Computers & Industrial Engineering 201 (2025) 110921

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

A dynamic risk interdependency network-based model for project risk assessment and treatment throughout a project life cycle ☆

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ARTICLE INFO

Keywords:
Risk interdependency network
Dynamic risk assessment
Risk propagation
Interpretive structural modeling
Monte Carlo simulation
Project life cycle

ABSTRACT

As the diverse, nonlinear coupled, and dynamic project risks have been increasingly plaguing contemporary projects throughout a project life cycle (PLC), an effective project risk management process is pivotal for project-driven organizations to cope with risks more proactively. This paper develops a dynamic and intelligent risk interdependency network (RIN) model to improve the decision-making in project risk assessment (PRA) and risk treatment throughout an entire PLC. By integrating the interpretive structural modeling (ISM) method into the Monte Carlo simulation (MCS), multiple risk characteristics and complexity-related aspects are simultaneously captured in the proposed model, including risk occurrence probability, risk impact on project objectives, cause–effect risk interdependencies, risk propagation behavior, risk stochastic behavior, and the dynamics of a phase-based project RIN during a PLC. The proposed RIN-driven risk indicators can effectively prioritize project risks and evaluate the project risk level either in a specific project phase or in an entire PLC, providing decision-makers with a more comprehensive and deeper understanding of the project risk profile along the implementation of a project. Further, more appropriate project risk treatment actions can be formulated under various treatment scenarios, and their performances are quantitatively evaluated through the proposed dynamic MCS-based RIN model. The feasibility and superiority of the proposed model are validated by a case study. The findings of this research should strengthen the capability of project risk management by providing a more informative decision basis for reliable PRA and effective project risk treatment.

1. Introduction

A project is a temporary endeavor undertaken that strives to deliver a unique product, service, or outcome bringing about tangible benefits or value addition (Marle et al., 2013; PMI, 2021; Rodríguez et al., 2016). In most cases, a project is regarded as a complex system that consists of numerous interrelated components of different natures and must achieve multiple interdependent or even contradictory objectives (Ellinas et al., 2018; Marle et al., 2013; Zhu & Mostafavi, 2018). For contemporary project-driven organizations, ensuring the successful delivery and operation of projects remains a critical issue (de Almeida Rodrigues et al., 2024; Okudan et al., 2021; Yang et al., 2021). As projects face growing complexities both from their interior (e.g., organizational and technical factors) and exterior (e.g., economic, social, and environmental factors) dynamic environments (Fang & Marle, 2012; Glette-Iversen et al., 2023; Taroun, 2014), diverse risks that threaten project outcomes can occur throughout a project life cycle (PLC) (Hwang et al., 2016; Islam et al., 2019). The “risk” is often defined as “the effect of uncertainty on objectives” (BSI, 2018) or “an uncertain event or condition that, if it occurs, has a positive or negative effect on one or more project objectives” (PMI, 2019). If project risks are not appropriately managed and controlled in time during the PLC, they can result in severe issues, such as delay in project schedule, cost overrun, quality deficiency, scope creep, and damage to an organization’s reputation, thereby further compromising the achievement of project objectives (Guan, Liu et al., 2020; PMI,

☆ This work is supported by research stipends from the University of New South Wales and the University of Technology Sydney. We would like to thank Dr. Shuo Yang for his contributions to conceiving the simulation algorithm of the proposed approach. We are grateful to the editors and anonymous reviewers for their invaluable comments and suggestions.

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https://doi.org/10.1016/j.cie.2025.110921
Received 18 January 2024; Received in revised form 9 December 2024; Accepted 22 January 2025
Available online 30 January 2025

2021; Zuo & Zio, 2024).

A systematic risk management process mainly involves the activities of communicating and consulting, establishing the scope, context, and criteria, and assessing, treating, monitoring, reviewing, recording, and reporting risks, which should be implemented iteratively, interactively, and dynamically (BSI, 2018). Project risk assessment (PRA), as a crucial part of the project risk management process, is often used to measure the importance of risks and evaluate the effects of hazardous events on a project through various analytical or simulation-based methods, including qualitative, semi-quantitative, quantitative, model-based, and knowledge-based techniques (Glette-Iversen et al., 2023; Wu et al., 2015; Zeng et al., 2007). The ultimate goal of PRA is to provide project decision-makers with a comprehensive understanding of a project's risk profile throughout an entire PLC and facilitate effective project management. In addition, project performances under different risk scenarios can also be estimated and predicted, contributing to the formulation of more proactive risk treatment solutions for a project (Dikmen et al., 2018; Mahmood et al., 2022; Yildiz et al., 2014). It is widely recognized that dealing with all identified project risks is impractical primarily because most projects are constrained by limited resources (Fang et al., 2017; Nicholas & Steyn, 2020), and it can be very challenging to simultaneously pay attention to all the risks and address them using required resources (de Almeida Rodrigues et al., 2024). In this regard, an effective project risk prioritization scheme is critical to facilitate a more efficient allocation of project resources when mitigating project risks.

Throughout a PLC, most project risks, particularly those with different natures, are often interrelated due to their inherently complex and varied cause–effect relationships (Chen et al., 2023; Fang & Marle, 2012; Wang et al., 2019; Williams, 2017). Such risk interdependencies (e.g., cause–effect and chronological relationships) can cause a cascading propagation from one risk to multiple downstream risks or a situation in which one risk is triggered owing to the occurrence of several upstream risks (Fan et al., 2012; Fang & Marle, 2012; Wang et al., 2022). In addition, the phenomenon of a risk loop is prone to appear, where several risks are in a closed causal path starting from the initial occurrence of a risk to the triggering of a set of subsequent risks until the initial risk arises again (Wang et al., 2019; Williams, 2017). For instance, a technical problem that occurs during the project implementation can result in the occurrence of the quality risk which subsequently leads to a delay in the project schedule, and then, the technical problem reoccurs because of the schedule delay and its influence is further amplified due to the cascading effects within this risk loop. The project risks involved in a risk loop are often heterogeneous (with different natures), and such risk loops can significantly increase the complexity of risk interdependencies regarding a project (Chen et al., 2023; Marle et al., 2013). In the extreme case, known as a chain reaction or domino effect, a modest risk (if left undetected and untreated) can eventually lead to disastrous effects on project outcomes and even project failure on account of cascading propagation via a series of risk interdependencies (Ellinas, 2019; Glette-Iversen et al., 2023; Helbing, 2013; Loosemore & Cheung, 2015). As a result, neglecting risk interdependencies and risk propagation behavior can cause an inevitable underestimation of project risks and thereby the inefficacy of subsequent risk treatment actions. To timely predicting the emergent behaviors of project risks derived from risk propagation and enhance the accuracy of PRA results, risk interdependency effects should be adequately investigated and taken into account in the PRA process, especially for large and complex projects.

The classical probability–impact (P–I) risk model, assuming risks are independent of their environments (Aven, 2016; Fang & Marle, 2012) and quantifying risk criticality (RC) simply based on the probability of risk occurrence and risk impact on project objectives (BSI, 2018; Nicholas & Steyn, 2020; PMI, 2021; Qin et al., 2016; Williams, 1993; Zeng et al., 2007), is no longer suitable for analyzing the propagation effects of interdependent project risks (Aven, 2016; Qazi & Akhtar, 2020; Taroun, 2014). To delve into the causes and effects of certain risks during the PRA process, multiple methods have been proposed and applied, such as failure mode and effects analysis (Carbone & Tippett, 2004; Zhang et al., 2024), fault tree analysis (Zeng & Skibniewski, 2013), influence diagrams (Dikmen et al., 2007), cause and effect (Ishikawa) diagrams (Luo et al., 2018), and risk breakdown structure (Holzmann & Spiegler, 2011; Liu et al., 2024). However, these approaches oversimplify risk interdependencies into linear causal relationships by using a risk list to decompose or classify project risks in the form of single-link trees, which are insufficient to model complex interdependencies among heterogeneous risks and the situation of risk loops.

To provide a deeper analysis of risk interdependencies, many researchers have encouraged a systematic view of project risks by incorporating "systems thinking" (Ahiaga-Dagbui et al., 2017; Loosemore & Cheung, 2015; Williams, 2017). More sophisticated methods, based on the structure of a network, have been explored for PRA to uncover the black box of complex risk interdependencies, including Bayesian belief network (BBN) (Abdelhafidh et al., 2023; Akhavan et al., 2021; Chen et al., 2023; Guan, Liu et al., 2020; Hu et al., 2013; Qazi & Dikmen, 2021; Wu et al., 2015), structural equation modeling (SEM) (Ahmadabadi & Heravi, 2019; Liu et al., 2016; Yildiz et al., 2014), design structure matrix (DSM) (Fang et al., 2017; Marle et al., 2013), interpretive structural modeling (ISM) (Guan, Abbasi et al., 2020; Iyer & Sagheer, 2010; Tavakolan & Etemadinia, 2017; Wu et al., 2015), decision making trial and evaluation laboratory (Chien et al., 2014; Hwang et al., 2016; Wu et al., 2019), and social network analysis (SNA) (Yang & Zou, 2014; Yuan et al., 2018; Zhang et al., 2020). However, these network-based analytical PRA methods are difficult to model the stochastic behavior of risk occurrence and the dynamic changes of an RIN along the implementation progress of a project. Compared with analytical PRA models, simulation techniques can better capture the dynamics of project systems (Law, 2015) and have great potential to generate various risk scenarios under uncertainties when estimating project risk conditions. The simulation-based PRA models have gained increasing attention in empirical research to support decision-making in complex engineering systems (Bai et al., 2024; Liu et al., 2024).

Monte Carlo simulation (MCS) is one of the most widely used simulation methods for PRA (Gao et al., 2019; Qazi et al., 2021; Qazi & Simsekler, 2021; Sadeghi et al., 2010). It is a quantitative decision-making tool that relies on the occurrence probability of an event to be estimated based on historical records or expert judgments. MCS is able to quantify the effects of identified risks on project performance using statistical indicators. By generating random values of input variables following a predetermined probability distribution, the stochastic behavior of risk occurrence is well captured in the MCS-based risk modeling (Guan et al., 2021; Zhang et al., 2017). Thus, the abilities of incorporating risk stochastic behavior and generating numerous risk scenarios make the MCS a promising nondeterministic method for PRA under uncertainties (Qazi & Simsekler, 2021; Sadeghi et al., 2010). Nevertheless, the main limitation of solely using MCS for PRA is that it cannot cope with possible risk interdependencies. Several existing studies have integrated MCS with some risk interdependency modeling methods, such as DSM (Wang et al., 2019), ISM (Guan et al., 2021), and BBN (Chen et al., 2023) to analyze project interdependent risks. Other simulation models have also been proposed for PRA, including system dynamics (Bai et al., 2024; Etemadinia & Tavakolan, 2021; Wang & Yuan, 2017), fuzzy cognitive mapping (der Landwehr et al., 2023), multi-agent simulation (Taillandier et al., 2015), and discrete event simulation (Li et al., 2018).

A project is also considered a time-related dynamic system. Unlike non-project operations in which everything tends to be stable, the objectives, tasks, activities, resources, and stakeholders regarding projects in the phases of a PLC are different and in a state of flux (Huseby & Skogen, 1992; Hwang et al., 2016). Consequently, project risks and associated cause–effect interdependencies can change dynamically as a project progresses. Additionally, owing to the inherent stochastic behavior of risk occurrence, a given risk's influence is not always constant for different project phases but varies with the number of its interrelated upstream risks. Incorporating the dynamics of a project risk interdependency network (RIN) into the PRA process, which has also been suggested by a few recent studies (Bai et al., 2024; Glette-Iversen et al., 2023; Guan, Liu et al., 2020; Liu et al., 2024; Wang et al., 2019, 2020), helps analyze risk propagation effects and evaluate how negative influences of diverse risks evolve throughout an entire PLC.

Although previous studies have expanded the knowledge of project risk management by handling different aspects of the growing complexity in the PRA process, few efforts have been made to comprehensively analyze project risks by simultaneously capturing multiple risk characteristics and the dynamics of a project RIN across different phases of a PLC. Furthermore, under the context of risk interdependencies, the project risk treatment process becomes more complicated because any treatment action on one interdependent risk can cause variations in the risk impact on its affected risks. In view of this, it is necessary to take into account the dynamics of a holistic project RIN during a PLC when reducing a project's risk level, rather than treating project risks as separate factors. To address these research gaps, this work aims to achieve three main research objectives: (i) developing a dynamic simulation-based RIN model for PRA that facilitates analyzing project risks throughout a PLC considering multiple risk characteristics and the dynamics of a project RIN; (ii) designing informative RIN-driven risk indicators to prioritize project risks and evaluate an overall project risk level considering risk propagation effects; and (iii) supporting the formulation of effective and efficient project risk treatment actions throughout a PLC under the context of risk interdependencies. Considering the merits of the ISM method in modeling complex risk interdependencies and the MCS method in capturing the stochastic behavior of risk occurrence, we combine the two methods to design a novel simulation-based RIN model for dynamic PRA and risk treatment throughout a PLC. In this paper, the "project phase" is defined as a collection of logically related project activities that culminate in completing one or more deliverables for a project (PMI, 2021). A sequence of project phases constitutes the PLC that a project goes through from initiation to closure.

In this study, a hierarchical phase-based project RIN is first established using the ISM method, in which identified project risks and cause–effect risk interdependencies (including possible risk loops) throughout an entire PLC are represented. Then, by integrating the phase-based project RIN into the MCS, a dynamic MCS-based RIN model is developed for PRA so that the stochastic behavior of risk occurrence and dynamic changes of a project RIN in a PLC are captured. Based on numerous risk scenarios generated by the dynamic PRA model, the simulated occurrence probability (SOP) indicator is proposed to evaluate the occurrence probability of a risk that may occur in a certain phase of the PLC. Further, by integrating the impact on project objectives (IO) of a risk with its SOP, two indicators – simulated local influence (SLI) and simulated global influence (SGI) – are designed to estimate a risk's influence at the local and global RIN levels, respectively. Subsequently, two project-level risk indicators, i.e., total risk loss (TRL) and total risk propagation loss (TRPL) are devised to evaluate an overall project risk level either in a specific project phase of the PLC or from the perspective of an entire PLC. Based on risk prioritization results by the proposed RIN-driven risk indicators, appropriate project risk treatment actions following different treatment scenarios (reflecting different risk attitudes and appetites of a group of project decision-makers) can be formulated. The performances of risk treatment actions can also be measured through the proposed PRA model and thus, a more effective risk treatment solution is determined. A case study on an industrial project is provided to explain the application of the proposed dynamic model to the decision-making in PRA and subsequent risk treatment implementations. The comparison results between the proposed dynamic MCS-based RIN model and the classical P–I risk model further validate the effectiveness and reliability of the proposed approach for assessing and treating project risks throughout a PLC.

Compared with previous related studies, as shown in Table 1, this work has three major contributions. Firstly, we propose a new dynamic MCS-based RIN model as an effective tool to systematically evaluate project risks and an overall project risk level considering complex risk interdependencies throughout an entire PLC. When modeling project risks, apart from the intrinsic attributes of a single risk itself, the causal influences from its interdependent risks that may trigger it directly or indirectly are also considered based on a phase-based project RIN. Project decision-makers can have a better understanding of how risks interact with each other via cause–effect interdependencies and how their local and global influences evolve dynamically along the project phases of a PLC. Secondly, the proposed intelligent PRA model simultaneously captures multiple characteristics of project risks and complexity-related aspects, including risk occurrence probability, risk impact on project objectives, complex risk interdependencies (involving risk loops), risk propagation behavior, risk stochastic behavior, and dynamic changes of project risks and risk interdependencies during a PLC. As such, more realistic and reliable PRA results can be obtained to effectively reflect the intricate nature of project risks in practice. Thirdly, this study provides detailed guidelines for formulating appropriate project risk treatment actions by employing the proposed RIN-driven risk indicators. Moreover, by re-evaluating project risk profile based on the proposed PRA model, the performances of project risk treatment actions under different treatment scenarios can be examined. This helps project decision-makers select a more effective risk treatment option among alternatives to deal with project risks more proactively according to a particular risk attitude and risk appetite (can be reflected by the PRA model inputs and selected risk treatment scenario).

The remainder of this paper is organized as follows. Section 2 introduces the methodology of developing a dynamic MCS-based RIN model for assessing and treating project risks throughout an entire PLC. Section 3 demonstrates the application of the proposed model based on a case study and further verifies its feasibility and effectiveness. The methodological and managerial implications of this work are discussed in Section 4. Section 5 concludes this paper with a summary of findings, existing limitations, and future research directions.

2. Proposed methodology

In this section, a dynamic MCS-based RIN model is established to improve the effectiveness and efficiency of decision-making in PRA and subsequent risk treatment throughout an entire PLC. Fig. 1 shows the overall framework of our proposed methodology. There are three significant stages: (i) developing a phase-based project RIN in the risk identification process; (ii) developing a dynamic MCS-based RIN model to conduct PRA; and (iii) planning appropriate project risk treatment actions and evaluating their effectiveness in the risk treatment process. The novelty of our proposed dynamic PRA model is that specific project phases of a PLC are considered when analyzing the resultant influences of project risks and their cause–effect interdependencies, bringing about a series of RIN-driven risk indicators to help prioritize individual risks (i.e., SOP_i^p, SLI_i^p, and SGI_i^p), quantify the project risk level in each phase of a PLC (i.e., TRL^p and $TRPL^p$), and evaluate the overall project risk level from an entire PLC perspective (i.e., TRL, and $TRPL$). Subsequently, based on the PRA results obtained, appropriate sets of project risk treatment actions are formulated given different treatment scenarios that can reflect the corresponding risk attitude and appetite of a group of project decision-makers. In addition, the performances of different project risk treatment options can also be examined through the proposed model to help project decision-makers determine a more effective solution to be implemented in practice.

