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A novel grey multi-objective binary linear programming model for risk assessment in supply chain management

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ABSTRACT

Robust and resilient agri-food supply chain management (AFSCM) is paramount to agribusinesses, given the many challenges and risks that this increased demand will bring in the coming decades. Interruptions caused by various risks to this crucial supply chain network, particularly in emerging economies, can put the lives of millions in danger, not to mention creating devastating impacts on the economy and the environment. Even so, there are only a limited number of quantitative risk management studies in the AFSCM literature. In this study, an integrated modified risk mitigation matrix (M-RMM) is developed to analyze the mitigation strategies for dealing with various risks in the context of the agri-food supply chain. The M-RMM is integrated with the grey multi-objective binary linear programming (GMOBLP) model to obtain the optimal risk mitigation strategies related to the three objective functions of risk, cost, and time minimization. The proposed model is a useful tool for formulating sustainable business policies and reducing food waste, and acquiring a context-specific (i.e., a developing economy), sector-specific (i.e., the agri-food processing sector), and multi-product (i.e., fresh and non-perishable) approach. The findings reveal that continuous training and development and vulnerability analysis of IT systems are the most effective risk mitigation strategies to lessen the impacts of lack of skilled personnel, sub-standard leadership, failure in IT systems, insufficient capacity to produce quality products, and poor customer relationships. The findings assist practitioners in managing risks in supply chains.

1. Introduction

It has been almost two decades since the agri-food industry began to embrace supply chain management (SCM) as a core concept for its competitiveness [88]. Agri-food supply chains (AFSCs) involve a set of activities in a farm-to-fork sequence encompassing land cultivation and the production of crops, as well as the processing, testing, packaging, warehousing, transportation, marketing, and distribution of food products [17,50,88]. AFSCs are distinctive from other supply chains (SCs) in many ways; relevant differences include (1) the nature of production, which is partly based on biological processes, thus increasing variability and risk; (2) the nature of the products, which have specific characteristics like perishability and bulkiness that require a certain type of SC; and (3) societal and consumer attitudes toward issues like food safety, animal welfare, and environmental impacts [25,66,68,99].

The vulnerability of SCs, including AFSCs, is of critical importance, because a single disruption may result in the collapse of the entire SC [39,42,49]. In addition, globalization and outsourcing have increased the severity and frequency of SC disruptions [55,105]. These concerns, coupled with potentially severe repercussions resulting from SC risk uncertainty, have given rise to an ever-increasing interest in SC risk research [43,51,91,104]. However, AFSC risk management is particularly important due to the specific characteristics of AFSCs, including the nature of the products and the production processes as well as societal and consumer concerns around food and agricultural goods. Because of these distinctive characteristics, risk management in AFSCs requires specially designed mathematical models and methods, since AFSCs, in comparison with manufacturing SCs, encompass more sources of uncertainty [12,14,31,86]. Fahimnia et al. [32], stressed that risk management has been less researched in the realm of agribusiness

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than in fields like engineering and decision sciences.

Robust strategies and resilient strategies refer to two modeling approaches that have been used for risk-mitigation management. Robust strategies in SCs are recognized as proactive risk mitigation measures and are suitable for business-as-usual risks (i.e., high probability, low consequence risks). On the other hand, resilient strategies are more concerned with the post-disruption recovery capacity and are apt for disruption risks (i.e., low probability, high consequence risks) [14,44,45]. Robustness in AFSCs is of special importance, because it can help organizations avoid food and resource wastage, while also enabling them to deal with risks efficiently by providing proactive mitigation strategies.

Borodin et al. [16] highlighted the significance of combining modeling and optimization approaches in the design of agricultural systems. Behzadi et al. [14] indicated that mathematical models for agricultural goods have attracted little attention, which is surprising as risk management in AFSCs is a highly critical task. Thus, the problem statement in our study is as follows: *"there is a paramount need to research the critical risks of AFSCs and advance proactive risk mitigation practices by suitable mathematical models, particularly in developing countries, to improve the robustness of this important SC and have an impact on the economy"*. In response to this call in the literature, as described in our problem statement, we define the following research question: *"RQ: How can a reliable and yet easy-to-use mathematical model be defined to effectively analyze supply chain risk impacts and mitigation strategies in the agri-food processing sector in Bangladesh?"*.

The research objectives (ROs) are as follows: RO1: to develop a reliable mathematical model to deal with supply chain risks and mitigation strategies. RO2: to apply the model in real-world cases in the agri-food processing sector in Bangladesh in order to construct a sustainable business policy to reduce food wastage.

To respond to the research question and reach our research objectives, we position our research mainly based on extending the risk mitigation matrix (RMM) introduced by Aqlan and Lam [9] and proposing a mathematical enhancement to the framework proposed by Ali et al. [4] to assessing risks in the food supply chain in Bangladesh with an emphasis on food wastage minimization. RMM is a very useful matrix-based tool that uses both semi-qualitative and quantitative data inputs to evaluate mitigation strategies against risks. We used the risks and mitigation strategies proposed by Ali et al. [4] as part of the inputs to our model. Ali et al. [4] identified risks by consulting 130 experts from food companies in Bangladesh. Although they identified risks and ranked them using a multi-criteria decision-making approach and proposed mitigation strategies, there was no analysis of the performance of those risk mitigation strategies in response to the identified risks. We adopted the risks and mitigations strategies from Ali et al. [4] and applied them in the same sector of the industry that is the agri-food processing sector in Bangladesh, utilizing our proposed model and then provided a comparative analysis. Thus, we believe our research contributes to the body of knowledge in the following terms:

(I) *An incremental contribution:* A modified risk mitigation matrix (M-RMM) for supply chain risk management is proposed. The proposed M-RMM is integrated with grey multi-objective binary linear programming (GMOBLP) model to obtain the optimal risk mitigation strategies in relation to the three objective functions of risk, cost and time minimization. As defined by Nicholson et al. [65], one aspect of incremental contribution is *neglect* that could apply to theories or methodologies. Our intent in this contribution fits this incremental contribution definition by Nicholson et al. [65] via focusing on neglected aspects in the original RMM model with the aim to improve it (see Section 7.1).

(II) *A replicatory contribution*: We apply the proposed model in the agri-food processing sector of the food supply chain by adopting a multi-product approach (both fresh and non-perishable products) in Bangladesh. We adapt and implement risks and mitigation

Table 1
Risks in agri-food supply chains.

Contribution	Food supply chain risks	Country/context
Zhao et al.,[106] explored the AFSC literature by evaluating risks using a multi-method approach. In this study, the authors identified and evaluated AFSC risks using a total interpretive structural modeling (TISM) approach and also fuzzy MICMAC.	• Lack of information sharing, supply-demand imbalance, shortage of skilled labor, fluctuation in market price, economic and political instability, lack of investment facility, faster technological development, insufficient infrastructural capacity.	Spain, France, Argentina and Italy
Khan et al.,[48] identified risks involved in the Halal food supply chain and evaluated these risks using a fuzzy analytic hierarchy process (AHP) model.	• Supply-related risks: raw-materials integrity problems, supplier failure, raw materials' cost. • Demand-related risks: Bullwhip effect risks, willingness to pay, Halal market, problems with production. • Production-related risks: equipment failure, process design problems, lack of skilled labor, problems with understanding Halal traditions. • Outsourcing risks: transportation, warehousing, marketing, and packaging issues. • Policy risks: lack of Halal-compliant policy, regulatory problems, information-flow problems.	India
Yazdani, Gonzalez, and Chatterjee[103] identified food risk drivers in the context of circular economies. The researchers used extended step-wise weight assessment ratio analysis (SWARA), failure mode and effect analysis (FMEA), and evaluation of data based on average assessment (EDAS) methods.	• Climate change, policy, human behaviors, financial risk.	Spain
Assefa, Meuwissen, and Oude[11] conducted in-depth interviews to understand price risk perceptions and management strategies in AFSC.	• High price of input items, instability, low volume, low quality of input products, late delivery, price volatility, demand uncertainty, instability in quality specification, poor on-time payment rates.	EU food chains
Nyamah et al.,[67] identified AFSC risks using a structured questionnaire. In addition, to clarify the relationship between identified risks and firms' performance, Pearson correlations were utilized. Finally, to interpret the impact of risks in AFSC, an ordinary least square regression model was used.	• Risks related to supply demand, environmental and biological issues, weather, operations and managerial issues, financial issues, policy, and infrastructure.	Ghana
Diabat, Govindan, and Panicker[28] investigated the interactions among food supply chain risks using an approach based on interpretive structural modeling (ISM).	• Micro-level, demand-related, supply-related and product/service-related risks, as well as information management-related risks.	Indian food products company
Guan, Dong, and Li[35] identified and assessed the food supply chain risk using a model based on the fuzzy AHP.	• Natural disasters, animal and plant diseases, quality defects, fluctuations in demand, quality of raw materials.	Dairy

strategies proposed by Ali et al. [4] as part of the inputs to our model to offer a differentiated replication or quasi-replication contribution [89]. A study by Ali et al. [4] lacks a performance analysis of mitigation strategies against identified risks. Thus, it is important to achieve empirical generalizations as without any benchmark to compare and contrast, findings are just isolated facts. We postulate this comparison between the outcome in Ali et al. [4] and the findings of our study both in the context of Bangladesh and in the sector of agri-food processing can yield a meaningful *replicatory contribution* as coined by Nicholson et al. [65].

The above contributions are discussed in detail in theoretical implications (Section 7.1) and practical implications (Section 7.2). The research gaps and highlights are also discussed in Section 2.3. The rest of the paper is organized as follows. In Section 2, the research context and literature are reviewed. The methodology is explained in Section 3. Case application and data collection are elaborated in Section 4. Results and sensitivity analysis are discussed in Sections 5 and 6, respectively. Section 7 discusses the implications of the findings and limitations. In Section 8, conclusions are provided.

2. Research context

In this section, we review the existing literature on issues relevant to our study, including AFSC risk assessment and treatment (Section 2.1) and quantitative decision tools in AFSCs (Section 2.2). We also identify key research gaps that the present study seeks to fill (Section 2.3).

2.1. Agri-food supply chain risk assessment and treatment

Gerhold, Wahl, and Dombrowsky [33] investigated risk perception and emergency food preparedness in Germany to improve the efficiency and resilience of food SCs. Sun and Wang [84], meanwhile, investigated food traceability vis-à-vis issues of food security; their study concerns ways to ensure food quality and SC efficiency by focusing on sourcing decisions that allow suppliers to be traced. Wang, Rodrigues, and Demir [96] outlined the role of inventory control in mitigating food waste. They indicated that food SC risk could be minimized by controlling inventory properly. Leat and Revoredo-Giha [52] investigated the challenges and risks in developing resilient AFSCs in the context of Scotland.

Esteso, Alemany, and Ortiz [31] reviewed current conceptual frameworks (CF) dealing with the “configuration of SC networks,” drawing on the hierarchical decision-making framework proposed by Tsolakis et al. [88]. Bode and Wagner [15] explored the frequency of SC disruptions by focusing on an upstream SC. Pereira, Scarpin, and Neto [72] conducted a survey to identify the risk and mitigation strategies used in mango supply chains in the Brazilian context. Janssen et al., [46] offered a stochastic model for perishable goods, taking into account micro-periodic inventory replenishment policies.

Table 1 provides a list of studies related to AFSC risks, summarizing the studies’ key contributions.

2.2. Quantitative decision tools in agri-food supply chains

Behzadi et al. [14] reviewed quantitative decision models used in studies of AFSC risk management; their findings emphasized the limited use of mathematical models within the field. Here, we provide a review of research on the quantitative decision tools that have been applied to supply chain risk management in the agri-food sector in the past few years (2015–2022).

Yang and Xu [101] demonstrated patterns of disruption and resilience in agri-grain supply chains in China using an analytical quantitative model. Chebolu-Subramanian and Gaukler [21] studied a food contamination event in a simplified SC model. Soto-Silva et al. [80] reviewed operational research models applied in fresh fruit SCs. An and Ouyang [7] developed a bi-level optimization model for a three-echelon food supply chain network, considering case studies from Illinois and Brazil. This model suggested solutions for maximizing profit while minimizing post-harvest loss (PHL). Nakandala, Lau, and Zhao [62] proposed an integrated model for risk assessment in a fresh food SC; the model combined fuzzy logic and hierarchical holographic modeling methods. Song and Zhuang [79] proposed a game-theoretical model for food risk assessment focusing on governments, manufacturers, and farms. Rathore, Thakkar, and Jha [76] investigated food SC disruptions using an integrated grey AHP and grey technique for order of preference by similarity to ideal solution (TOPSIS) methods. Prakash et al. [75] developed a framework for perishable food SC risk assessment using ISM, while Moazzam et al. [59] utilized an analytical model to investigate food quality and risk-related indicators for performance measurement systems. Chodur et al. [22] assessed the vulnerability of food systems using a fault tree analysis. Utomo, Onggo, and Eldridge [90] reviewed agent-based simulation in previous research on AFSC. Zhu et al. [107] reviewed the literature of mathematical modeling techniques to address problems in the sustainable food supply chain field. Ali et al. [4] analyzed food SC risks using a grey decision-making trial and evaluation laboratory (DEMATEL) approach, recommending mitigation strategies for food wastage management. Bottani et al. [19] developed a resilient food SC model for mitigating sudden risks; they proposed a bi-objective mixed-integer programming model and solved it using ant colony optimization technique. Srinivasan et al. [81] proposed a three-stage approach that supports food-sourcing decisions by incorporating climate change data. Onggo et al., [69] developed a mixed integer programming model for perishable inventory routing problems for AFSCs.

Boshkoska et al., [18] presented a decision support system based on machine learning and ontology technologies. Their study investigated the knowledge boundaries of the agri-food value chain. Voldrich, Wieser, and Zufferey [95] offered a multi-objective model for developing food supply chain monitoring systems. Mogale, Kumar, and Tiwari [60] developed a multi-period single objective mathematical model for food supply chains, with the aim of minimizing costs related to silo establishment, food-grain loss, transportation, carbon emissions, inventory holding, and risk penalty.

Negra et al., [64] offered science-based indicators and other decision tools that are able to find the index of the indicator in the domain of agri-sector companies. Assa, Sharifi, and Lyons [10] employed two frameworks (Pareto optimal and Stackelberg game setups) to model risk-management strategies by offering commodity-price insurance in AFSC.

Wei et al., [97] offered a unified modeling approach for investigating pricing and dual-channel selection in the retail food industry. The study confirmed that the optimizing of both operational process and logistics might give high profit from both channels without broadening the size of the service area. Yakavenka, et al., [102] developed a multi-objective model for designing a sustainable perishable food supply chain. In this study, a multi-objective (i.e., social-time, cost, and emission minimization) mixed-integer linear programming model was proposed to make the perishable food supply chain sustainable in the context of the North-Eastern European region.

Recently, Gupta, et al., [37] offered a fuzzy-based multi-objective Linear Program (FMOLP) model to integrate food storage, procurement, and distribution under resilience, quality, and cost. The study optimized the cost focusing the resilience maximization and food loss minimization in the case of India. Srivastava and Dashora, [82] identified the enablers from the literature to implement electronic traceability in the agri-food supply chain in India using fuzzy-based interpretive structural modeling approach and fuzzy MICMAC analysis. Pourmohammad-Zia, et al., [74] offered inventory control policies and dynamic pricing strategies in a two-level AFSC. The study developed an analytical model based on non-linear convex programming to solve the constructed model.

Moreno-Camacho, et al., [61] designed a sustainable food supply chain network for the Colombian dairy sector. The study offered a multi-objective mixed-integer linear programming model where three criteria and four decisions were considered (i.e., carbon emissions as environmental, total network costs as economic and work conditions and societal development as social criteria).

