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An Analytic Network Process Model for Risk Quantification of Mega Construction Projects

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ABSTRACT

Risk, complexity, and uncertainty are inherent components of megaprojects due to their unique features. However, existing project management practices lack a structured synthesis of these concepts, which leads to unrealistic risk assessments, ineffective management strategies, and poor project performance. In order to fill this gap, this research aims to develop a holistic risk quantification approach incorporating risk-related concepts. For this purpose, a conceptual risk assessment process developed for mega construction projects was operationalized with an Analytic Network Process (ANP) model. The weights of the risk sources in the ANP model were determined by the domain experts through a two-round Delphi study. With the purpose of improving the efficiency and reliability of the knowledge elicitation process, the Delphi study was supported by an interactive data collection tool capable of ANP calculations. The resulting model helped to prioritize the risk sources in mega construction projects. The validity of the findings was tested through the data of 11 mega construction projects. Validation studies revealed the potential of the ANP-based model in quantifying the project risks. Hence, the novel approach proposed in this study is expected to contribute both to the literature by unveiling the interactions between risk-related concepts and to the practitioners by assisting them in assessing the project risks more realistically. Although the risk quantification model has been developed for mega construction projects, it can also be implemented in other project-based industries with minor modifications.

Keywords: Risk, Complexity, Uncertainty, Analytic Network Process, Mega construction projects, Management strategies

1. Introduction

Risk management is a process of identifying, analyzing, responding, and monitoring events or conditions that have an effect on project objectives (Project Management Institute [PMI], 2017). In terms of contributions to their performance objectives, it has particular importance for construction projects characterized by large capital investments, long durations, a multitude of resources, a high number of stakeholders, volatile environments, and a high level of complexity (Cagliano et al., 2015). Therefore,

analyzing the risks that stem from these characteristics is a critical task in managing construction projects, especially large-scale ones (Chapman, 2016; Sanchez-Cazorla et al., 2016). In this respect, several quantitative techniques, such as probability and impact rating, Monte Carlo simulation, analytic hierarchy process (AHP), and fuzzy sets, are available for project risk assessment (Jung and Han, 2017).

Even though the risk is a widely discussed topic in the literature and several knowledge artifacts exist about managing risks in projects, the construction industry does not have a good reputation in terms of risk management practices (Taroun, 2014). Risk management is usually perceived as a “tick-the-box exercise” rather than a value creation process (Willumsen et al., 2019). The mechanically performed activities in traditional risk management practices lead project managers to focus on familiar, measurable, and controllable risks (Kutsch et al., 2014). However, the inefficiency of these practices in treating the risks emerging from unfamiliar sources hinders the wider adoption of risk management as a value-adding process. Thus, risk management practices are not frequently employed in the daily routine of even large and complex projects (de Carvalho and Rabechini Junior, 2015).

The gap between the theory and practice may be related to the disintegrated risk management approaches (Kardes et al., 2013). Poor conceptualization of risk-related factors, such as complexity and uncertainty, may result in inadequate risk models and, consequently, decrease the belief in practical benefits of risk management. As a risk source, the role of uncertainty in risk analysis has been highlighted by many researchers, such as Okudan et al. (2021), whereas the efforts aimed at handling complexity within a structured risk model are scarce. The existing knowledge sources in project management literature fall short of explaining how complexity can be integrated into risk quantification models along with uncertainty (Dikmen et al., 2021; Thomé et al., 2016). For this reason, traditional approaches are often criticized for not being effective under high complexity (Baccarini, 1996; Cicmil et al., 2006; Haimés, 2018; Thamhain, 2013). The ever-increasing complexity in construction projects requires new risk quantification approaches that account for the interactions between risk-related concepts (Eyboosh et al., 2011; Qazi et al., 2016).

Disintegrated risk management approaches may be one of the reasons why many large-scale construction projects underperform (Dimitriou et al., 2013; Flyvbjerg et al., 2003). Developing a holistic

risk model is especially important for megaprojects since they are not only exposed to more and greater risks but also characterized by complexity and uncertainty as a result of their structural properties (Boateng et al., 2015; Hu et al., 2015). Having cost figures reaching billions of dollars is one of the most prominent features of megaprojects (Flyvbjerg, 2014). Due to their physical size, megaprojects also require an enormous amount of resources (Biesenthal et al., 2018). Moreover, they usually have complex contractual arrangements that involve diverse stakeholders (Wu et al., 2018). Attracting a high level of public and political interest due to their impact on the “environment,” “ecology,” “economy,” “neighboring communities,” and “property owners” is another important aspect of megaprojects (Chapman, 2016). They are also the source of social and environmental concerns, including “anti-corruption,” “ecological protection,” “disaster mitigation,” “immigrant settlement,” “occupational health and safety,” “pollution control,” and “poverty eradication” (Ma et al., 2017). The presence of all these features makes it more challenging to achieve the performance objectives of megaprojects (Erol et al., 2020). For this reason, the success of a megaproject depends considerably on how well risk-related concepts are addressed during the decision-making processes (Dimitriou et al., 2013; Giezen, 2013; Kardes et al., 2013).

This study, therefore, aims to develop a risk quantification model for mega construction projects by integrating risk-related concepts. For this purpose, an Analytic Network Process (ANP) model incorporating the relationships between risk-related concepts was proposed. The weights of the risk sources in the ANP model were determined by the domain experts through a two-round Delphi study. The Delphi study was supported by an interactive data collection tool developed for this research to facilitate the ANP applications. After the model development, its risk quantification performance was tested with the data of 11 mega construction projects.

The remainder of the paper is organized as follows. Section 2 presents the research background on the relationships between risk-related concepts. In Section 3, an integrated risk assessment approach that constitutes the theoretical base of this study is introduced. Section 4 reviews the basic concepts of ANP. The steps of research methodology for developing an ANP-based risk quantification model are described in Section 5. Section 6 summarizes the research findings and discusses their implications. In Section 7,

studies performed to test the validity of the model are explained. Finally, Section 8 concludes the paper by presenting the contributions, limitations, and possible future research directions.

2. Relationships between risk-related concepts

Project Management Body of Knowledge (PMBOK) Guide (PMI, 2017, p. 720) defined risk as “an uncertain event or condition that, if it occurs, has a positive or negative effect on one or more project objectives.” This definition conceptualizes uncertainty as a source of risks. Uncertainties that may trigger risk events in projects can be categorized into two main groups. The “aleatory uncertainty” refers to stochastic variations in the future state of a parameter, whereas the “epistemic uncertainty” pertains to vagueness caused by imperfect information or lack of knowledge (Aven, 2016). Therefore, from the project management point of view, the former means uncertainty about the future, while the latter represents vagueness about the project.

On the other hand, as a risk source, the role of complexity is usually underestimated in the project management literature. The reason why complexity is not as closely associated with risk as uncertainty may be related to the fact that complexity is not a readily understood concept. There are different approaches in the literature to describe complexity. From the system perspective, complexity refers to the difficulty in understanding, describing, or controlling not only the functioning of the system but also its dynamic behavior (Kiridena and Sense, 2016). Such systems are often called the complex System of Systems (SoS). According to Haimes (2018), a complex SoS comprises several “interdependent and interconnected” systems with intrinsic characteristics. The SoS perspective may be valid for the projects as well. Nowadays, many construction projects can be considered as complex systems that include various “processes,” “activities,” “players,” “resources,” and “information,” which are dependent on each other (Zhu and Mostafavi, 2017). The existence of interwoven structures makes the behavior of these systems unpredictable because understanding the individual components is usually not enough to comprehend the overall functioning of the project system. Moreover, the fact that projects are “socially constructed entities” affected by the actions of diverse participants increases the dynamic behavior further (Whitty and Maylor, 2009). From the project management perspective, complexity can be defined as “the property of a project

which makes it difficult to understand, foresee and keep under control its overall behaviour, even when given reasonably complete information about the project system” (Vidal and Marle, 2008, p.1101). For this reason, both complexity and the actions taken to deal with it may affect the project objectives and thus result in risk events.

