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An Integrated Multi-Criteria Decision Making Model for the Assessment of Public Private Partnerships in Transportation Projects

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Abstract: Public–private partnership (PPP) infrastructure projects have attracted attention over the past few years. In this regard, the selection of private partners is an integral decision to ensure its success. The selection process needs to identify, scrutinize, and pre-qualify potential private partners that sustain the greatest potential in delivering the designated public–private partnership projects. To this end, this research paper proposes an integrated multi-criteria decision-making (MCDM) model for the purpose of selection of the best private partners in PPP projects. The developed model (HYBD_MCDM) is conceptualized based on two tiers of multi-criteria decision making. In the first tier, the fuzzy analytical network process (FANP) is exploited to scrutinize the relative importance of the priorities of the selection criteria of private partners. In this respect, the PPP selection criteria are categorized as safety, environmental, technical, financial, political policy, and managerial. In the second tier, a set of seven multi-criteria decision-making (MCDM) algorithms is leveraged to determine the best private partners to deliver PPP projects. These algorithms comprise the combined compromise solution (CoCoSo), simple weighted sum product (WISP), measurement alternatives and ranking according to compromise solution (MARCOS), combinative distance-based assessment (CODAS), weighted aggregate sum product assessment (WASPAS), technique for order of preference by similarity to ideal solution (TOPSIS), and FANP. Thereafter, the Copeland algorithm is deployed to amalgamate the obtained rankings from the seven MCDM algorithms. Four real-world case studies are analyzed to test the implementation and applicability of the developed integrated model. The results indicate that varying levels of importance were exhibited among the managerial, political, and safety and environmental criteria based on the nature of the infrastructure projects. Additionally, the financial and technical criteria were appended as the most important criteria across the different infrastructure projects. It can be argued that the developed model can guide executives of governments to appraise their partner's ability to achieve their strategic objectives. It also sheds light on prospective private partners' strengths, weaknesses, and capacities in an attempt to neutralize threats and exploit opportunities offered by today's construction business market.

Keywords: public–private partnership; infrastructure projects; multi-criteria decision making; fuzzy analytical network process; combined compromise solution; simple weighted sum product

MSC: 90B50

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Citation: Mohammed Abdelkader, E.; Zayed, T.; El Fathali, H.; Alfalah, G.; Al-Sakkaf, A.; Moselhi, O. An Integrated Multi-Criteria Decision Making Model for the Assessment of Public Private Partnerships in Transportation Projects. *Mathematics* **2023**, *11*, 3559. https://doi.org/10.3390/math11163559

Academic Editor: João Paulo Costa

Received: 24 July 2023
Revised: 11 August 2023
Accepted: 15 August 2023
Published: 17 August 2023

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1. Introduction

Evidently, rapid social and economic growth is continuing to engender massive demand from governments for investment in public infrastructure projects all over the world [1,2]. Such mounting pressures on governments, in addition to worldwide economic decline, mandates innovative project delivery systems, such as public–private partnership, which covers a wide spectrum of infrastructure projects, services, and/or facilities for public use [3,4]. At the global level, there is a steadily widening gap between the call for sustainable infrastructure facilities and the resources present for financing these investments from government budgets. Garvin [5] reported that PPP has been established as the most renowned choice for engaging private sector experience, knowledge, quality, discipline, and arrangements into the delivery of public projects and services, other than private financing. As a result, the possibility of private financing for complex construction projects in relation to PPP projects have become an increasingly crucial factor in international competition. PPP is increasingly adopted by many countries around the world in collaboration with private sector management expertise and discipline and alongside private financing. This public–private cooperation enables accomplishing greater value for investments, fostering more buildable, sustainable, and creative designs, and diminishing capital and operating costs while maintaining higher construction standards [6,7]. However, many PPP projects are abandoned or even called off due to several risks, such as the significant difference between public and private sector anticipations and the absence of incentives to draw sustainable financing from private funding sources at reasonable rates [8,9]. These risks vary from one project to another [10,11].

The quintessence of public–private partnership lies in the compilation of private project execution, private capital, and the delivery of public projects or services. A public–private partnership is an amalgamation of objectives and tasks of the two sectors with varying goals. The goal of the public sector lies in accommodating political or social well-being. On the contrary, the private sector aims to cooperate for commercial and financial purposes, which can be addressed through its rate of return [12–14]. Hence, the interaction and linkage between the private and public sectors are prominent for the successful implementation of PPP projects because a deteriorating relationship would easily result in controversy, misunderstanding, conflict, and dispute. Examining which factors can promote or hinder this relationship is quintessential for the success of PPP projects [15]. Necessitated factors for the successful delivery of PPP projects have been studied and identified by researchers; such factors can be delineated as risk identification and management, strategic financing strategies, procurement protocols, tendering processes, concessionaire selection methods and attributes, and government's roles and responsibilities [16,17]. In general, a PPP project's private partner is awarded their contract through a public tender, serving the public's interest by means of competition among contractors [18]. The most important factor prior to starting the PPP project is the selection process of the private partner. Proper selection of a private-sector partner who is able to adequately perform throughout the PPP development process is strategically important for the project's success [19,20]. The failed delivery of PPP projects induces notable political, economic, and social losses to the government [21].

In light of the foregoing, the paramount objective of this research paper was to design an integrated model to usher public sector and designated governmental entities in the identification and evaluation of private partners in PPP infrastructure projects. To accomplish the main objective of this study, the following sub-objectives needed to be fulfilled:

1. Study and determine the selection criteria for analyzing public–private partners in infrastructure projects.
2. Design an integrated multi-criteria decision-making model for selecting the best private partner.
3. Validate the developed model using different case studies of infrastructure projects.

The remainder of this research study is outlined in the following manner. Section 2 enumerates previous research efforts pertaining to the assessment of public–private partnerships. Section 3 describes the major components and steps of the developed MCDM model. Section 4 reports the different computational procedures of the MCDM algorithms used in this study. Section 5 expounds on the data collection processes necessitated to build the developed model. Section 6 elucidates the results of four real case studies based in Africa. Section 7 reports a critical analysis of the obtained results in the previous section. Section 8 highlights the primary conclusions, limitations of this research, and usefulness of the developed model.

2. Literature Review

This section reports some of the previously developed models for the selection of private partners. It also delineates some of the MCDM-based studies in supply chain management.

2.1. Previous Research Studies

This section explores some of the previous attempts to address the selection process of private partners in construction projects. Table 1 summarizes some of the previous research studies designated for examining critical success factors (CSFs) in PPP projects. Several researchers have explicated various critical success factors needed for embracing PPP projects. Liang and Jia [22] identified the prominent success factors for PPP projects. Questionnaire surveys were distributed to garner feedback from professionals of construction management. Exploratory factor analysis was performed to explore scores provided by respondents. The empirical findings showed that substantial correlations existed between short term goals of PPP projects, stakeholders' objectives, and benefits to community and industry. Muhammad and Johar [23] evaluated the differences and similarities of critical success factors that impact successful implementation of PPP housing projects in Nigeria and Malaysia. A mixed research method of interviews and questionnaire surveys was incorporated to define and prioritize the influential critical success factors. It was manifested that action against errant developers was the top CSF in Malaysia followed by consistent monitoring and then house buyer's demand in third place. In addition, a stable political system was ranked as the most important CSF in Nigeria and a reputable developer was ranked second, while equitable risk allocation was in the third rank.