2.3. Research gaps and highlights

After reviewing the literature, it is realized that there is a limited use of mathematical models within the AFSC field [13,14] while the gap is wider within the context of developing economies in particular, Bangladesh. Furthermore, risk management has been less researched in the realm of agribusiness than in fields like engineering and decision sciences [32]. On the other hand, there is a necessity for multi-product models, including both fresh and non-perishable agri-food products in AFSCs, as it has been gaining momentum in recent years [30]. To the best of our knowledge, there is no research in the literature applying this type of context-specific (i.e., a developing economy), sector-specific (i.e., the agri-food processing sector), mathematical model-oriented (i.e., the M-RMM model and mathematical programming optimization) and multi-product (i.e., fresh and non-perishable) approach in Bangladeshi AFSCs. Thus, the research gap is articulated as follows: *"There is an explicit need in the extant literature for a context-specific model-oriented and multi-product robust mathematical model to effectively evaluate supply chain risks in the agri-food processing sector in Bangladesh"*. Our research bridges this research gap by proposing a modified M-RMM and GMOBLP model and applying it in the context of the agri-food processing sector, accounting for a multi-product approach in Bangladesh. Our specific research highlights are summarized as follows:

- A new M-RMM is proposed.
- The proposed M-RMM is integrated with the GMOBLP model to obtain the optimal risk mitigation strategies in relation to the three objective functions of risk, cost, and time minimization.
- The proposed model is context-specific (i.e., a developing economy), sector-specific (i.e., the agri-food processing sector), mathematical model-oriented (i.e., the M-RMM model and mathematical programming optimization), and multi-product (i.e., fresh and non-perishable) in Bangladeshi AFSCs.
- The proposed integrated model is applied in the agri-food processing sector in Bangladesh. An empirical generalization in the context of AFSC in Bangladesh is provided by a comparative analysis of the findings between the outcome in prior research.

3. Methodology

This research is comprised of four main steps, which are presented in Fig. 1. In step 1, risks and proper risk mitigation strategies in AFSCs in Bangladesh are identified based on the findings of Ali et al. [4]. In step 2, the CRW for each identified risk is obtained utilizing the BWM (Section 3.2.). In step 3, the proposed M-RMM model is constructed by acquiring the required data (Section 3.3.). Eventually, the optimal risk mitigation strategies considering risk reduction, budget, and time schedule objectives are determined by solving a GMOBLP model (Section 3.4.).

3.1. Grey systems theory

Grey systems theory is an efficient approach utilized to solve uncertainty problems with discrete data and incomplete information. The systems which lack information are referred to as grey systems, and grey means poor, incomplete, or uncertain [24,54,58,83,94]. We have used grey systems theory due to its characteristics of dealing correctly with poor information and small samples of data [29,34,56,92]. The definitions in grey systems theory are presented in Appendix A of the supplementary material.

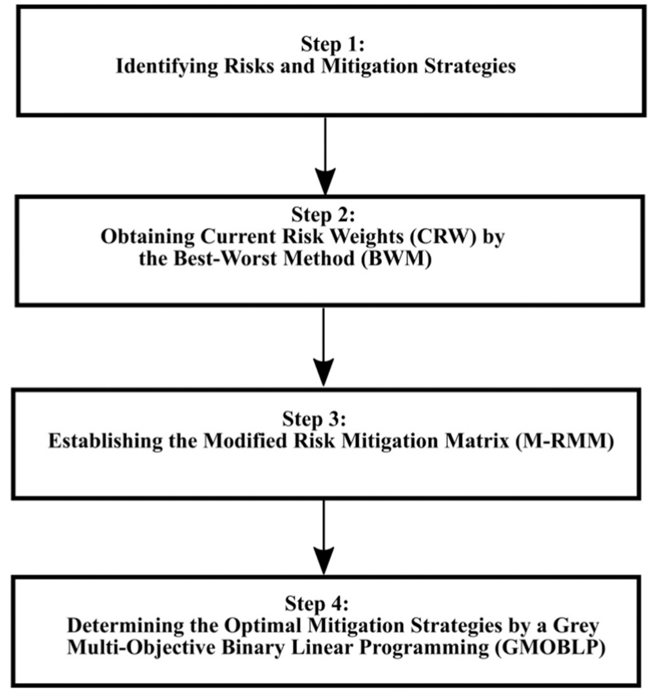

Fig. 1. Research steps.

3.2. Best-worst method

The BWM, proposed by Rezaei [77,78], is a new method that can be used in complex multiple criteria decision-making problems. It is a very convenient decision-making tool compared to other similar decision-making approaches [71,93]. Implementation steps of BWM are provided in Appendix B of the supplementary material.

3.3. Modified risk mitigation matrix model

After identifying suitable mitigation strategies as well as determining each risk's weight, the M-RMM is proposed as an extension of the original risk mitigation matrix (RMM), introduced by Aqlan and Lam [9]. The RMM is a two-dimensional matrix, where the columns represent the risks, and the rows show the mitigation strategies. Table 2 represents a typical example of our proposed M-RMM. In our proposed M-RMM, the following developments of the RMM are introduced: (1) A dimension of mitigation time is added, where values are shown in grey numbers; (2) CRW values are calculated based on BWM; (3) Mitigation cost values are shown in grey numbers. In Fig. 2, the process in the proposed model is shown in a flow diagram.

3.3.1. Risks and mitigation strategies

Risks and suitable mitigation strategies should be identified and utilized in the M-RMM model in order to assess the mitigation strategies which can be obtained from the literature or field studies.

3.3.2. CRW of each risk (w_i)

Each CRW value shows the severity of each risk, ranging from 0, meaning not being critical, to 1, meaning fully critical. From a qualitative perspective, risks can be categorized into three groups: red, yellow, and green conditions. Risks associated with the red condition are critical and need urgent consideration. The red condition means they are due to happen and have severe consequences for the system, whereas, on the other side, risks with the green condition are considered normal with a stable status, which means the system will remain safe. Within this spectrum, there are yellow risks, which are neither red nor green, but lie somewhere in the middle. In this study, a

Table 2
A general M-RMM.

Risks / Strategies	Risk 1	Risk 2	…	Risk *i*	…	Risk *n*	MS	MC	MT
Mitigation Strategy 1	r_{11}	r_{21}	…	r_{i1}	…	r_{n1}	ρ_1	$\tilde{c}_1$	$\tilde{t}_1$
Mitigation Strategy 2	r_{12}	r_{22}	…	r_{i2}	…	r_{n2}	ρ_2	$\tilde{c}_2$	$\tilde{t}_2$
…	…	…	…	…	…	…	…	…	…
Mitigation Strategy *j*	r_{1j}	r_{2j}	…	r_{ij}	…	r_{nj}	ρ_j	$\tilde{c}_j$	$\tilde{t}_j$
…	…	…	…	…	…	…	…	…	…
Mitigation Strategy *m*	r_{1m}	r_{2m}	…	r_{im}	…	r_{nm}	ρ_m	$\tilde{c}_m$	$\tilde{t}_m$
CRW	w_1	w_2	…	w_i	…	w_n			
AMRW	ζ_1	ζ_2	…	ζ_i	…	ζ_n			
Normalized AMRW	θ_1	θ_2	…	θ_i	…	θ_n			

quantitative approach was adopted rather than a qualitative approach by obtaining a CRW from applying BWM. The g_i^* (target or acceptable level of risk *i*) is also defined, which is set by decision-makers, and risks with a CRW lower than the threshold are acceptable and do not require urgent consideration; however, they still need to be dealt with.

3.3.3. Risk reduction/increase by each mitigation strategy (r_{ij})

The risk reduction/increase by each mitigation strategy is represented by a number and a sign. The number represents the value of the risk reduction/increase, which is set by experts and can be categorized into levels, as shown in Table 3. The sign can be positive (+) for a risk impact increase or negative (-) for a risk impact decrease. The possible values of r_{ij} are shown in Eq. (1).

$$r_{ij} = \{-1, -2, -3, -4, -5, 0, +1, +2, +3, +4, +5\} \quad (1)$$

3.3.4. Average value of risk reduction/increase (μ_i)

The μ_i is the average value of risk reduction/increase in the scale of 1–5, which is represented in Eq. (2). It is calculated for each risk and shows to what extent mitigation strategies can reduce or increase the risk's impact.

Table 3
Risk reduction/increase via a mitigation strategy [9].

Linguistic scale	Numerical scale
No Reduction or Increase (NR/I)	0
Very Low Increase (VLI)	+ 1
Low Increase (LI)	+ 2
Medium Increase (MI)	+ 3
High Increase (HI)	+ 4
Very High Increase (VHI)	+ 5
Very Low Reduction (VLR)	-1
Low Reduction (LR)	-2
Medium Reduction (MR)	-3
High Reduction (HR)	-4
Very High Reduction (VHR)	-5

$$\mu_i = \frac{\sum_{j=1}^{m} r_{ij}}{m} \ \forall\ i = 1, \ldots, n \quad (2)$$

3.3.5. Percentage of risk reduction/increase (p_i)

To calculate the percentage of risk reduction/increase, Eq. (3) can be applied and is shown by p_i.

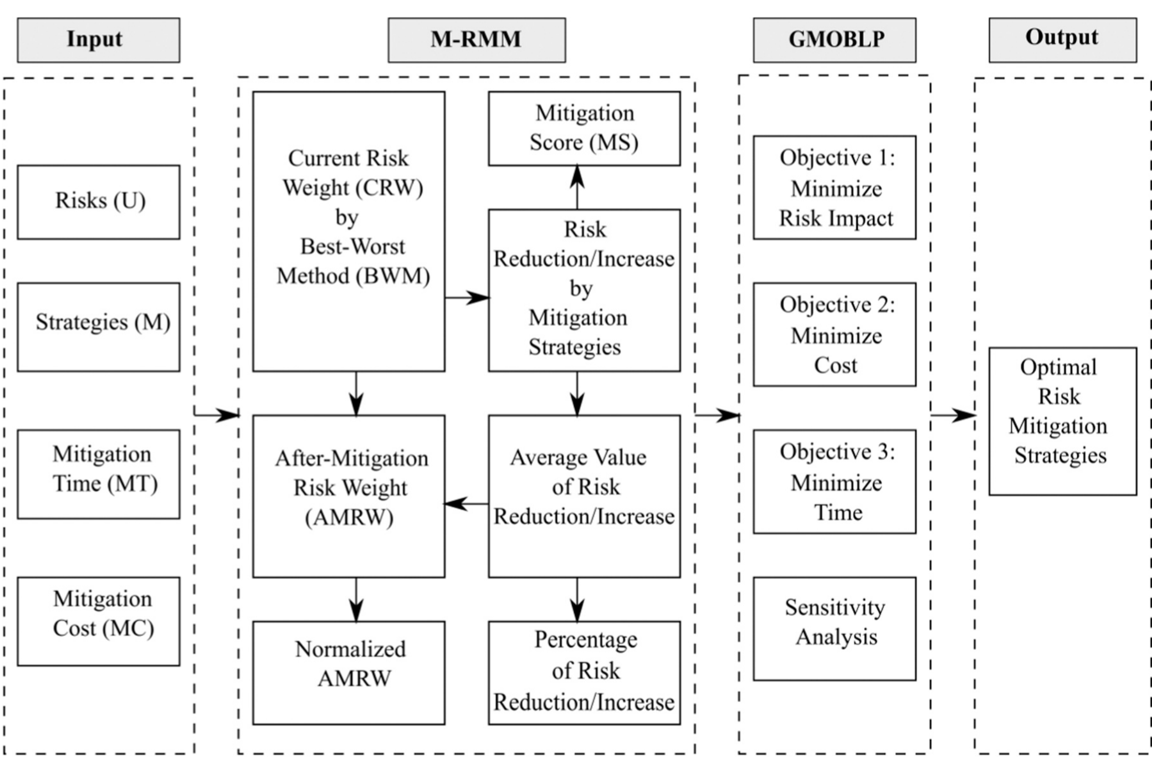

Fig. 2. The proposed model.

$$p_i = \left(\frac{\mu_i}{5}\right) \times 100 = 20\mu_i \ \forall\ i = 1, \ldots, n \tag{3}$$

3.3.6. After-mitigation risk weight (AMRW) (ζ_i)

AMRW values represent the new weights of risks after implementing mitigation strategies and can be obtained based on Eq. (4).

$$\zeta_i = w_i + \left(w_i \times \left(\frac{\mu_i}{5}\right)\right) \forall\ i = 1, \ldots, n \tag{4}$$

3.3.7. Normalized AMRW (θ_i)

The normalized values of AMRW is shown as θ_i and calculated by Eq. (5).

$$\theta_i = \frac{\zeta_i}{\sum_{i=1}^{n} \zeta_i} \ \forall\ i = 1, \ldots, n \tag{5}$$

3.3.8. Mitigation cost (MC) ($\tilde{c}_j$)

The projected MC of mitigation strategy j (i.e., $\tilde{c}_j$) is derived from experts' estimation and, in order to capture the uncertainty of involved experts, values are realized in the form of grey numbers.

3.3.9. Mitigation time (MT) ($\tilde{t}_j$)

The estimated MT is signified as $\tilde{t}_j$ for mitigation strategy j and is obtained based on the expected required time declared by experts. Values are acquired in grey numbers in order to incorporate the inbuilt uncertainty in identifying MT.

3.3.10. Mitigation score (MS) (ρ_j)

The ρ_j value is calculated for mitigation strategy j, as shown in Eq. (6). The negative sign of the ρ_j for a mitigation strategy j shows that, on average, strategy j is able to decrease risks' impact. On the other hand, the positive value of ρ_j indicates that the mitigation strategy is not a suitable strategy for dealing with the risks under evaluation.

$$\rho_j = \frac{\sum_{i=1}^{n} r_{ij}}{n} \ \forall\ j = 1, \ldots, m \tag{6}$$

3.4. GMOBLP model

By solving a GMOBLP, which includes optimizing three objectives, optimal mitigation strategies can be obtained: (1) minimizing risk, (2) minimizing the implementation cost of the mitigation strategies, and (3) minimizing the implementation time of the mitigation strategies. It means the resulting best strategies satisfy risk reduction, budget, and time schedule constraints under uncertainty in time and cost values, which are represented in grey numbers. The variables and parameters used in the mathematical model and their descriptions are presented as follows.

Notations	
Sets	
N	Set of risks ($i = 1, \ldots, n$)
n	Number of risks
M	Set of mitigation strategies ($j = 1, \ldots, m$)
m	Number of strategies
Parameters	
λ	Whitening coefficient $\lambda \in [0,1]$
w_i	Current level of risk i before implementing mitigation strategies
r_{ij}	Amount of reduction in risk i after implementing mitigation strategy j
μ_i	Average value of risk reduction/increase for risk i
p_i	Percentage of risk reduction/increase for risk i
ζ_i	After-mitigation risk weight (AMRW) for risk i
θ_i	Normalized AMRW for risk i
$\tilde{c}_j$	Evaluated cost of implementing mitigation strategy j (grey number)
ρ_j	Mitigation score (MS) for strategy j
g_i^*	Target (acceptable) level of risk i
$\tilde{B}$	Dedicated budget for risk mitigation (grey number)
δ	Percentage of budget to be spent on mitigation strategies
$\tilde{t}_j$	Assessed time of implementing mitigation strategy j (grey number)
$\tilde{S}$	Dedicated time for risk mitigation (grey number)
γ	Percentage of time to be spent on mitigation strategies
φ_l	Weight of the l^{th} objective function ($l = 1, 2, 3$)
Decision Variables	
X_j	$\begin{cases} 1 & \text{if mitigation strategy } j \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$

3.4.1. Model assumptions and parameter setting

- It is assumed that δ and γ, which are the percentage of budget and time to be spent on mitigation strategies, are equal to 100% (i.e., $\delta = \gamma = 1$).
- It is assumed that the g_i^* values are set by decision-makers as 0.75 (i.e., $g_i^* = 0.75$), meaning that risks with weights higher than this threshold can be assigned the red condition.
- It is assumed that whitening coefficient is equal to 0.50 (i.e., $\lambda = 0.50$).
- It is assumed that all three objective functions are equally important (i.e., $\varphi_1 = \varphi_2 = \varphi_3 = 0.33$).
- The w_i values, which are the current levels of risks before implementing response strategies, are the same as CRW values shown in Table 2 and obtained via BWM.
- The $\tilde{c}_j$ values (i.e., the evaluated cost of implementing mitigation strategy j) are shown in column *MC* in M-RMM and are in grey numbers, which can incorporate the uncertainty about the cost by providing a grey interval and are acquired based on the data provided by experts.
- The r_{ij} values indicate the amount of reduction in risk i after implementing the mitigation strategy j. They are acquired based on the data provided by experts.
- The $\tilde{t}_j$ values (i.e., assessed time of implementing mitigation strategy j) are shown in column *MT,* which are also in grey numbers and are acquired based on the data provided by experts.
- $\tilde{B}$ and $\tilde{S}$, which are the dedicated budget and time for the total implementation of risk mitigation strategies, respectively, are considered as grey numbers and are acquired based on the data provided by experts.

