (2022a) determined that the low punctuality of delivery goods (a_{42}) made claims and contract cancellation more uncertain, inducing higher costs for running ships.

In the potential highest risk related to nuclear-enterprise financial threats (A_6), we found that low-efficiency operation (a_{63}) and less cash flow (a_{65}) result from five and two predictors of seaport risk factors, respectively, in Table 3. Both factors have significant implications for the transhipment process (Do. Bagus and Hanaoka 2022b). Fahmiasari and Parikesit (2017) previously compared several routes according to journey costs for container shipping in Indonesia, such as the 'Nusantara Pendulum' and 'Sea Toll-way' and found the Sea Toll-way is 8% more efficient than the initial routes. However, both deviation and port costs have low competitiveness in North Maluku Province (Amin et al. 2021). This study's results agree with the recent findings that most of the market shares in Indonesia's container plan are more profitable in western rather than eastern Indonesia. Based on Table 3, both costs are significantly affected by the revenue of the seaport organisation.

Conclusions

In this study, the evaluation of parameter importance related to supply chain threats in Indonesia used RSGA to identify features and a MANOVA to assess the correlations among the conditional seaport risk factors and their dimensional threats, based on questionnaires distributed to seaport-fulcrum supply chain players. To evaluate the highest potential risk, we employed a decision protocol using rule induction of a rough set. The results indicate that 39 conditional seaport risks are dependent variables that can be predicted by the other 21 conditional seaport risk factors as independent variables. Then, the 15 features are considered as having the highest potential risk levels. The significance of this study to the existing literature is that it provides an analysis of seaport operational deficiencies that potentially affect supply chain continuity in the Indonesian context using RSGA and MANOVA. The predictive models identify areas where port operations can result in supply chain disruptions, thereby providing a clear list of indicators that are applicable to all ports.

Moreover, regarding practical implications, the identification of seaport risk factors for supply chain threats aids supply chain industries, such as logistics and shipping, by enhancing operational resilience and ensuring business sustainability. The results can support the study of combined problems among conditional seaport risk factors, and between many conditional seaport risk factors, from the perspectives of seaport managers, seaport operators, and seaport users, providing insight into seaport risk management. Furthermore, the predictive model allows seaport managers to monitor the impact of seaport risk on seaport operational activities.

Finally, in terms of managerial implications, seaport managers can use this list of indicators to regularly monitor activities and minimise supply chain disruptions. Seaport managers are encouraged to pay particular attention to the relational threat factors by working closely with seaport users and the authorities, especially where existing terminal designs cannot be easily revised. The monetary threat dimension should be considered in greater depth, as the disparity between western and eastern Indonesia is clearly a significant problem for cargo throughput. In addition, the prediction and interdependency diagnosis of the conditional seaport risk probabilities are carried out in a dynamic manner based on the information available in practical operations between port authorities and shipping lines. Thus, the results of this study pioneer the inclusion of different types of conditional seaport risks as key factors in the seaport risk resilience model.

This study also has some limitations, such as risk aversion analysis by seaport-fulcrum supply chain stakeholders, aggregated risk levels, and the representation of risk levels. The first problem might occur because of the uneven representation of respondents. Risk aversion analysis can only be performed if the data equally represent the seaport-fulcrum supply chain stakeholders. Different seaport locations and types of seaport activity could also produce diverse results related to risk aversion. The second and third issue are related to the possibility the RSGA could produce inconsistencies during the computation. Thus, future research can use a mathematical approach (e.g. fuzzy-rough set model) to more accurately express seaport risk levels.

Appendix A

See **Fig. 7**.

Dimension planning process threats (D1)

It is sourced by the peripheral environment such as changing market trends, market imbalances, and political clashes that will affect the planning processes and occurrences of surveillance threats.

To what extent do you consider the conditional factors at below can occur to disrupt the supply chain in the seaport?

Conditional risk factors (x11 - x18) *The perfect planning process of these conditional factors will lead to the lower risk.*	Highest	High	Medium	Low	Lowest
***The lack of seaport-enterprise strategic risk (x11)**					
***The lack of berth risk planning (x12)**					
***The lack of supply chain strategic risk planning (x13)**					
***The lack of ship risk planning (x14)**					
***The lack of handling process risk planning (x15)**					
***The lack of storage risk planning (x16)**					
***The lack of transfer risk planning (x17)**					
***The lack of distribution risk planning (x18)**					
Conditional risk factors (x19) *The reasonable planning process from this conditional factor will lead to the lower risk.*	Highest	High	Medium	Low	Lowest
***The deficiency of berth allocation risk planning (x19)**					

» Stimulus sets evaluation for D1

According to your evaluation above, some stimulus of risk factors will show up. Please give your evaluation on the stimulus sets to what extent do you consider in the combination of conditional risk factors has the ability to disrupt the supply chain continuity in the seaport as well as the probability occurrence from the sets.

