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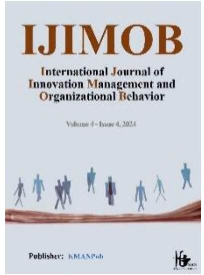

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Examining the Relationship between Risks Associated with Public-Private Partnership Projects in Emerging Markets Using Fuzzy Cognitive Mapping Methodology

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A B S T R A C T

Objective: The adoption of Public-Private Partnerships (PPPs) has sparked a surge in research interest in this area in recent years. This study aims to identify and prioritize the risks associated with PPP projects.

Methodology: A questionnaire was designed to assess the significance of each of the 35 research variables (risks) derived from the literature in explaining the risks associated with PPP projects. The respondents included experts in risk associated with PPP-based projects in emerging markets, specializing in policy making, production, sales, and export. These experts were considered knowledgeable due to their practical experience in management, expert, academic, and research activities related to risks and emerging projects and markets. Using purposive sampling and following a snowball method, semi-structured in-depth interviews were conducted with 19 experts until theoretical saturation was achieved.

Findings: The results were analyzed using the methodology of fuzzy cognitive maps, and the relationships between the research factors were examined.

Conclusion: The analysis revealed that financial constraints risk, demand risk, and government support risk are of high importance in the context of PPP projects.

Keywords: *Public-Private Partnerships (PPPs), Risk, Emerging Markets, Fuzzy Cognitive Mapping.*

1 Introduction

Infrastructure development has always been considered a catalyst for the economic growth of a country (Cui et al., 2018). With the increase in urban populations worldwide, the need for the development of social and economic infrastructures has become even more pronounced in recent years.

Previous research on infrastructure development indicates that there is a need for greater investment in this area to cover the infrastructure gap (Jokar et al., 2021a, 2021b; Li & Wang, 2019). A study reported that approximately 50 trillion dollars of infrastructure investment will be needed over the next decade globally (Iyer & Purkayastha, 2017). However, governments worldwide face challenges in keeping up with such massive investments; therefore, financial and participatory contributions from the private sector have led to innovative project delivery schemes, one of which is Public-Private Partnerships (PPPs) (Osei–Kyei et al., 2022). PPPs have particularly gained public attention globally after the global economic recession (Osei-Kyei & Chan, 2015; Osei–Kyei et al., 2022). The involvement of the private sector in providing public infrastructure has improved project performance levels (Liu et al., 2015). The ultimate reason for achieving better performance in such schemes is that the interests of public and private parties are aligned. These factors, along with others, stimulate the public sector to engage the private sector in delivering infrastructure projects; therefore, PPPs have emerged as a preferred and effective method for infrastructure provision, especially when large investments like road infrastructure projects are required (Sastoque et al., 2016). There is substantial evidence showing that PPPs perform better compared to traditional procurement systems where the public sector alone is responsible for project delivery (Raisbeck et al., 2010; Zhang et al., 2019). However, another aspect of public-private partnerships reveals that due to the complexity of financial arrangements, high investor return expectations, longer contract periods, and the risky nature of projects, it is not a panacea (Blanc-Brude & Makovsek, 2013). Moreover, inappropriate risk allocation and the public sector's tendency to transfer more project risks to the private sector negatively affect project objectives (Ahmadabadi & Heravi, 2019).

Therefore, efficient project risk management is crucial for the successful implementation of PPP projects. Previous PPP studies primarily focused on identifying and assessing risk. Risk allocation was somewhat considered but mostly in the realm of preferential risk allocation. The current study specifically focuses on risk allocation in PPPs based on the principle of allocating risk to the party best positioned to manage it; therefore, this study reviews existing literature on identifying, assessing, and allocating risk to provide further insights for theory and practice in risk management. This study aims to prioritize, assess, and allocate risks through the findings reviewed, using fuzzy cognitive mapping methodology, and it is expected that the findings will add to the knowledge base of risk management and explain risk management in PPP projects.

2 Methods and Materials

The objective of this section is to identify and classify risks in projects in emerging markets. In this regard, a questionnaire was designed to assess the importance of each of the 35 research variables (risks) derived from the literature (Table 1) in explaining the risks in projects in emerging markets from industry experts. The results were analyzed using the methodology of fuzzy cognitive maps, and the relationships between research factors were examined. Subsequently, the methodology of fuzzy cognitive maps was introduced, and the research data was analyzed based on it.