Table 1
Comparison of the proposed PRA approach with existing techniques.

Reference	Techniques for PRA	Type of techniques employed		Risk interdependency modeling		Risk loops	Risk occurrence probability	Risk impact on project objectives	Risk propagation effects	Risk stochastic behavior	Dynamic changes of risks & risk interdependencies	Project life cycle	Risk attitude & appetite
		Analytical	Simulation	Single-link tree	Network								
Carbone and Tippett (2004)	Failure mode and effects analysis (FMEA), risk matrix	✓	–	–	–	–	✓	✓	–	–	–	–	–
Dikmen et al. (2007)	Influence diagrams, fuzzy logic	✓	–	✓	–	–	–	–	–	–	–	–	–
Zeng et al. (2007)	Analytic hierarchy process (AHP), fuzzy reasoning, factor index	✓	–	–	–	–	✓	✓	–	–	–	–	–
Nasirzadeh et al. (2008)	System dynamics (SD), fuzzy logic	✓	✓	–	✓	✓	–	✓	✓	–	✓	✓	–
Iyer and Sagheer (2010)	Interpretive structural modeling (ISM), MICMAC analysis	✓	–	–	✓	–	–	–	✓	–	–	✓	–
Sadeghi et al. (2010)	Monte Carlo simulation (MCS), fuzzy logic	✓	✓	–	–	–	–	–	–	✓	–	–	–
Holzmann and Spiegler (2011)	Risk breakdown structure (RBS)	✓	–	✓	–	–	–	–	–	–	–	✓	–
Fang and Marle (2012)	Design structure matrix (DSM), AHP, ARENA software	✓	✓	–	✓	✓	✓	✓	✓	✓	–	–	–
Khanzadi et al. (2012)	SD, fuzzy logic	✓	✓	–	✓	✓	–	✓	✓	–	✓	✓	–
Hu et al. (2013)	Bayesian belief network (BBN)	✓	–	–	✓	–	✓	–	✓	–	–	–	–
Marle et al. (2013)	DSM, clustering, linear programming	✓	–	–	✓	✓	–	–	✓	–	–	–	–
Zeng and Skibniewski (2013)	Fault tree analysis (FTA)	✓	–	✓	–	–	✓	–	–	–	–	–	–
Chien et al. (2014)	Decision making trial and evaluation laboratory (DEMATEL)	✓	–	–	✓	–	–	–	✓	–	–	–	–
Yang and Zou (2014)	Social network analysis (SNA)	✓	–	–	✓	✓	–	–	✓	–	–	–	–
Yildiz et al. (2014)	Structural equation modeling (SEM)	✓	–	–	✓	–	–	–	✓	–	–	–	–
Taillandier et al. (2015)	Multi-agent simulation, MCS	✓	✓	–	–	–	✓	✓	✓	✓	–	✓	–
Wu et al. (2015)	ISM, BBN	✓	–	–	✓	–	✓	–	✓	–	–	–	–
Hwang et al. (2016)	DEMATEL	✓	–	–	✓	✓	–	–	✓	–	✓	✓	–
Liu et al. (2016)	SEM, risk criticality index	✓	–	–	✓	–	✓	✓	✓	–	–	–	–
Qin et al. (2016)	Statistical analysis, risk importance index	✓	–	–	–	–	✓	✓	–	–	–	✓	–

(*continued on next page*)

Table 1 (*continued*).

Fang et al. (2017)	DSM, importance measures	✓	–	–	✓	✓	✓	✓	✓	–	–	–	–
Tavakolan and Etemadinia (2017)	ISM, fuzzy logic, MICMAC analysis	✓	–	–	✓	✓	–	–	✓	–	–	–	–
Wang and Yuan (2017)	SD, risk importance index	✓	✓	–	✓	✓	✓	✓	✓	–	✓	–	–
Zhang et al. (2017)	MCS, fuzzy matter-element theory	✓	✓	–	–	–	✓	–	–	✓	–	–	–
Li et al. (2018)	SD, discrete event simulation	–	✓	–	✓	✓	✓	✓	✓	–	✓	–	–
Luo et al. (2018)	Cause and effect (Ishikawa) diagrams, FTA, risk matrix	✓	–	✓	–	–	✓	✓	–	–	–	–	–
Yuan et al. (2018)	SNA	✓	–	–	✓	✓	–	–	✓	–	–	–	–
Ahmadabadi and Heravi (2019)	SEM, DSM	✓	–	–	✓	–	–	–	✓	–	–	–	–
Gao et al. (2019)	MCS, project evaluation and review techniques	✓	✓	✓	–	–	✓	✓	✓	✓	✓	–	–
Wang et al. (2019)	DSM, MCS, SNA	✓	✓	–	✓	–	✓	✓	✓	✓	✓	–	–
Wu et al. (2019)	DEMATEL, triangular intuitionistic fuzzy number	✓	–	–	✓	✓	✓	✓	✓	–	–	✓	–
Guan, Abbasi et al. (2020)	ISM, MICMAC analysis	✓	–	–	✓	–	–	✓	✓	–	–	✓	–
Guan, Liu et al. (2020)	BBN, FTA, fuzzy set theory, risk matrix	✓	–	–	✓	–	✓	✓	✓	–	–	✓	–
Wang et al. (2020)	DSM, MCS, SNA	✓	✓	–	✓	–	✓	✓	✓	✓	✓	–	–
Zhang et al. (2020)	SNA	✓	–	–	✓	✓	–	–	✓	–	–	–	–
Akhavan et al. (2021)	BBN	✓	–	–	✓	–	✓	–	✓	–	–	–	–
Etemadinia and Tavakolan (2021)	ISM, SD	✓	✓	–	✓	✓	–	✓	✓	–	✓	–	✓
Guan et al. (2021)	ISM, MCS	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	–	–
Qazi and Dikmen (2021)	BBN, risk matrix	✓	–	–	✓	–	✓	✓	✓	–	–	–	✓
Qazi and Simsekler (2021)	MCS, risk matrix	✓	✓	–	–	–	✓	✓	–	✓	–	–	✓
Qazi et al. (2021)	MCS, risk matrix	✓	✓	–	–	–	✓	✓	–	✓	–	–	✓
Erol et al. (2022)	Analytic network process	✓	–	–	✓	–	–	–	✓	–	–	–	–
Chen et al. (2023)	BBN, MCS	✓	✓	–	✓	–	✓	✓	✓	✓	–	–	–
der Landwehr et al. (2023)	Fuzzy cognitive mapping	–	✓	–	✓	✓	–	✓	✓	–	–	–	–
Bai et al. (2024)	SD, Vensim software	✓	✓	–	✓	–	✓	✓	✓	–	✓	–	–
Liu et al. (2024)	RBS, adaptive simulation	✓	✓	–	✓	–	✓	✓	✓	✓	–	✓	✓
Zhang et al. (2024)	FMEA, multi-criteria group decision-making, regret theory	✓	–	–	–	–	✓	✓	–	–	–	–	✓
Number of previous studies	/	45	19	5	33	16	28	28	35	11	11	11	6
Current study	ISM, MCS	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	✓	✓

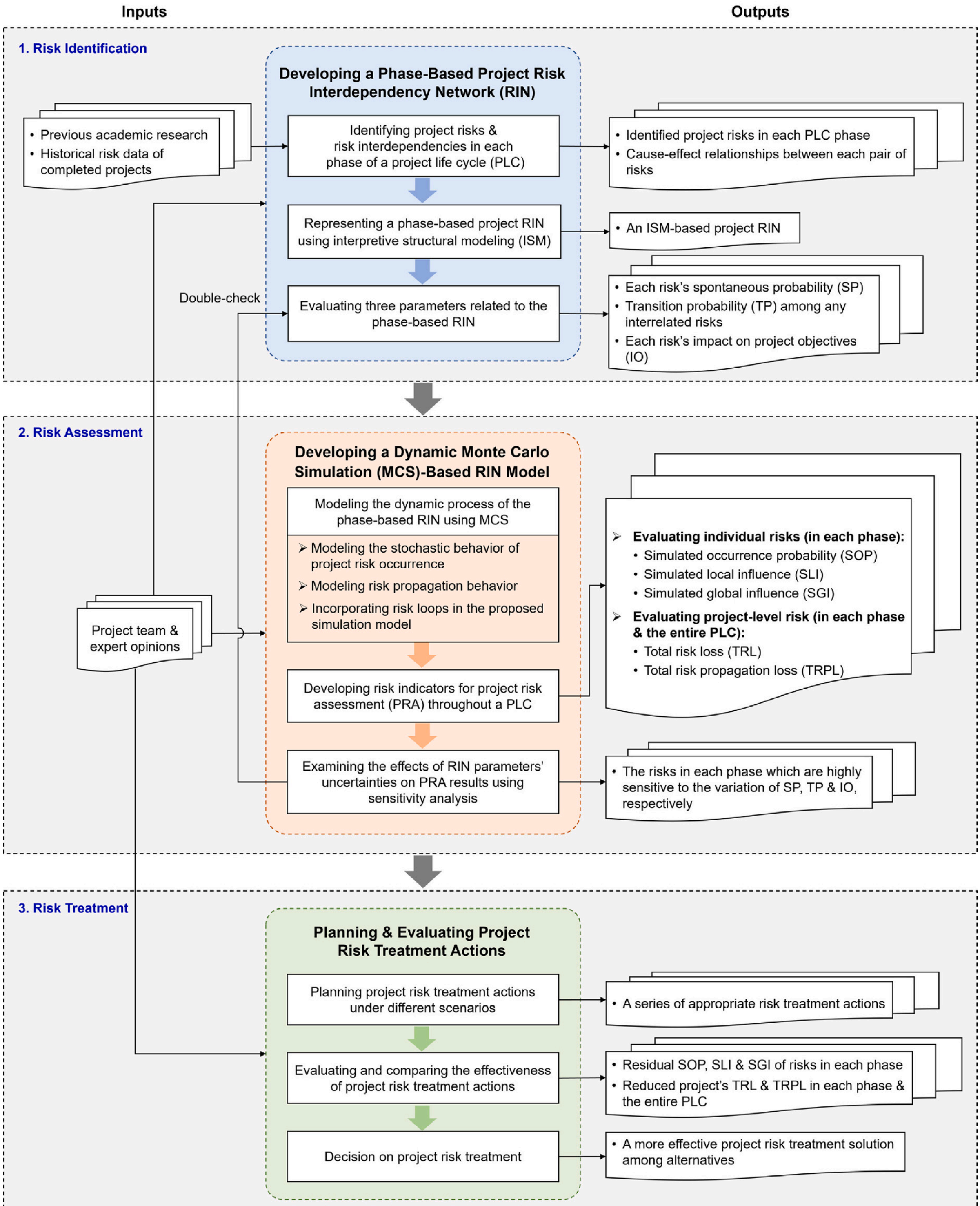

Fig. 1. The overall framework of the proposed methodology for PRA and risk treatment throughout a PLC.

2.1. Developing a phase-based project RIN

At the first stage of the framework in Fig. 1, a phase-based project RIN is developed using the ISM method, through which the identified project risks in each phase of a PLC and possible cause–effect interdependencies among the risks are presented systematically. The phase-based project RIN is further used in the following stages (i.e., risk assessment and risk treatment in Fig. 1) for analyzing and dealing with dynamic project risks in an entire PLC.

2.1.1. Identifying project risks and their interdependencies in each phase of a PLC

The project risks that may occur in each phase of a PLC can be identified by referring to existing related academic studies, utilizing historical risk data from similar completed projects, and collecting professional opinions from project team members and domain experts (based on their knowledge, practical experience, and risk preferences). Note that one risk may occur in several project phases, so the same risks could be identified in different phases of a PLC. The direct cause–effect interdependencies between any pair of identified project risks, that is, the possible precedence relationships with the type of "leading to" or "influencing", can be determined using Delphi-based approaches. As the risks occurring in previous phases of a PLC can give rise to the occurrence of their interdependent risks in the following project phase(s), particular direct risk interdependencies that span several project phases during a PLC should also be identified.

2.1.2. Representing a phase-based project RIN using the ISM method

The identified project risks and associated direct risk interdependencies are essential elements of a project RIN, represented by nodes and directed links in a network, respectively. In the study, we adopt the ISM process to systematically develop a hierarchical phase-based project RIN. The ISM method (Warfield, 1974) is very effective in transforming unclear and poorly articulated mental models of a system into well-defined analytical models in which all possible pairwise relations and the hierarchy of the system elements are considered. In the context of representing project risks and their interdependencies, the ISM method has the advantages of highly reducing the number of required interrelationship queries among project risks through transitive inference and being able to involve possible risk loops caused by complex risk interdependencies (Guan, Abbasi et al., 2020; Guan et al., 2021; Tavakolan & Etemadinia, 2017). The main steps of the ISM process (Guan, Abbasi et al., 2020; Guan et al., 2021; Kwak et al., 2018; Wu et al., 2015) for constructing a hierarchical phase-based project RIN are described in detail as follows.

First, a binary and square structural self-interaction matrix (SSIM), represented by $A = (a_{ij})_{n \times n}$, is constructed, involving identified project risks and direct risk interdependencies. If risk R_i is prone to affect risk R_j directly, the entry $a_{ij} = 1$; otherwise, the entry $a_{ij} = 0$. Then, by applying the rationale shown in Eq. (1), the SSIM is transformed into a final reachability matrix (RM) in which indirect interdependencies between R_i and R_j are also obtained. As a result, the risk cascading propagation (or risk causal path) from R_i to R_j via intermediate risks can be identified.

$$(A + I_n)^{K-1} \neq (A + I_n)^K = (A + I_n)^{K+1} = RM, \quad K = 2, 3, 4, \dots \tag{1}$$

where n denotes the total number of identified project risks throughout a PLC; I_n is an identity matrix, expressed as $I_n = diag(1, 1, \dots, 1)$; $(A + I_n)^K$ represents an intermediate reachability matrix with K intermediates; and RM is the final reachability matrix obtained.

Further, based on the final RM, each risk's reachability set (RS), antecedent set (AS), and intersection set (IS, i.e., the overlap of RS and AS) can be obtained using Eqs. (2)–(4), respectively. Next, according to Eq. (5), all the identified project risks are partitioned into associated hierarchical levels. If a risk's RS is the same as its IS, the risk will be selected to occupy the first top-level of a hierarchy structure.

$$RS(R_i) = \{R_j \mid m_{ij} = 1\}, \quad i = 1, 2, \dots, n;\ j = 1, 2, \dots, n \tag{2}$$

$$AS(R_i) = \{R_j \mid m_{ji} = 1\} \tag{3}$$

$$IS(R_i) = \{RS(R_i) \cap AS(R_i)\} \tag{4}$$

$$LS_l = \{R_i \mid IS(R_i) = RS(R_i)\}, \quad l = 1, 2, \dots, L \tag{5}$$

where m_{ij} and m_{ji} denote the value (0 or 1) of (i, j) and (j, i) entries in the RM, respectively; $RS(R_i)$, $AS(R_i)$, and $IS(R_i)$ represent the reachability set, antecedent set, and intersection set of the risk R_i, respectively; l is the numerical order of partitioned levels (the smaller the l, the higher the level of a risk in the hierarchy); L is the total number of partitioned levels; and LS_l denotes a set of risks located in the lth level of the hierarchy.

After removing the risks that have already been determined, the next top-level risks are subsequently identified in the same way, and this step will continue until all the identified risks are assigned to respective hierarchical levels. Note that due to risk propagation effects, the risks located at higher levels of a hierarchy are likely to be more affected by their interdependent risks.

The final step is generating a directed graph to illustrate the hierarchical phase-based project RIN, where conceptual inconsistencies should also be double-checked. The nodes positioned in different hierarchical levels and different project phases represent the identified project risks during a PLC, while the directed link between a pair of nodes indicates the direct cause–effect risk interdependency they have within the same project phase or across different phases. It should be noted that a risk loop can only occur in the same project phase instead of across several phases. Additionally, all the associated risks in a risk loop are located in the same hierarchical level of the ISM-based project RIN. Therefore, the proposed hierarchical phase-based project RIN contributes to an efficient identification of possible risk loops among plenty of complex risk interdependencies.

2.1.3. Evaluating three parameters related to the phase-based project RIN

From the perspective of a phase-based project RIN, the occurrence probability of a risk incorporates two aspects: the spontaneous probability (SP) of a risk and the transition probability (TP) associated with direct interrelated risks. Three RIN-related parameters – each risk's SP, the TP between interdependent risks, and each risk's impact on project objectives (IO) – are essential inputs of the developed dynamic MCS-based RIN model for PRA (see Section 2.2). The values of the three parameters can be estimated by project team members and experts. The probability values in terms of SP and TP are in the interval $(0, 1)$, and the values of IO are on a quantitative scale either in the interval $(0, 1)$ or using the loss of money.

2.2. Developing a dynamic MCS-based RIN model

By integrating the hierarchical phase-based project RIN into the Monte Carlo simulation (MCS) method, a dynamic MCS-based RIN model that supports the PRA throughout a PLC is developed at the second stage of the proposed framework (see Fig. 1), aiming to achieve the first and second research objectives of this work (previously mentioned in Section 1). The originalities of the proposed dynamic PRA model are as follows: (i) the stochastic behavior of risk occurrence and risk propagation behavior are modeled by generating various scenarios related to the dynamic changes of a phase-based project RIN throughout a PLC; (ii) the loop phenomenon within a project RIN is analyzed by a proposed five-step "hypothesis–test" process in the model; (iii) a series of RIN-driven risk indicators are devised to prioritize project individual risks and evaluate the project risk level regarding each project phase as well as the overall project risk level from an entire PLC; and (iv) by incorporating a sensitivity analysis, the effects of uncertainties in the estimated values of RIN parameters on PRA results are further examined, helping project decision-makers properly adjust the PRA model's input values (i.e., SP, TP, and IO) for improving the model's robustness in practice.