Fig. 7 A section of the questionnaire

Appendix B

See **Table 5**

Table 5 The reduction set from the result of the rough set-based genetic algorithm

No.	The sets of reduction attribute	No.	The sets of reduction attribute
1	$a_{15}, a_{24}, a_{26}, a_{48}, a_{81}, a_{101}$	26	$a_{14}, a_{34}, a_{64}, a_{81}, a_{82}, a_{96}$
2	$a_{42}, a_{61}, a_{92}, a_{102}, a_{104}, a_{105}$	27	$a_{34}, a_{43}, a_{52}, a_{92}, a_{94}, a_{104}$
3	$a_{13}, a_{21}, a_{63}, a_{66}, a_{91}, a_{102}$	28	$a_{26}, a_{41}, a_{72}, a_{82}, a_{93}, a_{103}$
4	$a_{16}, a_{25}, a_{31}, a_{54}, a_{61}, a_{103}$	29	$a_{14}, a_{15}, a_{42}, a_{61}, a_{94}, a_{96}$
5	$a_{34}, a_{39}, a_{53}, a_{73}, a_{81}, a_{101}$	30	$a_{11}, a_{19}, a_{24}, a_{34}, a_{35}, a_{72}, a_{81}$
6	$a_{44}, a_{51}, a_{96}, a_{103}, a_{104}$	31	$a_{15}, a_{27}, a_{31}, a_{38}, a_{71}, a_{91}$
7	$a_{18}, a_{38}, a_{39}, a_{43}, a_{92}, a_{105}$	32	$a_{14}, a_{38}, a_{61}, a_{64}, a_{94}, a_{105}$
8	$a_{15}, a_{25}, a_{47}, a_{52}, a_{91}, a_{93}$	33	$a_{21}, a_{33}, a_{34}, a_{51}, a_{73}, a_{101}$
9	$a_{13}, a_{23}, a_{41}, a_{46}, a_{62}, a_{72}, a_{95}$	34	$a_{52}, a_{53}, a_{82}, a_{91}, a_{102}, a_{104}$
10	$a_{33}, a_{34}, a_{41}, a_{43}, a_{101}, a_{105}$	35	$a_{31}, a_{62}, a_{63}, a_{72}, a_{92}, a_{103}$
11	$a_{44}, a_{51}, a_{96}, a_{103}, a_{104}$	36	$a_{26}, a_{31}, a_{53}, a_{54}, a_{82}, a_{91}$
12	$a_{18}, a_{38}, a_{39}, a_{43}, a_{92}, a_{105}$	37	$a_{18}, a_{34}, a_{54}, a_{91}, a_{101}$
13	$a_{15}, a_{25}, a_{47}, a_{52}, a_{91}, a_{93}$	38	$a_{15}, a_{24}, a_{72}, a_{81}, a_{91}, a_{101}$
14	$a_{13}, a_{23}, a_{41}, a_{46}, a_{62}, a_{72}, a_{95}$	39	$a_{26}, a_{27}, a_{34}, a_{82}, a_{96}, a_{101}$
15	$a_{33}, a_{34}, a_{41}, a_{43}, a_{101}, a_{105}$	40	$a_{12}, a_{15}, a_{19}, a_{22}, a_{43}, a_{96}, a_{103}$
16	$a_{16}, a_{31}, a_{39}, a_{66}, a_{72}, a_{81}$	41	$a_{18}, a_{23}, a_{26}, a_{43}, a_{62}, a_{101}$
17	$a_{15}, a_{17}, a_{25}, a_{91}, a_{94}, a_{103}$	42	$a_{17}, a_{19}, a_{32}, a_{44}, a_{66}, a_{94}$
18	$a_{14}, a_{26}, a_{36}, a_{48}, a_{66}, a_{83}, a_{101}$	43	$a_{27}, a_{32}, a_{42}, a_{63}, a_{94}, a_{102}$
19	$a_{18}, a_{47}, a_{62}, a_{63}, a_{95}, a_{101}$	44	$a_{19}, a_{33}, a_{44}, a_{55}, a_{105}$
20	$a_{16}, a_{31}, a_{39}, a_{66}, a_{72}, a_{81}$	45	$a_{35}, a_{44}, a_{54}, a_{95}, a_{104}, a_{105}$
21	$a_{33}, a_{38}, a_{43}, a_{95}, a_{105}$	46	$a_{26}, a_{39}, a_{42}, a_{73}, a_{81}, a_{91}$
22	$a_{15}, a_{17}, a_{25}, a_{91}, a_{94}, a_{103}$	47	$a_{19}, a_{24}, a_{38}, a_{42}, a_{61}, a_{102}, a_{103}$
23	$a_{25}, a_{37}, a_{64}, a_{73}, a_{94}, a_{102}$	48	$a_{15}, a_{21}, a_{22}, a_{36}, a_{91}, a_{102}$
24	$a_{14}, a_{24}, a_{38}, a_{44}, a_{94}, a_{105}$	49	$a_{14}, a_{35}, a_{43}, a_{46}, a_{96}, a_{102}, a_{105}$
25	$a_{18}, a_{34}, a_{64}, a_{71}, a_{103}, a_{105}$	50	$a_{14}, a_{34}, a_{52}, a_{95}, a_{104}$