In this study, the population consists of experts from construction companies and all stakeholders involved in the investment of infrastructure projects in the country who are familiar with these types of issues in such projects (PPP-based projects in emerging markets). Evidence shows that in the Delphi method, the number of participants is usually less than 50 people, mostly between 15 to 20 people. It should also be noted that since not all individuals in the population are accessible, a limited number of 20 people were used.

In this study, an expert is someone who:

a) Has a degree in management or accounting.

b) Has at least a master's degree.

c) Has at least fifteen years of work experience.

d) Has at least five years of managerial experience.

2.1 The Process of Creating Fuzzy Cognitive Maps

Fuzzy cognitive mapping is a modeling methodology for complex decision-making systems. A fuzzy cognitive map describes the behavior of a system based on its concepts, where each concept represents an identity, state, variable, or a characteristic of the system. Fuzzy cognitive maps are used in simulations, modeling organizational strategies, supporting the formulation of strategic issues, analyzing decisions, creating knowledge bases, identifying management issues, analyzing failure modes (FMEA), specifying system requirements, supporting urban design, managing relationships in airline services, and enhancing network operations. The concept of cognitive maps was first introduced and applied by Axelrod (1976). A cognitive map is a diagram designed to express a person's cause-and-effect viewpoint about a specific area, which is then used to analyze the impacts of alternatives such as policies or

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business decisions in achieving specific goals. The methodology developed by Rodriguez Repiso et al. (2006) uses four matrices: the Initial Success Matrix (IMS), the Fuzzified Success Matrix (FZMS), the Success Relationship Power Matrix (SRMS), and the Final Success Matrix (FMS) to create fuzzy cognitive maps.

It should be noted that when the SRMS matrix is completed, some of the data contained in it may be misleading. Not all factors presented in the matrix are related, and there is not always a causal relationship between them. Expert judgment is needed to analyze the data and convert SRMS into the Final Success Matrix. During data analysis in the SRMS matrix, two vectors may randomly correlate; while logically, the two related indicators/concepts might be completely unrelated. These unconventional relationships can be easily identified by expert analysis. In this study, a focus group method was used for the final expert review. In the final display of the fuzzy cognitive map, each arrow between factors "i" and "j" has a weighted value. This value indicates the strength of the direct or inverse causality between the two factors and corresponds to the value presented in the Final Success Matrix in the cell at row "i" and column "j". The steps for developing a fuzzy cognitive map are described below:

2.2 *Initial Success Matrix*

The Initial Success Matrix is an [n × m] matrix where "n" is the number of key success factors, also referred to as concepts or variables, and "m" is the number of people interviewed to gather data. Each element Oij of the matrix represents the importance that individual "j" assigns to the specific concept "i", which can vary across different projects and even for different success factors within a single project because these results will later be converted into a fuzzy set with values between zero and one. Elements Oi1, Oi2, ..., Oim are vector elements Vi associated with the key success factors belonging to row "i" of the matrix.

2.3 *Fuzzified Success Matrix*

Numeric vectors Vi are transferred to fuzzy sets where each element of the fuzzy set affirms the membership level of element Oij in vector Vi. Numeric vectors with values between zero and one are converted into fuzzy sets as follows.

The maximum value in Vi is found and considered, meaning:

Relation 1)

$$\lfloor MAX(O_{iq}) \to X(O_{iq}) = 1 \rfloor$$

The maximum value in Vi is found and considered, meaning:

Relation 2)

$$\lfloor MAX(O_{iq}) \to X(O_{iq}) = 0 \rfloor$$

The ratio of all other elements of vector Vi in the range zero to one is determined, meaning:

Relation 3)

$$X_i(O_{ij}) = \frac{O_{ij} - Min(O_{ip})}{Max(O_{ip}) - Min(O_{ip})}$$

where the membership degree of element Oij in vector Vi is.

Direct estimation of values in the range zero to one can result in membership degrees that do not reflect the real world and are not confirmable through common reasoning. In such cases, introducing a higher or lower ceiling value by the data analyst is essential. Therefore, if Vi is a numeric vector of elements m associated with concept "i" and Oij, the higher and lower ceiling values for m as elements of Vi are as follows:

Relation 4)

$$\forall_j = 1 - mO_{ij}(O_{ij} >> \alpha_u) \to X_i(O_{ij}) = 1$$

Relation 5)

$$\forall_j = 1 - mO_{ij}(O_{ij} << \alpha_u) \to X_i(O_{ij}) = 0$$

The remaining vector elements are estimated in the range zero to one.