The review of uncertainty and complexity concepts suggests that they might affect the risk events in a similar manner. However, conceptual similarities between uncertainty and complexity caused the intermingling of these terms in the project management literature (Padalkar and Gopinath, 2016). In this respect, two main research approaches have been raised to explain their causality. According to the first school of thought, uncertainty is a driver of project complexity (Dunović et al., 2014; Geraldi et al., 2011). It may lead to more dynamics and interactions that increase the overall complexity level in the project system. In contrast to this view, some studies considered uncertainty as a consequence of project complexity (Florice et al., 2016; Vidal and Marle, 2008). Researchers of this stream believe that complexity may result in a more unpredictable project system, which increases uncertainty. There is also a lack of consensus regarding the relationship between complexity and risk. In some studies, complexity was accepted as the source of risk events (Qazi et al., 2016) while it was conceptualized as the outcome of project risk in some other studies (Bosch-Rekvelde et al., 2011). All of these perspectives explaining the relationships between risk-related concepts have merit, and they may help to model their interactions in a reliable way, which is one of the aims of project risk management. However, project management literature lacks the structured synthesis of these concepts as complexity, uncertainty, and risk are not treated from an integrated and holistic perspective (Thomé et al., 2016). More comprehensive risk models towards capturing the interactions between various risk sources may enable project managers to establish more realistic risk pictures. Therefore, there is a need for more research effort to develop new risk management approaches that can account for the interdependencies between risk-related concepts.

Although the issue of interdependency has been mentioned by several studies in the project risk management literature, they have usually focused on the relationship among individual risk factors. For example, Fang et al. (2012) utilized the network theory to reflect the interactions between risk factors and

compared the topological analysis with the traditional risk rating based on probability and impact scores. Ackermann et al. (2014) used causal maps in group decision-making to elicit the impact of the risk interactions from the point of view of diverse stakeholders. Yildiz et al. (2014) developed a “knowledge-based risk mapping tool” that analyzes various risk paths to estimate the cost of international construction projects. Zhang (2016) proposed an optimization model to select the most appropriate risk response strategies considering the interdependencies in a risk network. Qazi and Dikmen (2019) utilized a data-driven Bayesian Belief Network (BBN) methodology to model the interactions in a risk network. Yazdani et al. (2019) developed a fuzzy ANP model to reflect the relationships among “technical,” “external,” and “internal” risk factors in construction projects. In terms of modeling the relationships between risk-related concepts, on the other hand, there are only a limited number of studies in the literature. The Project Complexity and Risk Management (ProCRiM) process proposed by Qazi et al. (2016) addressed the interdependency between complexity and risk through BBNs. According to the ProCRiM process, project complexity elements constitute the source of various risk factors, which affect the project objectives and overall utility. Furthermore, Dikmen et al. (2021) proposed a meta-modeling approach that combines BBNs and artificial neural networks to capture non-linear interactions among the “complexity-uncertainty-performance triad” in construction projects. Nevertheless, these studies may not be comprehensive enough to model the network structure among the various risk sources particular to megaprojects. Due to their unique features, megaprojects require effective risk management practices that incorporate risk-related concepts (Kardes et al., 2013).

In order to fulfill this gap, this study proposes an analytical risk quantification model that considers the relationships between these concepts. For this purpose, a conceptual risk assessment process developed by the authors for mega construction projects was taken as the basis. The following section summarizes the main ideas of this process. For more detailed information, interested readers may consult Erol et al. (2020).

3. Integrated Risk Assessment Process (IRAP)

The glossary of the Society for Risk Analysis (SRA, 2015, p. 8) defined risk assessment as a “systematic process to comprehend the nature of risk, express and evaluate risk, with the available

knowledge.” Accordingly, a holistic risk assessment process that can integrate the concepts mentioned in Section 2 may facilitate modeling risks in a project. The Integrated Risk Assessment Process (IRAP) has been developed for this purpose to conceptualize the relationships between risk-related concepts more realistically (Erol et al., 2020). Fig. 1 depicts the process diagram of IRAP.

Fig. 1: Integrated Risk Assessment Process (IRAP)

IRAP starts with identifying the risk sources (complexity and uncertainty) of the project. At the commencement stage, the complexity factors can be identified by analyzing the characteristic features of the project, such as size, number of stakeholders, and technical difficulty. These factors constitute the “static complexity” of the project. Similarly, based on the existing knowledge and experience of the project management team, some uncertainty factors can be identified at the front end of the project. The second step of IRAP is formulating management strategies for the identified factors. The aim of these strategies is both to facilitate the management of complexity and uncertainty and reduce their magnitude in the project. However, strategies formulated to deal with the existing factors may trigger the emergence of new risk sources leading to secondary risks. For this reason, there is an iterative process between the first and second steps of IRAP. While the outcome of the traditional assessment methods is usually a risk checklist, the iterative process of IRAP is expected to result in a network that maps risks to complexity and uncertainty factors, together with the strategies formulated to manage them. The last step of IRAP is analyzing the constructed risk network. The network analysis is a crucial step of IRAP since it enables project managers to rate the risk sources by considering the interdependencies between various factors. Different analytical techniques can be utilized to analyze the factors in the risk network. The analysis could help to prioritize the risk sources, update previous strategies, and develop resilience strategies to recover from the adverse impact of identified risks as quickly as possible. As the precautions taken based on the network analysis may introduce new risk sources, there is a feedback loop to repeat the previous steps prior to the finalization of IRAP. Moreover, IRAP is based on analyzing the project risks with information available at a specific time. As the project progresses, a “dynamic complexity” may emerge due to the changes in the existing factors or the involvement of new ones. Similarly, uncertainties identified in the beginning may decrease,

or new uncertainty factors can appear. The dynamic nature of the projects also requires updating the existing management strategies as well as formulating new plans. Therefore, IRAP should be repeated periodically throughout the project.

Consequently, IRAP illustrated in Fig. 1 suggests a risk assessment approach for mega construction projects by integrating risk, complexity, uncertainty, and management strategies concepts. It should be noted that although IRAP has not been practically tested in past studies, it has been developed specifically for mega construction projects by exposing the necessity of using an integrated risk management approach. While the traditional risk assessment techniques are based on estimating the probability and impact of unknowns, IRAP promotes analyzing the static and dynamic complexity factors, together with the uncertainty factors, as potential risk sources in the project. In this way, it facilitates the exploration of all possible risk causes in the assessment process. Moreover, as distinct from the traditional risk management approaches composed of successive phases of identification, analysis, and response, IRAP incorporates the management strategies into all phases of the risk assessment process. Thus, it allows to identify and analyze the factors associated with the risk response actions. For these reasons, IRAP was selected as the theoretical base of this research.

As IRAP propounds a network structure among risk-related concepts, developing a network-based analytical model aligns with the risk assessment approach advocated in this study. In this respect, IRAP was operationalized via an ANP-based risk quantification model that prioritizes the risk sources. The following section presents a brief review of the basic concepts of ANP.

4. Basic concepts of ANP

ANP is a generalized form of AHP used in multi-criteria decision-making problems (Mu et al., 2020). While AHP is useful for hierarchical decision-making problems, ANP can model network structures as well (Saaty, 2005). Therefore, it has been applied to various decision-making problems in the project management domain, such as contractor selection (Cheng and Li, 2004), project selection (Grady et al., 2015), supplier selection (Lin et al., 2015), performance evaluation (Tohumcu and Karasakal, 2010),

stakeholder evaluation (Wang et al., 2018), quality improvement (Büyüközkan and Öztürkcan, 2010), and risk prioritization (Cao and Song, 2016).

The components of an ANP model comprise interconnected clusters and their elements. In order to determine the relative importance of the model components, they need to be compared in pairs (Saaty and Vargas, 2013). The pairwise comparisons serve to rate how many times more dominant is the given component than the compared component with respect to a specific criterion or attribute, usually called the “control criterion” (Saaty, 2005; Saaty and Vargas, 2013). The rating process is often performed by a group of experts on Saaty’s nine-point scale (Saaty, 2005). Accordingly, an expert has three possible options for the pairwise comparisons: Selecting the first alternative, selecting the second alternative, or considering them equally important. While the last option takes the value of “1,” the other options have to be rated according to Saaty’s nine-point scale. The local priorities of the compared alternatives are calculated over the comparison matrices derived from the pairwise comparisons. For this purpose, the priorities vector is obtained with matrix algebra shown in Eq. (1).

$$\hat{A} \cdot \vec{p} = \lambda_{\max} \cdot \vec{p} \quad (1)$$

where \hat{A} is the comparison matrix, λ_{\max} is the principal eigenvalue of the matrix \hat{A} , and \vec{p} is the priorities vector.