3.4.2. GMOBLP model

The GMOBLP is formulated as follows. Eq. (7) is the risk reduction objective function. Cost and time minimization objective functions are represented in Eqs. (8) and (9), respectively. Constraint (10) guarantees that the total cost is lower than the assigned percentage of budget. Constraint (11) ensures the total implementation of risk mitigation strategies should be accomplished in the specified timescale. Constraints (12) guarantee that the sum of risk reduction/increase for each risk by all mitigation strategies should be negative or equal to zero. While Constraints (13) indicate that the sum of risk reduction/increase by each mitigation strategy should be negative or equal to zero. Constraints (14) ensure that the normalized value of AMRW for each risk i is lower or equal to the g_i^* (target or acceptable level of risk i), which is defined by a decision-maker. Finally, Constraints (15) represent that all variables are binary values (0 or 1).

$$MinZ_1 = \sum_{i=1}^{n} \sum_{j=1}^{m} r_{ij} X_j \tag{7}$$

$$MinZ_2 = \sum_{j=1}^{m} \widetilde{c}_j X_j \tag{8}$$

$$MinZ_3 = \sum_{j=1}^{m} \widetilde{t}_j X_j \tag{9}$$

s.t.

$$\sum_{j=1}^{m} \widetilde{c}_j X_j \leq \delta \widetilde{B} \tag{10}$$

$$\sum_{j=1}^{m} \widetilde{t}_j X_j \leq \gamma \widetilde{S} \tag{11}$$

$$\sum_{j=1}^{m} r_{ij} X_j \leq 0 \ \forall \ i \in N \tag{12}$$

$$\sum_{i=1}^{n} r_{ij} X_j \leq 0 \ \forall \ j \in M \tag{13}$$

$$\frac{w_i + \left(\frac{w_i}{5m} \sum_{j=1}^{m} r_{ij} X_j\right)}{\sum_{i=1}^{n} \left[w_i + \left(\frac{w_i}{5m} \sum_{j=1}^{m} r_{ij}\right) \right]} \leq g_i^* \ \forall \ i \in N \tag{14}$$

$$X_j \in \{0, 1\} \ \forall \ j \in M \tag{15}$$

4. Case application: the agri-food processing sector

The proposed model is applied in the agri-food processing sector of Bangladesh's AFSCs. Bangladesh is a developing country with rapidly growing agri-food processing companies. Demand for food is increasing throughout the country, which has a fast-growing population. However, around 5.5% of procured food is wasted in Bangladesh due to spoilage and other factors [26,27]. Hence, it is necessary to build robust AFSCs to fulfil the demand and reduce food wastage, while also minimizing the impact of SC risks. We selected 10 case companies from the approximately 246 medium-sized agri-food processing companies in Bangladesh. During the selection process, the size of the companies, market share, and reputation in the market were considered. Company-1 is a dairy processing company located in the Gazipur, Dhaka area. The main products of this dairy processing company are fresh milk and powdered milk. Case company-2 is a rice and wheat processing company located in Chittagong that produces various types of bread and cookies for the local market as well as the international market. Company-3 operates in the confectionery industry producing various types of sweets, and is located in Dhaka. Companies-4 and 5 are oilseed processing businesses located in Chittagon and produce coconut oil, olive oil, and soybean oil. Company-6 is a fruit and vegetable processing company and is located in the Gazipur, Dhaka area, processing fresh fruits (mainly bananas, mangos, jackfruit, and guavas) and fresh vegetables (mainly potatoes, tomatoes, eggplants, water gourds, pumpkins, and leafy green vegetables). Companies 7–10 are meat, poultry, and fish processing companies operating in the Mymensingh, Dhaka, and Chittagong regions.

Details about the experts herein are provided in Table 4. Experts are selected based on their years of experience and knowledge of AFSCs in Bangladesh.

4.1. Data collection

The data collection process is explained in two sections for the BWM (Section 4.1.1.) and the M-RMM model (Section 4.1.2.).

4.1.1. Data collection for the BWM

Initially, 10 experts were contacted to obtain their consent for participation in this study. Then, a meeting was arranged to conduct data collection. In the session, the research topic and the potential contribution of the study, as well as the data collection, were explained. The survey that was used for the BWM method, together with all the related data for our BWM calculations, are provided in Appendix B of the supplementary material (Tables B1-B5).

Table 4
Profiles of experts involved in the study.

Expert no.	Position	Experience (Years)
1	Supply chain manager (company 1)	24
2	Logistics manager (company 2)	18
3	Quality control manager (company 3)	20
4	Chief chemist (company 4)	22
5	Senior production manager (company 5)	26
6	Production manager (company 6)	21
7	Supply chain manager (company 7)	23
8	Quality control manager (company 8)	19
9	Food chemist (company 9)	18
10	Logistics executive (company 10)	15

4.1.2. Data collection for the M-RMM model

The data collection questionnaires for the M-RMM model are provided in Appendix C of the supplementary material. The required steps of the data collection procedure for M-RMM are explained as follows.

Step 1: Acquiring r_{ij} values.

Each expert was asked to provide their assessment of the risk reductions/increases associated with each mitigation strategy using a verbal scale represented in Table 3. For example, a question for evaluating risk reduction/increase by leadership training (S2) strategy is provided in Table C1 in the Appendix C of the supplementary material. Then, by replacing the linguistic phrases with the corresponding values provided in Table 3 and getting the average values of 10 experts, the final r_{ij} obtained, as shown in Table 8.

Step 2: Obtaining $\widetilde{c}_j$ values (MC).

The projected cost of each mitigation strategy j (i.e., $\widetilde{c}_j$), which is defined in 100,000 TK,[4] is obtained from the experts' inputs in the form of grey numbers so as to provide experts with a flexible range to handle uncertainty (i.e., lower bound is the minimum approximate cost and upper bound is the maximum approximate cost). The question utilized for data collection in this step is provided in Appendix C of the supplementary material - Table C2. Then, by calculating the average of all MC values provided by the ten experts, the final MC values are obtained and shown in grey numbers (Table 5). The crisp values are obtained based on Equation (A8), considering $\lambda = 0.50$.

Step 3: Obtaining $\widetilde{B}$ value.

The estimated budget for the total implementation of risk mitigation strategies is acquired from experts (Appendix C in supplementary material-Table C3). The average budget is 21,250,000 TK using Equation (A9).

Step 4: Obtaining $\widetilde{t}_j$ values (MT).

Similar to step 2, the estimated time for each mitigation strategy can be obtained using the question provided in Appendix C in supplementary material-Table C4. The aggregated MT values of all experts are provided in Table 6.

Step 5: Obtaining $\widetilde{S}$ value.

The time for the total implementation of risk mitigation strategies is estimated by asking experts (Appendix C in supplementary material-Table C5). The average is calculated as approximately 27 months and 9 days using Equation (A9).

[4] TK stands for the Bangladeshi taka, the currency of Bangladesh.

Table 5
The aggregated MC values by all experts (in 100,000 TK).

Strategies	MC	Crisp value $\lambda = \mathbf{0.50}$
Continuous training and development (S1)	[16.20, 20.70]	18.45
Leadership training (S2)	[21.10, 27.40]	24.25
Vulnerability analysis of IT systems (S3)	[22.10, 28.60]	25.35
Capacity planning (S4)	[31.70, 38.30]	35.00
Big data-enabled CRM (S5)	[15.90, 21.20]	18.55

Table 6
The aggregated MT values by all experts (in months).

Strategies	MT	Crisp value $\lambda = \mathbf{0.50}$
Continuous training and development (S1)	[7.70, 12.90]	10.30
Leadership training (S2)	[6.30, 10.20]	8.25
Vulnerability analysis of IT systems (S3)	[4.70, 7.90]	6.30
Capacity planning (S4)	[9.30, 15.80]	12.55
Big data-enabled CRM (S5)	[7.00, 11.10]	9.05

5. Results

This section illustrates the results of the BWM analysis, the M-RMM, and GMOBLP analysis.

5.1. The best-worst method analysis

Based on the findings in Ali et al. [4], the most critical risks in Bangladesh's AFSCs are listed in Table 7. Then, the BWM is applied using the required data (Section 4.1.1). The related calculations are carried out based on steps in Appendix B in supplementary material, and their respective CRW values are obtained and represented in Table 7.

As can be seen in Table 7, the most critical risks in prioritized order are lack of skilled personnel (R1), sub-standard leadership (R2), failure in IT systems (R3), insufficient capacity (R4), and poor customer relationships (R5).

5.2. The M-RMM and GMOBLP analysis

In this section, the five suggested mitigation strategies in Ali et al. [4] are considered as continuous training and development (S1), leadership training (S2), vulnerability analysis of IT systems (S3), capacity planning (S4), and big data-enabled CRM (S5). The M-RMM is constructed (Table 8) based on the collected data (Section 4.1.2.), and the CRW values are calculated by BWM analysis.

As it is evident in the M-RMM (Table 8), the order of AMRW is almost the same as CRW, and the only change is the order of insufficient capacity (R4) and poor customer relationships (R5). However, the criticality of all risks is reduced, as shown in the AMRW row of the M-RMM (Table 8). Due to normalization, the values for AMRW indicate a slight increase for R1 and R5 compared to the CRW values. Nonetheless, three out of five risks (i.e., R2, R3, R4) have lower normalized AMRW values in comparison with the CRW values.

Using values in Table 8, the GMOBLP is constructed based on Eqs. (7)–(15), considering that $n = m = 5$, $g_i^* = 0.75$, $\widetilde{B} = [180.00, 245.00]$, $\delta = \gamma = 1$, and $\widetilde{S} = [23.00, 31.60]$. For solving the GMOBLP, the grey numbers were converted into crisp values and then the mathematical model was solved using a weighted max-min approach [6,47,108]. Utilizing Equation (A9), the crisp values of MC and MT are calculated assuming that $\lambda = 0.5$, where $\lambda \in [0, 1]$ is a whitening coefficient. The MC and MT are represented as $\widetilde{c}_j$ and $\widetilde{t}_j$ values in our mathematical model, respectively. Also, by using Equation (A9), the crisp value for the dedicated budget for risk mitigation strategy implementation is determined to be 212.50 (in 100,000 TK), while the dedicated time for the total implementation of risk mitigation strategies is calculated as 27.30 (in months). The obtained payoff values for the three objective functions are shown in Table 9. It provides the optimal objective function values and solutions, and each is solved separately. The ideal solution (IS) and non-ideal solution (NIS) represent the minimum (ideal) and maximum (worst or non-ideal) values for our minimization objective functions, respectively.

Ultimately, to construct Model (17), which is a single objective function, we need to consider Eq. (16) based on the weighted max-min model formulation [6]. This is because all three objective functions are minimization functions.

$$\mu_Z = \begin{cases} 1 & Z < Z^{IS} \\ \frac{Z^{NIS} - Z}{Z^{NIS} - Z^{IS}} & Z^{IS} \leq Z \leq Z^{NIS} \\ 0 & Z > Z^{NIS} \end{cases} \tag{16}$$

Thus, we have for Z_1:

$$\mu_{Z_1} = \begin{cases} 1 & Z_1 < -35.70 \\ \frac{0 - Z_1}{0 + 35.70} = \frac{-Z_1}{35.70} & -35.70 \leq Z_1 \leq 0 \\ 0 & Z_1 > 0 \end{cases}$$

For Z_2:

Table 7
The five AFSC risks in Bangladesh and the calculated CRW [4].

Risks	Definition	CRW obtained from BWM
Lack of skilled personnel (R1)	Unskilled personnel might pose considerable risks in executing business processes or supply chains.	0.3283
Sub-standard leadership (R2)	Sub-standard leadership hampers reaching enterprise and supply chain objectives.	0.2794
Failure in IT systems (R3)	IT system failure can disrupt business operations, such as sales, production, and cash flow in the supply chain.	0.2399
Insufficient capacity (R4)	The necessary capacity to produce quality products and meet customer demand is insufficient.	0.0791
Poor customer relationships (R5)	Providing a structure such as a customer relationship management (CRM) to maintain a good relationship with customers is necessary for supply chain.	0.0733

Table 8
The M-RMM for AFSC risk management in Bangladesh.

Risks / Strategies	R1	R2	R3	R4	R5	MS	MC[a]	MT[b]
S1	-4.60	-4.70	0.00	0.00	-0.60	-1.98	[16.2, 20.7]	[7.7, 12.9]
S2	-3.90	-5.00	-0.20	0.00	-2.10	-2.24	[21.1, 27.4]	[6.3, 10.2]
S3	0.00	-3.00	-5.00	-3.20	0.00	-2.24	[22.1, 28.6]	[4.7, 7.9]
S4	0.00	-1.80	-4.40	-5.00	-2.10	-2.66	[31.7, 38.3]	[9.3, 15.8]
S5	0.00	0.00	-4.60	-4.00	-4.40	-2.60	[15.9, 21.2]	[7.0, 11.1]
CRW	0.3283	0.2794	0.2399	0.0791	0.0733			
AMRW	0.2167	0.1173	0.1036	0.0405	0.0463			
Normalized AMRW	0.4131	0.2237	0.1976	0.0772	0.0883			

[a] in 100,000 TK
[b] in months

$$\mu_{Z_2} = \begin{cases} 1 & Z_2 < 0 \\ \frac{84.6 - Z_2}{84.6 - 0} = 1 - \frac{Z_2}{84.6} & 0 \le Z_2 \le 84.6 \\ 0 & Z_2 > 84.6 \end{cases}$$

For Z_3:

$$\mu_{Z_3} = \begin{cases} 1 & Z_3 < 0 \\ \frac{27.1 - Z_3}{27.1 - 0} = 1 - \frac{Z_3}{27.1} & 0 \le Z_3 \le 27.1 \\ 0 & Z_3 > 27.1 \end{cases}$$

The φ_l is the weight of the l^{th} objective function (l = 1,2,3). In this study, all objectives are considered equally important ($\varphi_1 = \varphi_2 = \varphi_3 = 0.333$). In Model (17), Z_1, Z_2 and Z_3 can be replaced by Eqs. (7)–(9), and $\tilde{c}_j$ and $\tilde{t}_j$ can be obtained based on Tables 5 and 6, respectively ($\lambda = 0.5$).

$$\begin{aligned}
&Max\xi \\
&\text{s.t.} \\
&\varphi_1 \times \xi \le -\frac{Z_1}{35.70} \\
&\varphi_2 \times \xi \le 1 - \frac{Z_2}{84.6} \\
&\varphi_3 \times \xi \le 1 - \frac{Z_3}{27.1} \\
&\sum_{j=1}^{5} \tilde{c}_j X_j \le 212.50 \\
&\sum_{j=1}^{5} \tilde{t}_j X_j \le 27.30 \\
&\sum_{j=1}^{5} r_{ij} X_j \le 0 \ \forall \ i \in \{1, 2, 3, 4, 5\} \\
&\sum_{i=1}^{5} r_{ij} X_j \le 0 \ \forall \ j \in \{1, 2, 3, 4, 5\} \\
&\frac{w_i + \left(\frac{w_i}{25}\sum_{j=1}^{5} r_{ij} X_j\right)}{\sum_{i=1}^{5}\left[w_i + \left(\frac{w_i}{25}\sum_{j=1}^{5} r_{ij}\right)\right]} \le 0.75 \ \forall \ i \in \{1, 2, 3, 4, 5\} \\
&\varphi_1 + \varphi_2 + \varphi_3 = 1 \\
&0 \le \xi \le 1 \\
&X_j \in \{0, 1\} \ \forall \ j \in \{1, 2, 3, 4, 5\}
\end{aligned} \tag{17}$$

We reached global optimum points in a matter of milliseconds by solving Model (17) on a laptop computer model MacBook Air-2013 (Technical specification: 1.3 GHz dual-core Intel Core i5, and 4 GB of 1600 MHz LPDDR3 onboard memory) using LINGO software. The optimal values are obtained as $\xi = 1.0$ and $X = (1, 0, 1, 0, 0)$. It shows that, under current parameter settings, only risk mitigation strategies S1 (i.e., continuous training and development) and S3 (i.e., vulnerability analysis of IT systems) should be adopted and implemented to achieve a Pareto-optimal solution for the three objective functions. The compromise point obtained for objective function values are $Z_1 = -21.10$, $Z_2 = 43.80$ and $Z_3 = 16.60$. It indicates that by implementing S1 and S3 mitigation strategies, which are the best trade-off solutions under current parameter settings, the total implementation cost of risk mitigation strategies is estimated as 4380,000 TK within the timescale of approximately 16 months and 18 days.