Appendix C

See **Table 6**

Table 6 The discernibility matrix of reduction attribute sets

Reduction attribute sets	Set 1	Set 4	Set 5	Set 10	Set 16	Set 21	Set 23	Set 26	Set 29	Set 32	Set 37	Set 41	Set 45	Set 46	Set 48
Set 1		–	a_{81}, a_{101}	a_{101}	a_{81}	–	–	a_{81}	a_{81}	–	a_{101}	a_{26}, a_{101}	–	a_{81}	a_{15}
Set 4	–		–	–	a_{16}, a_{31}	–	a_{25}	–	a_{61}	a_{61}	a_{54}	–	a_{54}	–	–
Set 5	a_{81}, a_{101}	–		a_{34}, a_{101}	a_{39}, a_{81}	–	a_{73}	a_{34}, a_{81}	–	–	a_{34}, a_{101}	a_{101}	–	a_{39}, a_{73}, a_{81}	–
Set 10	a_{101}	–	a_{34}, a_{101}		–	a_{33}, a_{43}, a_{105}	–	a_{34}	–	a_{105}	a_{34}, a_{101}	a_{43}, a_{101}	a_{105}	–	–
Set 16	a_{81}	a_{16}, a_{31}	a_{39}, a_{81}	–		–	–	a_{81}	–	–	–	–	–	a_{81}	–
Set 21	–	–	–	a_{33}, a_{43}, a_{105}	–		–	–	–	a_{38}, a_{105}	–	a_{43}	a_{155}, a_{105}	–	–
Set 23	–	a_{25}	a_{73}	–	–	–		a_{62}	a_{94}	a_{62}, a_{94}	–	–	–	a_{73}	a_{102}
Set 26	a_{81}	–	a_{34}, a_{81}	a_{34}	a_{81}	–	a_{62}		a_{14}, a_{96}	$a_{14}, a_{62},$	a_{34}	–	–	a_{81}	–
Set 29	a_{81}	a_{61}	–	–	–	–	a_{94}	a_{14}, a_{96}		a_{14}, a_{61}, a_{94}	–	–	–	a_{42}	a_{15}
Set 32	–	a_{61}	–	a_{105}	–	a_{38}, a_{105}	a_{62}, a_{94}	$a_{14}, a_{62},$	a_{14}, a_{61}, a_{94}		–	–	a_{105}	–	–
Set 37	a_{101}	a_{54}	a_{34}, a_{101}	a_{34}, a_{101}	–	–	–	a_{34}	–	–		a_{18}, a_{101}	–	a_{91}	a_{91}
Set 41	a_{26}, a_{101}	–	a_{101}	a_{43}, a_{101}	–	a_{43}	–	–	–	–	a_{18}, a_{101}		–	–	–
Set 45	–	a_{54}	–	a_{105}	–	a_{95}, a_{105}	–	–	–	a_{105}	–	–		–	–
Set 46	a_{81}	–	a_{39}, a_{73}, a_{81}	–	a_{81}	–	a_{73}	a_{81}	a_{42}	–	a_{91}	–	–		a_{91}
Set 48	a_{15}	–	–	–	–	–	a_{102}	–	a_{15}	–	a_{91}	–	–	a_{91}	