The consistency ratio of a comparison matrix is another critical aspect related to the ANP calculations. In order to achieve a higher degree of reliability in the model, selections of the expert must be sufficiently consistent. For this reason, the consistency ratio of a comparison matrix should remain within a specific limit (Saaty, 2005). Calculation of the consistency ratio involves a two-step process. The first step is calculating the consistency index according to Eq. (2).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (2)$$

where CI is the consistency index, λ_{\max} is the principal eigenvalue of the comparison matrix, and n is the size of the square comparison matrix.

In the second step, the consistency ratio is calculated by dividing the consistency index with the corresponding random index value, as shown in Eq. (3).

$$CR = \frac{CI}{RI} \quad (3)$$

where CR is the consistency ratio, and RI is the value of the random index.

The random index comprises the experimental values proposed by Saaty (1980) for different matrix sizes. For a perfectly consistent comparison matrix, the consistency ratio calculated by Eqs. (2) and (3) should be 0.

When the required consistency is satisfied for each comparison matrix, global priorities of the model components are calculated through three-step supermatrix operations. A supermatrix is a two-dimensional matrix constructed by bringing the elements of different matrices together (Saaty, 2005). In this respect, the first step is constructing the unweighted supermatrix by placing priorities vectors in the appropriate columns. This process serves to get global priorities through a single supermatrix by gathering the local priorities from the comparison matrices. The second step is converting the unweighted supermatrix into a weighted supermatrix by multiplying its values with the corresponding cluster weights. The cluster weights are determined by the pairwise comparisons of the related clusters. The weighted supermatrix is a column stochastic matrix, where values at each column add up to one (Saaty and Vargas, 2013). Finally, the weighted supermatrix is transformed into a limit supermatrix in the third step. In order to build this matrix, the weighted supermatrix has to be raised to the powers until all columns are stabilized (Saaty and Vargas, 2013). As a result of these operations, a limit supermatrix that unveils the relative importance weights for every component in the ANP model is obtained. The next section describes the methodology employed to develop the ANP-based risk quantification model of this research.

5. Research methodology

Fig. 2 demonstrates the steps of the research methodology. First, an ANP model was built by linking the themes of IRAP. Based on this model, comparison sets for the pairwise comparisons of the components were determined. Then, a two-round Delphi study was conducted with the domain experts. In the first

round, pairwise comparisons of the experts were acquired separately through questionnaires. In the second round, a panel was organized to reach a consensus among the experts. In order to facilitate the knowledge elicitation process in the Delphi study, a spreadsheet-based data collection tool capable of performing the ANP calculations was developed. Finally, by using consolidated results from the Delphi study, the ANP supermatrix calculations were made to obtain weighted parameters to be rated during the risk assessment of mega construction projects. The following sections elaborate on the steps of the research methodology.

Fig. 2: Research methodology

5.1. Development of the ANP model

The analytical model proposed in this study seeks to operationalize the conceptual risk assessment process introduced in Section 3. In this respect, the risk, complexity, uncertainty, and management strategies themes of IRAP constituted the main components of the ANP model. Then, a risk assessment model was developed by establishing links between these four themes. The overview of the proposed model is shown in Fig. 3.

Fig. 3: ANP model

Although the analytical model presented in Fig. 3 basically has a hierarchical structure, the interlinks between the management strategies and other main clusters turn it into a network structure. The node at the highest level of the hierarchy indicates that measuring the overall risk of a mega construction project is the primary goal of the model. The risk score is calculated over eight risk factors. Country-related political and economic risks (R1), financial risks (R2), contractual risks (R3), owner-related risks (R4), procurement risks (R5), project management and organization risks (R6), construction-related/technological risks (R7), and design risks (R8) represent the typical risk factors in mega construction projects (Erol et al., 2020). These risk factors are connected to three main clusters. In accordance with IRAP, complexity, uncertainty, and the secondary risks stem from the management strategies are the main sources of the risk events.

The complexity cluster is composed of 17 factors under the technical (T), organizational (O), and environmental (E) categories. These categories were selected based on the TOE framework, developed by Bosch-Rekvelde et al. (2011) for large engineering projects. Nonetheless, the complexity factors in the

original framework were reduced by identifying the most relevant items for mega construction projects (Erol et al., 2020). Accordingly, size of the project (C1), variety of financial institutions or sponsors (C4), inadequacy of the contract (C6), unavailability of resources (labor, material, equipment) (C10), interactions between the project disciplines (C11), cultural diversity (C12), and staff and equipment mobility (C14) are related to organizational complexity. Lack of technical experience (C7), changes in the project scope (C8), unrealistic project targets (C9), multiple critical paths (parallel activities) (C13), technological novelty of the project (C16), and originality of the project design (C17) represent technical dimension. Finally, strategic importance of the project (C2), political or macroeconomic instability (C3), interactions between the stakeholders (C5), and physical and logistic constraints (C15) reflect environmental issues.

The uncertainty cluster contains two main categories according to the uncertainty types classified by Aven (2016). While uncertainty about the future (U1) refers to stochastic variations or randomness in the future state of the parameters (aleatory uncertainty), vagueness about the project (U2) pertains to ambiguity caused by imperfect information or lack of knowledge about the project parameters (epistemic uncertainty).

Management strategies cluster, on the other hand, reflects two distinct approaches categorized by Koppenjan et al. (2011) to address the complexity and uncertainty. The flexibility strategy (S1) is based on the “prepare-and-commit” approach that focuses on responsiveness and adapting to the changes that happen in different stages of the project. In contrast, the control strategy (S2) has the “predict-and-control” perspective with a more rigid and detailed plan to be followed throughout the project.

Consequently, the overall risk of a mega construction project can be calculated by rating the parameters at the lowest level of the hierarchy. These parameters, consisting of 17 complexity factors and two uncertainty categories, are the risk sources of the project. Even though management strategies are not the parameters to be rated during the risk assessment, they constitute the network structure of the model by linking the other parameters. According to this structure, initially, the effectiveness of the flexibility and control strategies on the eight risk factors are evaluated. Then, the contribution of the three complexity and two uncertainty categories to risk factors are compared separately when flexibility or control strategies are implemented. Thus, management strategies influence the weights of the complexity and uncertainty

categories in the risk assessment model. Furthermore, since the implemented strategies affect the magnitude of complexity or uncertainty, they need to be considered during the rating of the risk sources as well.

Although the analytical model presents a comprehensive risk quantification approach for mega construction projects by integrating risk-related factors, there were some assumptions to simplify the application of ANP. These assumptions are listed as follows:

- i. The relationship between complexity and risk was established by connecting the risk factors to the three complexity categories only. If they had been linked to the 17 complexity factors, the number of pairwise comparisons would have increased significantly.
- ii. The possible relationships among the three complexity categories were not taken into account.
- iii. Uncertainty was represented by two generic categories only. Nevertheless, it is possible to define new factors under these categories by distributing their weights to the associated factors.
- iv. The relationship between complexity and uncertainty was set through management strategies. The possible direct interactions between them were ignored.
- v. Management strategies refer to all actions taken for either complexity, uncertainty, or risk. However, the direct impact of management strategies on the complexity and uncertainty was not evaluated during the pairwise comparisons since they were not linked to the complexity and uncertainty categories with two-way arrows. In other words, the effectiveness of the flexibility and control strategies were considered only for the risk factors induced by complexity and uncertainty.

In order to determine the weights of the parameters in the ANP model, they need to be compared with each other. Based on the links between these parameters, 122 pairwise comparisons that constituted the 34 comparison matrices under 11 comparison sets were identified.