2.4 *Success Relationship Power Matrix*

The Success Relationship Power Matrix is an [n × n] matrix. Rows and columns relate to the matrix of key success factors, and each element in the matrix represents the relationship between factor "i" and factor "j". Additionally, Sij can accept values in the range of [-1, 1]. Each key success factor is represented as a numeric vector Si containing elements n for each concept shown in the map. There are three possible relationships between two concepts “i” and “j” (Sij):

Sij > 0 indicates a direct (positive) causality between concepts “j” and “i”. This means that an increase in the value of concept “i” causes an increase in the value of concept “j”.

Sij < 0 indicates an inverse (negative) causality between concepts “i” and “j”. This means that an increase in the value of concept “i” causes a decrease in the value of concept “j”.

Sij = 0 indicates that there is no relationship between concepts “i” and “j”. Therefore, when determining the values of Sij, three parameters must be considered: the sign of Sij,

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which indicates the presence of a relationship between concepts “i” and “j”; the strength of Sij, which shows how strongly concept “i” affects concept “j”; and the causality path, which indicates whether concept “i” causes “j” or vice versa.

2.5 Determining the Duality of Relationships

Numeric vectors IMS, in FZMS, are converted into fuzzy sets. Given vectors V1 and V2 associated with factors 1 and 2 and membership degrees j in vectors V1, V2, these vectors exclusively have an increasing relationship (a direct relationship between concepts 1 and 2 with Sij > 0). If similar across all or most elements associated with both vectors; and vectors V1 and V2 exclusively have a decreasing relationship between concepts 1 and 2 if similar across all or most elements associated with both vectors, then Sij < 0.

Determining the Strength of Relationships: The proximity of the relationship between two vectors V1 and V2 based on the calculation of similarity between these two vectors confirms the strength of the relationship between concepts 1 and 2 in relation to these two vectors as represented in SRMS. The proximity of the relationship between two vectors is based on the distance between the two vectors based on the concept of vector distance. The mathematical procedure for calculating "similarity" between these two vectors represents an approach described by Schneider et al. (2012).

For vectors that are directly related and those that have an inverse relationship, a different calculation is required. If vectors V1 and V2 have a direct relationship, then the closest relationship between them for each (j) (j=1, …, m) when is:

Relation 6)

$$d_j = \left|X_1(v_j) - X_2(v_j)\right|$$

and AD is the average distance between vectors V1 and V2.

Relation 7)

$$AD = \frac{\sum_{j=1}^{m}\left|d_j\right|}{m}$$

The proximity or similarity S between the two vectors based on this equation is shown as:

Relation 8)

S = 1 - AD

S = 1 indicates complete similarity and S = 0 indicates the maximum degree of dissimilarity.

2.6 Final Success Index

When the SRMS matrix is completed, some of the data contained in it may be misleading. Not all key success factors presented in the matrix are related, and there is not always a causal relationship between them. Expert judgment is needed to analyze the data and convert SRMS to the Final Success Matrix, which only includes those fuzzy numeric elements that represent causal relationships between the key success factors. During data analysis in the SRMS matrix, two vectors can be considered as potentially related. Vectors can represent close mathematical relationships while logically, the two indices/concepts could be considered completely unrelated to each other. These unconventional relationships can be easily identified by expert analysis.

2.7 Graphic Representation of the Fuzzy Cognitive Map

The graphic representation of the Final Success Matrix as a fuzzy cognitive map creates a targeted cognitive map to outline the key success factors. In the final display, each arrow between factors “i” and “j” has a weighted value. This value indicates the strength of the direct or inverse causality between both factors and corresponds to the value presented in the Final Success Matrix in the cell provided in row “i” and column “j”. This visual representation provides a clear and intuitive understanding of the relationships and their strengths between various concepts within the system, facilitating decision-makers in grasping the complexity and interdependencies of different factors involved.

The development and use of fuzzy cognitive maps provide a robust tool for understanding and managing complex systems across various domains. By allowing the mapping of soft knowledge and perceptions, these maps enable the aggregation of human expert opinions into a coherent model that can be analyzed and manipulated to explore different scenarios, predict outcomes, and formulate strategies. This flexibility makes fuzzy cognitive maps particularly valuable in strategic planning and policy analysis, where the variables are numerous and the relationships between them can be highly intricate and dynamic.