Table 1. Summary of previous research attempts devoted for analyzing success factors in PPP projects (authors' own work).

Reference	Year	Analysis Technique	Significant Factors (F)/Obstacles (O)
Liang and Jia [22]	2018	Exploratory factor analysis	Short-term goals of PPP projects, stakeholders' objectives, and benefits to community and industry (F)
Muhammad and Johar [23]	2019	Relative importance index	Action against errant developers and consistent monitoring (F)
Kavishe and Chileshe [24]	2019	Qualitative analysis of semi-structured interviews	Dedicated team of professionals to oversee the PPP projects (F)
Helmy et al. [25]	2020	Structural equation modelling	Managerial and operational and legal-related factors (F)
Alteneiji et al. [26]	2020	Relative importance index	Good governance, government commitment, commitment and responsibility of the public and private sectors (F)
Abukeshek et al. [27]	2021	Relative importance index	Efficient safety management plan, efficient project performance modeling and efficient quality management plan (F)
Surachman et al. [28]	2021	Delphi method and analytical hierarchy process	Community readiness, private sector readiness and public sector readiness (F)

Table 1. *Cont.*

Reference	Year	Analysis Technique	Significant Factors (F)/Obstacles (O)
Adiyanti and Fathurrahman [29]	2021	Qualitative analysis	Asset quality, strength of consortium, political environment (F)
Chourasia et al. [30]	2021	PLS-SEM	Cooperative environment, process characteristics and private characteristics (F)
Ngulie et al. [31]	2021	Relative importance index	Transparent procurement process, public awareness and detailed project planning (F)
Batra [32]	2021	Thematic analysis	Bureaucratic procedures, legislative mechanism and procurement process (O)
Kandawinna et al. [33]	2022	Weighted mean average and relative importance index	Transparency in procurement, communication between parties, and appropriate risk allocation (F)
Osei-Kyei et al. [34]	2022	Kendall's coefficient of concordance, mean score and one-way analysis of variance	Affordability, reduced social isolation of residents and improvement of emotional well-being of residents (F)
Othman and Khallaf [35]	2022	Relative importance index	Political and regulatory barriers (O) and skilled and efficient parties alongside well-prepared contract documents (F)
Ongel et al. [36]	2023	Analytical network process	Contractor's expertise besides technical and management competencies, and resource availability (F)
Kukah et al. [37]	2023	Delphi survey, mean score ranking, Kendall's coefficient of correlation and Cronbach's alpha coefficient	Shared authority, communication and trust between private and public sector, and necessity of power project (F)
Zhang et al. [38]	2023	ISM and MICMAC	Absence of enabling institutional environment, government reliability, and inadequate study and insufficient data (O)
Kien et al. [39]	2023	Mean score method	Transparent legal framework, public and private commitments and responsibilities, and transparency in bidding (F)

Kavishe and Chileshe [24] delved into critical success projects of PPP housing projects in Tanzania. Semi-structured interviews alongside qualitative methods were utilized for data collection and its processing. The top critical success factor was a dedicated team of professionals to oversee the PPP projects. Likewise, official and unofficial site visits and inspection were second, and then government support and guarantees in the third rank. Helmy et al. [25] analyzed CSFs that affect the success of PPP projects in the Egyptian educational sector. They defined 21 factors that were categorized into four clusters, namely financial and economic, legal, political in addition to managerial and operational. The results of questionnaire surveys were then analyzed using structural equation modelling. It was inferred that managerial and operational factors constitute the highest level of importance followed by legal factors.

Alteneiji et al. [26] explored critical success factors for the execution of PPP in affordable housing projects. Questionnaire surveys were distributed to solicit feedback from the professionals in relation with the importance of the identified seventeen critical success factors. A relative importance index was then computed for each critical success factor independently based on a five-point Likert scale. They ranked good governance, government commitment, commitment and responsibility of the public and private sectors, political support and stability, and favorable legal framework as the highest implicating critical success factors. Abukeshek et al. [27] examined CSFs necessitated for the successful delivery of PP in sports infrastructure projects. The significance level of each CSF was perceived using relative importance index. They inferred that the most paramount CSFs are an efficient safety management plan and then an efficient project performance modeling followed by an efficient quality management plan.

Surachman et al. [28] explored CSFs of water PPP projects in Indonesia. They implemented a combined framework of Delphi method and analytical hierarchy process (AHP) to rank CSFs from the perspective of pertinent stakeholders. They highlighted that community readiness is the most important CSF followed by private sector readiness in the second place and then public sector readiness comes in the third place.

Adiyanti and Fathurrahman [29] studied key critical success factors for proper implementation of PPP in drinking water projects. Eleven factors were identified based on phone call interviews and governmental performance reports, and qualitative analysis was used for systematized analysis of the garnered data. The top five CSFs were found to be asset quality, strength of consortium, political environment, commitment of partners and national PPP unit. Chourasia et al. [30] analyzed the interdependencies between CSFs in PPP airport projects. Their study incorporated determining five main latent variables of government characteristics, public characteristics, private characteristics, process characteristics and cooperative environment. Likewise, they relied on partial least square structural equation modeling (PLS-SEM) to explore this interrelatedness. They pointed out that a cooperative environment is highly impactful on process characteristics, meanwhile process characteristics sustain a lesser influence on private characteristics.

Ngulie et al. [31] investigated potential CSFs for the implementation of PPP in municipal solid waste projects. A relative importance index was adopted to sort out the conceived critical success factors. They indicated that both the private and public sector mostly agree on the most significant CSFs. Batra [32] probed the obstacles and challenges for effective execution of PPP housing projects. The data were gathered through case studies, previous literature studies, interviews and questionnaire surveys. Thematic analysis was then utilized for qualitative scrutinization of the collected data. They identified the bureaucratic procedures, legislative mechanism and procurement process as the prominent hurdles of PPP housing projects.

Kandawinna et al. [33] analyzed CSFs for the successful adoption of PPP in higher-education-related projects. They used weighted mean average and relative importance index for measuring the criticality level for each of the tackled factors. It was highlighted that the top three critical success factors were transparency in procurement, communication between parties, and appropriate risk allocation. Osei-Kyei et al. [34] looked into the critical indicators for the implementation of PPP in retirement village projects. They utilized Kendall's coefficient of concordance, mean score and one-way analysis of variance in their work. It was derived that the three most significant factors were affordability, reduced social isolation of residents and improvement of emotional well-being of residents.