2.2.1. Modeling the dynamic process of the phase-based RIN using MCS

A new MCS method is explored in this study in order to model the dynamics of a phase-based project RIN throughout a PLC. As such, in the proposed dynamic MCS-based RIN model, the stochastic behavior of risk occurrence and risk propagation behavior are both captured in numerous possible RIN scenarios generated. In several previous studies on RIN simulation models (Liu et al., 2024; Wang et al., 2019, 2020), project risks were assumed to occur more than once during one simulation run in risk occurrence modeling, and the risk frequency (can be more than 1) was used to represent the average occurrence of project risks. In this work, however, we adopt a probability perspective when modeling the occurrence of project risks, and risk occurrence probability (between 0 and 1) is used to represent the expected occurrence rate of project risks. Thus, in our proposed simulation model, we assume that the status of risk occurrence (occurred or not) for each risk in a project RIN is determined once in every single simulation run.

Recall that in the context of risk interdependencies, whether a risk R_i occurs or not depends on its random factors out of the project RIN and its interdependent risks leading to it within the RIN. The SP of R_i represents the occurrence probability of R_i activated by its random factors, while the TP from a realized risk to R_i represents the occurrence probability of R_i triggered by the realized risk within the RIN. Therefore, in the proposed simulation process, to determine whether a risk occurs or not in a project phase, a dynamic threshold, i.e., the calculated occurrence probability (COP) of a risk is designed. According to the probability theory, a risk's COP in a specific phase is calculated based on the risk's SP and the related TP from its directly interdependent upstream risks which are realized, as shown in Eq. (6). Note that in each simulation run, a risk's COP varies with the dynamic changes of a project RIN.

$$COP_{i,t}^{p} = 1 - \left[(1 - SP_i^p) \times \prod_{k=1}^{m} (1 - TP_k^{i,p})\right], \quad m = 0, 1, 2, \ldots ; p = 1, 2, 3, \ldots \tag{6}$$

where $COP_{i,t}^{p}$ represents the calculated occurrence probability of R_i in the pth project phase for the tth simulation run; SP_i^p denotes the spontaneous probability of R_i in the pth project phase; m is the number of the risks that have occurred and directly affect R_i in the pth project phase for the tth simulation run; and $TP_k^{i,p}$ is the transition probability associated with the kth link leading to R_i in the pth project phase for the tth simulation run.

By using the tailored Monte Carlo method, presented in Eq. (7), the stochastic behavior of risk occurrence in a PLC is modeled. That is, if a random number (RN) generated (in the interval $(0, 1)$) concerning R_i (in a specific project phase of a PLC) is no more than R_i's COP in one simulation run, then R_i occurs, otherwise, R_i does not occur. Moreover, to determine the occurrence status of all the risks of a phase-based project RIN in one simulation run, the occurrence status of an interdependent risk in a specific phase also depends on whether its interrelated risks (directly or indirectly) on risk propagation paths have previously realized or not (based on their corresponding COPs obtained). Therefore, the propagation behavior regarding interdependent risks within an RIN is also captured when modeling the occurrence of project risks. Accordingly, in the following Section 2.2.2, the proposed RIN-driven risk indicators for evaluating project individual risks and the project-level risk take into account the risk propagation effects within a phase-based project RIN.

$$mc_{i,t}^{p} = \begin{cases} 1, & RN_{i,t}^{p} \le COP_{i,t}^{p} \\ 0, & RN_{i,t}^{p} > COP_{i,t}^{p} \end{cases} \tag{7}$$

where $mc_{i,t}^{p}$ means whether R_i occurs (i.e., $mc_{i,t}^{p} = 1$) or not (i.e., $mc_{i,t}^{p} = 0$) in the pth phase for the tth simulation run; and $RN_{i,t}^{p}$ is the random number generated regarding R_i in the pth phase for the tth simulation run.

As risk loops may emerge in a phase-based project RIN, we design a "hypothesis–test" process and incorporate it into the proposed dynamic MCS-based RIN model to address such complexity in the risk propagation via risk interdependencies. This approach contributes to minimizing the number of risks to be hypothesized in a project RIN involving multiple risk loops. By modeling the risk loop phenomenon, more accurate PRA results can be obtained from the simulation model. For each simulation run of the dynamic PRA model, the five main steps of the "hypothesis–test" process are implemented as follows:

Step 1. Making a hypothesis on the occurrence status (will occur or not) of one or more risks directly affecting R_i within a loop;

Step 2. Calculating the COP of R_i in the pth phase (i.e., COP_i^p) using Eq. (6) and then determining whether R_i occurs or not based on Eq. (7);

Step 3. Proceeding with calculating COP values of other risks in the phase-based RIN and further determining their occurrence status; however, if there is another risk loop, repeating Steps 1–3 until a simulation run is completed;

Step 4. Testing whether the inferred occurrence status of the risks (those are made assumptions in Step 1) is the same as the null hypothesis or not;

Step 5. Retaining the simulation runs with consistent results (i.e., the occurrence status of hypothetical risks obtained from a simulation run are in line with the null hypotheses) and removing the invalid runs (i.e., the occurrence status of hypothetical risks obtained from a simulation run are inconsistent with the null hypotheses).

The pseudocode of the tailored MCS algorithm for modeling the dynamic process of a phase-based project RIN throughout an entire PLC is presented in Fig. A.1 (see Appendix A). The proposed new algorithm can model the dynamic changes of a phase-based project RIN during a PLC either with or without risk loops while considering the stochastic behavior of risk occurrence and risk propagation behavior. The numerous RIN scenarios obtained from the dynamic MCS-based model will be used for PRA in the next part.

2.2.2. Developing risk indicators for PRA throughout a PLC

In this section, we develop a series of RIN-driven risk indicators to quantitatively evaluate project individual risks in each project phase and the project-level risk either in each project phase or in an entire PLC, particularly dedicated to achieving the second research objective of this paper. Considering numerous risk scenarios generated from the proposed dynamic simulation process of a phase-based project RIN, the simulated occurrence probability (SOP) of a risk in a specific project phase can be calculated according to Eq. (8). In our study, the SOP of risk R_i indicates the expected occurrence probability of R_i in the pth phase, which considers all the causal influences from its interdependent risks (occurred either in the pth phase or in the previous phases) within the phase-based project RIN. It is worth noting that the difference between the SOP of R_i and its SP denotes the propagation effects of upstream interdependent risks on R_i in the form of occurrence probability.

$$SOP_i^p = \frac{n(R_i)^p}{N} \tag{8}$$

where SOP_i^p represents the simulated occurrence probability of R_i in the pth phase; N is the number of valid simulation runs; and $n(R_i^p)$ is the number of times that R_i has occurred in the pth phase for all valid simulation runs.

An appropriate criterion, adapted from Fang and Marle (2012), is set to terminate the dynamic RIN simulation process, as described in Eq. (9). When the sum of the squared difference of SOP for all the project risks (in an entire PLC) between designed adjacent iteration groups is less than a threshold h, the simulation process will be terminated. In this paper, to save computing time, the value of h is determined according to a convergence diagram after running a sufficient number of simulations. Subsequently, an appropriate number of simulation runs in the experiment is obtained to evaluate project risks.

$$\sum_{i=1}^{n} \sum_{p=1}^{q} (\Delta SOP_i^p)^2 < h \tag{9}$$

where n represents the number of all identified risks of a project (if a risk occurs in several phases of a PLC, then the risk is only counted once); q is the total number of project phases of a PLC; and ΔSOP_i^p denotes the difference of the simulated occurrence probabilities of R_i (in the pth phase) between designed adjacent iteration groups of a simulation process.

By combining a risk's SOP with its IO (i.e., risk impact on project objectives), another six indicators are devised to quantitatively evaluate the risk influences from a local (i.e., SLI_i^p, TRL^p, and TRL) and a global (i.e., SGI_i^p, $TRPL^p$, and $TRPL$) phase-based project RIN viewpoints, which are described in detail as follows.

At the local level of a phase-based project RIN, the simulated local influence (SLI) regarding R_i in the pth phase is quantified by multiplying its SOP_i^p and IO_i^p, as expressed in Eq. (10). Accordingly, using Eq. (11), we can further evaluate the project total risk loss resulting from the risks that have occurred in the pth phase, represented as TRL^p. Consequently, the project total risk loss from an entire PLC perspective (i.e., TRL) is calculated by summing up the project total risk loss corresponding to each project phase of a PLC, as shown in Eq. (12).

$$SLI_i^p = SOP_i^p \times IO_i^p \tag{10}$$

$$TRL^p = \sum_{i=1}^{n} SLI_i^p \tag{11}$$

$$TRL = \sum_{p=1}^{q} TRL^p \tag{12}$$

At the global level of a project RIN, the simulated global influence (SGI) regarding R_i that is produced in the pth phase is calculated by Eq. (13), indicating the resultant influence on R_i's interdependent risks due to the occurrence of R_i, that is, the propagation effects of R_i in the form of risk influence. Then, the indicator $TRPL^p$, the project total propagation risk loss resulting from the risks occurred in the pth phase, is calculated according to Eq. (14). Further, based on Eq. (15), the indicator $TRPL$ that represents the project total risk propagation loss in an entire PLC is obtained by summing up the project total propagation risk loss corresponding to each project phase of a PLC.

$$SGI_i^p = \sum SLI_j^{i,p} - \sum SLI_j^{i,p\prime} \tag{13}$$

where $\sum SLI_j^{i,p}$ is the sum of SLI of all the risks R_j that can be directly or indirectly affected by R_i (in the pth phase) within a phase-based RIN, including the influences from R_i, other upstream interdependent risks inside the RIN, and related factors outside the RIN; and $\sum SLI_j^{i,p\prime}$ represents, when R_i does not occur in the pth phase, the sum of SLI associated with all the risks R_j that can be directly or indirectly affected by R_i within the RIN, considering only the influences from other upstream interdependent risks inside the RIN and related factors outside the RIN.

$$TRPL^p = \sum_{i=1}^{n} SGI_i^p \tag{14}$$

$$TRPL = \sum_{p=1}^{q} TRPL^p \tag{15}$$

The three proposed risk indicators for evaluating project individual risks, i.e., SOP_i^p, SLI_i^p, and SGI_i^p are very useful for prioritizing project risks throughout a PLC considering risk propagation effects, so project decision-makers can formulate more appropriate risk treatment actions to mitigate critical risks in corresponding PLC phases. Looking at the proposed project-level risk indicators, TRL^p and $TRPL^p$ equip decision-makers with a deeper understanding of the expected inducible risk influences with respect to each PLC phase, and TRL and $TRPL$ provide a reliable way to quantitatively evaluate the overall project risk level from local and global project RIN aspects, respectively.

2.2.3. Examining the effects of phase-based RIN parameters' uncertainties on PRA results using sensitivity analysis

For the proposed dynamic MCS-based RIN model, as the model input values concerning the phase-based RIN parameters (i.e., SP, TP, and IO) are often collected from empirical judgments, they may involve uncertainties in nature. To improve the robustness of the PRA model in practice, a sensitivity analysis is incorporated into the PRA model to examine the effects of input value variations (regarding each risk's SP and IO as well as the TP between interdependent risks) on the PRA results. Therefore, the sensitivity of each risk's SLI or SGI in a specific project phase to the value variations of the three RIN parameters is estimated, respectively. Correspondingly, the risks in each project phase that are highly sensitive to the variation of SP, TP, and IO can be identified, respectively, meaning that more attention should be paid to these risks when re-evaluating the RIN parameters. Moreover, the sensitivity of the proposed PRA model can also be evaluated by investigating to what extent a project's TRL or TRPL in an entire PLC will change with the value variations of the model inputs.

2.3. Planning and evaluating project risk treatment actions

After obtaining the PRA results of a project from the dynamic simulation model, at the third stage of the proposed framework (see Fig. 1), effective and efficient project risk treatment actions during a PLC can be formulated proactively under different treatment scenarios. The dynamic MCS-based RIN model (as presented in the second stage of the proposed framework in Fig. 1), apart from supporting the PRA throughout a PLC, also plays a key role in facilitating evaluating the performances of alternative project risk treatment actions and then determining a more effective risk treatment solution to be implemented. This section aims to achieve the third research objective of this paper.

2.3.1. Planning project risk treatment actions under different scenarios

In this work, different from the traditional project risk treatment practice that only focuses on mitigating project individual risks, alleviating critical risk interdependencies is also investigated to reduce risk propagation effects throughout an entire PLC. Based on risk prioritization results in terms of SOP_i^p, SLI_i^p, and SGI_i^p, the risk treatment actions related to reducing a risk's SP, reducing the TP between interdependent risks, and weakening a risk's IO can be planned. Note that mitigating the IO of project risks during a project risk treatment implementation is not the major concern in this paper. The proposed key principles of formulating appropriate project risk treatment actions are listed below: (i) the risks having similar SOP and SP but both at a high level indicate that they are mainly affected by random factors outside the RIN, so their SP should be reduced; (ii) the risks with high SOP but low SP are more likely affected by their interdependent risks and thus, more attention should be paid to weaken the direct risk interdependencies leading to these risks by reducing associated TP; (iii) the risks with high SLI and SOP can be mitigated through (i) or (ii); and (iv) considering that the risks with high SGI are prone to cause a wide range of risk propagation in the RIN, the TP associated with their output links can be reduced to weaken risk propagation effects, while in the case of such risks having numerous output links, their SOP can be minimized by reducing their SP or the TP of their input links, thereby mitigating risk propagation effects.

Project risk treatment actions under different treatment scenarios can also be planned on the basis of PRA results in order to reflect different risk attitudes and appetites of project decision-makers. In this study, the risk prioritization results for a project are mainly used to design multiple risk treatment scenarios by determining what kind of risks and/or risk interdependencies are deemed critical. For instance, one risk treatment scenario could be that the project risks ranked top 20% in terms of SOP, SLI, and SGI are all targeted in the project risk treatment process in line with the aforementioned risk treatment principles. As such, a series of project risk treatment actions under different treatment scenarios can be formulated for further evaluation.

2.3.2. Evaluating and comparing the effectiveness of project risk treatment actions

By updating the proposed PRA model's input values associated with SP and TP, the performances of different risk treatment actions can be examined based on the risk re-evaluation of a project. The performance of a planned risk treatment action is evaluated by comparing the updated values regarding the proposed risk indicators to their original values before implementing the risk treatment action. Specifically, in terms of project individual risks in their specific phases, the lower the residual values of SOP_i^p, SLI_i^p, and SGI_i^p obtained, the higher the effectiveness of a risk treatment action. From the perspective of the project risk level in each phase, the higher the reduced values of a project's TRL^p and $TRPL^p$, the better the performance of a risk treatment action. Moreover, looking at the overall project risk level in an entire PLC, the higher the reduced values of a project's TRL and $TRPL$, the more effective the risk treatment action.

2.3.3. Decision on project risk treatment

Based on the performances of appropriate project risk treatment actions obtained from the previous step, decision-makers can select a more effective risk treatment solution among alternatives aligning with their agreed risk attitude and appetite. The first selection criterion is that the project risk treatment action can minimize a project's TRL and $TRPL$, respectively, compared with other planned treatment alternatives. However, for other cases, several other selection criteria could be further considered by project decision-makers according to their preferences and practice, including the reduced value of project's TRL^p or $TRPL^p$ for each phase, and the residual SOP_i^p, SLI_i^p, or SGI_i^p for some particular risks in specific phases.

3. Application and results

In this section, a case study is provided to demonstrate the application of the proposed intelligent model for PRA and risk treatment throughout a PLC. A sample industrial project, originally from the study of Wang et al. (2020), is used in the current work after introducing the specific project phases of a PLC and the required risk data (i.e., SP and IO of risks considering PLC phases, and TP associated with risk interdependencies during a PLC). The industrial project aims to develop an artificial intelligence-based model for predicting medical items which will be integrated into a hospital logistics system. The analysis results obtained from our proposed dynamic MCS-based RIN model are further compared with those from the classical P–I risk model, which verifies the feasibility and robustness of the proposed model in enhancing the decision-making of PRA and subsequent risk treatment. The simulation process was implemented in MATLAB R2017b on a Windows 10 PC with Intel® Core™ i7–6700 CPU at 3.40 GHz and 16.0 GB of RAM.

3.1. Developing a phase-based project RIN

The original project risk-related data, including the estimated SP and IO (represented by the loss of money) of 16 identified risks, and the estimated TP regarding 26 identified direct risk interdependencies were collected by a primary project member who was in charge of the project risk management process. In this paper, the entire PLC of the sample project was divided into three project phases: project planning (P1), model design (P2), and model validation and verification (P3). Then, the project risks for each PLC phase were identified, and the associated SP and IO corresponding to their specific project phases (i.e., SP_i^p and IO_i^p of R_i in the pth phase) were further estimated according to original risk datasets of the project, as shown in Table 2. For this project case, some risks reoccur in several project phases but with different values of SP and IO, including R01–R04, R13, and R16.

Subsequently, the direct interdependencies between any pair of risks in an entire PLC were all updated based on the initial ones and assigned with appropriate TP values. For example, if R06 occurs in P1, it can trigger R05 to occur in P2 with the probability of 0.9 (i.e., the associated TP) and thus, there is a cause–effect interdependency between R06(P1) and R05(P2). In Fig. 2, a total number of 32 direct risk interdependencies and their associated TP during the three-phase PLC of the sample project are presented.