5.2. Delphi study with an interactive data collection tool

Following the development of the ANP model, the comparison sets were evaluated by five domain experts with a two-round Delphi study. Using the geometric mean of the questionnaire data or conducting a Delphi process are convenient ways of expert knowledge elicitation in ANP studies (Kheybari et al., 2020). Although the geometric mean approach has certain advantages in terms of achieving the consistency

of the comparison matrices (Aull-Hyde et al., 2006), a Delphi study consisting of successive rounds can ensure the consideration of multiple viewpoints and prevent possible misunderstandings (Hallowell and Gambatese, 2010). In this study, the latter was adopted to build an analytical model with the consensus of the experts. Delphi method is a flexible way of collecting expert opinions through successive rounds of questionnaires and feedback (Vidal et al., 2011). For this reason, it has been frequently used in ANP-based research studies (Afzal et al., 2020; He et al., 2015; Hsu et al., 2011; Karamoozian et al., 2019; Valipour et al., 2015).

The expert group consisted of a risk management consultant, a lead project management specialist, a senior project manager, an assistant professor, and a professor. The average experience of the expert group in the construction industry was 17.4 years. While the industry practitioners had expertise in preparing risk management plans for large-scale construction projects, the academic experts giving consultancy and training services to construction companies were highly experienced in project risk management. Although using a high number of experts is suitable for the Delphi studies based on surveys only, it may be inconvenient for the expert panels (Li et al., 2019). Moreover, the qualification of the experts is considered more important than their numbers (Dikmen et al., 2010). Thus, owing to their experience and knowledge, the pairwise comparisons elicited from these experts are believed to be reliable for determining the weights of the ANP model.

In the first round of the Delphi study, the questionnaire that contains the 122 pairwise comparisons in the ANP model was sent to the experts separately. The experts answered the questions via a spreadsheet-based data collection tool developed to facilitate the comparison procedure. The tool was capable of performing the ANP calculations as well. Implementing the ANP studies with standard questionnaire forms could be a tedious process. Furthermore, they lack a feedback mechanism to warn the respondents against the inconsistency in the pairwise comparisons. On the other hand, despite the existence of commercial ANP software, such as Super Decisions, Expert Choice, and Decision Lens, they may not be accessible or applicable to all experts. The spreadsheet-based tool could be practically used without any requirement for prior knowledge. Moreover, it was specifically designed for this study to inform the experts about the ANP

model and guide them for the pairwise comparisons. The index page of the tool involved general explanations about the ANP model and links to the 11 comparison sets. Furthermore, experts were provided with more detailed information about the operations they are required to perform on the screen of each comparison set.

Following the instructions in the data collection tool, each expert answered the pairwise comparison questions on Saaty's nine-point scale. The data collection tool was designed to assist the experts in making the selections for each comparison set. Fig. 4 exemplifies the pairwise comparisons in one of these sets. The data collection tool was also capable of alerting experts in case of an invalid selection. For example, the pairwise comparison rating must be "1" if the compared alternatives are selected as equally important. Similarly, the rating cannot be "1" if they are not equally important.

Fig. 4: Pairwise comparison example in the data collection tool

As soon as the experts complete the pairwise comparisons of a comparison matrix, the data collection tool was showing the local priorities calculated according to Eq. (1). Although there are different methods to derive these priorities, such as the left eigenvalue, the geometric mean (logarithmic least squares), and the mean of the normalized values (Ishizaka and Lusti, 2006), the data collection tool has adhered to the principal right eigenvector approach of Saaty (2005). The accuracy of the priorities vector calculations has been confirmed by experiments in the Super Decisions software that uses the same approach. Fig. 5 illustrates the calculation of the priorities vector by the tool.

Fig. 5: Calculation of the priorities in the data collection tool

As shown in Fig. 5, the data collection tool was also capable of calculating the consistency ratio using Eqs. (2) and (3). In this study, the maximum acceptable value of the consistency ratio was selected 0.1 as recommended by Saaty (2005). Based on this number, the data collection tool was checking whether the comparison matrix is consistent or not. In case the pairwise comparisons result in a consistency ratio greater than 0.1, the tool was providing instant feedback for experts to reconsider their selections. Fig. 6 exemplifies the warning message given in case a high consistency rate is calculated.

Fig. 6: The feedback given by the data collection tool for the consistency ratio

Consequently, the first round was concluded by collecting the questionnaires answered by the experts. Since there are three possible options for the pairwise comparisons, four categories were identified related to the selections of the experts in the first round. In Category A, all experts prefer the same option. According to Category B, four experts select the same option, while the other expert picks another option. In Category C, there is an option chosen by three experts. The remaining two experts may either select the same alternative option or favor different alternatives. Finally, Category D contains the two options chosen by two experts and the other option preferred by the fifth expert.

In the second round of the Delphi study, an online panel was conducted with the experts who participated in the first round. Prior to the meeting, all pairwise comparisons made in the first round were shared with the experts to provide information about the other selections. The aim of the panel was to build a consensus among the participants. In particular, they were expected to reach an agreement on the comparisons selected differently in the first round. According to the results in the first round, at least four experts selected the same option in 68% of the pairwise comparisons. For these comparisons, the consensus was reached rather quickly. Experts suggested using the average of the initial ratings for the comparisons that belong to Category A. With a few exceptions, the majority opinion was accepted for the comparisons that included two alternative options in both Category B and some parts of Category C. On the other hand, there were also comparisons that contained three alternative options in Category D and some parts of Category C. The discussions for these items took more time to settle. When the experts agreed on the comparisons, their selections were immediately entered into the data collection tool to check the consistency ratio. For a few comparisons that the experts remained unsettled, different alternatives were tried in the tool to inform them about the consistency of these alternatives. As a result of the expert panel that took approximately two hours, the pairwise comparisons of the experts were refined in a consistent manner.

5.3. Supermatrix calculations

The two-round Delphi study resulted in 34 consolidated comparison matrices under 11 comparison sets. The priorities vectors in these matrices were utilized to calculate the weights of the parameters in the ANP model for risk quantification. For this purpose, three-step supermatrix operations explained in Section

4 were applied. First, a 33 by 33 unweighted supermatrix was constructed. The rows and columns of this matrix were composed of 17 complexity factors (C1 to C17), three complexity categories (T, O, and E), two uncertainty categories (U1 and U2), two management strategies (S1 and S2), eight risk factors (R1 to R8), and the overall risk of the mega construction project (OR). Then, the weights calculated for the complexity, uncertainty, and management strategies clusters were multiplied with the related columns of the unweighted supermatrix to develop a weighted supermatrix. Thus, a column stochastic matrix was obtained, where the summation of values in each of the 33 columns became one. Finally, the weighted supermatrix was raised to powers until it converges. In this study, values of the weighted supermatrix were stabilized after taking its fourth power. The resulting limit supermatrix revealed the relative importance weight of each component in the model.

It should be noted that, while constructing the supermatrices, it was assumed that a sink parameter depends only on itself, as suggested by Saaty and Vargas (2013) for the hierarchical models. For this reason, the value of 1 was put on the supermatrix positions where 17 complexity factors and two uncertainty categories have the same row and column numbers. The accuracy of the supermatrix calculations was validated using the “identity at sinks” algorithm of the Super Decisions software. Findings derived from these calculations are discussed in the next section.

6. Results and discussions

The unweighted supermatrix constructed by priorities vectors is tabulated in Table 1.

Table 1: The unweighted supermatrix

The values in the unweighted supermatrix show the impact of the components on each other. For instance, values in the OR column represent the contribution of each risk factor to the overall risk of a mega construction project according to the local priorities derived from the first comparison sets. These values demonstrate that experts place more emphasis on the external risk factors, such as R1 and R2, which are usually beyond the control of project management. In contrast to uncontrollable factors, the technical risks, such as R7 and R8, were determined to be less important in terms of their contribution to the overall mega construction project risk.