Othman and Khallaf [35] identified key factors and barriers in renewable energy PPP projects. In addition, they investigated the risk severity of main barriers. They illustrated that political and regulatory barriers are the primary obstacles in renewable energy PPP projects. Additionally, skilled and efficient parties alongside well-prepared contract documents were regarded as the vital CSFs. Ongel et al. [36] created a MCDM-based model for exploring CSFs in healthcare PPP projects. They identified thirty-three CSFs that fell under the umbrella of six main clusters. They deployed an analytical network process (ANP) to mark the relative importance of priorities for each CSF. They derived that the most prominent CSFs are contractor's expertise besides technical and management competencies, and resource availability.

Kukah et al. [37] evaluated the critical success factors of PPP power projects. A two-round Delphi survey was leveraged to prepare a list of critical success factors. They were assessed by the help of mean score ranking, Kendall's coefficient of correlation and Cronbach's alpha coefficient. The perceived topmost factors included shared authority, communication and trust between the private and public sector besides necessity of power project. Zhang et al. [38] mapped a set of barriers for implementing PPP in remediation projects. The Delphi method was adopted to refine the retrieved list of barriers from the literature. The interrelationships between the barriers alongside their hierarchical structure were examined using interpretative structural modeling (ISM) and Cross-Impact Matrix

Multiplication Applied to Classification (MICMAC). Their analysis demonstrated absence of enabling institutional environment, government reliability and inadequate study and insufficient data as the most notable barriers. Kien et al. [39] addressed the factors affecting the success of PPP transportation projects. In this context, the mean score method was leveraged to sort the identified influencing factors. According to their results, it was indicated that adequate and transparent legal framework, public and private commitments and responsibilities, and transparency in bidding as the foremost success factors. Apart from MCDM-based models, adaptive stochastic models were newly introduced in the areas of project management and PPP projects. Wang et al. [40] estimated countries' experience in PPP projects implementation stepping on the Bayesian hierarchical model. Kowalska-Styczeń et al. [41] proposed a stochastic game method to allocate staff to projects. In their method, a multi-step stochastic game algorithm for random graph coloring can provide an adaptive self-learning within uncertain conditions. Their model involves the use of binary segmentation to look into the number and position of change points. Then, these change points were accommodated as informative priors in their Bayesian model. In view of the reported studies, it can be understood that there is a growing need for PPP projects as a result of the limited amount of funds available for government, which necessitates the development of a methodical method for the selection of private partners. It can be also conceived that despite several research efforts addressing PPP projects, there is lack of structured and synthesized method for evaluating and selecting private partners in PPP projects that can house the various and key aspects of these projects meanwhile accommodating the uncertainties and interdependences pertaining to the selection process. In this context, the majority of the perceived studies shed light on possible critical success factors and potential barriers depending on type of project and its location. Nonetheless, little attention was paid to the selection of private partners. It is also conceived that there is notable lack of research work on PPP for infrastructure projects in Africa. PPP can play a vital role in infrastructure development, which contributes to Africa's 2063 agenda and sustainable development goals [42–45]. Likewise, examining current literature elucidates that there is a lack of investigation of integrated MCDM models that can compile the strengths of a set of MCDM models and circumvent the shortcomings of utilizing single MCDM models.

2.2. MCDM in Supply Chain Management

The selection of sustainable suppliers is one of the paramount decisions in construction supply chain management. Usually, MCDM-based methods are adopted to address such problems. Cengiz et al. [46] assessed construction material suppliers stepping on an analytical network process. Their assessment process was established on 10 main judging criteria such as supplier profile, cost, time, geographical location, payment method, etc. Wang et al. [47] created an integrated framework for the selection of resilient construction suppliers. The weights of decision criteria were interpreted using an analytical hierarchy process. GRA was subsequently harnessed to rank suppliers according to their resilience performance. He and Zhang [48] built a hybrid model that encompassed the utilization of factor analysis, data envelopment analysis and AHP. Factor analysis was first implemented to filter the judging indicators. This is followed by the application of data envelopment analysis (DEA) for creating the pairwise comparison matrices, and then AHP for sorting out cement suppliers. Yazdani et al. [49] incorporated a combination of decision-making trial and evaluation laboratory (DEMATEL) and best worth method (BWM) to find the weights of factors affecting supplier selection in construction supply chain planning. CoCoSo-G was then leveraged to assign a performance score for each supplier and sort them accordingly. Matić et al. [50] presented an integrated MCDM model for appraising suppliers in construction supply chains. The full consistency method (FUCOM) was first applied to identify the weights of social, environmental and economic criteria. Then, a rough complex proportional assessment (COPRAS) algorithm was developed to sort suppliers in construction companies.

Yazdani et al. [51] carried out a risk-based assessment of green suppliers. They utilized DEMATEL algorithm to estimate the weights of selection criteria. Secondly, evaluation based on distance from average solution (EDAS) algorithm was deployed to compare the suppliers' performances. Marzouk and Sabbah [52] presented a MCDM-based model that capitalizes on social indicators of sustainability assessment. The analytical hierarchy process was first employed to find the weights of 17 relative attributes like annual number of accidents, gender diversity, working hours, safety practices, among others. TOPSIS was then applied to rank construction suppliers under consideration. Hoseini et al. [53] introduced fuzzy-based model for sustainable supplier selection. In it, fuzzy best worst method (FBWM) was exploited to estimate the weights of social, environmental and economic attributes. A weighed fuzzy inference system was then designed to identify the most sustainable supplier. Dewi and Ramadhani [54] proposed a hybrid ANP-MARCOS model for ranking green suppliers in the construction industry. They implemented ANP to analyze their financial and environmental attributes, and MARCOS was undertaken to define the best green supplier. Tushar et al. [55] envisioned an integrated MCDM model for picking a circular supplier in construction domain. Their model comprised the use of a fuzzy analytical hierarchy process (FAHP) to assign relative weights to the selection criteria. Preference ranking organization method for enrichment of evaluations II (PROMETHEE II) was performed to prioritize circular suppliers from best to worst.

3. Research Methodology

The prominent objective of this research paper is to support governmental agencies with a decision-making platform for evaluation and prioritization of potential private partners for public–private partnership infrastructure projects. The framework of the developed research framework is outlined in Figure 1. The selection criteria are retrieved from reviewing previous literature studies on PPP infrastructure projects [4,56–75] alongside interviews with experts. To this end, a list of 34 selection criteria was defined in this study (9 main criteria and 25 sub-criteria). This list was amended by 12 professional experts in the field of PPP infrastructure projects for their assessment and verification. In this context, face to face interviews with experts were carried out to revise the identified selection factors. To ascertain prolific interviews, a list of questions and key discussion matters were sent before the designated dates of interviews so that interviewees could have sufficient time to prepare and garner related information. In addition, e-mails were sent to a group of practitioners, professionals, consultants and clients. Respondents rendered their feedback and suggestions in relation with the most important criteria. Hence, the criteria list was further tuned, and thus it compiled 23 selection criteria composed of 5 main criteria and 18 sub criteria. Table 2 reports the compiled list of selection criteria of private partners.