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3 Findings and Results

In this study, researchers deeply reviewed the literature on the subject and identified risks associated with public-private partnership (PPP) projects in emerging markets. They consulted experts and ultimately selected 35 risks that had higher repetition and frequency in various studies and were also considered more significant in the environment of PPP projects in Iran by the experts. These factors were identified as the initial list of risks related to PPP projects in emerging markets. Table 1 shows the list of these risks:

Table 1

Risks Related to PPPs Derived from Research Literature

Factor	Symbol
Design flaws	C19
Interest rate changes	C1
Unstable government	C20
Political interference	C2
Government support	C21
Financial constraints	C3
Low productivity	C22
Force majeure	C4
Expropriation	C5
Asset risk	C6
Material risk	C25
Public disapproval	C7
Testing new methods	C26
Lack of PPP experience	C27
Contractual changes	C28
Site availability	C29
Safety and security	C30
Commitment issues	C31
High financial cost	C32
Scope changes	C33
Inadequate authority	C34
Poor work	C35
Construction cost overrun	C17
Legal issues	C18
Demand risk	C24
Communication risk	C8
Construction time passage	C9
Approval issues	C10
Weather	C11
Geological settings	C12
Tax change	C13
Corruption	C14
Environment	C15
Inflation	C16

Initially, a preliminary matrix was created based on the scores that experts had given to the thirty-five factors in question. The scores that experts provided in the questionnaire regarding the impact of each factor on PPP projects in emerging markets were studied. The scores were on a 5-point Likert scale with values 1, 3, 5, 7, and 9, where a score of 1 means very low impact, 3 means low impact, 5 means moderate impact, 7 means high impact, and 9 means very high impact. The preliminary matrix is shown in Table 2.

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Table 2

Preliminary Matrix

Symbol	Criterion	Expert 1	Expert 2	Expert 3	...	Expert 19
C1	Interest rate changes	5	5	7	...	9
C2	Political interference	5	7	7	...	9
C3	Financial constraints	7	7	7	...	5
C4	Force majeure	7	7	7	...	5
...	...	...	...	...	...	...
C35	Poor work	9	9	9	...	9

Subsequently, the fuzzy matrix of factors was developed. To prevent response bias, a minimum threshold of 3 and a maximum of 9 were considered for the responses. Table 3 shows the fuzzified matrix of factors. For example, the calculation is as follows: X1 (O11) = (5 - 3) / (9 - 3) = 0.333

Table 3

Fuzzified Matrix of Factors

Symbol	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10	Expert 11	Expert 12	Expert 13	Expert 14	Expert 15	Expert 16	Expert 17	Expert 18	Expert 19
C1	0.33	0.33	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C2	0.33	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
C3	0.67	0.67	0.67	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.33	0.33
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
C35	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.67	0.67	1.00	1.00	1.00	1.00	1.00	1.00	1.00

The fuzzified matrix entries, $X_i(O_{ij})$, show the normalized impact scores given by each expert. These scores range from 0.00 (minimum impact) to 1.00 (maximum impact) based on the scale adjustments described.

Then, the relationship strength matrix was developed. Table 4 displays a part of this matrix, where the relationship of each of the 35 research factors with each other is shown. For example, the calculation of S=1−0.017=0.983.

Table 4

Part of the Relationship Strength Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	0.00	0.98	0.88	0.84	0.93	0.91	0.91	0.88	0.79	0.82	0.79	0.82	0.81	0.74	0.74
C2	0.98	0.00	0.89	0.86	0.91	0.89	0.89	0.89	0.81	0.84	0.81	0.84	0.82	0.75	0.75
C3	0.88	0.89	0.00	0.96	0.84	0.79	0.79	0.79	0.77	0.84	0.81	0.77	0.89	0.68	0.68
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
C15	0.74	0.75	0.68	0.65	0.67	0.72	0.79	0.79	0.74	0.81	0.77	0.88	0.79	0.93	0.00

This matrix quantifies the direct and inverse relationships between all key factors. Values close to 1 indicate a strong positive relationship, values close to -1 indicate a strong negative relationship, and values close to 0 indicate no significant relationship. This matrix aids in understanding the interdependencies and influences among the different factors considered in the study.