By employing the ISM process, a hierarchical three-phase-based RIN of the sample project (see Fig. 2) was established to present the identified project risks and their direct and indirect cause–effect interdependencies throughout a PLC. Firstly, a binary and square SSIM was developed to illustrate the direct risk interdependencies between the project risks in P1, P2, and P3, and Fig. B.1 (in Appendix B) presents the results. Secondly, by using Eq. (1), the SSIM was transformed into a final RM, as shown in Fig. B.2 (in Appendix B). Thirdly, based on the RM, the reachability, antecedent, and intersection sets of each identified risk in the three phases were obtained according to Eqs. (2)–(4), respectively. Further, by using Eq. (5), we partitioned all the identified risks of the sample project throughout its PLC into ten hierarchical levels from L1 (the top level) to L10 (the last level). As an example, Table B.1 (in Appendix B) shows the reachability, antecedent, and intersection sets of ten risks (with specific project phases) from each hierarchical level. Finally, as presented in Fig. 2, the ISM-based project RIN with a three-phase PLC was developed, in which nodes represent project risks in specific project phases, and the directed links (within a project phase or across different phases) between a pair of nodes denote the direct cause–effect interdependencies therein.

Due to the risk propagation behavior, the risks located in higher positions of the hierarchy in Fig. 2 (e.g., R03(P2) and R01(P3)) can either be highly influenced by their interdependent risks or lead to the occurrence of downstream risks located in even higher levels. The source risks in the project RIN include R01(P1), R13(P1), R01(P2), and R01(P3) which are not affected by any other risks; on the contrary, R04(P1), R03(P2), and R02(P3), located in the top level of the RIN, are the accumulation risks that cannot trigger the occurrence of any other risks. In addition, based on the hierarchical phase-based project RIN, it becomes easier to identify the risk loops involved: two main risk loops all exist in P2, and the involved risks are all located at L5. One risk loop is "R02(P2) → R04(P2) → R05(P2) → R08(P2) → R16(P2) → R13(P2) → R02(P2)", and the other is "R02(P2) → R09(P2) → R08(P2) → R16(P2) → R13(P2) → R02(P2)". Therefore, the risk loop phenomenon appearing in the project RIN was then modeled using the designed five-step "hypothesis–test" process (see Section 2.2.1) in the proposed dynamic MCS-based RIN model, and associated risk propagation effects were also included in the PRA results (Section 3.2).

3.2. PRA results

3.2.1. Assessment results of project individual risks in each phase

During the simulation process of the proposed PRA model, the function $rand(0,1)$ was set to automatically generate RNs following the uniform probability distribution in the interval $(0,1)$. Using Eq. (6), the COP of each risk in a project phase was calculated from one simulation run. A risk's occurrence status (occurred or not) in a project phase was thus determined by comparing the RN generated with its COP based on Eq. (7). In the simulation process, the number of simulation runs was set from 1000 in the first iteration group and then increased by 1000 in subsequent iteration groups until reached 300,000 in the 300th iteration group. Fig. 3 presents the convergence diagram of the simulation process for PRA, which is also used to determine the appropriate number of simulation runs. As shown in Fig. 3, the sum of the squared differences of SOP for all project risks (throughout the PLC) between adjacent iteration groups tends to converge around 10^{-4} in this simulation process. As a result, the threshold h (in Eq. (9)) was assigned 10^{-4}. To obtain more stable results and take into account the run-time efficiency, the simulation process was terminated after 300,000 simulation runs, out of which 144,986 runs were deemed valid for assessing project risks.

Table 2
Project risks and estimated values regarding spontaneous probability (SP) and impact on project objectives (IO) in a three-phase life cycle of the sample project.

Risk no.	Risk description	PLC phase	SP_i^p	IO_i^p ($100)
R01	Language problems and cultural conflicts	P1	0.6	0.8
		P2	0.8	0.9
		P3	0.4	1.0
R02	Communication problems between teams	P1	0.3	1.8
		P2	0.4	1.9
		P3	0.2	2.0
R03	Unclear milestone and technical route	P1	0.7	2.3
		P2	0.6	2.5
R04	Lack of professional medical knowledge	P1	0.6	0.9
		P2	0.5	1.0
R05	Poor analysis of the factors regarding medical items	P2	0.3	0.5
R06	Poor selection of medical items	P1	0.4	1.8
R07	Poor selection of existing database	P1	0.4	1.0
R08	Building and training the model repeatedly	P2	0.3	3.0
R09	Interface problem among the software platforms of different terms	P2	0.6	2.0
R10	Poor quality of the data from hospital and logistics company	P2	0.2	1.4
R11	Poor effectiveness and efficiency of the model developed	P3	0.2	4.0
R12	Too much investigation involved	P3	0.1	2.0
R13	Tense partnerships among teams	P1	0.3	1.3
		P2	0.4	1.4
		P3	0.2	1.5
R14	Too many tests on the model	P3	0.2	2.0
R15	Project scope creep	P2	0.4	1.6
R16	Too much rework for the team in charge of modeling	P2	0.4	2.8
		P3	0.3	3.0

Note: PLC phase: Project planning (P1); Model design (P2); and Model validation and verification (P3).

Table 3
Risk prioritization of the sample project in a PLC using different indicators.

Ranking	From our proposed dynamic MCS-based RIN model									From the classical P–I risk model				
	SOP_i^p			SLI_i^p ($100)			SGI_i^p ($100)			SP_i^p		RC_i^p ($100)		
	Risk	Value	(%)	Risk	Value	(%)	Risk	Value	(%)	Risk	Value	Risk	Value	(%)
1	R14(P3)	0.889	7.10	R11(P3)	3.014	14.06	R03(P1)	18.163	8.48	R01(P2)	0.8	R03(P1)	1.61	11.53
2	R05(P2)	0.839	13.58	R08(P2)	2.323	24.41	R05(P2)	18.079	16.93	R03(P1)	0.7	R03(P2)	1.50	22.20
3	R01(P2)	0.798	19.58	R16(P2)	2.121	33.69	R07(P1)	17.369	25.04	R03(P2)	0.6	R09(P2)	1.20	30.49
4	R07(P1)	0.796	25.57	R14(P3)	1.778	41.13	R01(P2)	17.017	32.99	R09(P2)	0.6	R16(P2)	1.12	38.15
5	R13(P3)	0.794	31.51	R03(P1)	1.761	48.48	R01(P1)	16.035	40.47	R04(P1)	0.6	R08(P2)	0.90	44.08
6	R08(P2)	0.774	37.23	R03(P2)	1.645	55.21	R06(P1)	15.456	47.69	R01(P1)	0.6	R16(P3)	0.90	50.00
7	R03(P1)	0.766	42.84	R16(P3)	1.638	61.90	R08(P2)	15.394	54.88	R04(P2)	0.5	R11(P3)	0.80	55.13
8	R16(P2)	0.758	48.36	R09(P2)	1.251	66.52	R16(P2)	15.053	61.91	R16(P2)	0.4	R02(P2)	0.76	59.95
9	R11(P3)	0.754	53.82	R02(P2)	1.236	71.06	R02(P2)	13.170	68.06	R02(P2)	0.4	R01(P2)	0.72	64.45
10	R10(P2)	0.737	59.09	R06(P1)	1.215	75.48	R09(P2)	12.745	74.02	R06(P1)	0.4	R06(P1)	0.72	68.96
11	R06(P1)	0.675	63.61	R13(P3)	1.191	79.78	R04(P2)	12.627	79.91	R15(P2)	0.4	R15(P2)	0.64	72.83
12	R03(P2)	0.658	67.93	R10(P2)	1.031	83.22	R02(P1)	11.902	85.47	R13(P2)	0.4	R13(P2)	0.56	76.07
13	R02(P2)	0.650	72.15	R02(P1)	0.824	85.56	R13(P2)	10.365	90.31	R01(P3)	0.4	R02(P1)	0.54	79.15
14	R04(P1)	0.638	76.23	R07(P1)	0.796	87.74	R13(P1)	7.933	94.02	R07(P1)	0.4	R04(P1)	0.54	82.23
15	R09(P2)	0.626	80.16	R15(P2)	0.780	89.84	R10(P2)	4.100	95.93	R08(P2)	0.3	R04(P2)	0.50	84.99
16	R01(P1)	0.603	83.82	R12(P3)	0.760	91.83	R14(P3)	3.291	97.47	R16(P3)	0.3	R01(P1)	0.48	87.60
17	R04(P2)	0.598	87.43	R02(P3)	0.759	93.82	R11(P3)	1.609	98.22	R02(P1)	0.3	R01(P3)	0.40	89.57
18	R16(P3)	0.546	90.40	R01(P2)	0.718	95.58	R16(P3)	1.102	98.73	R13(P1)	0.3	R02(P3)	0.40	91.55
19	R15(P2)	0.488	92.67	R13(P2)	0.680	97.14	R15(P2)	0.877	99.14	R05(P2)	0.3	R07(P1)	0.40	93.52
20	R13(P2)	0.486	94.92	R04(P2)	0.598	98.27	R12(P3)	0.811	99.52	R11(P3)	0.2	R14(P3)	0.40	95.50
21	R02(P1)	0.458	96.84	R04(P1)	0.574	99.27	R13(P3)	0.653	99.83	R02(P3)	0.2	R13(P1)	0.39	97.39
22	R01(P3)	0.399	98.05	R01(P1)	0.483	99.77	R01(P3)	0.369	100.00	R14(P3)	0.2	R13(P3)	0.30	98.58
23	R12(P3)	0.380	99.03	R05(P2)	0.419	99.94	R02(P3)	0	100.00	R13(P3)	0.2	R10(P2)	0.28	99.61
24	R02(P3)	0.379	100.00	R01(P3)	0.399	100.00	R03(P2)	0	100.00	R10(P2)	0.2	R12(P3)	0.20	100.00
25	R13(P1)	0.299	100.00	R13(P1)	0.388	100.00	R04(P1)	0	100.00	R12(P3)	0.1	R05(P2)	0.15	100.00

Considering numerous scenarios of the project RIN in a PLC generated during the dynamic simulation process, each risk's SOP, SLI, and SGI in the three project phases (i.e., P1, P2, and P3) were obtained using Eqs. (8), (10) and (13), respectively. Table 3 presents the risk prioritization results concerning the sample project in terms of five risk indicators: SOP_i^p, SLI_i^p, and SGI_i^p are related to our proposed dynamic MCS-based RIN model, while SP_i^p and RC_i^p (i.e., the risk criticality of R_i in the pth phase by multiplying SP_i^p and IO_i^p) are from the classical P–I risk model.

As can be seen in Table 3, most risks' SOP values are higher than their SP except for the source risks R01 (in P1, P2, and P3) and R13 (in P1). The results indicate that the propagation effects of interdependent risks can increase the occurrence probabilities of downstream risks that are directly or indirectly affected by other risks via cause–effect interdependency links. To be more specific, although some risks have lower SP, they can be heavily influenced by other interdependent risks in the project RIN and rank top in terms of SOP, such as R14(P3), R05(P2), and R13(P3). Additionally, even though the SOP values of

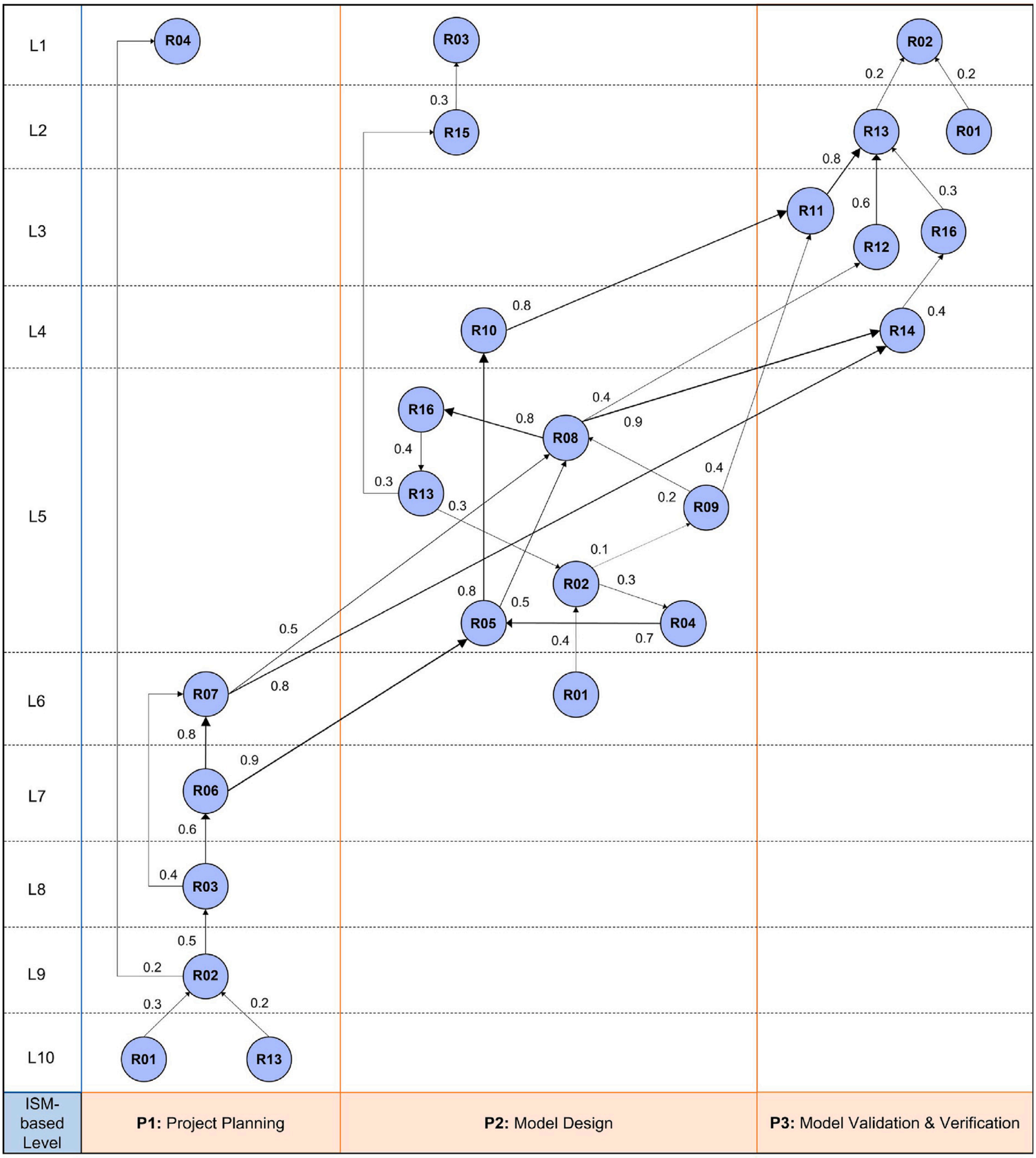

Fig. 2. The ISM-based RIN of the sample project with a three-phase PLC.

some particular risks are closer to their SP including R03(P1), R04(P1), R09(P2), and R04(P2), it is more realistic to estimate risk occurrence probability utilizing the proposed SOP indicator which considers the effects of risk propagation behavior. Note that all the source risks' SOP (i.e., R01(P1), R13(P1), R01(P2), and R01(P3)) are the same as their SP. This is because source risks are not affected by other risks and do not have upstream interdependent risks.

Looking at the risk influences on project objectives in each project phase, the SLI values of almost all the risks are higher than the risks' RC values (excluding the source risks), implying that the risk influences are amplified because of risk propagation effects. Although some of the risks were evaluated with similar values of RC_i^p, there is a notable difference in their SLI values, such as between R11(P3) and R02(P2), and between R14(P3) and R13(P1). By comparing the risk prioritization results by SLI_i^p with those by SGI_i^p, the risks with lower values of SLI can have higher values of SGI (e.g., R05(P2), R01(P1), and R01(P2)), which indicates that even though such risks produce fewer local influences on project objectives, their occurrence could increase the downstream associated interdependent risks' influences. The SGI regarding R04(P1), R03(P2), and R02(P3) are zero because they do not have output links in the project RIN and cannot affect any other risks.

Moreover, a Spearman rank correlation test was conducted to statistically examine the correlations among the five risk indicators: SOP_i^p, SLI_i^p, and SGI_i^p (based on the proposed PRA model); and SP_i^p and RC_i^p (based on the classical P–I risk model). The correlation coefficients are presented in Table 4.