Questionnaire surveys were then created to specify the level of relative importance of the selection criteria of private partners. In this regard, the fuzzy analytical network process is exploited in this research study to interpret relative importance priorities of selection criteria of private partners. Classical ANP and their crisp values are incapable of addressing inherent uncertainties and ambiguities accompanied with human cognition. Hence, FANP is leveraged herein to resolve intrinsic vagueness and imprecision associated with experts' subjective judgements [76–78]. Although analytical hierarchy process is widely used to deal with multi-criteria decision-making problems in real circumstances [79–81], it fails to provide satisfactory results in situations that need modelling interrelations and interactions between selection criteria being considered. Additionally, ANP is advised over other methods like full consistency method, best–worst method and level-based weighted assessment in situations that necessitate structured and interdependency-based modeling of complex problems [82,83]. To this end, FANP is utilized to accommodate interdependencies and influences between PPP selection criteria [84–87]. Furthermore, FANP was successfully and broadly implemented in diverse engineering-related applications. These comprised landfill site location [88], sustainability assessment of textile wastewater tech-

niques [89], prioritization of green building materials [90] and sorting of cyclone readiness activities [91].

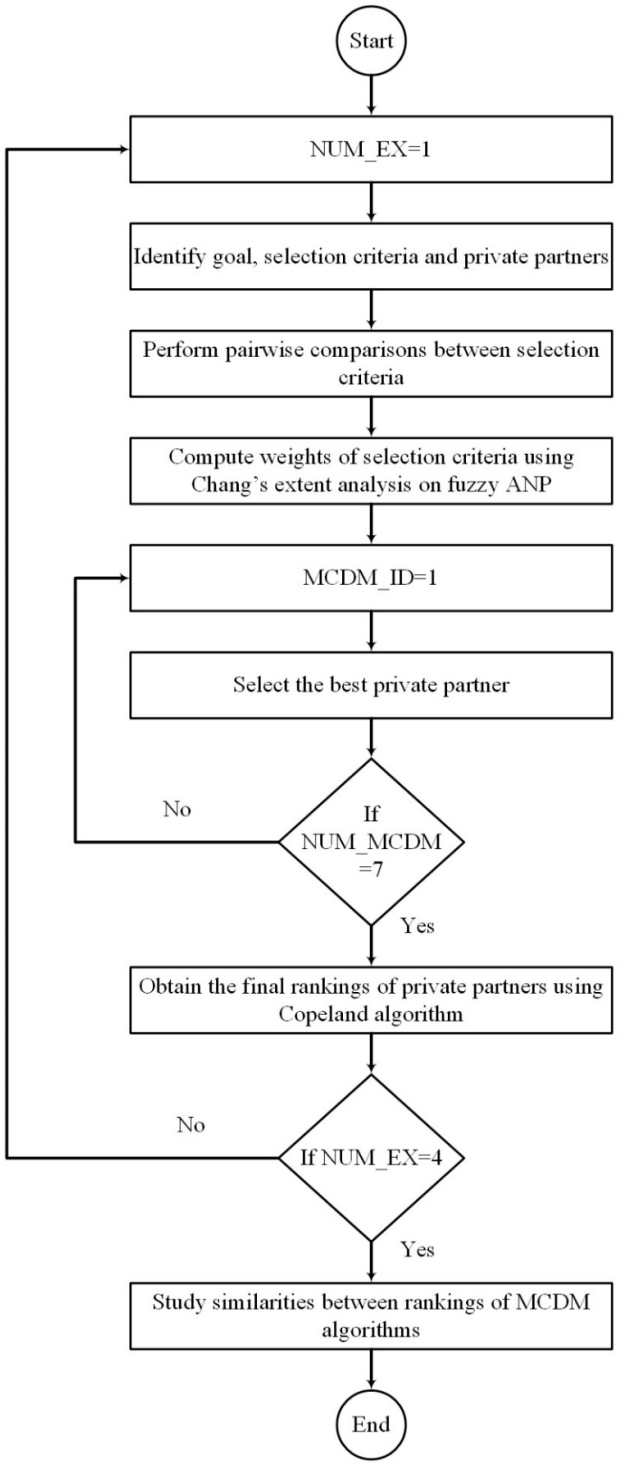


Figure 1. Framework of the developed integrated model for assessment of private partners in infrastructure projects (authors' own work).

Table 2. Main and sub criteria for evaluation of private partners in public private partnership infrastructure projects (authors' own work).

Main Criteria	Sub-Criteria	References
Financial (C_1)	C_{11}-Equity/Debt	Interviews with experts, [4,56,57,60–72,74]
	C_{12}-Government Control on tolls/tariffs	
	C_{13}-Financial Capacity	
	C_{14}-Foreign Financing	
Technical (C_2)	C_{21}-Capacity of design firm and its proposed design standers	Interviews with experts, [4–56,61,63,66,67,70,73,75]
	C_{22}-Operation and maintenance policy	
	C_{23}-Construction program and ability to meet its targeted milestone	
	C_{24}-Proposed Construction technology and methods	
Safety and Environment (C_3)	C_{31}-Proposed Environmental policy and management plan	Interviews with experts, [4,56,57,59,60,65,74]
	C_{32}-Conformance to laws and regulations	
	C_{33}-Qualification/experience of safety and environmental personal	
Managerial (C_4)	C_{41}-Demonstrated experience in delivery of similar projects	Interviews with experts, [4,41–45,47,49,52,53,56,59]
	C_{42}-Acceptance of risk transfer	
	C_{43}-Leadership and allocation of responsibilities in the association	
	C_{44}-Working and contractual relationships among Participants	
Political (C_5)	C_{51}-Understanding of Legal requirements	Interviews with experts, [62,69,71]
	C_{52}-Compliance with Permit requirements	
	C_{53}-Compliance with boycott trade laws	

No single MCDM model can guarantee the accuracy and robustness of evaluation processes in engineering-related applications [92–94]. Each MCDM model has its own advantages and shortcomings depending on the application [95,96]. Moreover, given the different basic rationale of each MCDM algorithm, different algorithms do not compile a single solution when attempting to solve real-world problems even when using the same pool of input data [97–99]. This entails the development of hybrid MCDM models that can blend endorse individual strengths and circumvent their weaknesses, inducing a reliable final outcome of multi-criteria decision making [100–102]. To this end, the developed HYBD_MCDM model leverages the use of seven multi-criteria decision making algorithms for the sake of prioritizing private partners in PPP infrastructure projects. These algorithms encapsulate CoCoSo, WISP, MARCOS, CODAS, WASPAS, TOPSIS and FANP. In this regard, the developed HYBD_MCDM model accommodates expert-based method (FANP) alongside ranking-based methods (CoCoSo, WISP, MARCOS, CODAS, WASPAS and TOPSIS) for sorting out private partners. This is expected to envision proper integration between human judgment and performance score-based assessment resulting in more efficacious decision. CoCoSo improves the accuracy of decision making, offers proper distinction between alternatives under consideration, and minimally impacted by their removal or addition [103,104]. WISP is a recently utility-based MCDM method that is simple and ranks alternatives in a systematized and accurate manner [105,106]. MARCOS is another new MCDM method that is accurate in dynamic environment and

it is highly stable against rank reversal phenomenon [107–109]. CODAS is a relatively advanced distance-based MCDM that ranks alternatives in a methodical scheme based on combining two types of distance: Euclidean and Taxicab [110,111]. The main advantage of WASPAS lies in its hybrid nature that can simultaneously combine weighed sum model and weighed product model [112,113]. Another advantage is its computational simplicity and robustness against rank reversal [114–116]. TOPSIS is acknowledged as one of the most renowned and practical methods in engineering domain [117,118]. It is also characterized by its straightforwardness, flexibility and easy interpretation [119,120].