The priorities obtained from the comparison matrices of the second and third sets indicate the contribution of two uncertainty and three complexity categories to each risk factor. Accordingly, U1 was a more influential uncertainty type for R1 and R2. In other words, uncertainty caused by stochastic variations was considered a more important source for the external risk factors. On the other hand, U2 was more significant than U1 for most of the risks. In particular, R8, R3, and R7 were more closely associated with the uncertainty caused by the lack of knowledge about the project system. The experts evaluated the impact of U1 and U2 on R5 as equal. In terms of complexity categories, environmental complexity was more significant for the external risk factors (R1 and R2), whereas technical complexity was more impactful for the technical risk factors (R7 and R8). For the remaining risk factors, organizational complexity was selected as the most significant category. It had the highest contribution percentage for the managerial and organizational risks (R6) in particular. These results propound that each complexity category has a more intense interaction with certain risk factors.

The contribution of 17 complexity factors to their respective categories was measured through fourth, fifth, and sixth comparison sets. Table 1 shows that C8 was the top factor that increases the technical complexity of mega construction projects. On the other hand, factors more closely related to the construction operations, such as C16 and C17, were considered less significant. However, as C7 had the second-highest percentage, the results also indicate that technical complexity is amplified when the technical experience is insufficient. For the organizational factors, C1 had the highest percentage, which implies that the magnitude of a mega construction project is the top contributor to the organizational complexity. C11 was another significant organizational complexity indicator. The impact of C12 and C14, on the other hand, was evaluated as considerably low. Finally, for the environmental complexity, C3 was the most significant factor. This result reveals that political and economic factors contribute more to the environmental complexity of mega construction projects. C5, which is related to the internal dynamics of the projects, was the second most important environmental complexity indicator. While the impact of C2 was limited, C15 was the least significant factor.

The seventh comparison set shed light on the effectiveness of two opposing approaches in managing different risk factors in mega construction projects. The unweighted supermatrix demonstrates that S1 was a more effective strategy, especially for R1 and R2. It means that developing flexible approaches for adapting to the changes was considered more appropriate for uncontrollable risk factors. Since the external conditions affect the procurement, too, the priority of S1 was higher for R5. On the other hand, S2 was more effective than S1 for R3, R6, R7, and R8. In particular, the experts thought that a robust planning approach could be more useful for the managerial and organizational issues of the project. On the other hand, the effectiveness of S1 and S2 was considered equal for R4. When all findings are interpreted together, it can be deduced that these two strategies should be used in balance to manage different risk factors effectively.

In the eighth and ninth comparison sets, the experts evaluated the contribution of uncertainty and complexity categories to risk factors when different management strategies are implemented. According to the values in the unweighted supermatrix, U2 was a more influential risk source than U1 when S1 is the strategy used. In contrast, U1 was a more significant uncertainty type under the effect of S2. These results manifest that while the “predict-and-control” approach is more effective for epistemic uncertainty, the “prepare-and-commit” approach is better suited for aleatory uncertainty. On the other hand, environmental complexity was the most significant risk source for the complexity categories, regardless of the implemented strategy. However, there was a considerable reduction in its impact when S1 is the strategy used. Therefore, flexible management strategies could be more effective in dealing with environmental complexity.

While the priorities that belong to the first nine comparison sets were utilized to build the unweighted supermatrix, the last two comparison sets served to obtain the cluster weights. In comparison set 10, the priorities calculated for complexity, uncertainty, and management strategies clusters with respect to their contribution to risks were 0.43303, 0.46647, and 0.10050, respectively. The findings strengthen the central argument of this research that complexity should be integrated into the risk assessment process since the experts assigned almost equal importance to complexity and uncertainty in terms of their contribution to

risk factors. Moreover, the calculated priorities signify that one out of 10 risk events is a secondary risk that stems from management strategies implemented for other factors. Finally, in comparison set 11, complexity and uncertainty clusters were compared with respect to their contribution to risks caused by management strategies. As the experts placed equal emphasis on them, the priority calculated for complexity and uncertainty clusters was 0.5 for both. In other words, the secondary risks caused by management strategies implemented to deal with either complexity or uncertainty were expected to have the same frequency in mega construction projects. The complete form of the cluster matrix is presented in Appendix A.

As a result, based on the procedure explained in Section 5.3, the weighted supermatrix (Appendix B) was obtained, which in turn was converted into the limit supermatrix given in Table 2. The limit supermatrix contains the importance weights derived for 17 complexity factors and two uncertainty categories to assess the eight risk factors as well as the overall risk of a mega construction project.

Table 2: The limit supermatrix

Although each risk source has different weights in Table 2, political or macroeconomic instability (C3), interactions between the stakeholders (C5), and size of the project (C1) were determined as the most influential complexity factors for the overall risk of a mega construction project. Among the uncertainty categories, the overall impact of the uncertainty about the future (U1) was higher. Even though the total weights of the complexity and uncertainty clusters were close to each other, as compared to the 17 complexity factors, U1 and U2 had higher weights since they represent a broader category. By summing up the values of the technical, organizational, and environmental factors, the weights of the complexity categories were calculated as 0.09642, 0.18516, and 0.20170, respectively. These numbers revealed that environmental complexity is the most significant complexity category for the overall risk, whereas the contribution of technical complexity is limited.

7. Testing and validation

The ANP model developed in this study helps to quantify the eight risk factors and overall risk of a mega construction project over 17 complexity factors and two uncertainty categories. In other words, complexity and uncertainty constitute the input parameters, whereas risk is the output parameter. In order

to test the risk quantification performance of the model, the actual data of complexity and uncertainty should be fed into the model, and the risk score calculated by the model should be compared with the real risk data. For this purpose, validation studies were conducted using the data of 11 mega construction projects constructed by Turkish contractors. Complexity, uncertainty, and risk data used in the analysis were collected from the senior managers of these projects on a five-point Likert scale through retrospective analysis. Descriptive information about the projects is presented in Table 3.

Table 3: Mega construction projects examined in the validation studies

The actual data provided by the project managers for 17 complexity factors and two uncertainty categories were multiplied with the corresponding weights of the ANP model to calculate the scores of eight risk factors as well as the overall risk. Fig. 7 illustrates this procedure with the data of one of the projects (P2) examined for the validation studies. In this project, the magnitude assigned by the project manager for U2 on the five-point Likert scale was 4.00. This score was multiplied by the corresponding risk weights (written on the arrows connected to U2) obtained from the limit supermatrix to calculate the contribution of U2 to each risk factor. By performing the same calculations for all risk sources (17 complexity factors and two uncertainty categories) with their corresponding weights, the total score of each risk factor could be found. For example, the total score calculated for R1 by considering all risk sources was 2.55 out of 5.00, whereas the contribution of U2 to this score was 0.36. Similarly, the score calculated for each risk factor was multiplied by the general risk weights (written on the arrows connected to OR) obtained from the unweighted supermatrix to determine the overall risk score of the project (2.78) together with the share of U2 (0.91).

Fig. 7: Risk calculations of the example project

The risk scores estimated by the ANP model were compared with the risk assessment scores given by the project managers to test the risk quantification performance of the model. For the example project, the comparison of the risk scores assigned by the manager on the five-point Likert scale and estimated by the model is shown in Fig. 8. The numbers in parentheses indicate the error rate of the prediction.

Fig. 8: Risk prediction performance in the example project

The same operations were repeated for all of the projects given in Table 3. Accordingly, the percentage error of the model in predicting the risk score of each factor was calculated based on the average values obtained from 11 projects, as shown in Eq. (4).

$$RSPE_j = \frac{\frac{1}{m} \sum_{k=1}^m RA_{jk} - \frac{1}{m} \sum_{k=1}^m RE_{jk}}{\frac{1}{m} \sum_{k=1}^m RA_{jk}} \times 100 \quad (4)$$

where $RSPE_j$ is the percentage error of the model in predicting the score of risk factor j , RA_{jk} is the actual score of risk factor j at project k , RE_{jk} is the score of risk factor j at project k estimated by the model, and m is the number of projects, which is 11 in this study.