The SOP_i^p possesses a significant positive correlation with SLI_i^p and SGI_i^p. Also, there is a stronger positive correlation between SLI_i^p

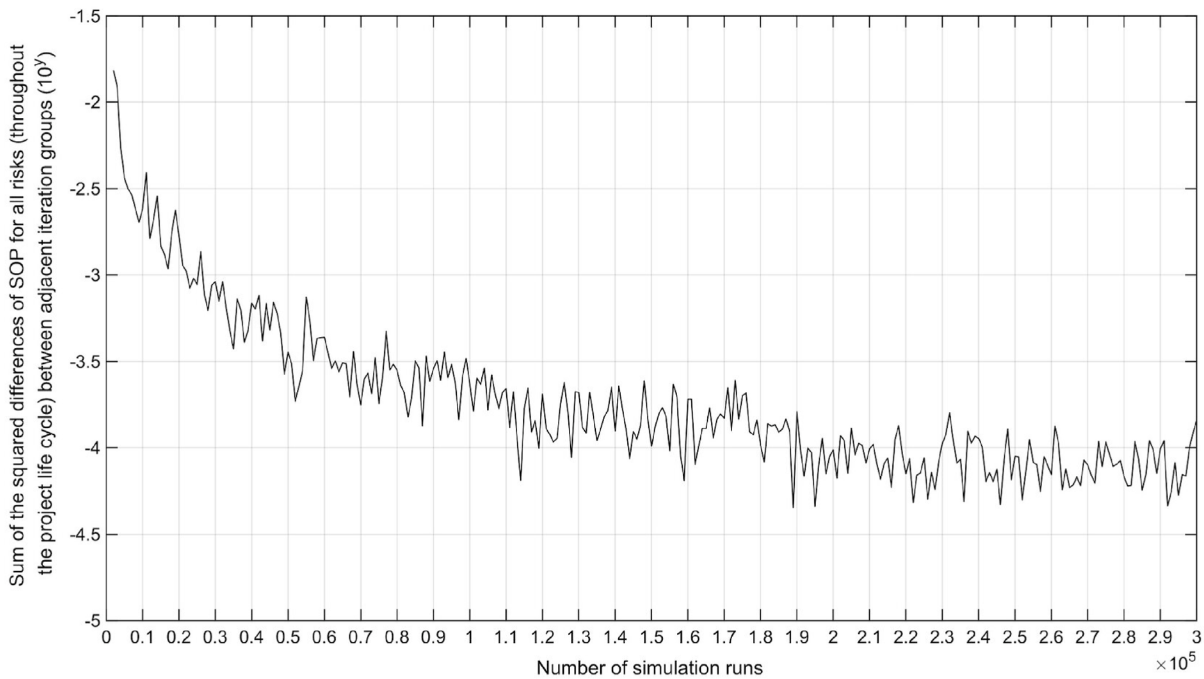

Fig. 3. The convergence diagram of the risk simulation process for the sample project.

Table 4
The Spearman rank correlation coefficients for five risk indicators in the case study of the sample project.

Risk indicator	SOP_i^p	SLI_i^p	SGI_i^p	SP_i^p
SOP_i^p	–			
SLI_i^p	0.452*	–		
SGI_i^p	0.486*	0.069	–	
SP_i^p	0.088	−0.146	0.368	–
RC_i^p	0.122	0.632**	0.184	0.551**

Note:
* Correlation is significant at the 0.05 level (2-tailed);
** Correlation is significant at the 0.01 level (2-tailed).

and RC_i^p, as well as between SP_i^p and RC_i^p. However, the correlation between SLI_i^p and SGI_i^p is very weak, mainly because the two indicators are heterogeneous which are designed to evaluate risk influences from different perspectives: at the local and global levels of a phase-based project RIN, respectively. As the same value regarding risk's IO is used in calculating SLI_i^p and RC_i^p, the correlation between these two indicators is relatively strong.

Overall, the project risk prioritization results from the proposed dynamic MCS-based RIN model are quite different from those obtained based on the classical P–I risk model, not only on the risk rankings but also on the quantitative risk occurrence probabilities and risk influences on project objectives, and the Spearman rank correlation coefficients further confirm the difference in PRA results. These findings demonstrate the necessities of considering risk interdependencies and using a phase-based project RIN for analyzing project risks through a PLC.

3.2.2. Assessment results of the project-level risk indicators

Based on Eq. (11), the expected project total risk loss (TRL) in P1, P2, and P3 was calculated as around $604, $1280, and $954, respectively. Observe that the resulting potential risk loss of the sample project in P2 is greater than that in P3 and P1. The probability distributions of the project TRL associated with P1, P2, and P3 were also analyzed considering numerous risk scenarios generated by the dynamic simulation process of the three-phase-based project RIN. Fig. 4(a)–(c) illustrate the results of the probability density function (PDF) and cumulative distribution function (CDF) related to the project TRL in P1, P2, and P3, respectively.

Specifically, Fig. 4(a) shows that during the project phase P1, the project risks tend to cause risk loss in the intervals of $600–$700 and $850–$900 (see the PDF histogram); while looking at the CDF curve, the risk loss in the $280–$890 interval accounts for about 80% of the TRL in P1. From Fig. 4(b), it can be seen that the risk loss related to the project phase P2 is more likely to occur (greater than the probability of 9%) in the intervals of $1292–$1368, $1444–$1520, and $1596–$1672; and the risk loss in the interval $800–$1710 accounts for around 80% of the TRL in P2. As shown in Fig. 4(c), the project risks in P3 are prone to result in risk loss in the intervals of $1012–$1104 and $1196–$1288; and about 80% of the TRL with respect to P3 is in the interval $400–$1350.

From the entire PLC of the sample project, the expected project TRL was calculated as around $2839 using Eq. (12). Fig. 4(d) shows the probability distribution of the project TRL under numerous scenarios of dynamic changes of the project RIN throughout a PLC. From the PDF histogram results, the potential project TRL in the five intervals of $3219–$3330, $2997–$3108, $3108–$3219, $2886–$2997, and $2775–$2886 are very likely to occur (in descending order), and each of them has a relatively strong probability greater than 7%. The CDF curve results show that the project TRL in the interval $2000–$3580 occupies approximately 80% of all the project risk loss in the entire PLC.

By using Eq. (14), the expected values of the project total risk propagation loss (TRPL) in P1, P2, and P3 were calculated as $8686, $11,943, and $783, respectively. Further, from the entire PLC perspective, the expected project TRPL was estimated as $21,412 according to Eq. (15). The project's TRL and TRPL provide decision-makers with more detailed information on the project potential risk loss either in each phase or during an entire PLC at both local and global RIN levels.

3.2.3. Examining the effects of RIN parameters' uncertainties on PRA results

A sensitivity analysis was conducted in this case study to examine to what extent the uncertainties in the input values of three kinds of RIN parameters (i.e., SP, TP, and IO, often collected from expert opinions) can influence the PRA results obtained from the proposed

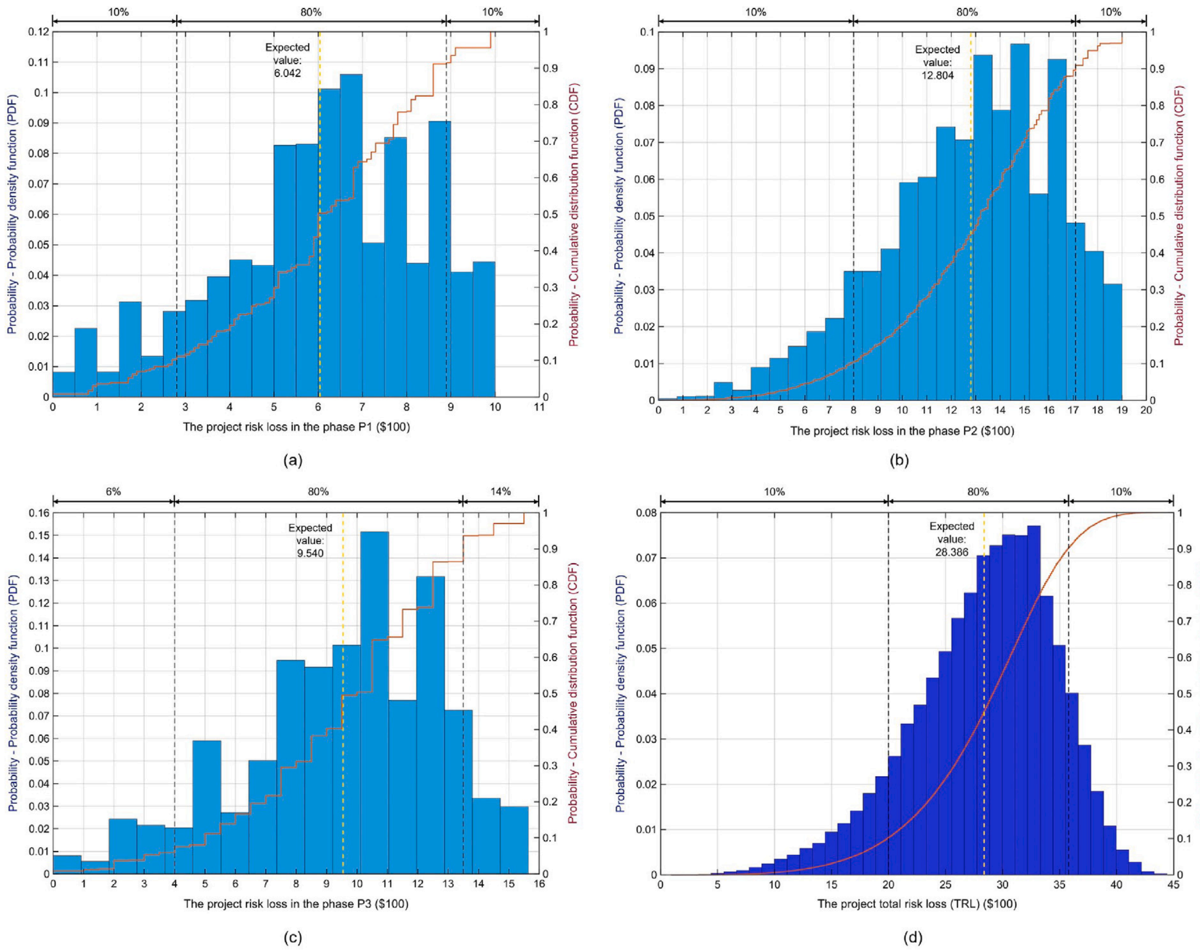

Fig. 4. Probability distributions of the project risk loss in the (a) phase P1, (b) phase P2, (c) phase P3, and (d) entire PLC of the sample project.

dynamic MCS-based RIN model, including each risk's SLI and SGI in a particular project phase, and the project's TRL and TRPL throughout an entire PLC. To this end, we set the model input values from three different levels, that is, "pessimistic", "most likely", and "optimistic", which were separately used as the input data in the dynamic simulation process of the proposed PRA model. Note that the SP and IO of each risk (shown in Table 2) and the TP related to each direct risk interdependency (presented in Fig. 2) were regarded as the "most likely" values. Due to a lack of sufficient data for the sample industrial project, we made rational assumptions on the "pessimistic" and "optimistic" values of the three kinds of RIN parameters. Accordingly, three groups of PRA results of the sample project were collected from the proposed PRA model during the sensitivity analysis. Fig. 5 shows two radar diagrams that illustrate the sensitivity of each risk's SLI and SGI to the value variations of RIN parameters, respectively.

From Fig. 5(a), we can see that the SLI for a majority of project risks are more sensitive to the value variations of IO than those of SP and TP. In particular, the change in IO values can highly affect the SLI of R11(P3), R08(P2), and R16(P2). Moreover, the SLI concerning R03(P2), R11(P3), and R03(P1) are more sensitive to the value variations of SP. In terms of the effects of the change in TP values, R11(P3)'s SLI is affected the most, while the sensitivities of other risks' SLI are relatively low, such as R04(P1), R09(P2), and R04(P2). As shown in Fig. 5(b), the SGI of the risks that can occur in P3 (e.g., R01(P3), R13(P3), and R12(P3)) are less sensitive to the value variations of SP, TP, and IO. However, the SGI regarding R01(P1), R03(P1), and R01(P2) tend to be more sensitive to the change in SP values than that of other risks; while for R05(P2), R16(P2), R07(P1), R08(P2), and R06(P1), their SGI are more sensitive to the change in TP values than other risks'. It is noticeable that the uncertainty in values of IO is more likely to influence the SGI of R03(P1), R05(P2), R07(P1), and R01(P2).

Furthermore, the sensitivities of the project's expected TRL and TRPL, in respect of the overall project throughout a PLC, to the value variations of the three RIN parameters (i.e., SP, TP, and IO) were also evaluated, which can be used to represent the proposed PRA model's sensitivities. Fig. 6 shows the results. Under the "most likely" scenario, the project's TRL and TRPL during an entire PLC were calculated as $2839 and $21,412, respectively. As illustrated in Fig. 6(a), when increasing the values of SP from the "optimistic" scenario to the "pessimistic" scenario, the TRL of the sample project increases from $1724 to $3529. Thus, the $1805 value change in the project's TRL ($3529 - 1724 = \$1805$) implies a 64% model sensitivity rate ($1805/2839 = 0.64$) with regard to the SP parameter. Likewise, the effects of value variations of the three RIN parameters on the project's TRL (see Fig. 6(a)) and TRPL (see Fig. 6(b)) in a PLC were all evaluated: (i) in terms of the SP parameter, the proposed model's sensitivity rates concerning TRL and TRPL are 64% and 112%, respectively; (ii) for the TP parameter, the proposed model's sensitivity rates regarding TRL and TRPL are 45% and 81%, respectively; and (iii) from the perspective of the IO parameter, the proposed model's sensitivity rates in terms of TRL and TRPL are both 100%. The results indicate that for the sample project, its TRPL is more likely to be affected by the uncertainties of the

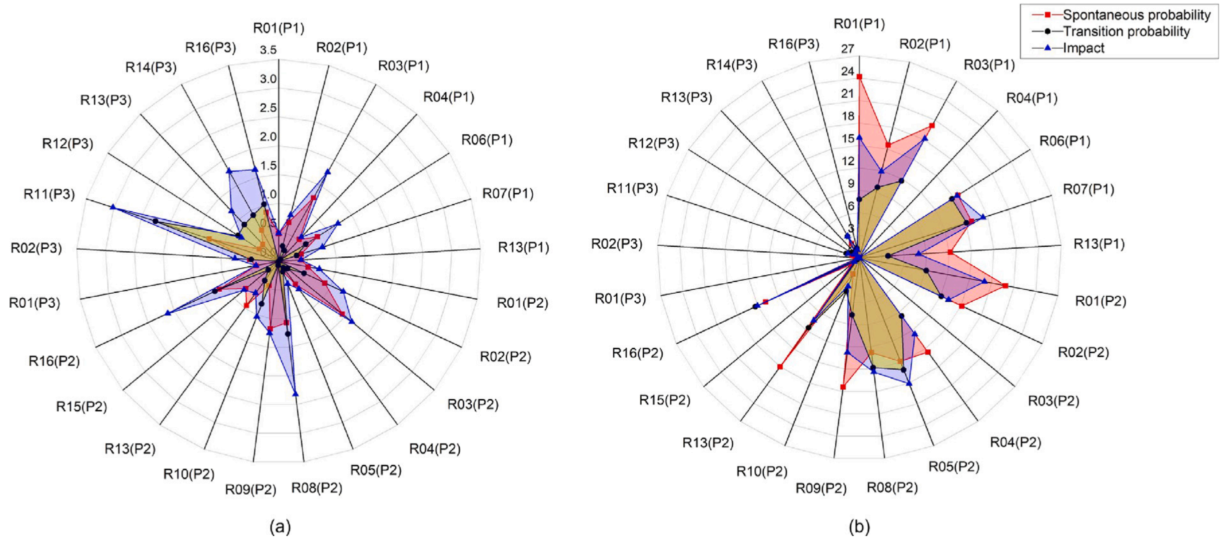

Fig. 5. Sensitivity radar diagrams of the sample project related to: (a) SLI ($100) of each risk in the entire PLC, and (b) SGI ($100) of each risk in the entire PLC.

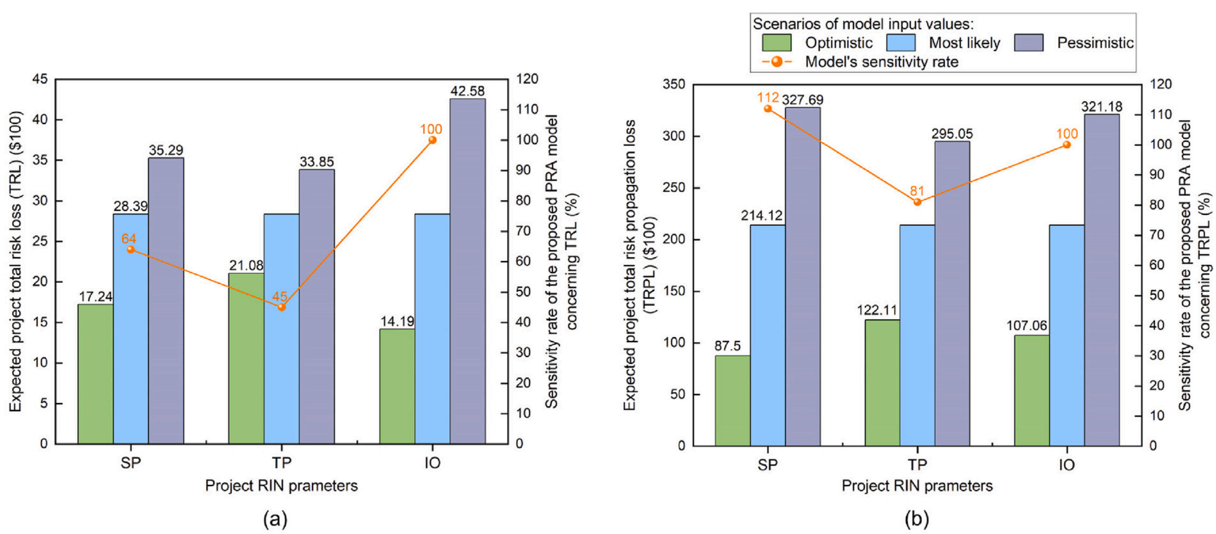

Fig. 6. Sensitivity analysis of the sample project's (a) expected TRL ($100) and (b) expected TRPL ($100) in the entire PLC regarding project RIN parameters under three scenarios.

three RIN parameters compared to its TRL throughout an entire PLC.