The symbol "NUM_MCDM" alludes to the number of used MCDM algorithms used in this research study. Hence, this research paper Copeland algorithm to blend the obtained rankings of seven MCDM algorithms into a final ranking of private partners. Copeland algorithm evinced its efficiency in dealing with complex and practical case studies such as evaluation of stormwater management alternatives [121], prioritization of road maintenance actions [122] and sustainability assessment of built environment [123]. The developed model is validated using four real PPP infrastructure projects in North Africa. The symbol "NUM_EX" alludes to the number of real projects tested in the present research paper. The correctness of the developed HYBD_MCDM is examined through three tiers. The first tier involves adopting Spearman's rank correlation analysis to measure the similarities between the generated rankings from the investigated MCDM models [124–126]. In the second tier, the obtained rankings from the developed HYBD_MCDM model are compared against CoCoSo, WISP, MARCOS, CODAS, WASPAS, TOPSIS, FANP and weighted product model (WPM). The third tier incorporates performing sensitivity analysis to test the stability of the developed model against variations in the changes in the weights of PPP selection criteria.

4. Model Development

This section describes some of the algorithms used in this research paper. Due to space size limitations, FANP, CoCoSo, WISP, MARCOS, CODAS, WASPAS and TOPSIS are only explained herein. More information about the computational procedures of TOPSIS and Copeland algorithms can be found from Wu et al. [127] and Mohseni et al. [128].

4.1. FANP

This study adopts a fuzzy interval rather than crisp values for accommodating the intrinsic uncertainties in this multi-criteria decision-making problem. Hence, the developed model relies on FANP that uses Chang's extent analysis method [129] to compute the relative importance weights of selection criteria. It is selected herein owing to their ease of computation, low computational requirements, and wide commonality when compared against other FAHP approaches [130–132]. Furthermore, it can integrate both quantitative and qualitative data inputs. In Chang's extent analysis method, a triangular fuzzy number is used for dealing with uncertainties and expressing linguistic evaluations of experts [133–135]. In addition, triangular fuzzy numbers are characterized by their wide applicability in similar civil engineering problems [136–139] and relative simplicity in modeling and calculation [140,141].

The membership of a triangular fuzzy number is denoted by three real numbers of (l, m, u). Equation (1) depicts a mathematical representation of the triangular membership function.

$$\mu_A(x) = \begin{cases} \frac{(x-l)}{(m-l)}; & l \le x \le m \\ \frac{(u-x)}{(u-m)}; & m \le x \le u \\ 0; & \text{otherwise} \end{cases} \quad (1)$$

A pairwise comparison is performed for every design criterion against other remaining criteria as shown in Equation (2). In this context, the term "a_{ij}" elucidates the level of relative influence of the i-th element when assessed against the j-th element, with respect to the control criterion. This study uses the triangular fuzzy scale proposed by Kahraman et al. [142] as expounded in Figure 2. As can be seen, the linguistic variables are depicted in the form of triangular fuzzy numbers. In this study, there are five linguistic

variables of equally important (EI), moderately important (MI), strongly important (SI), very strongly important (VSI) and absolutely important (AI). Their corresponding fuzzy numbers are [1/2, 2, 3/2], [1, 3/2, 2], [3/2, 2, 5/2], [2, 5/2, 3] and [5/2, 3, 7/2], respectively.

$$\widetilde{A} = \left(\widetilde{a}_{ij}\right)_{m\times n} = \begin{bmatrix} (1,1,1) & (l_{12},m_{12},u_{12}) & \dots & (l_{1n},m_{1n},u_{1n}) \\ (l_{21},m_{21},u_{21}) & (1,1,1) & \dots & (l_{2n},m_{2n},u_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (l_{n1},m_{n1},u_{n1}) & (l_{n2},m_{n2},u_{n2}) & \dots & (1,1,1) \end{bmatrix} \quad (2)$$

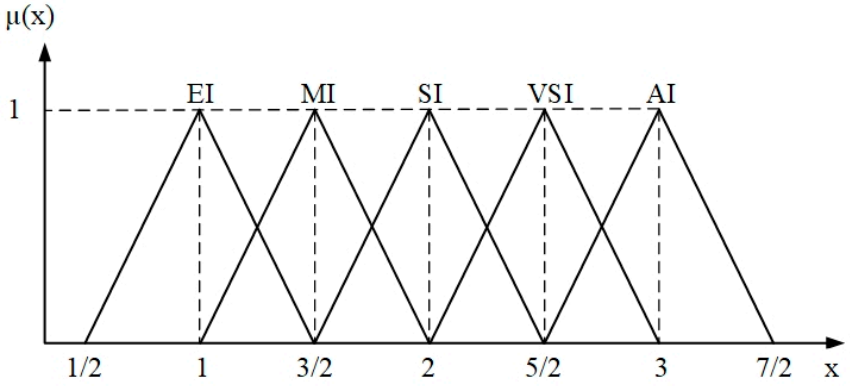


Figure 2. Linguistic scales for pairwise comparisons (authors' own work).

The values of fuzzy synthetic analysis with regard to the i-th object are presented in Equation (3).

$$\widetilde{S}_i = \sum_{j=1}^{n} \widetilde{a}_{ij} \bigotimes \left[\sum_{k=1}^{n}\sum_{j=1}^{n} \widetilde{a}_{kj}\right]^{-1} \quad (3)$$

The degrees of possibility of $\widetilde{S}_i \geq \widetilde{S}_j$ are then obtained by using Equations (4) and (5).

$$V\left(\widetilde{S}_i \geq \widetilde{S}_j\right) = \sup_{y\geq x}\left[\min\left(\widetilde{S}_i(x), \widetilde{S}_j(y)\right)\right] \quad (4)$$

$$V\left(\widetilde{S}_i \geq \widetilde{S}_j\right) = \begin{cases} 1 & m_i \geq m_j \\ \frac{u_i - l_j}{(u_i - m_i)+(m_j - l_j)} l_j \leq u_i & i.j = 1,\dots,n;\ j \neq i \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where:

$\widetilde{S}_i = (l_i, m_i, u_i), \widetilde{S}_j = (l_j, m_j, u_j)$ and $V\left(\widetilde{S}_i \geq \widetilde{S}_j\right)$ stand for the ordinates associated with the highest intersection point.