6. Sensitivity analysis

To evaluate the reliability of our model, a set of scenarios were designed with the aim to analyze the sensitivity of the obtained result based on model's all possible parameters in order to reach a reliable solution for the model. The sensitivity of results is tested by taking into account various values for φ and λ, signifying the weights of each objective function and whitening coefficient, respectively (see Section 6.1.). In Section 6.2. and Section 6.3., the sensitivity of results is analyzed by changing δ and γ, which are the percentage of budget and time available for mitigation strategies. In Section 6.4. the sensitivity of various g_i^* values is explored. It should be noted that the benchmark results in Section 5.2. were obtained under a base scenario, which is defined as $\varphi_1 = \varphi_2 = \varphi_3 = 0.33$, $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ and $\lambda = 0.50$, indicating strategy 1 (i.e., S1: continuous training and development) and strategy 3 (i.e., S3: vulnerability analysis of IT systems) should be chosen as the optimal risk mitigation strategies.

6.1. Sensitivity analysis for φ and λ values

Assuming $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ are fixed and $\lambda = 0.15$, seven scenarios for various weights of the three objective functions – risk reduction, cost, and time (i.e., φ_1, φ_2, φ_3) – are defined (Table 10). In scenario 1, under equal weights, the same strategies, S1 and S3, are

Table 9
Payoff table.

	$X = (0, 1, 1, 1, 0)$	$X = (0, 0, 0, 0, 0)$	Ideal Solution (IS)	Non-Ideal Solution (NIS)
$MinZ_1$	-35.70	0	-35.70	0
$MinZ_2$	84.6	0	0	84.6
$MinZ_3$	27.1	0	0	27.1

Table 10
Sensitivity of solutions under variousφ values and λ = 0.15 (δ = 1, γ = 1, g_i^* = 0.75).

Scenario	φ_1	φ_2	φ_3	ξ	Z_1	Z_2	Z_3	μ_{Z_1}	μ_{Z_2}	μ_{Z_3}	Solution
1	0.33	0.33	0.33	1.00	-21.10	39.96	13.66	0.56	0.45	0.41	S1, S3
2	0.10	0.10	0.80	0.97	-11.20	23.08	5.18	0.30	0.68	0.78	S3
3	0.80	0.10	0.10	1.00	-32.30	62.01	20.55	0.86	0.14	0.11	S1, S2, S3
4	0.10	0.80	0.10	0.96	-13.00	16.70	7.62	0.35	0.77	0.67	S5
5	0.70	0.15	0.15	1.00	-26.30	49.39	17.90	0.70	0.32	0.22	S4, S5
6	0.60	0.30	0.10	1.00	-23.20	49.57	18.76	0.62	0.32	0.19	S1, S4
7	0.60	0.10	0.30	1.00	-22.90	33.58	16.10	0.61	0.54	0.30	S1, S5

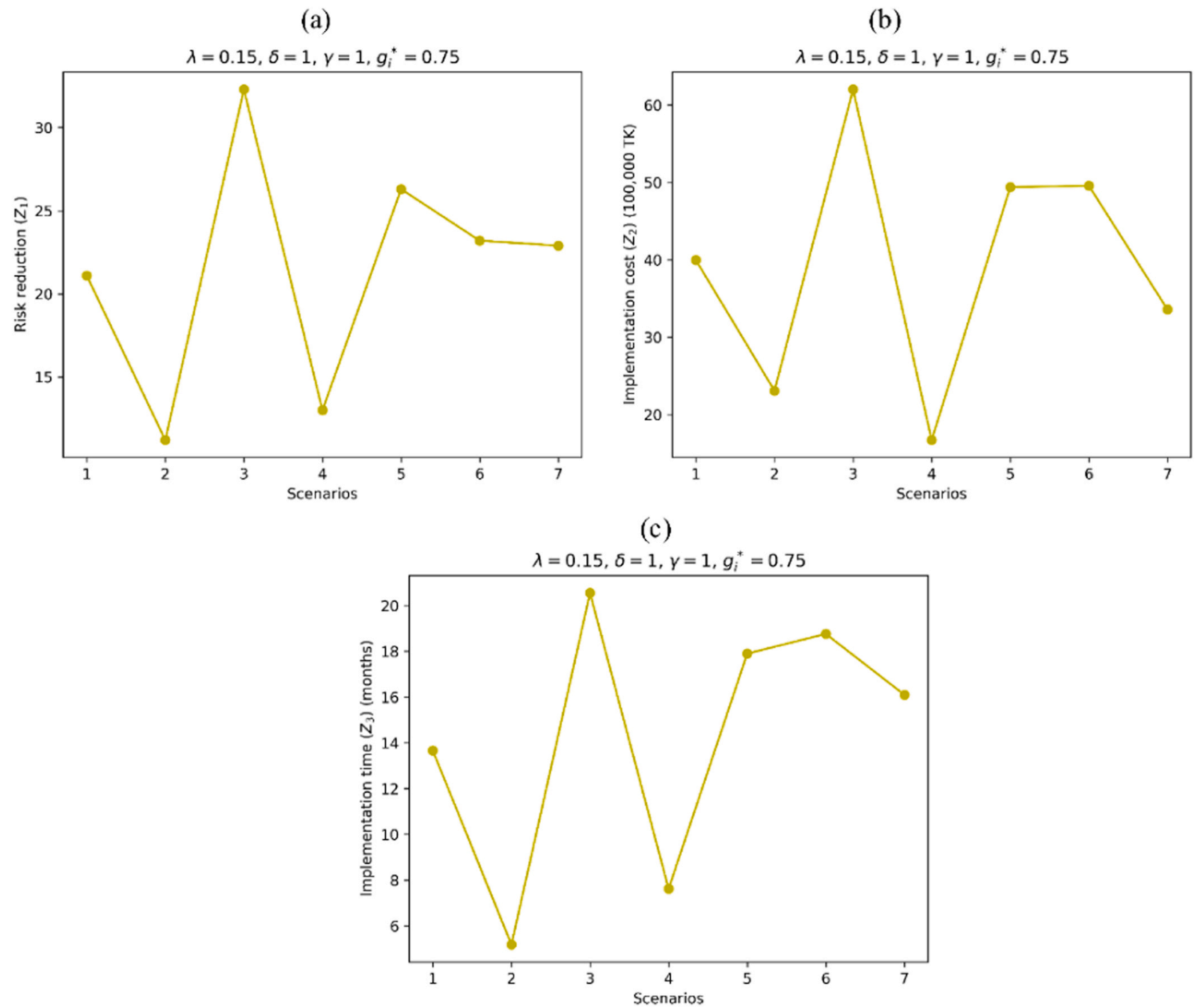

Fig. 3. Sensitivity analysis of (a) risk reduction (b) implementation cost and (c) implementation time for different scenarios of φ values and λ = 0.15.

obtained as optimal solutions. The S1 (i.e., continuous training and development) is obtained as one of the final solutions in four scenarios, S3 and S5 are obtained three times, S4 two times, and S2 once. In Fig. 3, the sensitivity analysis of the three objective functions (i.e., risk reduction, cost, and time) are depicted separately under seven defined scenarios in Table 10. In Fig. 3(a), the higher points, and in Fig. 3(b) and (c), the lower points are preferable. In Fig. 3(a), all values of the first objective function (Z_1) are negative. Thus, the absolute values representing the amount of risk reduction are considered.

The lower the value of whitening coefficient (λ), as in this case λ = 0.15, the corresponding values for evaluated cost of implementing mitigation strategy j ($\widetilde{c}_j$), dedicated budget for risk mitigation ($\widetilde{\boldsymbol{B}}$), assessed time of implementing mitigation strategy j ($\widetilde{t}_j$), dedicated time for risk mitigation ($\widetilde{S}$) in the mathematical model all tend to be closer to the lower bound of their respective grey intervals (see Equation (A8)).

By comparing just Fig. 3(a), 3(b), and 3(c); or Fig. 4(a), 4(b), and 4(c); or Fig. 5(a), 5(b), and 5(c); the trend of changes can be compared while λ, δ, γ, g_i^* values are controlled for and φ values are changing in each scenario.

However, if we compare all three charts (a) among Figs. 3, 4 and 5 for instance, Fig. 3(a), Fig. 4(a), and Fig. 5(a); or Fig. 3(b), Fig. 4(b), and Fig. 5(b); or Fig. 3(c), Fig. 4(c), and Fig. 5(c), then we can get a

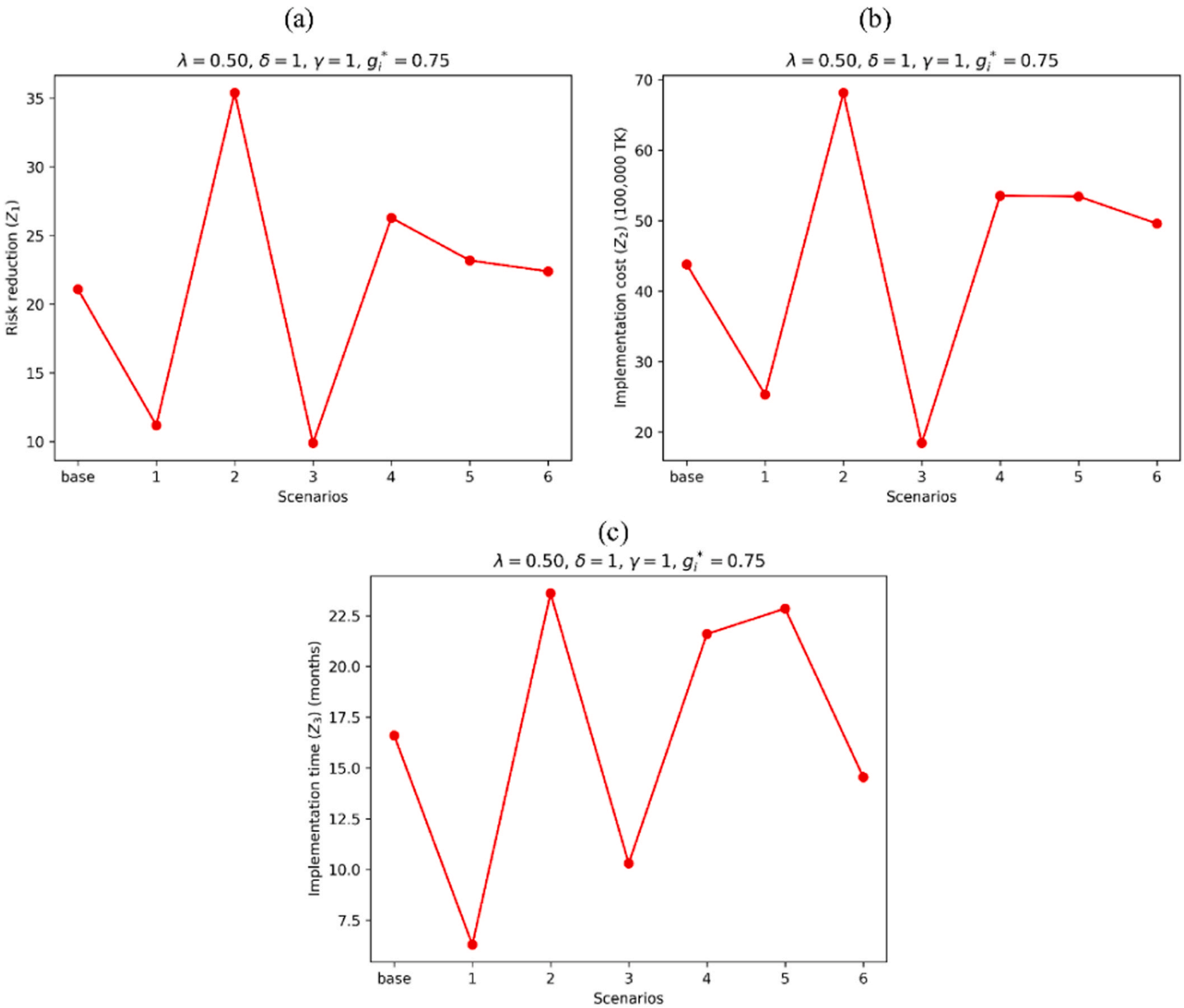

Fig. 4. Sensitivity analysis of (a) risk reduction (b) implementation cost and (c) implementation time for different scenarios of φ values and $\lambda = 0.50$.

sense of the extent of changes while φ, δ, γ, g_i^* values are controlled for and λ values are changing in each scenario. In other words, we are interested to observe the extent of changes by focusing on one specific objective function at a time.

Under $\lambda = 0.15$, compared to the scenario 1 in which all weights of objective functions are equal ($\varphi_1 = \varphi_2 = \varphi_3 = 0.33$), the extent of changes in optimal objective function values are measured. The summarized results for the sensitivity analysis by controlling for $\lambda = 0.15$, $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ are as follows:

Scenario 2: the weight of time objective function (Z_3) is the highest ($\varphi_3 = 0.80$) and weights of the risk reduction objective function (Z_1) and the cost objective function (Z_2) are the lowest ($\varphi_1 = \varphi_2 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is increased or the absolute value is decreased by 47% from -21.10 to -11.20 as can be observed in Fig. 3(a) (an undesirable change).
- The optimal value of the cost objective function (Z_2) is decreased by 42% from 39.96 to 23.08 as can be observed in Fig. 3(b) (a desirable change).
- The optimal value of the time objective function (Z_3) is decreased by 62% from 13.66 to 5.18 as can be observed in Fig. 3(c) (a desirable change).

The solution result from scenario 2 in this case, still confirms the S3 as the selected strategy compared to the base scenario in which S1 and S3 were selected. The analysis shows that by assigning higher weights to the time objective function (Z_3) in this case, only optimal value of risk reduction objective function (Z_1) changes undesirably while the optimal value of cost objective function (Z_2) changes in a desirable direction.

Scenario 3: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.80$) and weights of the cost objective function (Z_2) and the time objective function (Z_3) are the lowest ($\varphi_2 = \varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 53% from -21.10 to -32.30 as can be observed in Fig. 3(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 55% from 39.96 to 62.01 as can be observed in Fig. 3(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 50% from 13.66 to 20.55 as can be observed in Fig. 3(c) (an undesirable change).