To form the final matrix, a focus group of six members was established. The members of the focus group consisted of six experts from the industry who also had experience in risk. Based on their opinions, meaningless relationships among the research factors were eliminated, and the causal direction of the relationships was determined. The results of this review are shown in Table 5, and the diagram of the fuzzy cognitive map is presented in Figure 1:

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Table 5

Part of the Final Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	0.00	0.98	0.88	0.00	0.93	0.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.98	0.00	0.89	0.00	0.91	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C3	0.88	0.89	0.00	0.96	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.68	0.68
C4	0.84	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.65	0.65
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
C15	0.00	0.00	0.68	0.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.88	0.00	0.93	0.00

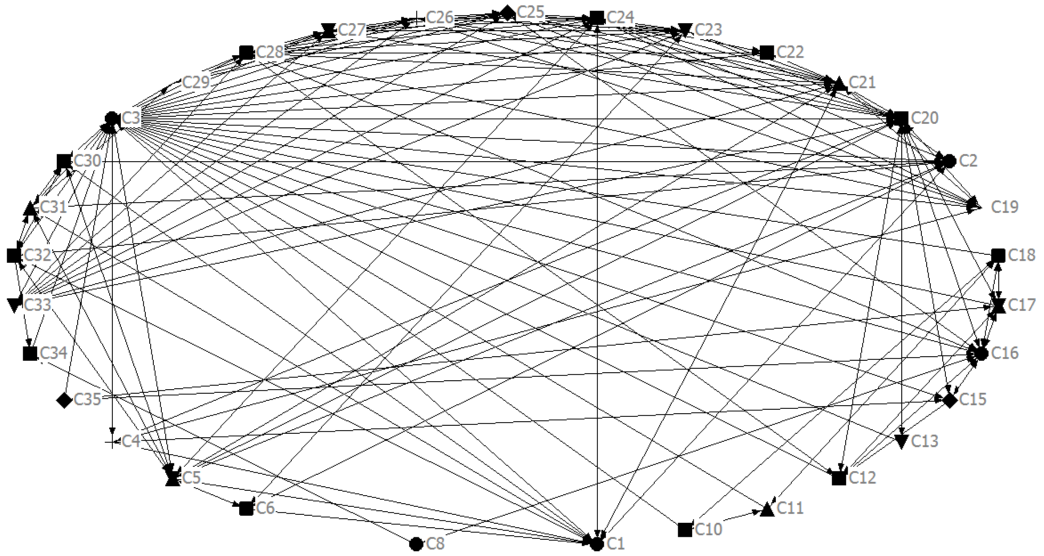
Table 6

Degrees of Influence, Affectedness, and Centrality of Factors

Concepts	Degree of Influence	Degree of Affectedness	Degree of Centrality
C1	8.26	9.11	17.37
C2	8.26	8.26	16.53
...	...	...	...
C35	3.61	2.81	6.42

Figure 1

Map Diagram



Centrality (Centrality) is essentially the sum of the two previous factors. Each factor with a higher degree of centrality has either a higher outward influence (od) or a higher inward affectedness (id) relative to other factors and is considered important in the system in both cases and should be taken into account.

Table 7

Prioritization of Risks Based on Highest Degree of Centrality

Concepts	Risks	Degree of Centrality	Priority
C3	Financial Constraints	32.14	1
C24	Demand Risk	24.33	2
C21	Government Support	22.53	3
C25	Material Risk	21.21	4
...	...	...	...
C13	Tax Change	1.74	35