The next step involves obtaining the degree of possibility for $\widetilde{S}_i$ to be more than all the other $(n-1)$ convex fuzzy numbers S_j as presented in Equation (6).

$$\left(\widetilde{S}_i \leq \widetilde{S}_j \middle| j = 1,2,\dots,n, i \neq j\right) = \min_{j\in(1,\dots,n) i\neq j}\left[V\left(\widetilde{S}_i \geq \widetilde{S}_j\right)\right] \quad (6)$$

The final step comprises finding the normalized priority vector $W = (w_1, w_2, \dots, w_n)^T$ using Equation (7).

$$W_i = \frac{V\left(\widetilde{S}_i \geq \widetilde{S}_j \middle| j = 1,2,\dots,n, i \neq j\right)}{\sum_{k=1}^{n} V\left(\widetilde{S}_k \geq \widetilde{S}_j \middle| j = 1,2,\dots,n, j \neq k\right)} \quad (7)$$

The generated eigenvectors from the pair-wise comparison matrices are compiled in an arranged pattern to create a matrix named the supermatrix. The column vector represents the impact, with regard to a base control criterion, of a certain group of elements of a component on a specific element of another or the same component present at the top. If no relationship is present between two elements, the respective entry is zero in the supermatrix. The weighted supermatrix is generated by mapping the influence of all clusters. Then, the limit supermatrix is then obtained by raising the weighted supermatrix to a large power until it converges [143]. The values stored in the limit supermatrix denote the desired relative importance priorities for selection criteria of PPP.

4.2. CoCoSo

COCOSO is one of the recent MCDM algorithms that was presented by Yazdani et al. [142]. This algorithm ranks a pre-defined set of alternatives based on merging simple additive weighting and exponentially weighted product models. The steps of the COCOSO algorithm are presented in detail as follows [144]:

The compromise normalization processes for the cost and benefit attributes are performed using Equations (8) and (9), respectively.

$$r_{ij} = \frac{\max\limits_{i} x_{ij} - x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}} \tag{8}$$

$$r_{ij} = \frac{x_{ij} - \min\limits_{i} x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}} \tag{9}$$

where:

r_{ij} is the normalized measure of performance of the i-th alternative on the j-th criteria.

The weighted compatibility sequence (S_i) and power weight of compatibility sequences (P_i) for each alternative are computed using Equations (10) and (11), respectively.

$$S_i = \sum_{j=1}^{n} w_j \times r_{ij} \tag{10}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{11}$$

The relative weights of tackled alternative are compiled using three aggregation techniques. Equation (12) demonstrates the sum of arithmetic mean for the sums of scores of weighted sum and weighted product models. Equation (13) demonstrates the sum of relative scores of weighted sum and weighted product models assessed to the best. Equation (14) demonstrates a compromise trade-off between the scores of weighted sum and weighted product models. Usually, the value of the parameter λ is assumed as 0.5 or it can be set based on the experts' judgements.

$$K_{ia} = \frac{S_i + P_i}{\sum_{i=1}^{m} S_i + P_i} \tag{12}$$

$$K_{ib} = \frac{S_i}{\min\limits_{i} S_i} + \frac{P_i}{\min\limits_{i} P_i} \tag{13}$$

$$K_{ic} = \frac{(\lambda) S_i + (1-\lambda) P_i}{(\lambda) \max\limits_{i} S_i + (1-\lambda) \max\limits_{i} P_i}, 0 \le \lambda \le 1 \tag{14}$$

The final score associated with each alternative is calculated using Equation (15). In this respect, the alternatives are ranked in a descending arrangement, whereas higher values of K_i indicate more significant alternatives.

$$K_i = (K_{ia} \times K_{ib} \times K_{ic})^{\frac{1}{3}} + \frac{1}{3}(K_{ia} + K_{ib} + K_{ic}) \tag{15}$$

4.3. WISP

WISP is a newly developed MCDM algorithm that blends four relationships between the benefit and cost attributes to interpret the overall utility of the alternative. The steps of WISP algorithm are delineated in the following lines [106]:

The normalized decision matrix is established using Equation (16) in order to convert the input decision matrix into normalized unitless values.

$$r_{ij} = \frac{x_{ij}}{\max\limits_{i} x_{ij}} \tag{16}$$

where:

r_{ij} is a normalized dimensionless value of the i-th alternative on the j-th criteria.

The next step comprises computing four utility measures for the benefit and cost attributes using Equations (17)–(20).

$$u_i^{wsd} = \sum_{j \epsilon \Omega_{max}} r_{ij} \times w_j - \sum_{j \epsilon \Omega_{min}} r_{ij} \times w_j \tag{17}$$

$$u_i^{wpd} = \prod_{j \epsilon \Omega_{max}} r_{ij} \times w_j - \prod_{j \epsilon \Omega_{min}} r_{ij} \times w_j \tag{18}$$

$$u_i^{wsr} = \frac{\sum_{j \epsilon \Omega_{max}} r_{ij} \times w_j}{\sum_{j \epsilon \Omega_{min}} r_{ij} \times w_j} \tag{19}$$

$$u_i^{wpr} = \frac{\prod_{j \epsilon \Omega_{max}} r_{ij} \times w_j}{\prod_{j \epsilon \Omega_{min}} r_{ij} \times w_j} \tag{20}$$

where:

u_i^{wsd} and u_i^{wpd} represent the difference between the impact of benefit and cost attributes on the final utility of alternative i based on weight sum and weighted product models, respectively. u_i^{wsr} and u_i^{wpr} represent the ratio of benefit and cost attributes on the final utility of alternative i based on weight sum and weighted product models, respectively.

The four utility measures are re-calculated using Equations (21)–(24).

$$u^{-}{}_i^{wsd} = \frac{u_i^{wsd}}{\left(1 + u_{max_i}^{wsd}\right)} \tag{21}$$

$$u^{-}{}_i^{wpd} = \frac{u_i^{wpd}}{\left(1 + u_{max_i}^{wpd}\right)} \tag{22}$$

$$u^{-}{}_i^{wsr} = \frac{u_i^{wsr}}{\left(1 + u_{max_i}^{wsr}\right)} \tag{23}$$

$$u^{-}{}_i^{wpr} = \frac{u_i^{wpr}}{\left(1 + u_{max_i}^{wpr}\right)} \tag{24}$$

where:

$u^{-}{}_i^{wsd}$, $u^{-}{}_i^{wpd}$, $u^{-}{}_i^{wsr}$ and $u^{-}{}_i^{wpr}$ stand for the normalized recalculated values of u_i^{wsd}, u_i^{wpd}, u_i^{wsr} and u_i^{wpr}, respectively. The values of u_i^{wsd} and u_i^{wsr} can be negative, positive

or zero. Hence, they should be translated into the interval [0, 1] using Equations (21)–(24) before calculating the overall utility of each alternative.