The above sensitivity analysis results provide more specific information for project decision-makers to double-check the model input values (related to the three RIN parameters) and improve the model's robustness when conducting PRA, especially paying more attention to the aforementioned unstable project risks. For example, considering the model's sensitivity with respect to the project's TRPL, the SP values regarding R01(P1), R03(P1), and R01(P2), as well as the TP values of R05(P2), R16(P2), R07(P1), R08(P2) and R06(P1) should be carefully evaluated when collecting expert opinions in order to obtain more realistic PRA results. Focusing on the model's sensitivity from the perspective of both TRL and TRPL, the IO values of R11(P3), R08(P2), R03(P1), R05(P2), and R07(P1) should also be double-checked carefully as well.

3.3. Planning and evaluating project risk treatment actions

Based on the risk prioritization results (related to SOP_i^p, SLI_i^p, and SGI_i^p) from the proposed dynamic MCS-based RIN model, we designed nine risk treatment scenarios that can represent the different levels of risk attitudes and risk appetites of a group of project decision-makers to formulate appropriate risk treatment actions for the sample industrial project. In addition, to demonstrate the effectiveness and superiority of the proposed PRA model, the risk treatment actions formulated using the PRA results from the classical P–I risk model (related to SP_i^p and RC_i^p) were also devised under each risk treatment scenario, and their performances were then compared with those from the proposed PRA model. In risk treatment implementation, as risk interdependencies are ignored in the classical P–I risk model, only critical risks were mitigated according to the classical P–I risk model; while for the proposed PRA model, not only were critical risks mitigated in the risk treatment, but

Table 5
Risk treatment actions (under the “top 20%" risk treatment scenario) for the sample project based on the two compared PRA models.

Compared PRA models	Under the “top 20%” risk treatment scenario		
	Risk treatment action	Reducing risks’ SP in the corresponding PLC phase	Cutting off risk interdependencies
Classical P–I risk model	Action 0	R03(P1)	–
Dynamic MCS-basedRIN model	Action 1	R01(P2), R05(P2), R11(P3), R14(P3)	R03(P1) → R06(P1), R03(P1) → R07(P1), R06(P1) → R05(P2), R07(P1) → R14(P3), R04(P2) → R05(P2), R05(P2) → R08(P2), R05(P2) → R10(P2), R08(P2) → R14(P3), R09(P2) → R11(P3), R10(P2) → R11(P3)
	Action 2	R01(P2)	R03(P1) → R06(P1), R03(P1) → R07(P1), R06(P1) → R05(P2), R07(P1) → R14(P3), R04(P2) → R05(P2), R05(P2) → R08(P2), R05(P2) → R10(P2), R08(P2) → R14(P3), R09(P2) → R11(P3), R10(P2) → R11(P3)
	Action 3	R01(P2), R05(P2), R11(P3), R14(P3), R03(P1)	R02(P1) → R03(P1), R06(P1) → R05(P2), R07(P1) → R14(P3), R04(P2) → R05(P2), R05(P2) → R08(P2), R05(P2) → R10(P2), R08(P2) → R14(P3), R09(P2) → R11(P3), R10(P2) → R11(P3)
	Action 4	R01(P2), R05(P2), R11(P3), R14(P3)	R03(P1) → R06(P1), R03(P1) → R07(P1), R06(P1) → R05(P2), R07(P1) → R14(P3), R04(P2) → R05(P2), R08(P2) → R14(P3), R09(P2) → R11(P3), R10(P2) → R11(P3)
	Action 5	R01(P2), R11(P3), R14(P3)	R03(P1) → R06(P1), R03(P1) → R07(P1), R07(P1) → R14(P3), R05(P2) → R08(P2), R05(P2) → R10(P2), R08(P2) → R14(P3), R09(P2) → R11(P3), R10(P2) → R11(P3)

also significant risk interdependencies were weakened. In this work, we assume that the SP of a risk in a project phase can be reduced to zero, and a direct link between two interdependent risks can be completely cut off, that is, the TP associated with a risk interdependency can be reduced to zero.

Based on the risk rankings in terms of the normalized values of the five aforementioned risk indicators, the following nine risk treatment scenarios adopted to formulate risk treatment actions were designed: the “above-average”, “top 20%”, “top 30%”, “top 40%”, “top 50%”, “top 60%”, “top 70%”, “top 80%”, and “top 90%” risk treatment scenarios. Aligning with a specific top percentage, the critical risks regarding SOP_i^p, SLI_i^p, SGI_i^p, and RC_i^p can be determined based on the four “(%)” columns in Table 3, respectively. Under the “top 20%” risk treatment scenario, we formulated one risk treatment action (Action 0) for the sample project based on the PRA results from the classical P–I risk model and five appropriate risk treatment actions (Actions 1–5) using the PRA results from the proposed dynamic MCS-based RIN model. Table 5 shows the detailed risk treatment actions according to the proposed risk treatment principles mentioned in Section 2.3.1. Specifically, for the classical P–I risk model, as R03(P1) is regarded as a critical risk (within the “top 20%” risk ranking) in terms of its RC, reducing R03’s SP to zero in phase P1 (i.e., $SP[R03(P1)] = 0$) was proposed as the risk treatment action (i.e., Action 0). For the proposed dynamic MCS-based RIN model, R14(P3), R05(P2), and R01(P2) are deemed the critical risks by SOP_i^p, R11(P3) by SLI_i^p, and R03(P1) and R05(P2) by SGI_i^p, and Actions 1–5 were proposed as the alternatives aligning with the key risk treatment principles.

It is worth noting that the higher the percentage indicated in the designed project risk treatment scenarios, the more the risks or risk interdependencies tend to be mitigated or weakened for the sample project. Thus, the designed nine risk treatment scenarios can represent nine levels of risk attitudes and risk appetites. The “lower percentage” risk treatment scenarios (e.g., “top 20%” and “top 30%” in this case) were used to reflect a group of the project decision-makers’ risk-seeking attitude and a higher risk appetite that more risks can be accepted or retained. The “higher percentage” risk treatment scenarios (e.g., “top 80%” and “top 90%” in this case) can reflect a group of the project decision-makers’ risk-aversion attitude and a lower risk appetite that fewer risks tend to be accepted. Moreover, the “above-average” and “top 50%” risk treatment scenarios were included to represent the risk-neutral attitude of a group of decision-makers and a neutral tendency of risk appetite. The “top 10%” risk treatment scenario was not considered in this case study. This is because no such critical risks were identified using the PRA results obtained from the classical P–I risk model.

In this paper, to elaborate how a more effective project risk treatment solution can be selected among alternatives, we particularly use the five risk treatment actions (Actions 1–5) formulated under the “top 20%” risk treatment scenario as an example. Fig. 7 presents the residual SOP, SLI, and SGI of each risk in its related project phase after implementing each of the five risk treatment actions. As indicated by Fig. 7(a), the performances of Actions 1–5 in reducing a majority of project risks’ SOP are very similar, except for R03(P1), R05(P2), R11(P3), and R14(P3) which are highly reduced by Action 3 as well. From Fig. 7(b), the performances of Actions 1–5 in mitigating project risks’ SLI are almost the same, but Action 3 can highly reduce the SLI of R03(P1) while Action 2 is less effective in reducing the SLI of R11(P3) and R14(P3). As shown in Fig. 7(c), there is no large difference among the performances of the five actions in mitigating risks’ SGI; nonetheless, Action 3 is more effective in weakening R01(P1)’s SGI than the other four actions.

Additionally, when looking at the reduced values of the project’s TRL and TRPL in each project phase and from the entire PLC, the overall performances of Actions 1–5 under the “top 20%” risk treatment scenario were compared in Table 6. The results show that Action 3 performs the best in mitigating the project’s TRL and TRPL in P1, P2, P3, and the entire PLC compared to the other four actions. It is worth noting that for the sample project, although cutting off the output links of R03(P1) in Action 1 and reducing the SP of R03(P1) and the TP of R03(P1)’s input link in Action 3 can both significantly mitigate R03(P1)’s SGI, Action 3 also performs better in mitigating the SLI of R03(P1). In addition, the effectiveness of Action 1 is nearly the same with that of Action 4, indicating that cutting off the two output links of R05(P2) makes almost no difference in the project risk treatment performance. Therefore, based on the above results, Action 3 is the most effective risk treatment solution among the five alternatives.

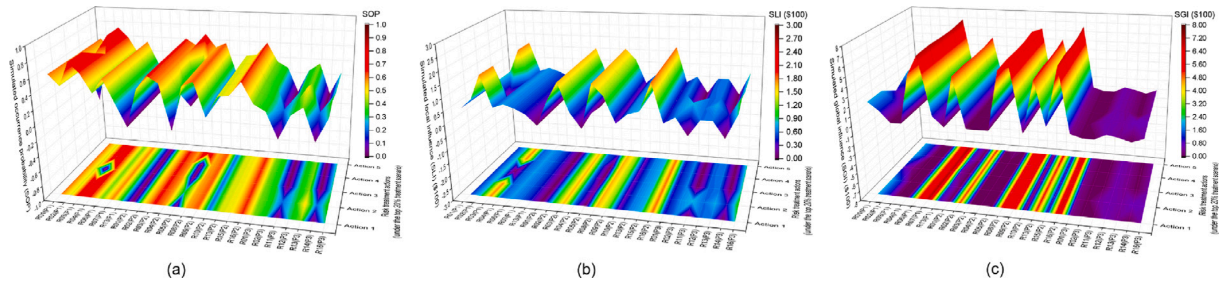

Fig. 7. The performances of five risk treatment actions under the "top 20%" risk treatment scenario based on the proposed PRA model: (a) the residual SOP of project risks in each phase, (b) the residual SLI of project risks in each phase, and (c) the residual SGI of project risks in each phase.

Table 6
The performances of five risk treatment actions under the "top 20%" risk treatment scenario based on the proposed PRA model: reduced project TRL and reduced project TRPL.

Risk treatment action	Reduced project TRL				Reduced project TRPL			
	P1	P2	P3	PLC	P1	P2	P3	PLC
Action 1	$69	$325	$640	$1034	$7071	$8928	$619	$16,618
Action 2	$69	$310	$485	$864	$7053	$8879	$488	$16,419
Action 3	$247	$325	$640	$1213	$7324	$8931	$619	$16,875
Action 4	$69	$325	$640	$1034	$7071	$8928	$619	$16,618
Action 5	$70	$288	$640	$997	$7030	$8797	$618	$16,446

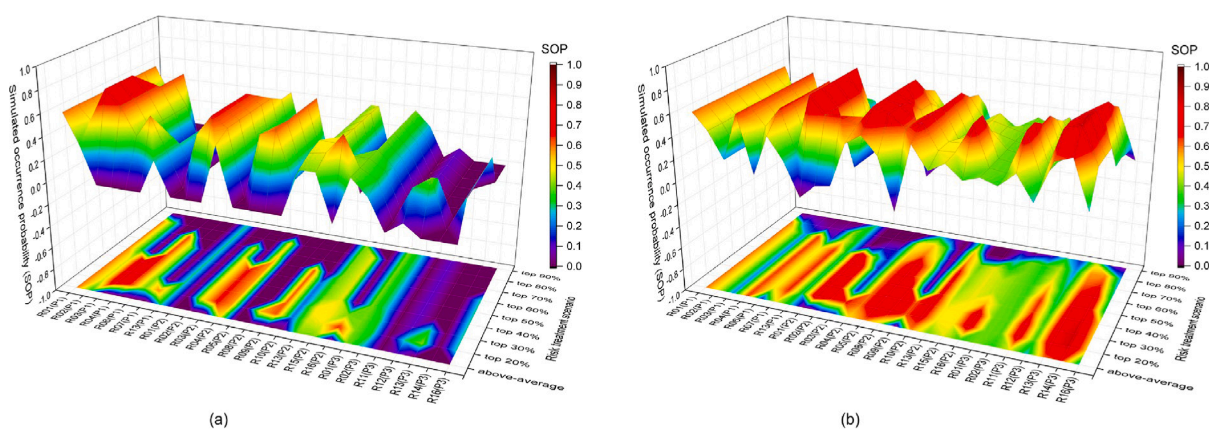

Fig. 8. The residual SOP of project risks throughout a PLC after implementing risk treatment actions based on (a) the proposed dynamic MCS-based RIN model and (b) the classical P–I risk model under nine treatment scenarios.

To compare our proposed dynamic MCS-based RIN model with the classical P–I risk model, corresponding potential risk treatment actions under the aforementioned nine risk treatment scenarios were formulated for the sample project. Note that we used Action 1 here under the "top 20%" risk treatment scenario. The comparison results of project risk treatment performances are illustrated in Figs. 8 through 10 as well as in Table 7.

Fig. 8 presents the residual SOP of each risk in its related PLC phase after conducting different risk treatment actions under the nine treatment scenarios. By comparing Fig. 8(a) (based on the proposed dynamic MCS-based RIN model) with Fig. 8(b) (based on the classical P–I risk model), we see that for all the treatment scenarios, the risk treatment actions formulated using the proposed PRA model can highly reduce the occurrence probabilities of a majority of project risks. Even though the residual SOP of R03(P1), R03(P2), and R09(P2) calculated from the classical P–I risk model are lower than those from the proposed PRA model in several treatment scenarios, more project risks, especially those that may occur in P2 and P3, were greatly mitigated or fully eliminated by implementing the risk treatment actions devised from the proposed PRA model.

Fig. 9 illustrates the residual SLI of each risk in its related PLC phase after conducting different risk treatment actions considering the nine treatment scenarios. As shown in Fig. 9(a), for all the nine treatment scenarios, the risk treatment actions formulated based on the proposed dynamic MCS-based RIN model can reduce a majority of project risks' SLI to a greater extent (only except for R03(P1), R03(P2), and R09(P2)), compared with the updated SLI results obtained from the classical P–I risk model after addressing critical risks (see in Fig. 9(b)). Particularly, by implementing the risk treatment actions based on the proposed PRA model, the updated SLI values regarding a number of project risks in P2 and P3, such as R08(P2), R16(P2), R11(P3), and R14(P3), were greatly reduced.

Fig. 10 describes the residual SGI of each risk in related PLC phases after implementing different risk treatment actions corresponding to the nine treatment scenarios. Through comparing Fig. 10(a) (based on the proposed dynamic MCS-based RIN model) with Fig. 10(b) (based on the classical P–I risk model), the risk treatment actions formulated using the proposed PRA model are much more effective in significantly reducing the SGI values of project risks in a PLC (especially in P1 and P2) than those from the traditional PRA model. It is worth noting that

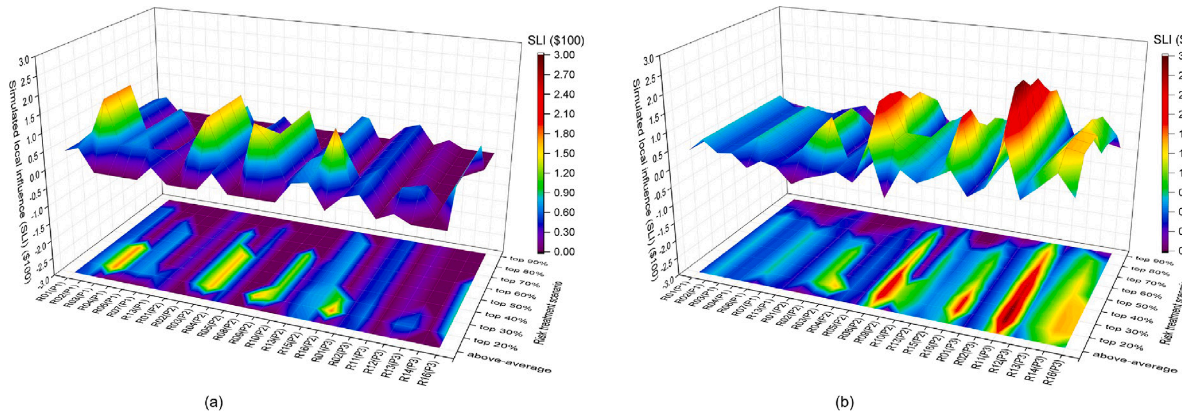

Fig. 9. The residual SLI of project risks throughout a PLC after implementing risk treatment actions based on (a) the proposed dynamic MCS-based RIN model and (b) the classical P–I risk model under nine treatment scenarios.

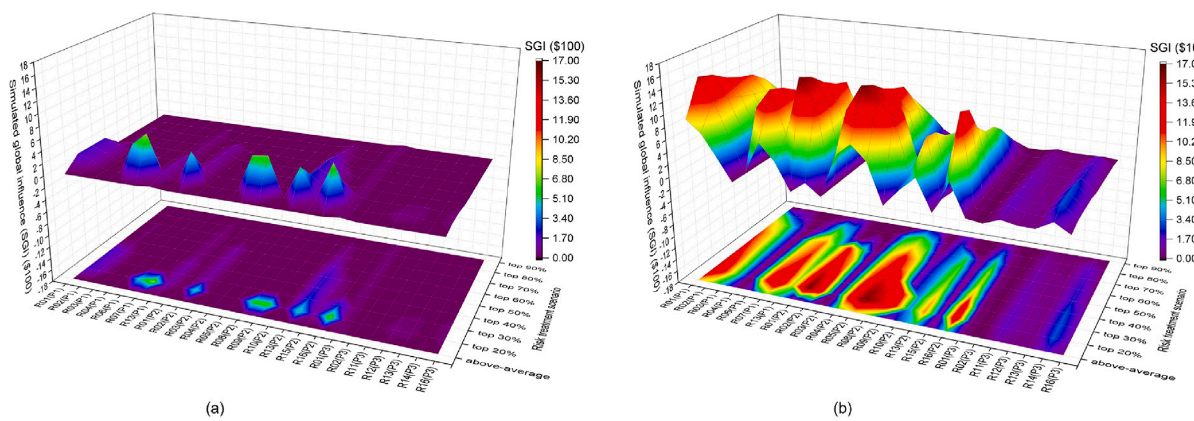

Fig. 10. The residual SGI of project risks throughout a PLC after implementing risk treatment actions based on (a) the proposed dynamic MCS-based RIN model and (b) the classical P–I risk model under nine treatment scenarios.

for the project risks that can occur in P3, there are no significant differences between the performances of the risk treatment actions proposed from the two compared PRA models. This is because compared to the project risks that can occur in P1 and P2, the project risks related to the last project phase P3 have fewer risk interdependencies that lead to downstream risks, and thus, they cause much less SGI. In addition, as shown in Fig. 9(b) and Fig. 10(b), regarding the implementation of risk treatment actions formulated from the classical P–I risk model, although the residual SLI of some risks have been reduced to a lower level for most risk treatment scenarios, including R01(P1), R07(P1), R01(P2), and R05(P2), these risks can largely influence the interdependent downstream risks and thus still have higher residual SGI due to their propagation effects.