Table 4 shows the RSPE score calculated by Eq. (4) for each risk factor. According to these results, the prediction error of the ANP model was less than 10% for financial risks (R2), contractual risks (R3), procurement risks (R5), and design risks (R8). The model showed superior performance, especially in predicting the scores of design risks. Nonetheless, the accuracy of the model in predicting the scores of country-related political and economic risks (R1), owner-related risks (R4), project management and organization risks (R6), and construction-related/technological risks (R7) was not as good as other factors. In particular, the prediction error was greater than 20% for project management and organization risks and construction-related/technological risks. The poor performance of the model in quantifying some risk factors may be caused by the fact that participants of this study represented the perspective of the contractors only. For example, the reason why the average score of the owner-related risks estimated by the model was considerably less than the average score supplied by the participants could be explained by the bias of the project managers. In contrast to this factor, the score given by the model for the project management and organization risks was remarkably higher than the score assigned by the participants. The project managers might have underestimated the risk score of this factor as it is more closely associated with their performance. As the average risk score of eight factors may balance the impact of the over-scored or under-scored risk factors, an additional performance test was carried out based on the overall risk score of each project.

Table 4: Accuracy of the model in predicting the scores of risk factors

For the second test, the overall risk score of each project was calculated by taking the weighted average of the actual risk score for eight factors. These calculations were performed with the general risk weights shown in Fig. 7 so that comparisons can be consistent. Then, the overall risk scores calculated for each project were compared with those estimated by the model. Thus, the percentage error of the model in predicting the overall project risk score was calculated according to Eq. (5).

$$MAPE = \frac{1}{m} \sum_{k=1}^m \left| \frac{ORA_k - ORE_k}{ORA_k} \right| \times 100 \quad (5)$$

where MAPE is the mean absolute percentage error of the model in predicting the overall risk score of 11 projects, ORA_k is the actual overall risk score of project k , and ORE_k is the overall risk score of project k estimated by the model.

Table 5 displays the absolute percentage error (APE) of each project. Accordingly, most of the projects had an error rate of less than 10%. The MAPE calculated by Eq. (5) for all projects was 8.70%. When the highest (17.51%) and the lowest (1.07%) error rates were excluded, the MAPE was slightly reduced to 8.57%. Consequently, validation studies revealed the potential of the ANP model in quantifying the risks of mega construction projects. Although the performance of the model in terms of quantifying R1, R4, R6, and R7 was not as good as R2, R3, R5, and R8, the prediction accuracy was considered satisfactory for the overall risk of a mega construction project. Except for P3, the error rate was within reasonable limits for all projects.

Table 5: Accuracy of the model in predicting the overall risk scores of projects

8. Conclusions

Although risk, complexity, and uncertainty inherently exist in megaprojects, project management literature lacks structured risk modeling approaches integrating them. Thus, this study aimed to develop an ANP-based risk quantification model for mega construction projects based on a conceptual risk assessment process. The weights of the parameters in the ANP model were assigned through a two-round Delphi study conducted with the domain experts. The questionnaire data obtained via an interactive data collection tool

in the first round were refined through an expert panel in the second round. The resulting analytical model enabled the prioritization of the risk sources in mega construction projects. The performance of the ANP model was tested through the data of 11 mega construction projects. Validation studies revealed the potential of the proposed model in measuring the risks of mega construction projects.

This research can make theoretical and practical contributions to the body of knowledge. The main benefit of the ANP-based risk quantification model is that it provided a novel approach to account for the interrelations between the complexity, uncertainty, and management strategies during the risk assessment. While the traditional risk quantification techniques are usually based on analyzing the uncertainty factors as the source of risk events, the proposed model allows incorporating complexity into risk assessment by considering the mediating role of management strategies as well. It also provides more insights into the relationships between risk-related concepts. Local priorities derived from the comparison sets serve to interpret the conceptual links between risk, complexity, uncertainty, and management strategies through numerical values. Global priority weights, on the other hand, explain the combined impact of these links on different risk factors. Researchers can benefit from these findings to develop conceptual or analytical models for risk-related concepts. Moreover, the data collection tool introduced in this paper can be replicated by researchers to improve both the knowledge elicitation process and the reliability of the results in ANP-based future studies. In terms of practical contributions, the weights of the ANP model revealed the most significant risk sources in mega construction projects. The managers of mega construction projects can utilize the research findings to evaluate the factors to be included in their risk plans. Furthermore, they can customize the risk assessment approach proposed in this paper according to their projects. It can help them draw a more comprehensive risk picture by capturing the risks originated from both complexity and uncertainty as well as the secondary risks concerning management strategies. Hence, this study can pave the way for the adoption of project risk management by more practitioners.

Despite the contributions of this research, it also has some limitations. First of all, the analytical model was subject to assumptions described in Section 5.1 to simplify the application of ANP. A more detailed risk quantification model could capture all principles of IRAP more realistically. Secondly, risk scores were

calculated over the weights of 17 complexity factors and two uncertainty categories, determined based on the subjective judgment of the experts. Nonetheless, it is possible to customize the number of parameters and generic weights for project-specific applications by following the methodology described in this research. Another limitation could be related to the validation tests. Risk, complexity, and uncertainty are not the parameters that can be measured objectively. Even though the ratings for input and output parameters of the model were supplied by the same participants, they represent the subjective view of the project managers from the contractor's perspective only. Assessing the risks with the participation of more stakeholders may better reflect the risk levels in the projects and thus the validity of the model. Additionally, participants rated the parameters by considering the general situation in their projects. The complexity and uncertainty parameters assessed at a specific time of the project may represent the risks anticipated for that time frame more realistically.

This study also proposes future research directions. The practical benefits and shortcomings of the proposed risk quantification approach can be appraised through demonstrative case studies. Moreover, the findings reported for mega construction projects in this study can be compared with other projects undertaken in different sectors. Although IRAP was operationalized with an ANP model in this research, future studies can use other network-based quantitative methods, such as Bayesian networks, network theory, and system dynamics, to report their advantages and disadvantages over ANP. Future studies may also include developing decision support tools to facilitate the implementation of integrated risk assessment approaches. Finally, it should be noted that this paper is a part of a research and development project entitled “PRICOVIS: Development of a Computer-Based Tool for Visualization of Complexity and Risk in Mega Construction Projects.” The research findings form a basis to develop a computer-based visualization tool, which will provide a better understanding and management of complexity and risk encountered in mega construction projects. In this respect, the visualization of the interactions between risk-related concepts is a promising research topic.

CRedit authorship contribution statement

Huseyin Erol: Formal analysis, Methodology, Software, Validation, Writing - Original Draft. **Irem Dikmen:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing - Review & Editing. **Guzide Atasoy:** Conceptualization, Project administration, Writing - Review & Editing. **M. Talat Birgonul:** Funding acquisition, Project administration, Supervision.

Declaration of Competing Interest

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

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Appendix A

Table A.1: The cluster matrix

Appendix B

Table B.1: The weighted supermatrix

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Table 3: Mega construction projects examined in the validation studies

ID	Type	Cost (\$ Billion)	Start Year	Status
P1	Power plant	0.782	2016	In progress
P2	Transport infrastructure	1.200	2008	Completed
P3	Hospital	0.600	2015	Completed
P4	Hospital	0.300	2013	In progress
P5	Pipeline	0.413	2016	Completed
P6	Hospital	0.290	2014	In progress
P7	Airport	0.275	2014	Completed
P8	Pipeline	1.788	2002	Completed
P9	Transport infrastructure	3.600	2004	Completed
P10	Transport infrastructure	7.500	2013	Completed
P11	Power plant	0.632	2014	Completed

Table 4: Accuracy of the model in predicting the scores of risk factors

ID	RA	RE	RSPE (%)
R1	3.68	3.09	16.13
R2	2.82	3.06	-8.46
R3	3.32	3.14	5.44
R4	3.73	3.10	16.91
R5	2.91	3.08	-5.84
R6	2.50	3.10	-24.11
R7	2.50	3.01	-20.56
R8	3.09	3.02	2.38

Table 5: Accuracy of the model in predicting the overall risk scores of projects

ID	ORA	ORE	APE (%)
P1	3.21	3.40	5.38
P2	2.78	3.12	10.66
P3	2.81	3.41	17.51
P4	4.04	3.83	5.44
P5	2.03	2.32	12.79
P6	2.67	2.44	9.58
P7	2.86	2.69	6.23
P8	4.26	4.87	12.61
P9	2.75	2.69	2.23
P10	3.21	3.18	1.07
P11	3.29	3.75	12.24