Appendix D

See **Table 7**

Table 7 Predictive model with significance test (t-test) by predictors

	β_0	a_{14}	a_{15}	a_{16}	a_{18}	a_{25}	a_{26}	a_{33}	a_{34}	a_{38}	a_{39}	a_{42}	a_{43}	a_{54}	a_{61}	a_{73}	a_{91}	a_{95}	a_{101}	a_{102}	a_{104}	a_{105}
a_{11}	0.82	0.16	**0.00**	0.17	**0.03**	0.84	0.09	0.49	0.27	0.80	0.71	0.09	0.28	0.25	0.84	0.32	0.06	0.16	**0.04**	**0.05**	0.55	0.24
a_{12}	0.64	**0.01**	0.27	**0.04**	0.39	0.17	**0.03**	0.25	0.86	0.25	0.40	0.38	0.66	0.59	0.75	0.37	0.87	0.15	0.31	0.51	0.24	0.24
a_{13}	**0.00**	0.41	**0.01**	0.44	0.13	**0.00**	**0.00**	**0.02**	0.17	0.11	**0.00**	0.40	0.90	**0.02**	0.75	**0.01**	0.24	0.72	0.08	0.14	0.19	0.93
a_{17}	0.22	0.61	0.20	**0.03**	**0.00**	0.10	0.39	0.23	0.54	0.23	0.32	0.59	**0.00**	0.94	0.33	0.61	0.49	0.29	0.13	0.94	0.09	0.69
a_{19}	0.97	**0.01**	0.06	0.06	0.07	0.97	0.37	0.63	0.67	0.77	0.10	0.28	0.06	0.87	0.13	0.45	0.07	0.50	0.06	**0.04**	0.38	0.13
a_{21}	0.40	0.19	0.58	0.81	0.42	**0.00**	0.39	0.64	0.13	0.92	1.00	0.43	0.21	0.82	0.16	0.27	**0.01**	0.90	0.23	0.41	0.70	0.57
a_{22}	0.62	0.35	0.35	0.16	0.26	**0.00**	0.20	0.28	0.26	0.07	**0.02**	0.74	0.50	0.67	0.06	**0.02**	0.16	**0.00**	0.39	0.94	0.40	0.98
a_{23}	**0.03**	0.08	0.41	0.80	0.37	0.07	**0.00**	0.10	0.78	0.30	0.34	**0.00**	0.35	0.89	0.07	**0.01**	0.61	0.15	**0.01**	0.75	0.72	0.34
a_{24}	0.40	0.86	0.94	0.64	0.34	**0.03**	**0.02**	0.69	0.46	0.78	**0.03**	**0.00**	0.85	0.11	0.55	0.53	0.48	0.12	**0.01**	0.07	0.33	0.53
a_{27}	**0.00**	**0.02**	0.07	**0.04**	0.70	**0.00**	**0.00**	0.43	0.77	**0.01**	**0.00**	0.17	0.38	0.71	0.48	**0.03**	0.34	0.41	0.17	0.17	0.16	0.15
a_{31}	0.08	0.99	**0.05**	0.19	**0.05**	0.61	0.71	**0.01**	0.06	0.20	0.40	0.36	0.73	0.90	0.20	0.89	0.53	**0.02**	0.09	0.86	0.22	0.62
a_{32}	0.58	0.63	0.74	0.90	0.06	0.22	0.76	0.01	0.90	**0.02**	**0.00**	0.33	**0.00**	0.51	0.64	0.58	0.77	0.31	**0.01**	0.42	0.67	0.56
…																						
a_{71}	0.36	0.85	**0.04**	0.09	**0.00**	0.22	0.11	**0.01**	0.63	**0.01**	0.50	0.78	**0.03**	0.93	**0.03**	**0.00**	0.37	0.47	0.24	0.98	0.80	**0.02**
a_{72}	0.59	0.11	0.52	0.98	0.31	0.42	**0.00**	0.47	**0.03**	0.80	0.79	0.76	0.08	0.76	**0.00**	**0.00**	0.55	**0.03**	0.61	0.82	0.06	0.47
a_{81}	0.05	0.16	0.61	0.10	0.14	0.63	0.05	0.19	0.38	0.60	0.29	0.56	0.84	0.59	0.57	0.23	0.10	0.14	0.98	0.13	0.89	0.37
a_{82}	**0.04**	**0.03**	0.25	0.35	0.94	0.77	0.74	0.45	0.54	0.93	0.08	0.30	0.16	0.23	0.97	**0.03**	0.76	0.46	0.13	0.84	0.86	0.36
a_{83}	**0.00**	0.09	**0.01**	**0.02**	0.09	0.09	**0.02**	0.26	0.62	0.12	**0.00**	**0.00**	0.10	0.17	0.08	**0.05**	0.28	0.29	0.13	0.06	**0.01**	**0.00**
a_{92}	0.48	**0.03**	0.28	0.07	0.16	0.60	0.32	0.13	**0.04**	0.20	0.58	0.25	0.11	0.16	0.33	0.43	**0.00**	**0.00**	0.13	0.98	0.59	0.46
a_{93}	0.22	0.95	0.33	0.11	**0.03**	0.11	0.60	0.10	0.65	0.10	0.68	0.87	0.24	0.20	0.32	0.51	0.39	**0.00**	**0.00**	0.13	0.02	**0.00**
a_{94}	0.09	0.10	**0.02**	**0.01**	0.23	0.56	0.62	**0.04**	0.18	**0.01**	0.29	0.49	**0.03**	0.88	0.73	0.13	0.46	**0.00**	0.88	0.28	0.62	0.38
a_{96}	0.06	0.37	0.52	**0.03**	0.24	0.63	0.07	0.15	0.97	0.05	0.90	0.85	0.64	0.43	0.34	0.96	0.06	0.91	0.35	0.08	0.21	**0.02**
a_{103}	**0.00**	**0.04**	0.10	0.55	0.16	**0.01**	0.08	0.58	0.69	0.77	**0.02**	0.12	0.28	0.22	0.91	0.28	0.27	0.75	0.29	0.19	0.74	0.57