Based on the reduced values of the overall project's TRL and TRPL, the performances of different risk treatment actions corresponding to the proposed PRA model and the classical P–I risk model were further compared from an entire PLC perspective. Table 7 presents the comparison results. For each treatment scenario, the risk treatment actions formulated based on the proposed PRA model can highly reduce both the project's TRL and TRPL compared to those from the classical P–I risk model. With respect to the average values of "reduced project TRL" and "reduced project TRPL" when considering all the nine treatment scenarios, the risk treatment actions formulated based on the proposed PRA model can alleviate almost twice the average reduced values of those from the classical P–I risk model. Therefore, the comparison results of the project risk treatment performances demonstrate that the risk treatment actions developed based on the proposed dynamic MCS-based RIN model are more effective, which further validates the proposed model's effectiveness and reliability for PRA and proactive risk treatment.

4. Discussion

4.1. Comparison of research results

The proposed dynamic MCS-based RIN model makes significant improvements in PRA and subsequent project risk treatment by introducing the dynamics of project risks and associated cause–effect risk interdependencies throughout an entire PLC into the traditional project risk management framework. Moreover, some other project risk characteristics including risk occurrence probability, risk impact on project objectives, risk propagation behavior, and risk stochastic behavior are also considered in the proposed PRA model. Therefore, more comprehensive and realistic PRA results represented by RIN-driven risk indicators can be obtained in each project phase and an entire PLC. Subsequently, from a global RIN perspective, more effective and efficient risk treatment actions can be formulated to minimize the cascading propagation of negative risk influences.

By comparing the analysis results of our proposed PRA model with those from the classical P–I risk model (only risks' SP and IO are considered) in the case study, the research findings further demonstrate that: (i) if chronological and cause–effect risk interdependencies are totally ignored in the PRA process, the estimated risk occurrence probabilities and risk influences on project objectives would be largely underestimated, leading to serious deviation from the real fact of project risk profile in practice; (ii) in a phase-based project RIN, a risk with lower local influence can cause severe global influence due to risk propagation behavior; (iii) apart from mitigating critical risks in the risk treatment process, alleviating risk propagation effects by cutting off or weakening critical risk interdependencies is of significance to

Table 7
The performances of risk treatment actions under different treatment scenarios related to two compared PRA models.

Risk treatment scenario	Risk treatment action developed from the proposed dynamic MCS-based RIN model		Risk treatment action developed from the classical P–I risk model	
	Reduced project TRL(PLC)	Reduced project TRPL(PLC)	Reduced project TRL(PLC)	Reduced project TRPL(PLC)
Above-average	$2408	$21,359	$1248	$13,736
Top 20% (Action 1)	$1034	$16,618	$232	$2886
Top 30%	$1378	$20,172	$361	$3973
Top 40%	$1566	$20,566	$599	$7097
Top 50%	$1765	$20,924	$766	$8598
Top 60%	$1957	$21,076	$873	$9720
Top 70%	$2250	$21,240	$1248	$13,736
Top 80%	$2396	$21,322	$1708	$16,931
Top 90%	$2631	$21,383	$2387	$20,374
Average value	$1932	$20,518	$1047	$10,783

improve the efficacy of risk treatment implementation; and (iv) if the critical project risks and risk propagation effects can be well controlled in earlier project phases of a PLC, the occurrence probabilities and negative influences of their downstream interdependent risks would be significantly reduced in the following project phases.

4.2. Methodological contributions

The key methodological contributions of this paper to existing project risk management literature are as follows. First, although some previous research has incorporated cause–effect risk interdependencies into the PRA process, they mainly focused on static PRA models, such as BBN (Guan, Liu et al., 2020; Hu et al., 2013; Wu et al., 2015), SEM (Liu et al., 2016; Yildiz et al., 2014), DSM (Fang et al., 2017; Marle et al., 2013), ISM (Guan, Abbasi et al., 2020; Iyer & Sagheer, 2010; Tavakolan & Etemadinia, 2017), and SNA (Yang & Zou, 2014; Zhang et al., 2020). In the current study, we developed a dynamic PRA model that captures the dynamics of a project RIN throughout an entire PLC, enabling project decision-makers to evaluate how the influences of project risks evolve along project phases.

In addition, as shown in Fig. 1, by integrating a phase-based project RIN (established using the ISM method) into the theoretical framework of MCS, the proposed PRA model is able to take into account complex risk interdependencies, risk loop phenomenon, and the stochastic behavior of risk occurrence and generate numerous dynamic project RIN scenarios during a PLC for analyzing project risks. In this regard, the proposed PRA model is superior to other models simply using the MCS to evaluate project risks while ignoring risk interdependencies (Gao et al., 2019; Qazi et al., 2021; Qazi & Simsekler, 2021; Sadeghi et al., 2010; Zhang et al., 2017). Unlike the RIN simulation model in the studies of Liu et al. (2024) and Wang et al. (2019, 2020), our proposed model has also considered the risk interdependencies within a project phase and the dynamics of RIN across different project phases.

Then, considering numerous risk scenarios generated from the proposed dynamic MCS-based RIN model, a series of RIN-driven risk indicators were devised to quantify project individual risks (using SOP_i^p, SLI_i^p, and SGI_i^p) and the project risk level (using TRL^p and $TRPL^p$) in each project phase, as well as to evaluate the overall project risk level from an entire PLC perspective (using TRL and $TRPL$). Moreover, the stand-alone risks without any links in a phase-based project RIN can also be evaluated based on the proposed PRA model, other than the interdependent risks. Note that the values of SGI regarding stand-alone risks are zero because there are no risk propagation effects derived from them.

Furthermore, the proposed dynamic MCS-based RIN model also provides an integrated platform that not only helps formulate proactive project risk treatment actions based on the PRA results obtained but also facilitates examining their effectiveness via re-evaluating PRA results after the risk treatment implementation. The proposed PRA model can also be employed to model the evolution of positive project risks (i.e., opportunities) throughout a PLC and evaluate their resultant positive effects on project objectives.

4.3. Managerial implications

The findings from this study bring about several managerial implications in practice. Firstly, this study provides project decision-makers with insights into regarding project risk management as a dynamic and nonlinear process, so that multiple complexity-related aspects, including risk stochastic behavior, risk propagation behavior, and dynamic changes of a phase-based project RIN throughout a PLC, can be involved in PRA to obtain more realistic PRA results.

Secondly, the proposed RIN-driven risk indicators can be easily utilized in practice to facilitate prioritizing project individual risks and evaluating an overall project risk level either in a specific project phase or in an entire PLC. After developing a phase-based project RIN according to the three major steps in the risk identification process (see Fig. 1), project decision-makers only need to input the estimated three kinds of RIN parameters (i.e., each risk's SP and IO as well as the TP between interdependent risks) into the proposed dynamic MCS-based RIN model to obtain the calculated values regarding different risk indicators. Therefore, project decision-makers can be well equipped with a more comprehensive perception of critical project risks and the potential project risk losses in each project phase or an entire PLC from both local and global levels of a project RIN.

Thirdly, the proposed dynamic PRA process makes it possible to enhance the effectiveness and efficiency of project risk treatment by controlling the propagation effects of interdependent risks from a global project RIN perspective. In addition, by re-evaluating the project risk profile after implementing the planned risk treatment actions, the decision-makers of a project can examine the performances of alternative risk treatment actions under various treatment scenarios, enabling project decision-makers to select a more effective project risk treatment solution aligning with their agreed risk attitude and risk appetite.

Fourthly, the overall framework established for PRA and project risk treatment throughout a PLC (see Fig. 1) is a generic one that can be applied to other similar engineering practices by updating the input risk-related data corresponding to a specific project. Moreover, as the input data (i.e., the network structure of a phase-based project RIN, estimated numerical values of the three kinds of RIN parameters regarding SP, TP, and IO) of the proposed PRA model mainly rely on the opinions/judgments from the project team and experts, the model can be easily implemented and understood at a reasonable level, so that all stakeholders of a project can engage their knowledge and experience during the decision-making processes of PRA and subsequent risk treatment.

Lastly, the proposed dynamic MCS-based RIN model is very flexible and can be used at any project phase of a PLC. If new risk information of a project is captured throughout a PLC, the resultant PRA results and corresponding risk treatment actions of the project can be updated accordingly in time without developing a new PRA model from scratch. Thus, project decision-makers can obtain timely PRA results to support proactive risk treatment for a project.

5. Conclusions

As contemporary projects are more complex under uncertain and dynamic environments, the project risks are becoming more diverse, interdependent, and intricate to deal with, which constantly plague project-driven organizations for securing the success of projects. The dynamic changes of project risks throughout a PLC also complicate the project risk management process. In existing studies, although many quantitative techniques have been developed for PRA, there is a limited focus on investigating an integrated and comprehensive framework for PRA and subsequent risk treatment in a PLC considering complex risk interdependencies. In addition, the commonly used P–I risk model-based risk indicators are insufficient in evaluating project risks throughout a PLC. For better decision-making in risk management, it is also crucial to develop interdependency-based risk indicators to evaluate project risks more realistically under complex environments. Moreover, the computing difficulty in analyzing an extensive number of project risks challenges many existing quantitative PRA techniques to be used in practice.

To overcome these challenges, this paper proposes a new dynamic MCS-based RIN model to improve the decision-making in PRA and risk treatment in the course of a PLC. By integrating ISM and the classical P–I risk model into the theoretical framework of MCS, multiple risk characteristics and complexity-related aspects were simultaneously modeled in PRA, including risk occurrence probability, risk impact on project objectives, the stochastic behavior of risk occurrence, risk propagation effects, possible risk loops in a project RIN, and the dynamics of a project RIN throughout an entire PLC. To facilitate prioritizing project individual risks and evaluating the project risk level in terms of specific project phases and an entire PLC, a series of RIN-driven risk indicators were designed.

In the case study of a sample industrial project, the effects of uncertainties in the proposed model's inputs on PRA results were investigated using a sensitivity analysis. Moreover, the effectiveness of the proposed dynamic MCS-based RIN model was compared with that of the classical P–I risk model by evaluating the performances of risk treatment actions developed from the two PRA models under nine treatment scenarios. The comparison results demonstrate that the proposed model is much more effective for the decision-making in PRA and project risk treatment, through which more realistic and detailed PRA results have been obtained and project risk loss has been significantly reduced by mitigating critical risks and controlling risk propagation effects throughout a PLC. Ultimately, the three main research objectives of this study are achieved. The research findings accentuate the significance of considering the chronological and complex cause–effect risk interdependencies for dynamic PRA and risk treatment throughout an entire PLC. The project decision-makers can be equipped with a deeper understanding of the dynamics of project critical risks and risk interdependencies across project phases and how the expected project risk losses change dynamically throughout a PLC. Consequently, more appropriate project risk treatment actions can be planned and implemented more proactively and efficiently.

Nonetheless, this paper still has the following limitations which also suggest some directions for future research: (i) due to a lack of sufficient project risk data, we only focused on one specific industrial project case in the case study to quantitatively compare the proposed dynamic MCS-based RIN model with the classical P–I risk model. Our proposed model for risk assessment and subsequent treatment can be applied to other engineering or business projects/scenarios and further compared to other risk assessment models once risk-related data are available; (ii) we incorporated the aspect of risk attitude and appetite regarding a group of project decision-makers in formulating several risk treatment scenarios, while not considering different risk attitudes and appetites for each decision-maker. The ordered weighted average operators could be combined with the current model to analyze the attitudinal characteristics of each decision-maker in the group decision-making process of risk management; (iii) the proposed PRA solution does not apply to the modeling and analysis of positive and negative project risks within solely one project RIN. In this regard, a feedback mechanism that supports the evaluation of the net risk influences can be incorporated into the proposed model; (iv) the simulation process may take more time when the proposed dynamic PRA model is applied to a complex project whose RIN involves a high number of risk loops. To reduce the convergence time, an appropriate heuristic algorithm can be integrated into the simulation process; (v) the proposed dynamic MCS-based RIN model did not consider the risk position attribute within a project RIN. In future work, the SNA method could be combined with the existing model to further analyze how the structure and pattern of a project RIN evolves dynamically throughout a PLC as well as the resultant effects on PRA results; and (vi) the cost of each risk treatment action and project resource constraints were not considered in this work when formulating risk treatment actions. To improve the project risk treatment decision-making, an optimization model helping intelligently select the optimal risk treatment solution can be investigated and further integrated with the current PRA model.

CRediT authorship contribution statement

Li Guan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alireza Abbasi:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Formal analysis. **Michael J. Ryan:** Writing – review & editing, Visualization, Supervision. **José M. Merigó:** Writing – review & editing, Visualization, Supervision, Resources.

Acknowledgments

This work is supported by research stipends from the University of New South Wales, Australia and the University of Technology Sydney, Australia. We would like to thank Dr. Shuo Yang for his contributions to conceiving the simulation algorithm of the proposed approach. We are grateful to the editors and anonymous reviewers for their invaluable comments and suggestions.

Appendix A. Proposed simulation algorithm

See Fig. A.1.

Appendix B. Additional results of developing an ISM-based project RIN in the case study

See Figs. B.1 and B.2 and Table B.1.

Data availability

Data will be made available on request.

Simulation algorithm for modeling the dynamic process of a phase-based project RIN: Pseudocode

```
For runs ← 1000 to 300,000 by 1000
  For i ← 1 to runs
    For i_PLCphase ← 1 to n_PLCphase
      For j ← 1 to n (go through all the n nodes in the i_PLCphase within the network)
        While there is still a node whose COP has not been calculated in the i_PLCphase
            do find the nodes whose COPs have not been calculated in the i_PLCphase
            If there is no node that is ready (the COPs of all its interrelated pre-nodes are calculated)
              then find the node(s) that is the closest to ready (with the least number of uncalculated
                                    pre-nodes) and name it/them as close2ready node(s)
              n_close2ready ← the number of the close2ready nodes
              For i_close2ready ← 1 to n_close2ready
                  do assume the pre-nodes of the close2ready node have been calculated
                  score ← weighted sum of the number of ready nodes with the assumption
              End for
              Find the close2ready nodes with the highest score
              Make a hypothesis H0 on their interrelated pre-node(s)
              Set the close2ready nodes as ready nodes
        End while
        Choose one of the ready nodes as currentNode
        Find the influenceNode of the currentNode in the i_PLCphase
        For i_influenceNode ← influenceNode in the i_PLCphase
          if mc(i_influenceNode, i_PLCphase) = 1
            then TP_k ← TP(i_influenceNode, currentNode, i_PLCphase)
            elseif mc(i_influenceNode, i_PLCphase) = 0
                then TP_k ← 0
            NIP ← NIP * (1 - TP_k)
        End for
        If i_PLCphase ≠ 1
          then find the pre-node(s) of the currentNode that has/have occurred in previous PLC phases
          n_prePhaseNode ← the number of the nodes in previous PLC phases that can influence the
                                currentNode
          For i_ prePhaseNode ← prePhaseNode
            if mc(i_ prePhaseNode) = 1
              then TP_k ← TP(i_ prePhaseNode, currentNode)
              elseif mc(i_ prePhaseNode) = 0
                  then TP_k ← 0
              NIP ← NIP * (1 - TP_k)
          End for
        COP(currentNode, i_PLCphase) ← 1 – (1 – SP(currentNode, i_PLCphase )) * NIP
        mc(currentNode, i_PLCphase) ← rand <= COP(currentNode, i_PLCphase)
      End for
      If the interrelated pre-node(s) of the currentNode (in the i_PLCphase) is/are hypothesised
        If mc(pre-node) ≠ H0
          then discard this run and go to next run
    End for
  End for
End for
```

Fig. A.1. The proposed MCS algorithm for modeling the dynamic process of a phase-based project RIN throughout an entire PLC.

	j	P1							P2											P3						
i		R01	R02	R03	R04	R06	R07	R13	R01	R02	R03	R04	R05	R08	R09	R10	R13	R15	R16	R01	R02	R11	R12	R13	R14	R16
P1	R01	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R02	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R03	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R04	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R06	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	R07	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0
	R13	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
P2	R01	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R02	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	R03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R04	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	R05	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
	R08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0
	R09	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
	R10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
	R13	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	R15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
P3	R01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	R02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	R12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
	R13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	R14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
	R16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Fig. B.1. A binary structural self-interaction matrix (SSIM) in the case study.

Table B.1
Level partitioning information of ten risks of the sample project in each level.