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Figure 2

The Centrality of Factors

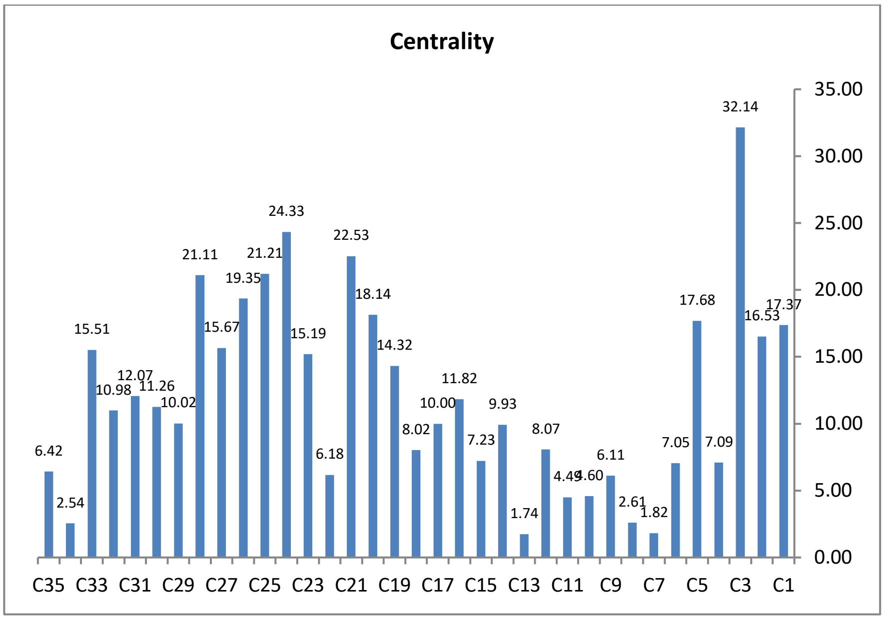

Figure 2 ranks risks based on their centrality scores, highlighting which factors are most central and therefore, potentially most impactful or critical in the PPP project environment, warranting more attention and management focus.

4 Discussion and Conclusion

Public-Private Partnerships (PPPs) have been revitalized in implementation over the past decade and have also gained increasing popularity among researchers. Such projects typically have longer life cycles than usual and are inherently complex, as many stakeholders involved are considered riskier than traditional procurement methods. Furthermore, risk sharing is a primary motivation for adopting such a technique for project delivery, which requires a more advanced understanding of existing risks. This study has addressed the use of current literature on the identification, evaluation, and allocation of risk in PPP projects. Identification, evaluation, and allocation of risk are the main areas studied in this article. Interest rate changes, political interference, financial constraints, and force majeure are some of the most common risks identified in the reviewed literature. Although most studies have identified these risks, this does not imply that they are the most critical. Different researchers have argued about the criticality of these risks. Other factors such as location, type, and manner of using PPPs must be considered to determine critical risks. As the research trend has increased, the methods used for risk assessment have become more objective with a focus on quantitative modeling. However, the findings of the reviewed articles indicate that there is still a significant gap in the practical implementation of such evaluation techniques. Professionals still rely on more subjective qualitative approaches. Risk allocation in PPP projects has also attracted significant attention from the research community. Researchers have used various approaches to allocate risk between the public and private sectors, with risk allocation based on preference and capability being the two common methods identified. Over the years, the literature has evolved from one to the other, with capability-based risk allocation, which is more targeted than preference-based allocation, gaining popularity over the past decade.

In this research, using fuzzy cognitive mapping methodology, the relationships among these factors (risks) were elucidated as shown in Figure 1. Based on the resulting model, a comprehensive understanding of how risks interact that affect PPP projects can be found; this facilitates the adoption and design of market development strategies for emerging markets because organizational strategists have a panoramic view of the impact and interactions of risks in the industry and can predict the impact of changes in any of the variables under a new strategy. However, the topic of risks in the industry is one that requires more attention from researchers and managers, as it is directly related to human

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capital as one of the main sources of competitive advantage for these organizations.

Also, in public-private partnerships, risk specialists should be such that they motivate both parties in terms of accepting responsibility. In some countries, in the implementation of public-private partnership projects, these projects should be such that the private sector uses its expertise and takes on a broader part of the work and a higher level of responsibility is transferred to them. According to some accepted studies, the lack of necessary skills in determining, evaluating, valuing, and transferring risk factors has led to a lack of significant revenues for governments. This article presents solutions and existing strategies for managing public-private partnership risk for public-private sectors. Given the country's progressive movement towards the privatization of government infrastructure projects (the law implementing the general policy of Article 44 of the Constitution), attention to techniques, studies, and experiences of different countries in managing the risk of such projects will significantly assist in the proper design of such projects in the country. Therefore, extensive studies on how to form, the necessary infrastructure, and factors influencing the success of these projects, and the legal and technical framework required for the implementation and management of public-private partnership project risks will have a significant impact on launching, executing, and achieving the objectives of transferring government infrastructure projects to the private sector.

Suggestions for Future Studies:

Use of other multi-criteria decision-making approaches to rank identified risks and compare results.

Definition of breakdown structures and cause-and-effect diagrams for risks and determining a response strategy for each risk.

Use of other risk quantification methods such as Failure Mode and Effects Analysis (FMEA) in risk quantification and then ranking risks and comparing results.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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