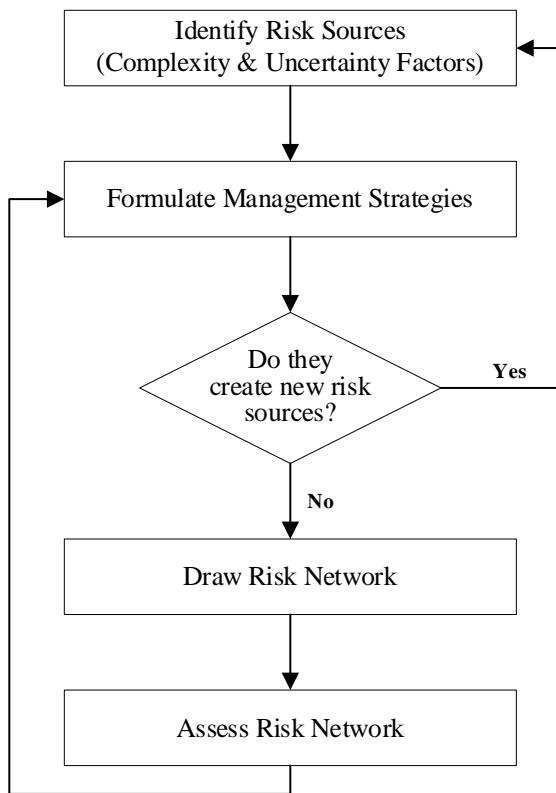


Fig. 1: Integrated Risk Assessment Process (IRAP)

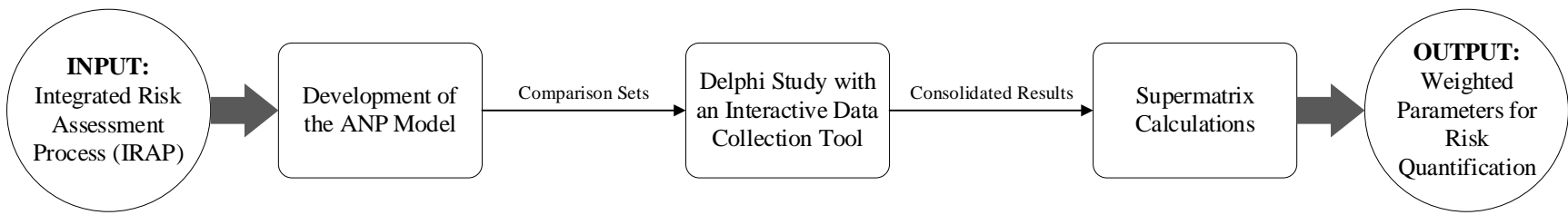


Fig. 2: Research methodology

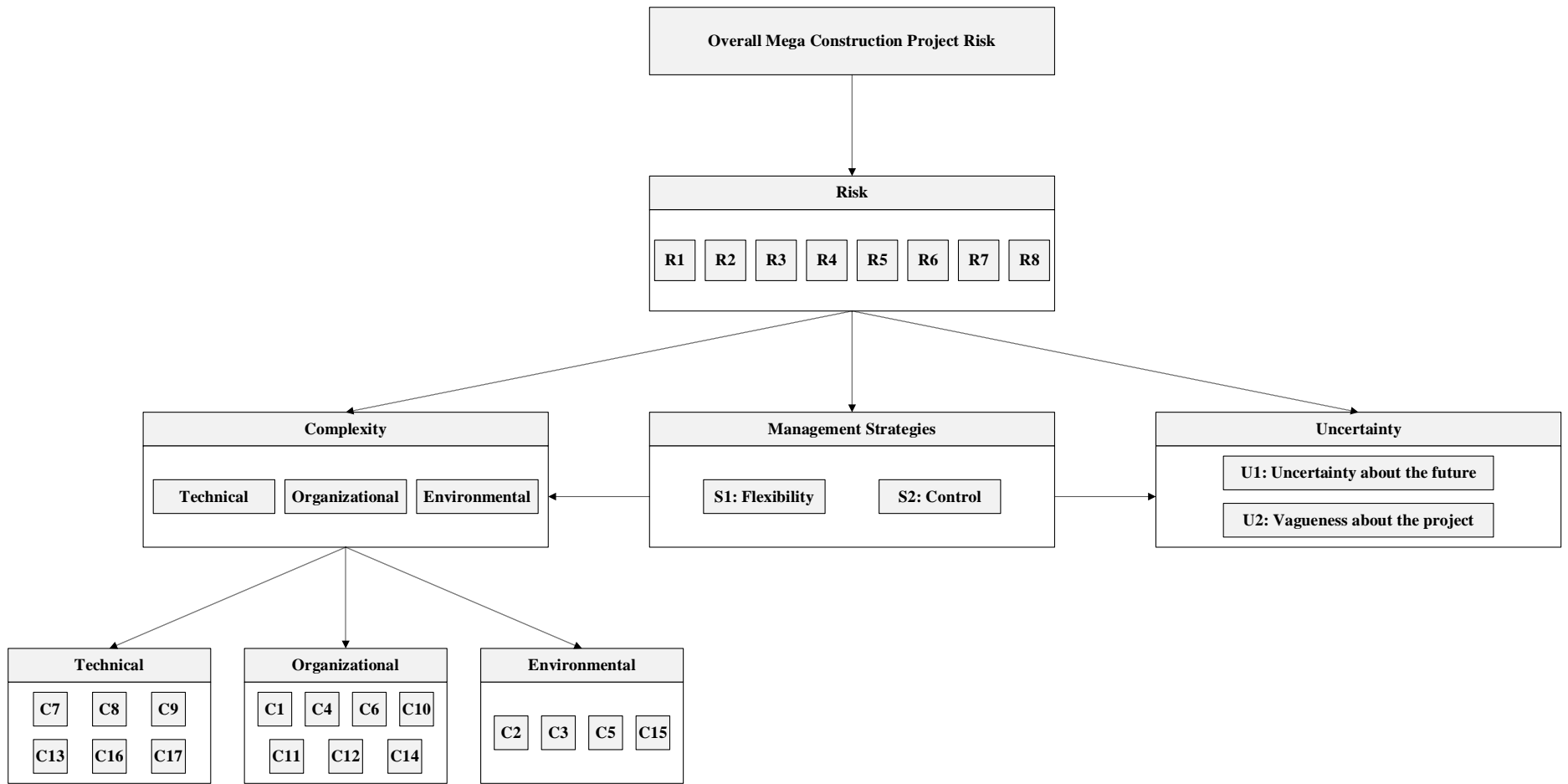


Fig. 3: ANP model

Pairwise Comparison of Environmental Factors with respect to Environmental Complexity			
<p>In this set, you are asked to compare the four environmental complexity factors based on their contribution to the environmental complexity. For each comparison alternative, please answer the questions in cells C4 and D4. You will see the priority weights (B13:B16) of each environmental complexity factor when you complete the selections. If you get a warning about the consistency ratio (B17), please reconsider your comparisons. Environmental Complexity Factors: C2: Strategic importance of the project, C3: Political or macroeconomic instability, C5: Interactions between the stakeholders, C15: Physical and logistic constraints</p>			
Compared Alternatives		Among the alternatives compared, which one has a more significant contribution to the environmental complexity?	How much more significant is the alternative you have selected when compared to the other? (1: Equally, 2: Equally to Moderately, 3: Moderately, 4: Moderately to Strongly, 5: Strongly, 6: Strongly to Very Strongly, 7: Very Strongly, 8: Very Strongly to Extremely, 9: Extremely)
C2	C3	Equal	1
C2	C5	C5	4
C2	C15	C2	5
C3	C5	C5	3
C3	C15	C3	6
C5	C15	Please select	Please select
		C5	2
		C15	3
		Equal	4
			5
			6
			7
			8
			9

Fig. 4: Pairwise comparison example in the data collection tool

Results	
C2	18.369%
C3	20.596%
C5	56.680%
C15	4.355%
Consistency Ratio	0.02920

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previous comparison

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next comparison

Fig. 5: Calculation of the priorities in the data collection tool

Results	
C2	22.812%
C3	25.947%
C5	35.350%
C15	15.892%
Consistency Ratio	0.75208

The consistency ratio must be smaller than 0.1. Please reconsider your selections for the pairwise comparisons!