Bold indicates the significance of attributes ($p < 0.05$)

Appendix E

See **Fig. 8**

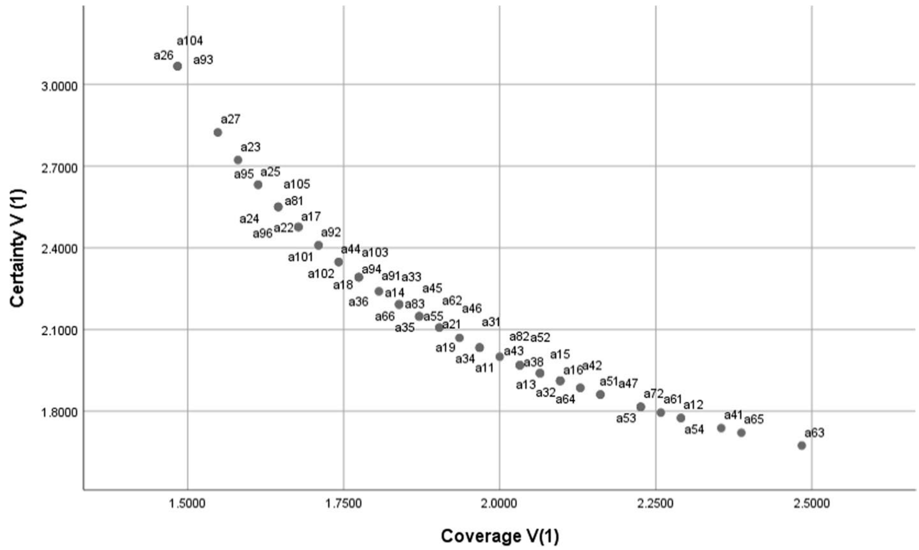

Fig. 8 The scatter plot between the highest interdependency and the highest implication of risk factors

Abbreviations

MANOVA	Multivariate analysis of variance
RSGA	Rough set-based genetic algorithm

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Author contributions

Conceptualization, methodology, software, formal analysis, investigation, resources, data curation, writing—original draft preparation, and visualization by M.R.D.B; validation and writing—review and editing by M.R.D.B. and S.H.; supervision by S.H. All authors have read and agreed to the published version of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

Data will be provided upon request.

Declarations

Competing interests

The authors declare that they have no competing interests.

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