The solution result from scenario 3 in this case, confirms both S1 and S3 as the selected strategies just like the base scenario in which

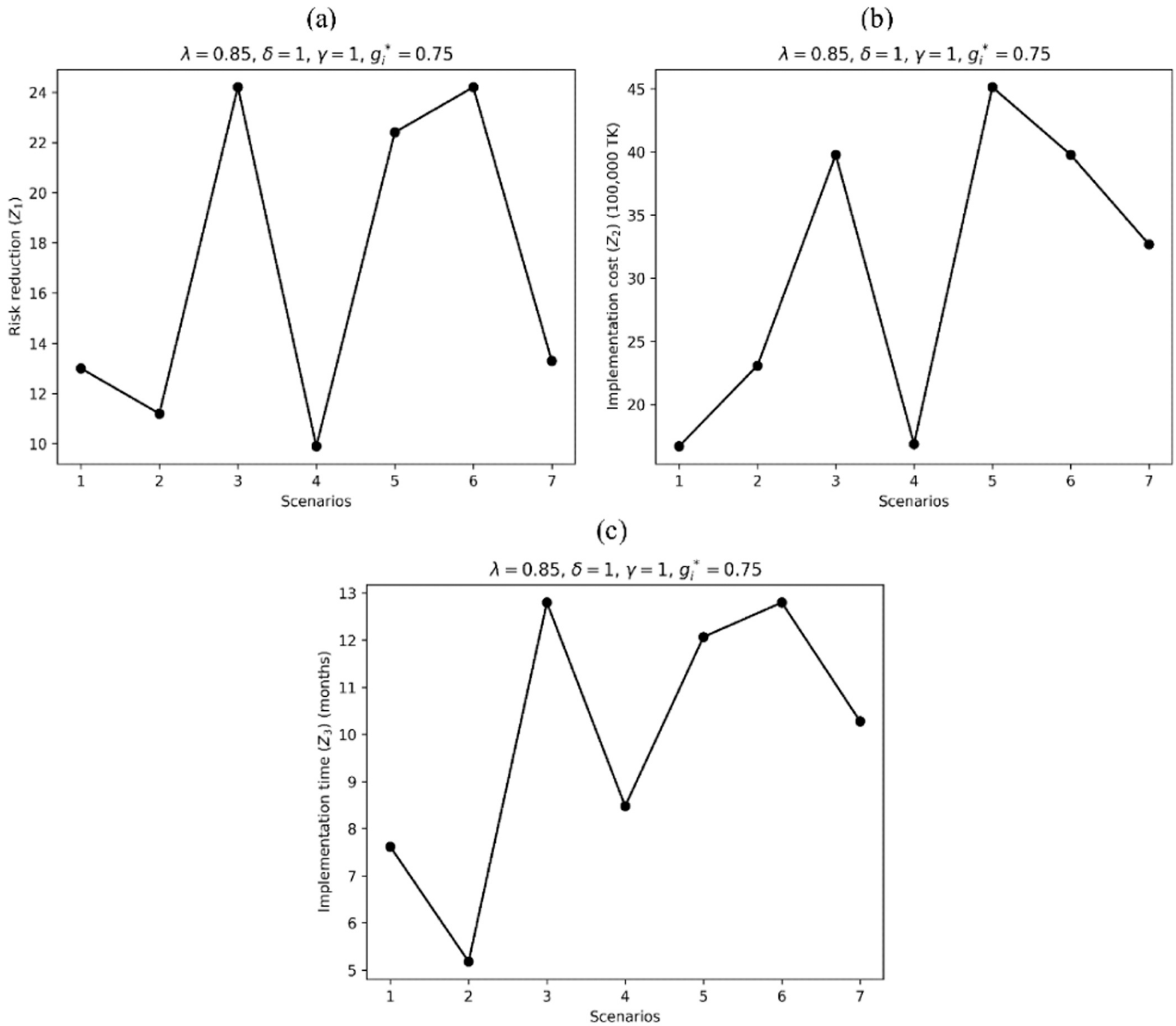

Fig. 5. Sensitivity analysis of (a) risk reduction (b) implementation cost and (c) implementation time for different scenarios of φ values and = 0.85.

S1 and S3 were selected. However, S2 was also selected as an additional strategy in the final solution. The analysis shows that by assigning higher weights to the risk reduction objective function (Z_1) in this case, the optimal values of both cost objective function (Z_2) and time objective function (Z_3) change undesirably compared to scenario 1.

Scenario 4: the weight of cost objective function (Z_2) is the highest ($\varphi_2 = 0.80$) and weights of the risk reduction objective function (Z_1) and the time objective function (Z_3) are the lowest ($\varphi_1 = \varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is increased or the absolute value is decreased by 38% from − 21.10 to − 13.00 as can be observed in Fig. 3(a) (an undesirable change).
- The optimal value of the cost objective function (Z_2) is decreased by 58% from 39.96 to 16.70 as can be observed in Fig. 3(b) (a desirable change).
- The optimal value of the time objective function (Z_3) is decreased by 44% from 13.66 to 7.62 as can be observed in Fig. 3(c) (a desirable change).

The solution result from scenario 4 in this case, does not confirm any of the selected strategies in the base scenario in which S1 and S3 were selected. Here, only S5 was selected as the chosen strategy in the final solution. The analysis shows that by assigning higher weights to the cost objective function (Z_2) in this case, obviously, the optimal value of the cost objective function (Z_2) will be the minimum. Moreover, the optimal value of the time objective function (Z_3) changes in a desirable direction by 44% decrease in value from scenario 1. The optimal value of risk reduction objective function (Z_1) changes undesirably compared to scenario 1 as the absolute value of the risk reduction is decreased by 38%. Thus, we can conclude that just like scenario 2, when either the cost or time objective functions (Z_2) or (Z_3) is the highest ($\varphi_3 = 0.80$) then the other one either the time and cost objective functions will also change desirably, or, in other words, their changes are in the same direction, unlike the risk reduction objective function (Z_1). This conclusion is not true in all scenarios (see scenario 7). The other conclusion is that in scenario 2 at least one of the strategies chosen in the base scenario is also identified as the solution (i.e., S3) whereas on the other hand, S5 is only selected which was not among chosen strategies in the base scenario. This result might indicate that giving higher weight to the time objective function (Z_3) in scenario 2 compared to assigning higher weight to the cost objective function (Z_2) in scenario 4 would result in a more similar result to our base

Table 11
Sensitivity of solutions under variousφ values and $\lambda = 0.50$ ($\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$).

Scenario	φ_1	φ_2	φ_3	ξ	Z_1	Z_2	Z_3	μ_{Z_1}	μ_{Z_2}	μ_{Z_3}	Solution
base	0.33	0.33	0.33	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
1	0.10	0.10	0.80	0.96	-11.20	25.35	6.30	0.31	0.70	0.77	S3
2	0.80	0.10	0.10	1.00	-35.40	68.15	23.60	0.99	0.19	0.13	S2, S3, S5
3	0.10	0.80	0.10	0.98	-9.90	18.45	10.30	0.28	0.78	0.62	S1
4	0.70	0.15	0.15	1.00	-26.30	53.55	21.60	0.74	0.37	0.20	S4, S5
5	0.60	0.30	0.10	1.00	-23.20	53.45	22.85	0.65	0.37	0.16	S1, S4
6	0.60	0.10	0.30	1.00	-22.40	49.60	14.55	0.63	0.41	0.46	S2, S3

scenario in which all weights of three objective functions were equal.

Scenario 5: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.70$) and weights of the cost objective function (Z_2) and the time objective function (Z_3) are equally low ($\varphi_2 = \varphi_3 = 0.15$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 25% from -21.10 to -26.30 as can be observed in Fig. 3(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 24% from 39.96 to 49.39 as can be observed in Fig. 3(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 31% from 13.66 to 17.90 as can be observed in Fig. 3(c) (an undesirable change).

The solution result from scenario 5 in this case, does not confirm any of the selected strategies in the base scenario in which S1 and S3 were selected. Scenario 5 is similar to scenario 3 in the sense that in both scenarios, the risk reduction objective function (Z_1) has the highest weight while cost and time objective functions (Z_2) or (Z_3) both have equal weights. The results of sensitivity analysis in this case show that final solution is sensitive to any slight changes of objective function weights.

Scenario 6: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.60$) and the weight of the cost objective function (Z_2) ($\varphi_2 = 0.30$) is higher than the weight of the time objective function (Z_3) ($\varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 10% from -21.10 to -23.20 as can be observed in Fig. 3(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 24% from 39.96 to 49.57 as can be observed in Fig. 3(b) (an undesirable change). This change is the same as the scenario 5.
- The optimal value of the time objective function (Z_3) is increased by 37% from 13.66 to 18.76 as can be observed in Fig. 3(c) (an undesirable change).

The solution result from scenario 6 in this case, still confirms the S1 as the selected strategy compared to the base scenario in which S1 and S3 were selected. The analysis shows that by assigning higher weights to the risk reduction objective function (Z_1) in this case, only optimal value of the risk reduction objective function (Z_1) changes desirably while optimal value of the cost objective function (Z_2) and optimal value of the time objective function (Z_3) change in an undesirable direction.

Scenario 7: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.60$) and weight of the time objective function (Z_3) ($\varphi_3 = 0.30$) is higher than the weight of the cost objective function (Z_2) ($\varphi_2 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 9% from -21.10 to -22.90 as can be observed in Fig. 3(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is decreased by 16% from 39.96 to 33.58 as can be observed in Fig. 3(b) (a desirable change).
- The optimal value of the time objective function (Z_3) is increased by 18% from 13.66 to 16.10 as can be observed in Fig. 3(c) (an undesirable change).

The solution result from scenario 7 in this case, still confirms the S1 as the selected strategy compared to the base scenario in which S1 and S3 were selected. The analysis shows that by assigning higher weights to the risk reduction objective function (Z_1) in this case, optimal values of risk reduction objective function (Z_1) and cost objective function (Z_2) change in a desirable direction while only optimal value of time objective function (Z_3) changes in an undesirable direction.

Assuming $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ are fixed and $\lambda = 0.50$, seven scenarios (1 base scenario and six others) for various weights of three objective functions – risk reduction, cost, and time (i.e., φ_1, φ_2, φ_3) – are defined (Table 11). The S3 appeared in four scenarios as the final optimal solution, followed by S1 three times, and S2, S4 and S5 each two times. In Fig. 4, the sensitivity analysis of the three objective functions (i.e., risk reduction, cost, and time) are depicted separately under the seven defined scenarios in Table 11. In Fig. 4(a), the higher points, and in Fig. 4(b) and (c), the lower points are preferable. In Fig. 4(a), all values of the first objective function (Z_1) are negative. Therefore, the absolute values representing the amount of risk reduction are considered.

Under $\lambda = 0.50$, compared to the base scenario in which all weights of objective functions are equal ($\varphi_1 = \varphi_2 = \varphi_3 = 0.33$), the extent of changes in optimal objective function values are measured. The summarized results for the sensitivity analysis by controlling for $\lambda = 0.50$, $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ are as follows:

Scenario 1: the weight of time objective function (Z_3) is the highest ($\varphi_3 = 0.80$) and weights of the risk reduction objective function (Z_1) and the cost objective function (Z_2) are the lowest ($\varphi_1 = \varphi_2 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is increased or the absolute value is decreased by 47% from -21.10 to -11.20 as can be observed in Fig. 4(a) (an undesirable change). This is the same as scenario 2 in Table 10 and depicted in Fig. 3(a).
- The optimal value of the cost objective function (Z_2) is decreased by 42% from 43.80 to 25.35 as can be observed in Fig. 4(b) (a desirable change). This amount of reduction (i.e., 42%) is the same as shown in scenario 2 in Fig. 3(b).
- The optimal value of the time objective function (Z_3) is decreased by 62% from 16.60 to 6.30 as can be observed in Fig. 4(c) (a desirable change). This amount of reduction (i.e., 62%) is the same as shown in scenario 2 in Fig. 3(c).

The solution result from scenario 1 in this case, confirms S3 as the selected strategy compared to the base scenario in which S1 and S3 were selected. This result is like the result of scenario 2 in Table 10. The analysis shows that by assigning higher weights to the time objective function (Z_3) in this case, only optimal value of risk reduction objective function (Z_1) changes undesirably while the optimal value of cost objective function (Z_2) and, obviously, the optimal value of time objective function (Z_3) change in a desirable direction.

Scenario 2: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.80$) and weights of the cost objective function (Z_2) and the time objective function (Z_3) are the lowest ($\varphi_2 = \varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 68% from − 21.10 to − 35.40 as can be observed in Fig. 4(a) (a desirable change). This increase in absolute value is higher than 53% in scenario 3 in Table 10 as shown in Fig. 3(a).
- The optimal value of the cost objective function (Z_2) is increased by 56% from 43.80 to 68.15 as can be observed in Fig. 4(b) (an undesirable change). This increase in 1% higher than in scenario 3 in Table 10 as depicted in Fig. 3(b).
- The optimal value of the time objective function (Z_3) is increased by 42% from 16.60 to 23.60 as can be observed in Fig. 4(c) (an undesirable change). This increase is 8% lower than the increase in scenario 3 in Table 10 as depicted in Fig. 3(c).

The solution result from scenario 2 in this case, confirms only S3 as the selected strategies while in the base scenario S1 and S3 were selected. However, S5 and S2 were also selected as additional strategies in the final solution. The analysis shows that by assigning higher weights to the risk reduction objective function (Z_1) in this case, the optimal values of both cost objective function (Z_2) and time objective function (Z_3) change undesirably compared to the base scenario. The other conclusion is that by increasing the value of whitening coefficient from $\lambda = 0.15$ to $\lambda = 0.50$ in this case, the extent of change in the optimal value of the risk reduction objective function (Z_1) is 15% higher. However, the undesirable change in the optimal value of the cost objective function (Z_2) is 1% higher and the undesirable change in the optimal value of the time objective function (Z_3) is 8% lower.

Scenario 3: the weight of cost objective function (Z_2) is the highest ($\varphi_2 = 0.80$) and weights of the risk reduction objective function (Z_1) and the time objective function (Z_3) are the lowest ($\varphi_1 = \varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is increased or the absolute value is decreased by 53% from − 21.10 to − 9.90 as can be observed in Fig. 4(a) (an undesirable change). This decrease in absolute value is 15% higher than the decrease in scenario 4 in Table 10 as shown in Fig. 3(a).
- The optimal value of the cost objective function (Z_2) is decreased by 58% from 43.80 to 18.45 as can be observed in Fig. 4(b) (a desirable change). The extent of change is the same as in scenario 4 in Table 10 as shown in Fig. 3(b).
- The optimal value of the time objective function (Z_3) is decreased by 38% from 16.60 to 10.30 as can be observed in Fig. 4(c) (a desirable change). This decrease is 6% lower than the decrease in scenario 4 in Table 10 as depicted in Fig. 3(c).

The solution result from scenario 3 in this case, unlike scenario 4 in Table 10, partly confirms selected strategies in the base scenario in which S1 and S3 were selected. Here, only S1 was selected as the chosen strategy in the final solution. The analysis shows that by assigning higher weights to the cost objective function (Z_2) in this case, obviously, the optimal value of the cost objective function (Z_2) will be the minimum. Moreover, the optimal value of the time objective function (Z_3) changes in a desirable direction by 38% decrease in value from the base scenario. The optimal value of risk reduction objective function (Z_1) changes undesirably compared to the base scenario as the absolute value of the risk reduction is decreased by 53%. Thus, by increasing the value of whitening coefficient from $\lambda = 0.15$ to $\lambda = 0.50$ in this case, the extent of change in the optimal value of the risk reduction objective function (Z_1) is 15% higher. However, the desirable change in the optimal value of the cost objective function (Z_2) shows no change compared to the case under $\lambda = 0.15$ (i.e., again 58% decrease). Finally, the desirable change in the optimal value of the time objective function (Z_3) is 6% lower than the 44% decrease in scenario 4 under $\lambda = 0.15$ in Table 10 and Fig. 3(c).

Scenario 4: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.70$) and weights of the cost objective function (Z_2) and the time objective function (Z_3) are equally low ($\varphi_2 = \varphi_3 = 0.15$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 25% from − 21.10 to − 26.30 as can be observed in Fig. 4(a) (a desirable change). The change of 25% rise is the same as in scenario 5 in Table 10 and shown in Fig. 3(a).
- The optimal value of the cost objective function (Z_2) is increased by 22% from 43.80 to 53.55 as can be observed in Fig. 4(b) (an undesirable change). The extent of this undesirable change is 2% lower than the 24% change in scenario 5 in Table 10 as depicted in Fig. 3(b).
- The optimal value of the time objective function (Z_3) is increased by 30% from 16.60 to 21.60 as can be observed in Fig. 4(c) (an undesirable change). This undesirable increase is 1% lower than the change in scenario 5 in Table 10 as depicted in Fig. 3(c).