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Fig. 6: The feedback given by the data collection tool for the consistency ratio

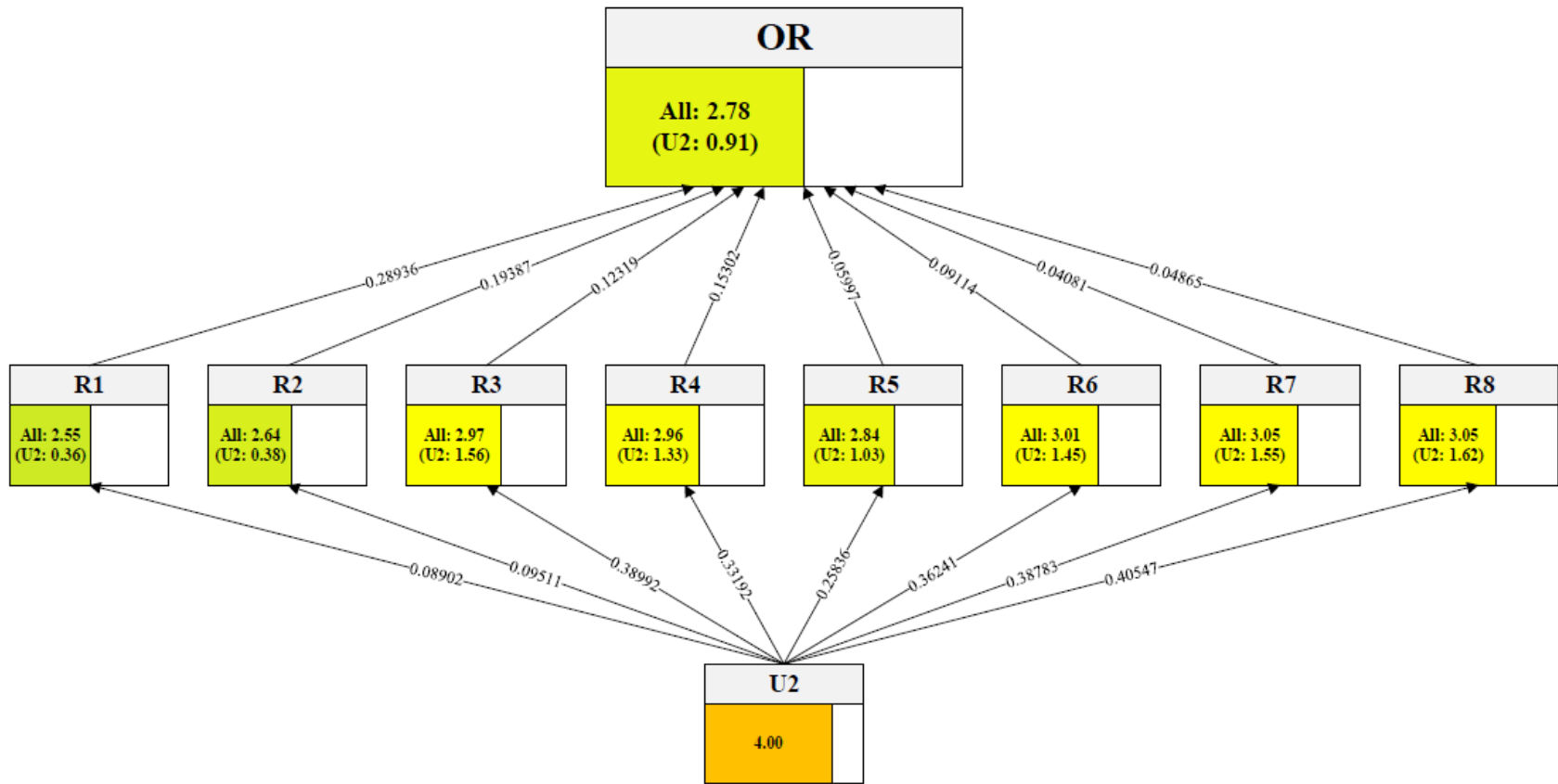


Fig. 7: Risk calculations of the example project

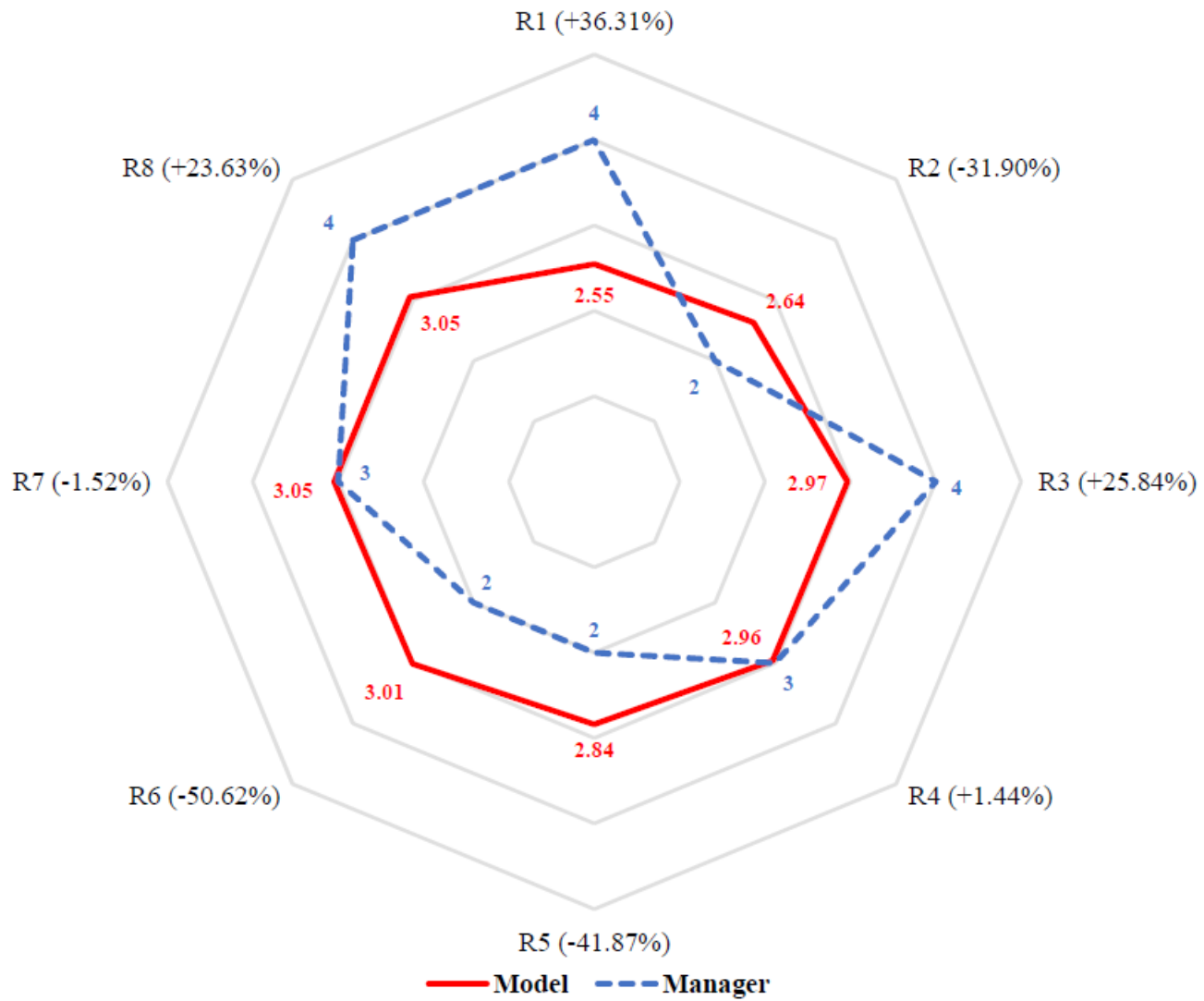


Fig. 8: Risk prediction performance in the example project