Risk No.	Reachability set	Antecedent set	Intersection set	Level
R04(P1)	R04(P1)	R01(P1), R02(P1), R04(P1), and R13(P1)	R04(P1)	L1
R13(P3)	R13(P3)	R01(P1), R02(P1), R03(P1), R06(P1), R07(P1), R13(P1), R01(P2), R02(P2), R04(P2), R05(P2), R08(P2), R09(P2), R10(P2), R13(P2), R16(P2), R11(P3), R12(P3), R13(P3), R14(P3), and R16(P3)	R13(P3)	L2
R16(P3)	R16(P3)	R01(P1), R02(P1), R03(P1), R06(P1), R07(P1), R13(P1), R01(P2), R02(P2), R04(P2), R05(P2), R08(P2), R09(P2), R13(P2), R16(P2), R14(P3), and R16(P3)	R16(P3)	L3
R10(P2)	R10(P2)	R01(P1), R02(P1), R03(P1), R06(P1), R07(P1), R13(P1), R01(P2), R02(P2), R04(P2), R05(P2), R08(P2), R09(P2), R10(P2), R13(P2), and R16(P2)	R10(P2)	L4
R02(P2)	R02(P2), R04(P2), R05(P2), R08(P2), R09(P2), R13(P2), and R16(P2)	R01(P1), R02(P1), R03(P1), R06(P1), R07(P1), R13(P1), R01(P2), R02(P2), R04(P2), R05(P2), R08(P2), R09(P2), R13(P2), and R16(P2)	R02(P2), R04(P2), R05(P2), R08(P2), R09(P2), R13(P2), and R16(P2)	L5
R07(P1)	R07(P1)	R01(P1), R02(P1), R03(P1), R06(P1), R07(P1), and R13(P1)	R07(P1)	L6
R06(P1)	R06(P1)	R01(P1), R02(P1), R03(P1), R06(P1), and R13(P1)	R06(P1)	L7
R03(P1)	R03(P1)	R01(P1), R02(P1), R03(P1), R13(P1)	R03(P1)	L8
R02(P1)	R02(P1)	R01(P1), R02(P1), R13(P1)	R02(P1)	L9
R13(P1)	R13(P1)	R13(P1)	R13(P1)	L10

	j	P1							P2											P3						
i		R01	R02	R03	R04	R06	R07	R13	R01	R02	R03	R04	R05	R08	R09	R10	R13	R15	R16	R01	R02	R11	R12	R13	R14	R16
P1	R01	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R02	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R03	0	0	1	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R04	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R06	0	0	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R07	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R13	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
P2	R01	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R02	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R03	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	R04	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R05	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R08	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R09	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	1	0	0
	R13	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
	R15	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
	R16	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
P3	R01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
	R02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	R11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0
	R12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0
	R13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0
	R14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1
	R16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1

Fig. B.2. A final reachability matrix (RM) in the case study.

References

Abdelhafidh, M., Fourati, M., & Chaari, L. (2023). Dynamic Bayesian network-based operational risk assessment for industrial water pipeline leakage. *Computers & Industrial Engineering*, *183*, Article 109466.

Ahiaga-Dagbui, D. D., Love, P. E., Smith, S. D., & Ackermann, F. (2017). Toward a systemic view to cost overrun causation in infrastructure projects: A review and implications for research. *Project Management Journal*, *48*(2), 88–98.

Ahmadabadi, A. A., & Heravi, G. (2019). Risk assessment framework of PPP-megaprojects focusing on risk interaction and project success. *Transportation Research Part A: Policy and Practice*, *124*, 169–188.

Akhavan, M., Sebt, M. V., & Ameli, M. (2021). Risk assessment modeling for knowledge based and startup projects based on feasibility studies: A Bayesian network approach. *Knowledge-Based Systems*, *222*, Article 106992.

Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. *European Journal of Operational Research*, *253*(1), 1–13.

Bai, L., Xie, Q., Lin, J., Liu, S., Wang, C., & Wang, L. (2024). Dynamic selection of risk response strategies with resource allocation for construction project portfolios. *Computers & Industrial Engineering*, *191*, Article 110116.

BSI (2018). *International standard ISO 31000: risk management–guidelines*: (2nd ed.). *Standard*, London, UK: British Standards Institution.

Carbone, T. A., & Tippett, D. D. (2004). Project risk management using the project risk FMEA. *Engineering Management Journal*, *16*(4), 28–35.

Chen, L., Lu, Q., & Han, D. (2023). A Bayesian-driven Monte Carlo approach for managing construction schedule risks of infrastructures under uncertainty. *Expert Systems with Applications*, *212*, Article 118810.

Chien, K.-F., Wu, Z.-H., & Huang, S.-C. (2014). Identifying and assessing critical risk factors for BIM projects: Empirical study. *Automation in Construction*, *45*, 1–15.

de Almeida Rodrigues, T., Ojiako, U., Marshall, A., de Miranda Mota, C. M., Dweiri, F. T., Chipulu, M., Ika, L., & AlRaeesi, E. J. H. (2024). Risk factor prioritization in infrastructure handover to operations. *International Journal of Project Management*, *42*(1), Article 102558.

Dikmen, I., Birgonul, M. T., & Han, S. (2007). Using fuzzy risk assessment to rate cost overrun risk in international construction projects. *International Journal of Project Management*, *25*(5), 494–505.

Dikmen, I., Budayan, C., Talat Birgonul, M., & Hayat, E. (2018). Effects of risk attitude and controllability assumption on risk ratings: Observational study on international construction project risk assessment. *Journal of Management in Engineering*, *34*(6), Article 04018037.

Ellinas, C. (2019). The domino effect: An empirical exposition of systemic risk across project networks. *Production and Operations Management*, *28*(1), 63–81.

Ellinas, C., Allan, N., & Johansson, A. (2018). Toward project complexity evaluation: A structural perspective. *IEEE Systems Journal*, *12*(1), 228–239.

Erol, H., Dikmen, I., Atasoy, G., & Birgonul, M. T. (2022). An analytic network process model for risk quantification of mega construction projects. *Expert Systems with Applications*, *191*, Article 116215.

Etemadinia, H., & Tavakolan, M. (2021). Using a hybrid system dynamics and interpretive structural modelling for risk analysis of design phase of the construction projects. *International Journal of Construction Management*, *21*(1), 93–112.

Fan, Z.-P., Suo, W.-L., & Feng, B. (2012). Identifying risk factors of IT outsourcing using interdependent information: An extended DEMATEL method. *Expert Systems with Applications*, *39*(3), 3832–3840.

Fang, C., & Marle, F. (2012). A simulation-based risk network model for decision support in project risk management. *Decision Support Systems*, *52*(3), 635–644.

Fang, C., Marle, F., & Xie, M. (2017). Applying importance measures to risk analysis in engineering project using a risk network model. *IEEE Systems Journal*, *11*(3), 1548–1556.

Gao, J., Ren, H., & Cai, W. (2019). Risk assessment of construction projects in China under traditional and industrial production modes. *Engineering, Construction and Architectural Management*, *26*(9), 2147–2168.

Glette-Iversen, I., Flage, R., & Aven, T. (2023). Extending and improving current frameworks for risk management and decision-making: A new approach for incorporating dynamic aspects of risk and uncertainty. *Safety Science*, *168*, Article 106317.

Guan, L., Abbasi, A., & Ryan, M. J. (2020). Analyzing green building project risk interdependencies using interpretive structural modeling. *Journal of Cleaner Production*, *256*, Article 120372.

Guan, L., Abbasi, A., & Ryan, M. J. (2021). A simulation-based risk interdependency network model for project risk assessment. *Decision Support Systems*, *148*, Article 113602.

Guan, L., Liu, Q., Abbasi, A., & Ryan, M. J. (2020). Developing a comprehensive risk assessment model based on fuzzy Bayesian belief network (FBBN). *Journal of Civil Engineering and Management*, *26*(7), 614–634.

Helbing, D. (2013). Globally networked risks and how to respond. *Nature*, *497*(7447), 51–59.
Holzmann, V., & Spiegler, I. (2011). Developing risk breakdown structure for information technology organizations. *International Journal of Project Management*, *29*(5), 537–546.
Hu, Y., Zhang, X., Ngai, E., Cai, R., & Liu, M. (2013). Software project risk analysis using Bayesian networks with causality constraints. *Decision Support Systems*, *56*, 439–449.
Huseby, A. B., & Skogen, S. (1992). Dynamic risk analysis: The DynRisk concept. *International Journal of Project Management*, *10*(3), 160–164.
Hwang, W., Hsiao, B., Chen, H.-G., & Chern, C.-C. (2016). Multiphase assessment of project risk interdependencies: Evidence from a university ISD project in Taiwan. *Project Management Journal*, *47*(1), 59–75.
Islam, M. S., Nepal, M. P., Skitmore, M., & Kabir, G. (2019). A knowledge-based expert system to assess power plant project cost overrun risks. *Expert Systems with Applications*, *136*, 12–32.
Iyer, K. C., & Sagheer, M. (2010). Hierarchical structuring of PPP risks using interpretative structural modeling. *Journal of Construction Engineering and Management*, *136*(2), 151–159.
Khanzadi, M., Nasirzadeh, F., & Alipour, M. (2012). Integrating system dynamics and fuzzy logic modeling to determine concession period in BOT projects. *Automation in Construction*, *22*, 368–376.
Kwak, D.-W., Rodrigues, V. S., Mason, R., Pettit, S., & Beresford, A. (2018). Risk interaction identification in international supply chain logistics: Developing a holistic model. *International Journal of Operations & Production Management*, *38*(2), 372–389.
der Landwehr, M. A., Trott, M., von Bülow, K., & von Viebahn, C. (2023). Pyrrhic victory? Towards a decision support system for simulation projects in industrial practice based on fuzzy cognitive mapping. *Computers & Industrial Engineering*, *186*, Article 109706.
Law, A. M. (2015). *Simulation modeling and analysis* (5th ed.). New York, USA: McGraw-Hill.
Li, C. Z., Hong, J., Fan, C., Xu, X., & Shen, G. Q. (2018). Schedule delay analysis of prefabricated housing production: A hybrid dynamic approach. *Journal of Cleaner Production*, *195*, 1533–1545.
Liu, S., Ding, R., & Wang, L. (2024). An adaptive simulation based decision support approach to respond risk propagation in new product development projects. *Decision Support Systems*, Article 114270.
Liu, J., Zhao, X., & Yan, P. (2016). Risk paths in international construction projects: Case study from Chinese contractors. *Journal of Construction Engineering and Management*, *142*(6), Article 05016002.
Loosemore, M., & Cheung, E. (2015). Implementing systems thinking to manage risk in public private partnership projects. *International Journal of Project Management*, *33*(6), 1325–1334.
Luo, T., Wu, C., & Duan, L. (2018). Fishbone diagram and risk matrix analysis method and its application in safety assessment of natural gas spherical tank. *Journal of Cleaner Production*, *174*, 296–304.
Mahmood, N., Butalia, T., Qin, R., & Manasrah, M. (2022). Concurrent events risk assessment generic models with enhanced reliability using fault tree analysis and expanded rotational fuzzy sets. *Expert Systems with Applications*, *197*, Article 116681.
Marle, F., Vidal, L., & Bocquet, J. (2013). Interactions-based risk clustering methodologies and algorithms for complex project management. *International Journal of Production Economics*, *142*(2), 225–234.
Nasirzadeh, F., Afshar, A., Khanzadi, M., & Howick, S. (2008). Integrating system dynamics and fuzzy logic modeling for construction risk management. *Construction Management and Economics*, *26*(11), 1197–1212.
Nicholas, J. M., & Steyn, H. (2020). *Project management for engineering, business and technology*. London, UK: Routledge.
Okudan, O., Budayan, C., & Dikmen, I. (2021). A knowledge-based risk management tool for construction projects using case-based reasoning. *Expert Systems with Applications*, *173*, Article 114776.
PMI (2019). *The standard for risk management in portfolios, programs, and projects*: *Standard*, Newtown Square, PA, USA: Project Management Institute.
PMI (2021). *The standard for project management and a guide to the project management body of knowledge (PMBOK guide)*: (7th ed.). *Standard*, Newtown Square, PA, USA: Project Management Institute.
Qazi, A., & Akhtar, P. (2020). Risk matrix driven supply chain risk management: Adapting risk matrix based tools to modelling interdependent risks and risk appetite. *Computers & Industrial Engineering*, *139*, Article 105351.
Qazi, A., & Dikmen, I. (2021). From risk matrices to risk networks in construction projects. *IEEE Transactions on Engineering Management*, *68*(5), 1449–1460.
Qazi, A., Shamayleh, A., El-Sayegh, S., & Formaneck, S. (2021). Prioritizing risks in sustainable construction projects using a risk matrix-based Monte Carlo Simulation approach. *Sustainable Cities and Society*, *65*, Article 102576.
Qazi, A., & Simsekler, M. C. E. (2021). Risk assessment of construction projects using Monte Carlo simulation. *International Journal of Managing Projects in Business*, *14*(5), 1202–1218.
Qin, X., Mo, Y., & Jing, L. (2016). Risk perceptions of the life-cycle of green buildings in China. *Journal of Cleaner Production*, *126*, 148–158.
Rodríguez, A., Ortega, F., & Concepción, R. (2016). A method for the evaluation of risk in IT projects. *Expert Systems with Applications*, *45*, 273–285.
Sadeghi, N., Fayek, A. R., & Pedrycz, W. (2010). Fuzzy Monte Carlo simulation and risk assessment in construction. *Computer-Aided Civil and Infrastructure Engineering*, *25*(4), 238–252.
Taillandier, F., Taillandier, P., Tepeli, E., Breysse, D., Mehdizadeh, R., & Khartabil, F. (2015). A multi-agent model to manage risks in construction project (SMACC). *Automation in Construction*, *58*, 1–18.
Taroun, A. (2014). Towards a better modeling and assessment of construction risk: Insights from a literature review. *International Journal of Project Management*, *32*(1), 101–115.
Tavakolan, M., & Etemadinia, H. (2017). Fuzzy weighted interpretive structural modeling: Improved method for identification of risk interactions in construction projects. *Journal of Construction Engineering and Management*, *143*(11), Article 04017084.
Wang, L., Goh, M., Ding, R., & Pretorius, L. (2019). Improved simulated annealing based risk interaction network model for project risk response decisions. *Decision Support Systems*, *122*, Article 113062.
Wang, L., Song, Y., Ding, R., & Goh, M. (2022). Delay-oriented risk network model for project risk response decisions. *Computers & Industrial Engineering*, *171*, Article 108370.
Wang, L., Sun, T., Qian, C., Goh, M., & Mishra, V. K. (2020). Applying social network analysis to genetic algorithm in optimizing project risk response decisions. *Information Sciences*, *512*, 1024–1042.
Wang, J., & Yuan, H. (2017). System dynamics approach for investigating the risk effects on schedule delay in infrastructure projects. *Journal of Management in Engineering*, *33*(1), Article 04016029.
Warfield, J. N. (1974). Developing interconnection matrices in structural modeling. *IEEE Transactions on Systems, Man and Cybernetics*, *SMC-4*(1), 81–87.
Williams, T. (1993). Risk-management infrastructures. *International Journal of Project Management*, *11*(1), 5–10.
Williams, T. (2017). The nature of risk in complex projects. *Project Management Journal*, *48*(4), 55–66.
Wu, Y., Ke, Y., Wang, J., Li, L., & Lin, X. (2019). Risk assessment in photovoltaic poverty alleviation projects in China under intuitionistic fuzzy environment. *Journal of Cleaner Production*, *219*, 587–600.
Wu, W.-S., Yang, C.-F., Chang, J.-C., Château, P.-A., & Chang, Y.-C. (2015). Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project. *Reliability Engineering & System Safety*, *142*, 515–524.
Yang, L., Lou, J., & Zhao, X. (2021). Risk response of complex projects: Risk association network method. *Journal of Management in Engineering*, *37*(4), Article 05021004.
Yang, R. J., & Zou, P. X. (2014). Stakeholder-associated risks and their interactions in complex green building projects: A social network model. *Building and Environment*, *73*, 208–222.
Yildiz, A. E., Dikmen, I., Birgonul, M. T., Ercoskun, K., & Alten, S. (2014). A knowledge-based risk mapping tool for cost estimation of international construction projects. *Automation in Construction*, *43*, 144–155.
Yuan, J., Chen, K., Li, W., Ji, C., Wang, Z., & Skibniewski, M. J. (2018). Social network analysis for social risks of construction projects in high-density urban areas in China. *Journal of Cleaner Production*, *198*, 940–961.
Zeng, J., An, M., & Smith, N. J. (2007). Application of a fuzzy based decision making methodology to construction project risk assessment. *International Journal of Project Management*, *25*(6), 589–600.
Zeng, Y., & Skibniewski, M. J. (2013). Risk assessment for enterprise resource planning (ERP) system implementations: A fault tree analysis approach. *Enterprise Information Systems*, *7*(3), 332–353.
Zhang, L., Huang, Y., Wu, X., & Skibniewski, M. J. (2017). Risk-based estimate for operational safety in complex projects under uncertainty. *Applied Soft Computing*, *54*, 108–120.
Zhang, Y., Tsai, C.-H., & Liao, P.-C. (2020). Rethinking risk propagation mechanism in public–private partnership projects: Network perspective. *Journal of Infrastructure Systems*, *26*(2), Article 04020011.
Zhang, P., Zhang, Z.-J., & Gong, D.-Q. (2024). An improved failure mode and effect analysis method for group decision-making in utility tunnels construction project risk evaluation. *Reliability Engineering & System Safety*, *244*, Article 109943.
Zhu, J., & Mostafavi, A. (2018). Performance assessment in complex engineering projects using a system-of-systems framework. *IEEE Systems Journal*, *12*(1), 262–273.
Zuo, F., & Zio, E. (2024). Managing secondary risks with optimal risk response strategy and risk-related resource scheduling. *Reliability Engineering & System Safety*, *245*, Article 110028.