The overall utility of each alternative is computed using Equation (25). In this regard, the tackled alternatives are sorted in a descending manner, whereas the largest overall utility value indicates a more preferred alternative.

$$u_i = \frac{1}{4}\left(u_i^{-wsd} + u_i^{-wpd} + u_i^{-wsr} + u_i^{-wpr}\right) \tag{25}$$

4.4. MARCOS

MARCOS is a novel MCDM algorithm that was first presented by Stević et al. [107]. It comprises the following computational procedures:

The ideal and anti-ideal solutions are defined hinging on the nature of attributes. In this regard, anti-ideal (AAI) and ideal (AI) solutions are regarded as the solutions with worst and best characteristics, respectively (see Equations (26) and (27)).

$AI = \max_i x_{ij}$ if $j \epsilon B$ and

$$\min_i x_{ij} \text{ if } j \epsilon C \tag{26}$$

$AAI = \min_i x_{ij}$ if $j \epsilon B$ and

$$\max_i x_{ij} \text{ if } j \epsilon C \tag{27}$$

where:

C and B represent the cost and benefit attributes, respectively.

The normalization of the elements in the decision matrix is performed by applying Equations (28) and (29), respectively.

$$n_{ij} = \frac{x_{ai}}{x_{ij}} \text{ if } j \epsilon C \tag{28}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}} \text{ if } j \epsilon B \tag{29}$$

The weighted normalized matrix is then obtained through the multiplication of the normalized matrix by the weights of criteria as shown in Equation (30).

$$v_{ij} = \sum_{j=1}^{n} n_{ij} \times w_j \tag{30}$$

In this step, the utility degrees of different alternatives are obtained, such that the utility degrees with respect to anti-ideal and ideal solutions are generated by applying Equations (31) and (32), respectively.

$$K_i^- = \frac{S_i}{S_{aai}} \tag{31}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{32}$$

Such that,

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{33}$$

where:

S_i is the summation of elements in the weighted decision matrix.

The next step is to compute the utility functions of each alternative ($f(K_i)$), which is a trade-off value of the alternatives with respect to anti-ideal and ideal solutions. The utility functions of alternatives can be obtained using Equation (34).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^p)}} \tag{34}$$

Such that,

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{35}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{36}$$

where:

$f(K_i^-)$ and $f(K_i^+)$ stand for the utility functions with respect to anti-ideal and ideal solutions, respectively. In addition, the rankings of alternatives are addressed on the basis of values of final utility functions, whereas higher values of $f(K_i)$ implicate more desirable alternative.

4.5. CODAS

CODAS is a MCDM algorithm that evaluates the desirability level of alternatives counting on two measures, namely Euclidean distance and Taxicab distance from the negative ideal solutions [145]. In this regard, Euclidean distance is the prominent assessment measures, whereas if the two alternatives sustain the same Euclidean distance. Then, Taxicab distance is utilized as a secondary measure to assess the designated alternatives. The procedures of CODAS algorithms are presented in the following lines [94]:

The first step incorporates the use of linear normalization to standardize the input decision matrix using Equations (37) and (38).

$$n_{ij} = \frac{x_{ij}}{\max(x_{ij})} \text{ if } j \epsilon N_b \tag{37}$$

$$n_{ij} = \frac{\min(x_{ij})}{x_{ij}} \text{ if } j \epsilon N_c \tag{38}$$

where:

N_c and N_b stand for the cost and benefit attributes criteria, respectively.

The second step involves computing the weighted normalized decision matrix using Equation (39).

$$v_{ij} = n_{ij} \times w_j \tag{39}$$

The negative ideal solution is then identified through Equations (40) and (41).

$$ns = [ns_j]_{1 \times m} \tag{40}$$

$$ns_j = \min_i(v_{ij}) \tag{41}$$

The next step involves interpreting the Euclidean (E_i) and Taxicab (T_i) distances of alternatives from negative ideal solutions using Equations (42) and (43), respectively.

$$E_i = \sqrt{\sum_{j=1}^{n} (v_{ij} - ns_j)^2} \tag{42}$$

$$T_i = \sum_{j=1}^{n} \left| v_{ij} - ns_j \right| \tag{43}$$

The fifth step comprises obtaining the relative assessment matrix as given in Equations (44) and (45).

$$R_a = [h_{ik}]_{n \times n} \tag{44}$$

$$h_{ik} = (E_i - E_k) + \Psi(E_i - E_k) \times (T_i - T_k) \tag{45}$$

where:

k ϵ {1, 2, 3, 4, 6, ..., n}. Ψ is a threshold function that specifies the equality of the Euclidean distances of two alternatives, and it is determined using Equation (46).

$$\Psi(x) = \begin{cases} 1 & \text{if } |x| > \tau \\ 0 & \text{if} |x| < \tau \end{cases} \tag{46}$$

where:

τ stands for a threshold parameter, which usually ranges between 0.01 and 0.05, and it is set as 0.02 in this research paper. In addition, it is worth pointing out that if the difference between the Euclidean distance of the alternative is more than the threshold value. Hence, Taxicab distance is used to compare the design alternatives.

The last step involves computing the overall assessment score as given in Equation (47). In this context, higher values of H_i induce a better rank for the alternative.

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{47}$$

4.6. WASPAS

WASPAS is one of the MCDM algorithms that was first proposed by Zavadskas et al. [146], whereas it offers a unique blending between the widely-known MCDM algorithms of weighted sum model (WSM) and weighted product model (WPM). In this respect, the basic step-by-step procedures of WASPAS are presented in the following lines [144]:

The first procedure is the normalization of the input decision matrix. The normalization processes of the benefit and cost indicators are carried out using Equations (48) and (49), respectively.

$$\bar{x_{ij}} = \frac{x_{ij}}{\max(x_{ij})} \tag{48}$$

$$\bar{x_{ij}} = \frac{\min(x_{ij})}{x_{ij}} \tag{49}$$

where:

$\bar{x_{ij}}$ is the normalized measure of performance of the i-th alternative with regard to the j-th indicator.

The total relative importance of the i-th alternative on the basis of the weighted sum model and weighted product model can be obtained with the help of Equations (50) and (51), respectively.

$$Q^{(1)}{}_i = \sum_{j=1}^{n} w_j \times \bar{x_{ij}} \tag{50}$$

$$Q^{(2)}{}_i = \prod_{j=1}^{n} x^{-}{}_{ij}^{w_j} \tag{51}$$

The joint relative importance of the i-th alternative can be obtained using the general Equation (52) based on compiling the preference scores retrieved from the weighted sum model and weighted product model.

$$Q_i = \lambda Q^{(1)}{}_i + (1-\lambda) Q^{(2)}{}_i = \lambda \sum_{j=1}^{n} w_j \times x_{ij}^{-} + (1-\lambda) \prod_{j=1}^{n} x^{-}{}_{ij}^{w_j} \quad (52)$$

where:

λ is a coefficient of WAPAS that lies between zero and one. WASPAS behaves as WSM if $\lambda = 1$, and it is transformed to WPM if $\lambda = 0$. In this research paper, λ is taken as 0.5 to assume a proper tradeoff between WSM and WPM.