The solution result from scenario 4 in this case does not confirm any of the selected strategies in the base scenario in which S1 and S3 were selected. Scenario 4 is similar to scenario 2 in the sense that in both scenarios, the risk reduction objective function (Z_1) has the highest weight while cost and time objective functions (Z_2) or (Z_3) both have equal weights. The results of sensitivity analysis in this case show that final solution is sensitive to any slight changes of objective function weights. The other conclusion is that by increasing the value of whitening coefficient from $\lambda = 0.15$ to $\lambda = 0.50$ in this case, the solution (i.e., S4 and S5) did not change. Furthermore, the extent of change in the optimal value of the risk reduction objective function (Z_1) is unchanged while the extent of change in the optimal value of the cost objective function (Z_2) is 2% lower and the extent of change in the optimal value of the time objective function (Z_3) is 1% lower.

Scenario 5: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.60$) and the weight of the cost objective function (Z_2) ($\varphi_2 = 0.30$) is higher than the weight of the time objective function (Z_3) ($\varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 10% from − 21.10 to − 23.20 as can be observed in Fig. 4(a) (a desirable change). This is the same as scenario 6 in Table 10 and depicted in Fig. 3(a).
- The optimal value of the cost objective function (Z_2) is increased by 22% from 43.80 to 53.45 as can be observed in Fig. 4(b) (an undesirable change). This change is 2% lower than the undesirable change in the scenario 6 in Table 10 and plotted in Fig. 3(b).
- The optimal value of the time objective function (Z_3) is increased by 38% from 16.60 to 22.85 as can be observed in Fig. 4(c) (an undesirable change). The extent of the undesirable change is 1% higher than change in the scenario 6 in Table 10 and plotted in Fig. 3(c).

The solution result from scenario 5 in this case, still confirms the S1 as the selected strategy compared to the base scenario in which S1 and S3 were selected. The analysis shows that by assigning higher weights to the risk reduction objective function (Z_1) in this case, only optimal value of the risk reduction objective function (Z_1) changes desirably while optimal value of the cost objective function (Z_2) and optimal value of the time objective function (Z_3) change in an undesirable direction. The other conclusion is that by increasing the value of whitening coefficient from $\lambda = 0.15$ to $\lambda = 0.50$ in this case, the solution (i.e., S1 and S4) did not change (see scenario 6 in Table 10). Moreover, the extent of change in the optimal value of the risk reduction objective function (Z_1) is unchanged while the extent of change in the optimal value of the cost objective function (Z_2) is 2% lower and the change in the optimal value of the time objective function (Z_3) is 1% higher.

Scenario 6: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.60$) and weight of the time objective function

(Z_3) ($\varphi_3 = 0.30$) is higher than the weight of the cost objective function (Z_2) ($\varphi_2 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 6% from − 21.10 to − 22.40 as can be observed in Fig. 4(a) (a desirable change). This is 3% lower than the change in scenario 7 in Table 10 as depicted in Fig. 3(a).
- The optimal value of the cost objective function (Z_2) is increased by 13% from 43.80 to 49.60 as can be observed in Fig. 4(b) (an undesirable change). The extent and direction of change are both different from scenario 7 in Table 10 as it was 16% decrease in Fig. 3(b).
- The optimal value of the time objective function (Z_3) is decreased by 12% from 16.60 to 14.55 as can be observed in Fig. 4(c) (a desirable change). The extent and direction of change are both different from scenario 7 in Table 10 as it was 18% increase in Fig. 3(c).

The solution result from scenario 6 in this case, still confirms the S3 as the selected strategy compared to the base scenario in which S1 and S3 were selected. The analysis shows that by assigning higher weights to the risk reduction objective function (Z_1) in this case, optimal values of risk reduction objective function (Z_1) and time objective function (Z_3) change in a desirable direction while only optimal value of cost objective function (Z_2) changes in an undesirable direction. The other conclusion is that by increasing the value of whitening coefficient from $\lambda = 0.15$ to $\lambda = 0.50$ in this case, the extent of change in the optimal value of the risk reduction objective function (Z_1) is 3% lower. Furthermore, in the optimal value of the cost objective function (Z_2) both the extent and direction of change is different accounting for 16% decrease in Fig. 3(b) and scenario 7. Finally, the extent and direction of change is also different in the optimal value of the time objective function (Z_3) representing 18% increase as depicted in Fig. 3(c) and scenario 7.

Assuming $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ are fixed and $\lambda = 0.85$, the seven scenarios for various weights of the three objective functions – risk reduction, cost and time (i.e., $\varphi_1, \varphi_2, \varphi_3$) – are defined (Table 12). The S3 appeared in four scenarios as a final solution, followed by S5 three times, and S1, S2 and S4 each two times. In Fig. 5, the sensitivity analysis of the three objective functions (i.e., risk reduction, cost, and time) are depicted separately under the seven defined scenarios in Table 12. In Fig. 5(a), the higher points and, in Fig. 5(b) and (c), the lower points are preferable. In Fig. 5(a), all values of the first objective function (Z_1) are negative. Thus, the absolute values representing the amount of risk reduction are considered.

Under $\lambda = 0.85$, compared to the scenario 1 in which all weights of objective functions are equal ($\varphi_1 = \varphi_2 = \varphi_3 = 0.33$), the extent of changes in optimal objective function values are measured. The summarized results for the sensitivity analysis by controlling for $\lambda = 0.85$, $\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$ are as follows:

Scenario 2: the weight of time objective function (Z_3) is the highest ($\varphi_3 = 0.80$) and weights of the risk reduction objective function (Z_1) and the cost objective function (Z_2) are the lowest ($\varphi_1 = \varphi_2 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is increased or the absolute value is decreased by 14% from − 13.00 to − 11.20 as can be observed in Fig. 5(a) (an undesirable change).
- The optimal value of the cost objective function (Z_2) is increased by 38% from 16.70 to 23.08 as can be observed in Fig. 5(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is decreased by 32% from 7.62 to 5.18 as can be observed in Fig. 5(c) (a desirable change).

The solution result from scenario 2 in this case, confirms S3 as the selected strategy compared to the base scenario in which S1 and S3 were selected. This result is like the result of scenario 2 in Table 10 ($\lambda = 0.15$) and scenario 1 in Table 11 ($\lambda = 0.50$). It can be understood that by increasing the value of whitening coefficient to $\lambda = 0.85$ in this case, the extent of change in the optimal value of the risk reduction objective function (Z_1) is 33% lower than 47% in both scenario 2 in Table 10 and depicted in Fig. 3(a) ($\lambda = 0.15$) and in scenario 1 in Table 11 and depicted in Fig. 4(a) ($\lambda = 0.50$). The extent and direction of change in the optimal value of the cost objective function (Z_2) is different from 42% reduction both in scenario 2 in Table 10 and depicted in Fig. 3(b) ($\lambda = 0.15$) and in scenario 1 in Table 11 and depicted in Fig. 4(b) ($\lambda = 0.50$). The extent of change in the optimal value of the time objective function (Z_3) is 24% lower than 62% in both scenario 2 in Table 10 and depicted in Fig. 3(c) ($\lambda = 0.15$) and in scenario 1 in Table 11 and depicted in Fig. 4(c) ($\lambda = 0.50$).

Scenario 3: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.80$) and weights of the cost objective function (Z_2) and the time objective function (Z_3) are the lowest ($\varphi_2 = \varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 86% from − 13.00 to − 24.20 as can be observed in Fig. 5(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 138% from 16.70 to 39.78 as can be observed in Fig. 5(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 68% from 7.62 to 12.80 as can be observed in Fig. 5(c) (an undesirable change).

The solution result from scenario 3 in this case, confirms only S3 as the selected strategies while in the base scenario S1 and S3 were selected. However, S5 was also selected as additional strategies in the final solution. Both S3 and S5 were also selected in scenario 2 in Table 11 ($\lambda = 0.50$) while only S3 was selected in scenario 3 in Table 10 ($\lambda = 0.15$). By increasing the value of whitening coefficient to $\lambda = 0.85$ in this case, the extent of change in the optimal values of all three objective functions are higher than the extent of change under two other values of whitening coefficient.

Scenario 4: the weight of cost objective function (Z_2) is the highest ($\varphi_2 = 0.80$) and weights of the risk reduction objective function (Z_1) and the time objective function (Z_3) are the lowest ($\varphi_1 = \varphi_3 = 0.10$):

Table 12
Sensitivity of solutions under variousφ values and $\lambda = 0.85$ ($\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$).

Scenario	φ_1	φ_2	φ_3	ξ	Z_1	Z_2	Z_3	μ_{Z_1}	μ_{Z_2}	μ_{Z_3}	Solution
1	0.33	0.33	0.33	1.00	-13.00	16.70	7.62	0.37	0.73	0.61	S5
2	0.10	0.10	0.80	0.78	-11.20	23.08	5.18	0.32	0.63	0.74	S3
3	0.80	0.10	0.10	0.85	-24.20	39.78	12.80	0.68	0.36	0.35	S3, S5
4	0.10	0.80	0.10	0.84	-9.90	16.88	8.48	0.28	0.73	0.57	S1
5	0.70	0.15	0.15	0.83	-22.40	45.13	12.07	0.63	0.27	0.39	S2, S3
6	0.60	0.30	0.10	0.74	-24.20	39.78	12.80	0.68	0.36	0.35	S3, S5
7	0.60	0.10	0.30	0.63	-13.30	32.69	10.28	0.38	0.47	0.48	S4

- The optimal value of the risk reduction objective function (Z_1) is increased or the absolute value is decreased by 24% from − 13.00 to − 9.90 as can be observed in Fig. 5(a) (an undesirable change).
- The optimal value of the cost objective function (Z_2) is slightly increased by 1% from 16.70 to 16.88 as can be observed in Fig. 5(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 11% from 7.62 to 8.48 as can be observed in Fig. 5(c) (an undesirable change).

The solution result from scenario 4 in this case, unlike scenario 4 in Table 10 ($\lambda = 0.15$), partly confirms selected strategies in the base scenario in which S1 and S3 were selected. Here, only S1 was selected as the chosen strategy in the final solution just similar to scenario 3 in Table 11 ($\lambda = 0.50$). The analysis shows that by assigning higher weights to the cost objective function (Z_2) in this case, almost all the optimal values of the three objective functions changed in an undesirable direction. By increasing the value of whitening coefficient to $\lambda = 0.85$ in this case, the direction of the change in the optimal value of the risk reduction objective function (Z_1) just like previous values of λ is in an undesirable direction but the extent of the change is the lowest by 24% ($\lambda = 0.85$), 38% in scenario 4 in Table 10 ($\lambda = 0.15$), 53% in scenario 3 in Table 11 ($\lambda = 0.50$). The extent of the change in the optimal value of the cost objective function (Z_2) is negligible compared to 58% decrease in both scenario 4 in Table 10 ($\lambda = 0.15$), and in scenario 3 in Table 11 ($\lambda = 0.50$). The change in the optimal value of the cost objective function (Z_3) is in the opposite direction to 38% decrease in scenario 3 in Table 11 ($\lambda = 0.50$) and 44% decrease in Table 10 ($\lambda = 0.15$).

Scenario 5: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.70$) and weights of the cost objective function (Z_2) and the time objective function (Z_3) are equally low ($\varphi_2 = \varphi_3 = 0.15$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 72% from − 13.00 to − 22.40 as can be observed in Fig. 5(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 170% from 16.70 to 45.13 as can be observed in Fig. 5(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 58% from 7.62 to 12.07 as can be observed in Fig. 5(c) (an undesirable change).

The solution result from scenario 5 in this case, identifies S2 and S3 as the selected strategies. This result confirms only S3 as one of the selected strategies from the base scenario in which S1 and S3 were selected. This solution is different from resulted solution in scenario 4 in Table 11 ($\lambda = 0.50$) and in scenario 5 in Table 10 ($\lambda = 0.15$) in which S4 and S5 were selected. Here, scenario 5 is similar to scenario 3 in the sense that in both scenarios, the risk reduction objective function (Z_1) has the highest weight while cost and time objective functions (Z_2) or (Z_3) both have equal weights. The results of sensitivity analysis in this case show that final solution is sensitive to any slight changes of objective function weights. By increasing the value of whitening coefficient to $\lambda = 0.85$ in this case, the extent of the change in the optimal value of the risk reduction objective function (Z_1) (i.e., 72%) is higher than 25% in scenario 4 in Table 11 as shown in Fig. 4(a) ($\lambda = 0.50$) and in scenario 5 in Table 10 as shown in Fig. 3(a) ($\lambda = 0.15$). Moreover, the extent of the undesirable change in the optimal value of the cost objective function (Z_2) (i.e., 170%) is higher than 22% in scenario 4 in Table 11 as shown in Fig. 4(b) ($\lambda = 0.50$) and 24% in scenario 5 in Table 10 as shown in Fig. 3(b) ($\lambda = 0.15$). Finally, the extent of the undesirable change in the optimal value of the time objective function (Z_3) (i.e., 58%) is higher than 30% in scenario 4 in Table 11 as depicted in Fig. 4(c) ($\lambda = 0.50$) and 31% in scenario 5 in Table 10 as shown in Fig. 3(c) ($\lambda = 0.15$).

Scenario 6: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.60$) and the weight of the cost objective function (Z_2) ($\varphi_2 = 0.30$) is higher than the weight of the time objective function (Z_3) ($\varphi_3 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 86% from − 13.00 to − 24.20 as can be observed in Fig. 5(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 138% from 16.70 to 39.78 as can be observed in Fig. 5(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 68% from 7.62 to 12.80 as can be observed in Fig. 5(c) (an undesirable change).

The solution result from scenario 6 in this case, identifies S3 and S5 as the selected strategies. This result confirms only S3 as one of the selected strategies from the base scenario in which S1 and S3 were selected. This solution is different from resulted solution in scenario 5 in Table 11 ($\lambda = 0.50$) and in scenario 6 in Table 10 ($\lambda = 0.15$) in which S1 and S4 were selected. By increasing the value of whitening coefficient to $\lambda = 0.85$ in this case, the extent of the change in the optimal value of the risk reduction objective function (Z_1) (i.e., 86%) is higher than 10% in scenario 5 in Table 11 as shown in Fig. 4(a) ($\lambda = 0.50$) and in scenario 6 in Table 10 as shown in Fig. 3(a) ($\lambda = 0.15$). Moreover, the extent of the undesirable change in the optimal value of the cost objective function (Z_2) (i.e., 138%) is higher than 22% in scenario 5 in Table 11 as shown in Fig. 4(b) ($\lambda = 0.50$) and 24% in scenario 6 in Table 10 as shown in Fig. 3(b) ($\lambda = 0.15$). Finally, the extent of the undesirable change in the optimal value of the time objective function (Z_3) (i.e., 68%) is higher than 38% in scenario 5 in Table 11 as depicted in Fig. 4(c) ($\lambda = 0.50$) and 37% in scenario 6 in Table 10 as shown in Fig. 3(c) ($\lambda = 0.15$).

Scenario 7: the weight of risk reduction objective function (Z_1) is the highest ($\varphi_1 = 0.60$) and weight of the time objective function (Z_3) ($\varphi_3 = 0.30$) is higher than the weight of the cost objective function (Z_2) ($\varphi_2 = 0.10$):

- The optimal value of the risk reduction objective function (Z_1) is decreased or the absolute value is increased by 2% from − 13.00 to − 13.30 as can be observed in Fig. 5(a) (a desirable change).
- The optimal value of the cost objective function (Z_2) is increased by 96% from 16.70 to 32.69 as can be observed in Fig. 5(b) (an undesirable change).
- The optimal value of the time objective function (Z_3) is increased by 35% from 7.62 to 10.28 as can be observed in Fig. 5(c) (an undesirable change).

The sensitivity analysis under scenario 7 shows erratic changes. The solution result from scenario 7 in this case is S4, that does not confirm any of the selected strategies in the base scenario in which S1 and S3 were selected. This solution is different from resulted solution from scenario 6 in Table 11 ($\lambda = 0.50$) in which S2 and S3 were selected and also different from scenario 7 in Table 10 ($\lambda = 0.15$) in which S1 and S5 were selected. By increasing the value of whitening coefficient to $\lambda = 0.85$ in this case, the extent of the change in the optimal value of the risk reduction objective function (Z_1) (i.e., 2%) is lower than the 6% in scenario 6 in Table 11 as shown in Fig. 4(a) ($\lambda = 0.50$) and also the 9% in scenario 7 in Table 10 as shown in Fig. 3(a) ($\lambda = 0.15$). Moreover, the extent of the undesirable change (i.e., increase) in the optimal value of the cost objective function (Z_2) (i.e., 96%) is higher than 13% increase in scenario 6 in Table 11 as shown in Fig. 4(b) ($\lambda = 0.50$). However, the direction and extent of the change in the optimal value of the cost objective function (Z_2) in scenario 7 in Table 10 as shown in Fig. 3(b) ($\lambda = 0.15$) is decrease and 16%. Finally, the extent of the undesirable change (i.e., increase) in the optimal value of the time objective function (Z_3) (i.e., 35%) is higher than 18% increase in scenario 7 in Table 10 as depicted in Fig. 3(c) ($\lambda = 0.15$). However, the direction and extent of the change in the optimal value of the time objective function (Z_3) in scenario 6 in Table 11 as shown in Fig. 4(c) ($\lambda = 0.50$) is decrease and 12%.

Table 13
Optimal solution frequency of each strategy under variousφ values ($\delta = 1$, $\gamma = 1$, $g_i^* = 0.75$).

Risk mitigation strategies	$\lambda = 0.15$	$\lambda = 0.50$	$\lambda = 0.85$	Total
Continuous training and development (S1)	4	3	1	8
Leadership training (S2)	1	2	1	4
Vulnerability analysis of IT systems (S3)	3	4	4	11
Capacity planning (S4)	2	2	1	5
Big data-enabled CRM (S5)	3	2	3	8
Total	13	13	10	36

Putting all the sensitivity analyses in this section together, as presented in Table 13, the frequency that each strategy appeared in the obtained optimal solutions is counted based on Tables 10–12. It can be realized that S3, S1, and S5 are the most significant optimal solutions by appearing 11, 8, and 8 times in the optimal solutions. Overall, the sensitivity analysis for φ and λ values shows that the chosen strategies S1 and S3, obtained from the base scenario, are meaningful and confirmed.

6.2. Sensitivity analysis for δ values

The sensitivity of the optimal solutions is analyzed by changing the percentage values of the budget to be spent on mitigation strategies (δ) under the six defined scenarios and one base scenario (Table 14). In Fig. 6, the sensitivity analysis of the three objective functions (i.e., risk reduction, cost, and time) are depicted separately under the seven defined scenarios in Table 14. As can be seen, only in scenario one with the lowest percentage (i.e., $\delta = 0.10$) did the optimal solution change, indicating that the results are not sensitive to changes in the available budget unless it is exceptionally insufficient and low.

6.3. Sensitivity analysis for γ values

The sensitivity of the optimal solutions is analyzed by changing the time available for mitigation strategies (γ) under the six defined scenarios and one base scenario (Table 15). In Fig. 7, the sensitivity analysis of the three objective functions (i.e., risk reduction, cost, and time) are depicted separately under the seven defined scenarios in Table 15. It is observed that by providing at least 70% of the available time, the optimal strategies did not change; however, under scenarios 3 and 4, new optimal strategies (i.e., S5 and S4) were obtained, indicating a slight sensitivity to the γ values.

6.4. Sensitivity analysis for $\mathbf{g}_i^*$ values

The sensitivity of the optimal solutions is analyzed by changing g_i^* values under the four defined scenarios and one base scenario (Table 16). In Fig. 8, the sensitivity analysis of the three objective functions (i.e., risk reduction, cost, and time) are depicted separately under the seven defined scenarios in Table 16. Given these results, optimal solutions are confirmed, and sensitivity is negligible.

To summarize the analysis, findings are illustrated in Fig. 9.

7. Discussions and implications

7.1. Theoretical implications

The versatile proposed mathematical model (i.e., the hybrid M-RMM and GMOBLP) is novel within the current body of knowledge on AFSC risk management. It can facilitate the decision-making process of identifying the optimal risk mitigation strategies for dealing with identified risks in any decision-making context. The theoretical implications of the research are twofold. First, we develop a risk mitigation model, M-RMM, by (a) adding mitigation time dimension, (b) using BWM to calculate CRW, and (c) adding mitigation cost values. Second, we apply GMOBLP to obtain optimal risk mitigation strategies in relation to the three objective functions of risk impact minimization, cost minimization, and time minimization. Gupta et al. [38] discovered that applying multiple mitigation strategies is more efficient than applying one stand-alone strategy in risk reduction. Grey systems theory has the merit of dealing properly with poor information and small samples of data [56]. In our mathematical model, we have to deal with the uncertainty regarding estimating cost, time and budget as well as collecting data from a small sample of experts. In our proposed M-RMM, the following extensions of the original RMM are introduced:

(1) *A new dimension of mitigation time is added, where values are shown in grey numbers.*
This was missing in the original RMM as time plays a critical role in dealing with risk mitigation strategies in risk management.
(2) *CRW values are calculated based on BWM.*
In previous studies for quantifying risks, researchers primarily used the traditional approach of multiplying the occurrence likelihood or probability of each risk by its impact severity [9,40,62]. In this study, we have instead introduced CRW values, which estimate current risk weight using the BWM. In this way, the critical importance of risks can be captured more efficiently relative to the current status of the system and the purpose of the risk analysis at the firm level. The reason is that BWM can uncover the pair-wise relationships between risks by comparing risks with each other. Thus, one final weight can be estimated by experts through pair-wise comparisons accounting for the consistency of the comparisons. This method contrasts with the traditional approach, in which two values have to be estimated for each risk (i.e., impact and likelihood).
(3) *Mitigation cost values are shown in grey numbers.*

Table 14
Sensitivity of solutions under various δ values ($\varphi_1 = \varphi_2 = \varphi_3 = 0.33$, $\lambda = 0.50$, $\gamma = 1$, $g_i^* = 0.75$).

Scenario	δ	ξ	Z_1	Z_2	Z_3	μ_{Z_1}	μ_{Z_2}	μ_{Z_3}	Solution
1	0.10	1.00	-13.00	18.55	9.05	0.36	0.78	0.67	S5
2	0.25	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
3	0.40	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
4	0.55	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
5	0.70	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
6	0.90	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
base	1.00	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3

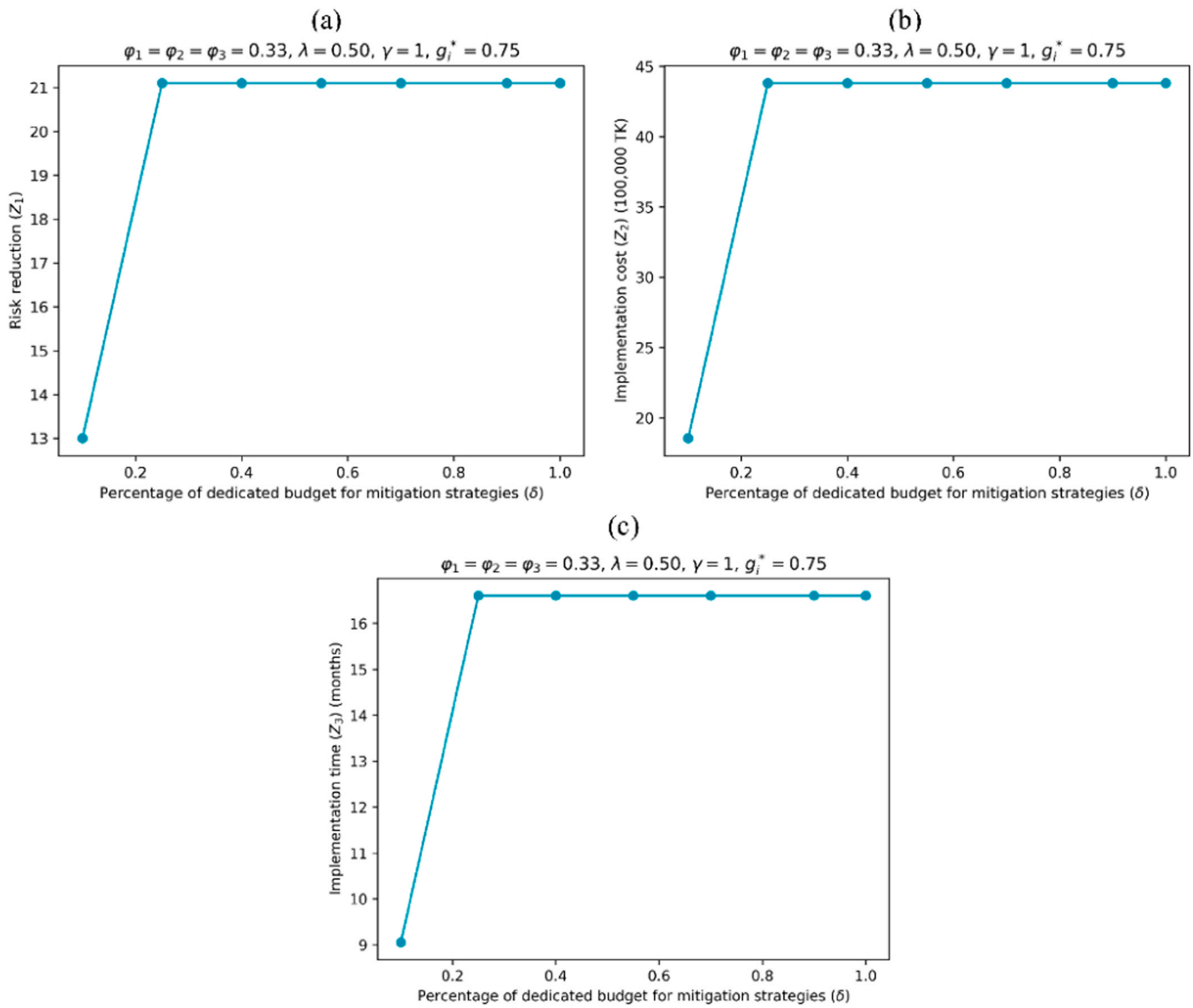

Fig. 6. Sensitivity analysis of (a) risk reduction (b) implementation cost and (c) implementation time for different percentages of dedicated budget for all mitigation strategies (δ).

The grey numbers provide an opportunity to incorporate the uncertainty around the cost estimations by offering a range instead of a single point cost value. It is believed that a range of cost estimations can represent the real-world situation better.

7.2. Practical implications

It is imperative for decision-makers in Bangladeshi AFSCs to realize the practical implications of the study in order to improve the robustness of AFSCs. The findings can help policymakers understand the most critical risks and, thereby, the most effective risk mitigation strategies to reduce food wastage in Bangladesh. The proposed model is context-specific (i.e., a developing economy), sector-specific (i.e., the agri-food processing sector), mathematical model-oriented (i.e., the M-RMM model and mathematical programming optimization), and multi-product (i.e., fresh and non-perishable) in Bangladeshi AFSCs. The results from the BWM analysis in the M-RMM revealed that R1 (lack of skilled personnel) (i.e., $w_1 = 0.3283$) is the most critical risk in AFSCs in Bangladesh, as shown in the M-RMM by

Table 15
Sensitivity of solutions under various γ values ($\varphi_1 = \varphi_2 = \varphi_3 = 0.33$, $\lambda = 0.50$, $\delta = 1$, $g_i^* = 0.75$).

Scenario	γ	ξ	Z_1	Z_2	Z_3	μ_{Z_1}	μ_{Z_2}	μ_{Z_3}	Solution
1	0.10	0.00	0.00	0.00	0.00	0.00	1.00	1.00	N/A*
2	0.25	0.95	-11.20	25.35	6.30	0.31	0.70	0.77	S3
3	0.40	1.00	-13.00	18.55	9.05	0.36	0.78	0.67	S5
4	0.55	1.00	-13.30	35.00	12.55	0.37	0.59	0.54	S4
5	0.70	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
6	0.90	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
base	1.00	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3

N/A* = no feasible solution

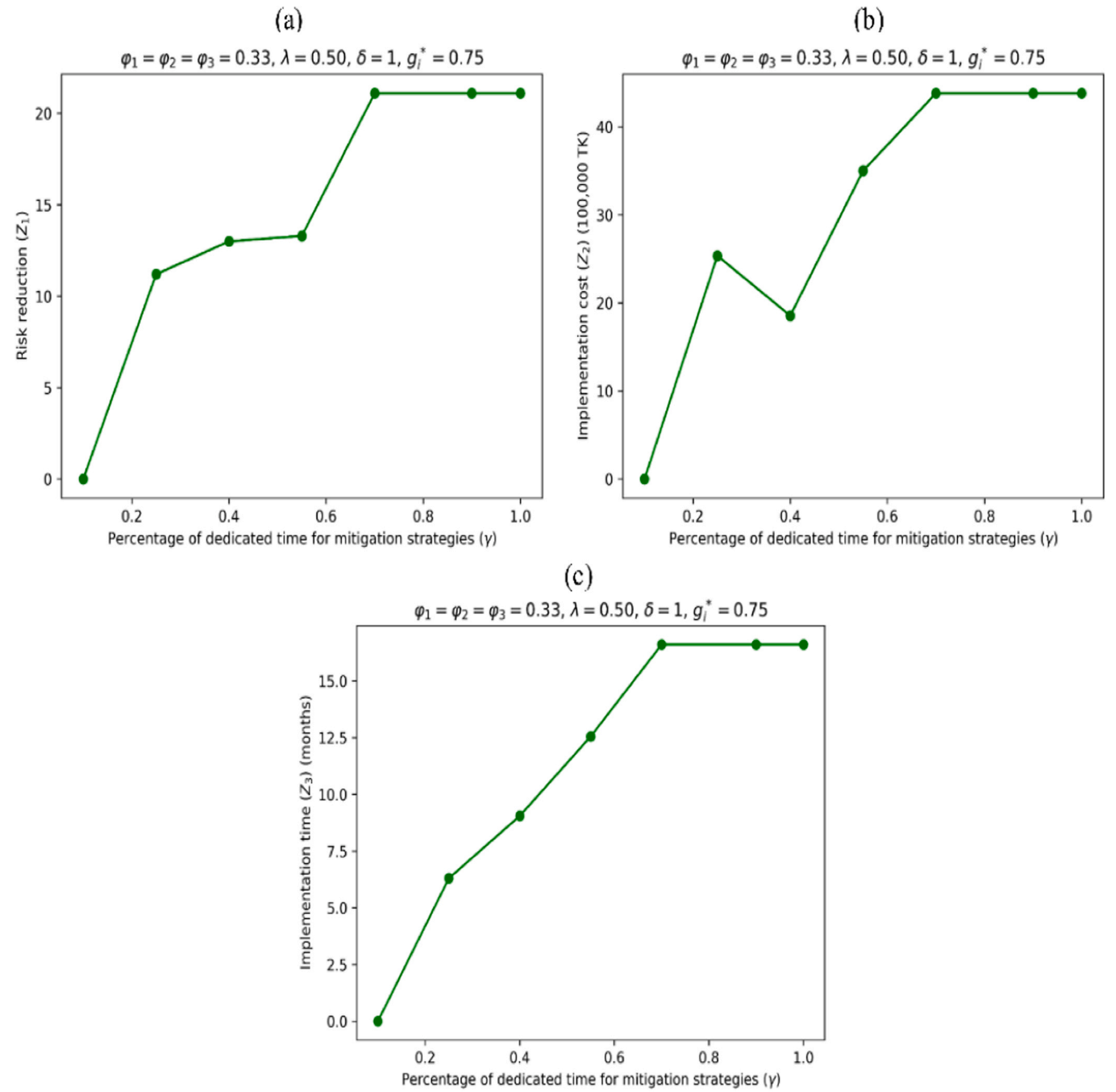

Fig. 7. Sensitivity analysis of (a) risk reduction (b) implementation cost and (c) implementation time for different percentages of dedicated time for all mitigation strategies (γ).

having the highest CRW (see Table 7). The other risks in order of importance are R2 (sub-standard leadership) ($w_2 = 0.2794$), R3 (failure in IT systems ($w_3 = 0.2399$), R4 (insufficient capacity) ($w_4 = 0.0791$) and R5 (poor customer relationships) ($w_5 = 0.0733$). The order of all important risks in Ali et al. [4] is also confirmed in our study. The lack of skilled personnel in both studies is identified as the most critical risk, followed by *sub-standard leadership*, *failure in IT systems*, *insufficient capacity*, and *poor customer relationships*.

Table 16
Sensitivity of solutions under various g_i^* values ($\varphi_1 = \varphi_2 = \varphi_3 = 0.33$, $\lambda = 0.50$, $\delta = 1$, $\gamma = 1$).

Scenario	g_i^*	ξ	Z_1	Z_2	Z_3	μ_{Z_1}	μ_{Z_2}	μ_{Z_3}	Solution
base	0.75	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
1	0.45	0.25	-32.30	68.05	24.85	0.90	0.20	0.08	S1, S2, S3
2	0.55	1.00	-24.20	42.80	17.30	0.68	0.49	0.36	S2, S5
3	0.85	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3
4	0.95	1.00	-21.10	43.80	16.60	0.59	0.48	0.39	S1, S3

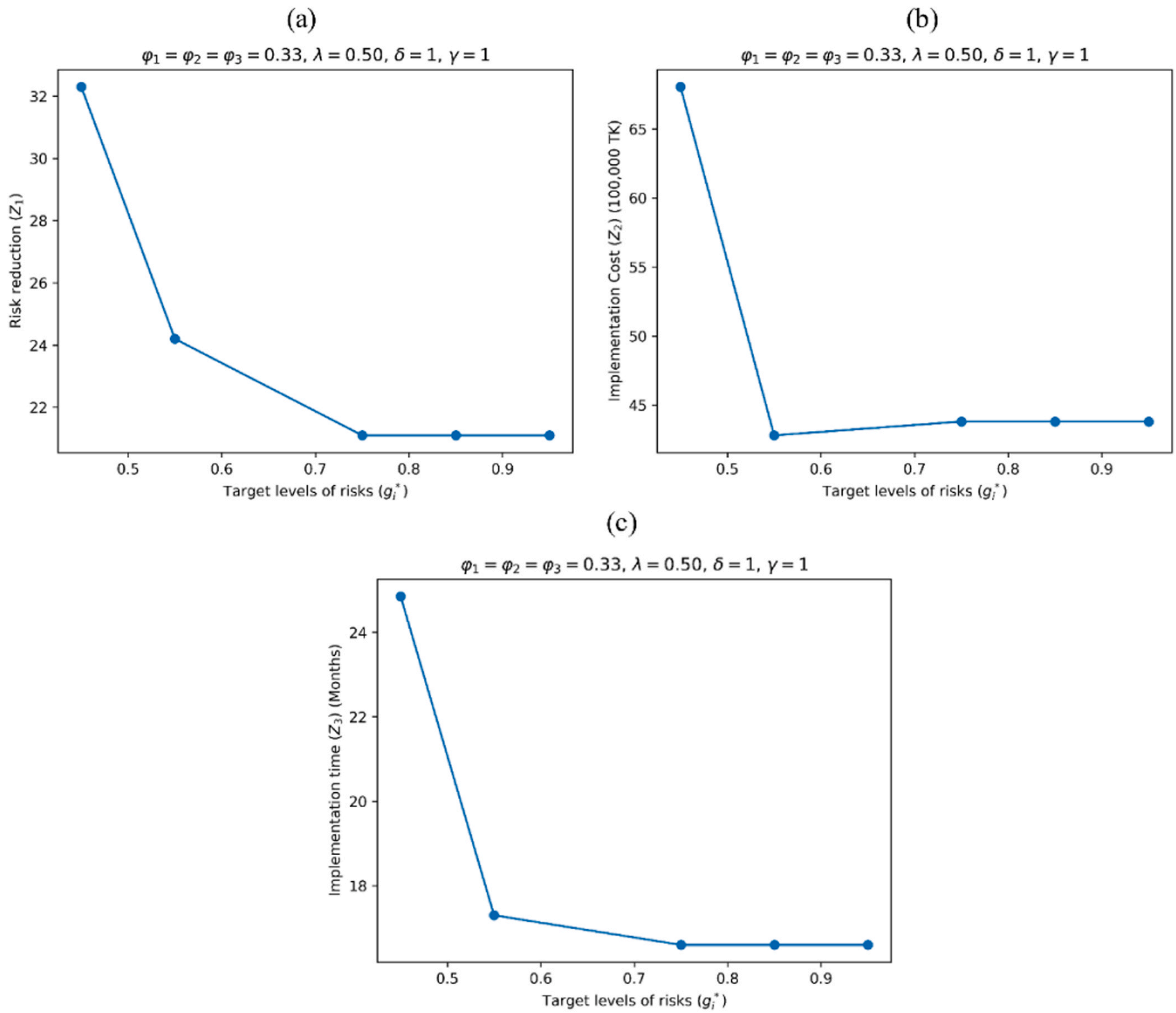

Fig. 8. Sensitivity analysis of (a) risk reduction (b) implementation cost and (c) implementation time for different target levels of risks (g_i^*).

After implementing risk mitigation strategies, new weights of risks (i.e., normalized AMRW) are obtained, and risks are ranked as follows: R1 (lack of skilled personnel) ($\theta_1 = 0.4131$), R2 (sub-standard leadership) ($\theta_2 = 0.2237$), R3 (failure in IT systems) ($\theta_3 = 0.1976$), R5 (poor customer relationships) ($\theta_5 = 0.0883$), and R4 (insufficient capacity) ($\theta_4 = 0.0772$). The findings from solving the GMOBLP show that *continuous training and development (S1)* and *vulnerability analysis of IT systems (S3)* are the most effective risk mitigation strategies. The mathematical model is able to obtain the optimal total implementation time and cost of risk mitigation strategies. It indicates that by implementing S1 and S3 mitigation strategies, which comprise the best Pareto-optimal solution, the total implementation cost of risk mitigation strategies is estimated to be 4,380,000 TK within a timescale of approximately 16 months and 18 days.

In previous research, Zhao et al. [106] confirmed the importance of a lack of skilled workers when it comes to data sharing and use of IT in the context of AFSCs. Ali et al. [4] likewise identified this problem as the most critical risk—as did we in the present study (i.e., lack of skilled personnel: R1). Our findings suggest that continuous training and development (S1) can be particularly effective in dealing with this risk. Unskilled personnel may cause extensive wastage in the production process, with Papargyropoulou et al. [70] having confirmed that skilled personnel are critical in minimizing food wastage. This risk can be addressed by continuous training within the company or by outsourcing the required training to educational institutes.

Sub-standard leadership (R2) was ranked as the second most critical risk. Again, prior studies confirm the importance of this risk, indicating that poor leadership can be the cause of huge food wastage [70,73]. Similarly, Akhtar et al. [2] identified theoretical links between leadership practices and sustainability in AFSCs (dairy, meat, fruits, and vegetables). Moreover, Akhtar et al. [3] indicated that data-driven and adaptive leadership in comparison with traditional leadership practices (i.e., participative and directive leadership styles) is an essential tool for managing modern AFSCs.

Failure in IT systems (R3) was the third critical risk within AFSCs identified in our study, in line with previous findings. Thus, Williams, Wikström, and Löfgren [98] indicated that failure in IT systems may result in excessive food production, causing significant spoilage. Vulnerability analysis of IT systems (S3) can be used to manage this risk [4]. More generally, it is crucial to understand the key role played by IT and information and communication technology (ICT) in today's complex AFSCs. This role needs to be considered for purposes of policy making and future investment, since IT and ICT can help firms gain a competitive advantage by ensuring the smooth, safe, and resilient flow

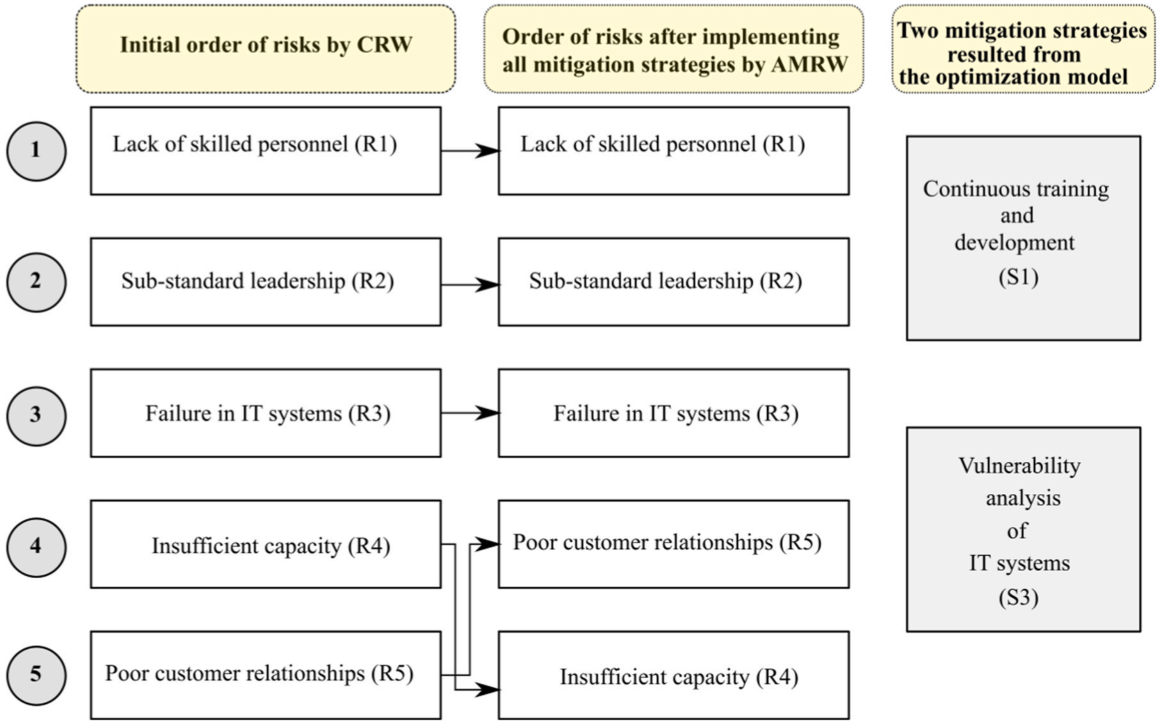

Fig. 9. Order of risks and obtained optimal mitigation strategies.

of information. The reliable flow of information is of special importance in emerging economies like Bangladesh. Cash [20] noted that the agriculture sector has become increasingly information-dependent, necessitating a broad range of technical information for appropriate decision-making in this sector. However, large-scale information asymmetry exists in nearly all levels of AFSCs in developing countries, resulting in food waste throughout the chain [5]. New information technologies, such as precision agriculture or global positioning systems integrated with affordable sensors and computerized technologies, would equip AFSC managers, particularly in developing countries, with the tools needed to monitor yields and be more efficient in production planning [36,53,80,82].

Insufficient capacity (R4) was the fourth critical risk identified in our study. This risk in the area of manufacturing production capacity can potentially lead to food wastage as well [4]. Food processing includes numerous operations such as drying, sieving, mixing, and cooking, to name just a few. These operations are all connected to the production capacity of a firm [87]. Therefore, a risk mitigation strategy (i.e., S4: capacity planning) was proposed to facilitate a smoother production system. By keeping the capacity high, this strategy can reduce the potential for food spoilage [70].

Finally, the fifth risk (i.e., R5: poor customer relationships) mainly concerns producers' ability to fulfill customers' taste preferences. This risk, too, can impact food wastage because consumption is directly related to food wastage while also being linked to good customer relationships [4]. The link between poor relationships between customers and producers, on the one hand, and post-harvest food losses and waste, on the other hand, was discussed in Hodges, Buzby, and Bennett [41]. In response to this risk, the researchers [4] proposed a big data-enabled customer relationship management strategy (S5); however, our findings pointed to other risk mitigation strategies, including continuous training and development (S1) and vulnerability analysis of IT systems (S3). Nonetheless, the use of Industry 4.0 technologies such as blockchain, the Internet of Things, and big data in agri-food supply chains in developing economies in dealing with risks and sustainability issues is gaining traction [1,57,63,85,100]. Furthermore, the concept of green premium (i.e., the higher price that consumers are willing to incur for green products) can be considered to explore customer satisfaction and managing relationships with customers to encourage a more sustainable consumption via certification [8,23].

7.3. Limitations

This research carries a few limitations. The first limitation is the primary data collected in this study are prone to be biased due to the nature of subjective judgments when humans are involved in the decision-making process. This can be improved by utilizing secondary data as well and implementing advanced artificial intelligence algorithms in future. Second, our focus in this study was on the robust mitigation strategies for risks (i.e., high probability, low consequence risks) as opposed to resilient mitigation strategies suitable for disruption risks such as COVID-19 pandemic (i.e., low probability, high consequence risks) which can be dealt with in future. Finally, the ten case companies are used as a backdrop in our research to verify the applicability of our proposed mathematical model within the agri-food processing sector of food supply chains in Bangladesh. Unlike the proposed mathematical model that is versatile and can be applied in other similar problems, the results of our study cannot be generalized to other AFSCs in other countries or sectors. Nonetheless, the proposed mathematical model has been proved to have significant merits, suggesting that it can be applied in AFSC settings in other countries as well as in different contexts involving similar decision-making problems.

8. Conclusions

Supply chains are comprised of sophisticated networks of upstream and downstream partners seeking collectively to enhance competitive advantage and add value. Rapid and continuing global population growth has created a massive demand for food while also increasing food wastage in the food supply chain. Thus, as articulated in our problem statement, *"there is a paramount need to research the critical risks of AFSCs and advance proactive risk mitigation practices by suitable mathematical models particularly in developing countries to improve the robustness of this important SC and have an impact on the economy"*. In this study, we dealt with robust strategies concerning proactive risk mitigation measures which are suitable for business-as-usual risks (i.e., high probability, low consequence risks). As discussed in the Introduction, what we defined robust strategies in SCs based on the one defined by Behzadi et al. [14] where they recognized robust strategies as proactive risk mitigation measures which are suitable for business-as-usual risks (i.e., high probability, low consequence risks). We answered the research question, *"How can a reliable and yet easy-to-use mathematical model be defined to effectively analyze supply chain risk impacts and mitigation strategies in the agri-food processing sector in Bangladesh?"*. We proposed a context-specific (i.e., a developing economy), sector-specific (i.e., the agri-food processing sector), mathematical model-oriented (i.e., the M-RMM model and mathematical programming optimization), and multi-product (i.e., fresh and non-perishable) model in Bangladeshi AFSCs. The proposed M-RMM was integrated with the GMOBLP model to obtain the optimal risk mitigation strategies in relation to the three objective functions of risk, cost, and time minimization. We also provided an empirical generalization in the context of AFSC in Bangladesh by comparing the findings.

The study analyzed the five risk mitigation strategies in the Bangladeshi agri-food processing sector proposed by Ali et al. [4], including continuous training and development (S1), leadership training (S2), vulnerability analysis of IT systems (S3), capacity planning (S4), and big data-enabled CRM (S5). These strategies were proposed to deal with five risks in the agri-food processing sector, including lack of skilled personnel (R1), sub-standard leadership (R2), failure in IT systems (R3), insufficient capacity (R4), and poor customer relationships (R5) (see Table 7). Results indicate that continuous training and development (S1) and vulnerability analysis of IT systems (S3) are the most suitable risk mitigation strategies for the specific context and sector in Bangladesh. The sensitivity analyses also confirmed the reliability of the obtained results. In future research, researchers may suggest an alternative design of experiments based on fractional factorial analysis to evaluate the sensitivity of final solution by just analyzing the impact of only more influential parameters instead of analyzing all parameters' impact on the sensitivity of final result to save cost and time of performing full analysis. It would be also interesting to investigate AFSC risks and mitigation strategies based on various agri-food products in a few sectors by applying mathematical frameworks and then compare findings. Researchers can also include sustainability matrix as a new dimension to be included in the RMM. It is worthwhile to apply the model to other SC contexts in other economies as well by applying resilient mitigation strategies to deal with disruption risks such as COVID-19 pandemic risk. Ultimately, researchers can take advantage of mixed primary and secondary data in future and reduce the results' dependence on subjective evaluations to strengthen the model's reliability and robustness.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.sca.2023.100012.

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