4.7. TOPSIS

TOPSIS is a MCDM algorithm that was first proposed by Hwang and Yoon [147]. The first step is the normalization of performance scores as shown in Equation (53).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x^2{}_{ij}}} \quad (53)$$

The next step involves obtaining the weighted normalized matrix through multiplying the normalized decision matrix by the weights of criteria (see Equation (54)).

$$v_{ij} = r_{ij} \times w_j \quad (54)$$

The third step is the identification of ideal and negative ideal solutions using Equation (55). They are determined based on the type of criteria under consideration (benefit or cost).

$$A^{+} = \left\{ \left(\max v_{ij} | j \in J \right), \left(\min v_{ij} | j \in J' \right), i = 1, 2, 3 \ldots M \right\} = \left\{ v_1^{+}, v_2^{+} \ldots\ldots\ldots v_N^{+} \right\} \quad (55)$$

$$A- = \left\{ \left(\min v_{ij} | j \in J \right), \left(\max v_{ij} | j \in J' \right), i = 1, 2, 3 \ldots M \right\} = \left\{ v_1^{-}, v_2^{-} \ldots\ldots\ldots v_N^{-} \right\} \quad (56)$$

where:

$$J = \{ j = 1, 2, 3, \ldots\ldots\ldots N | j \text{ associated with benefit criteria} \} \quad (57)$$

$$J\prime = \{ j = 1, 2, 3, \ldots\ldots\ldots N | j \text{ associated with cost criteria} \} \quad (58)$$

The fourth step is to compute the separate distance of each design alternative from the ideal and negative solutions using Equations (59) and (60), respectively.

$$s_i^{+} = \left(\sum_{j=1}^{n} \left(v_{ij} - v_j^{+} \right)^2 \right)^{\frac{1}{2}} \quad (59)$$

$$s_i^{-} = \left(\sum_{j=1}^{n} \left(v_{ij} - v_j^{-} \right)^2 \right)^{\frac{1}{2}} \quad (60)$$

The last step is computing the relative closeness for each alternative using Equation (61). The alternatives are sorted in a descending manner, whereas larger values of closeness coefficient denote better design alternatives.

$$c*_i = \frac{s-_i}{s*_i + s-_i} \quad (61)$$

4.8. Sensitivity Analysis

A sensitivity analysis is conducted to evaluate the robustness of the developed MCDM model. The present research study accommodates the one at a time (OAT), which is regarded as one of the most common methods for performing sensitivity analysis in multi-criteria decision analysis [148–150]. Herein, the OAT method is carried out by altering the weight of an earmarked PPP selection criteria from 20% to 100% with a percentage increment (step) of 20%. The weights of other PPP selection criteria are then calibrated proportionally to satisfy the additivity constraint. Hitherto, if the weight of the main changing PPP selection criteria under consideration is varied from w_ppp_i to $w_ppp_i^0$. Hence, the weights of the remaining PPP selection criteria are adjusted proportionally using Equation (62).

$$w_ppp_j = \frac{(1 - w_ppp_i)}{\left(1 - w_ppp_j^0\right)} \times w_ppp_j^0 \tag{62}$$

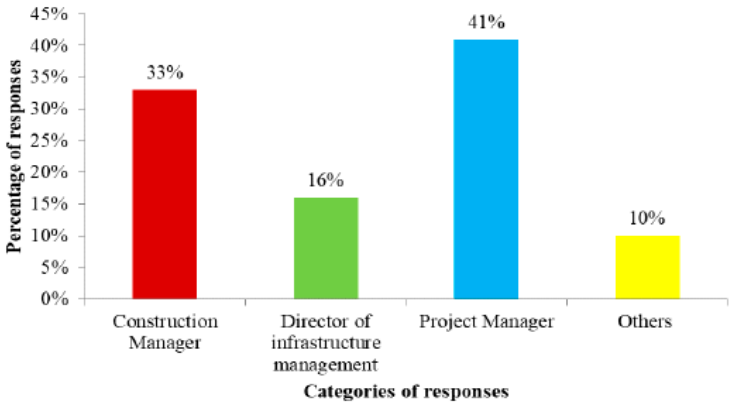
where:

w_ppp_j and $w_ppp_j^0$ are the updated and old weights of the remaining PPP selection criteria. w_ppp_i and $w_ppp_j^0$ denote the new and original weights of the main changing criteria, respectively.

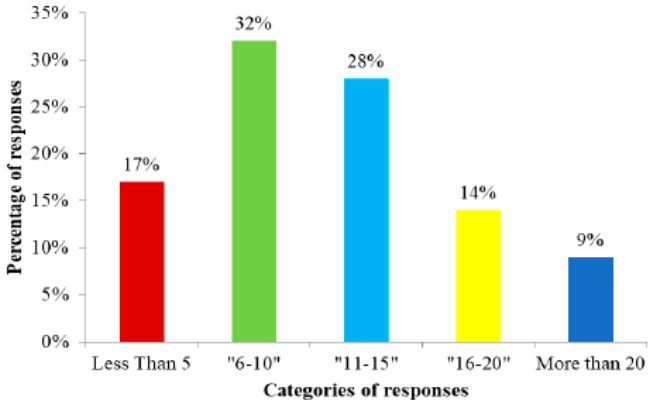
5. Data Collection

A questionnaire survey was mapped based on the selected criteria, and it was sent to experts and practitioners in the area of public–private partnership infrastructure projects in each project country. Hence, different importance weights are obtained for each case study that can accommodate their different technical, financial and demographic characteristics. Questionnaire surveys were sent to respondents either in hard copy or online format. The pool of respondents comprised personnel from the ministry of transportation in Libya, the African development bank in Morocco, the African development bank in Libya, the Ministry of infrastructure in Ghana, the Ministry of finance in Kenya, and the Ministry of national infrastructure and road safety in Nigeria, among others. For Libya, 35 experts were approached. Yet, a total of 30 responses were gathered, which comprised 8, 16 and 6 from public clients, private companies and academics, respectively. In addition, 26 out of 35, 12 out of 20 and 11 out of 20 were received in Tunisia, Ivory Coast and Senegal, respectively. The respondents were categorized by capitalizing on their position level and number of experience years in infrastructure projects as depicted in Figure 3.

It can be observed that 16% and 41% of responses were obtained from directors of infrastructure management and project managers, respectively. Additionally, it was found that 16% of responses were from directors of infrastructure management. Moreover, it can be viewed that 32% and 28% of respondents had 6–10 and 11–15 years of experience, respectively. The respondents were asked to fill pairwise comparison matrices for the main criteria and sub-criteria of private partners. In them, the selection criteria were assessed based on nine category scale. Three set of questions (A, B and C) were prepared in order to assess the selection criteria of PPP and determine the appropriate private partner. Table 3 explicates the set of questions earmarked for the evaluation of private partners in the developed model. The question set C is iterated for other tackled private partners. In the question set C, the expert is asked to identify an answer from a predefined discrete list of available options (absolutely satisfied, extremely satisfied, more than satisfied, satisfied, fairly satisfied, satisfied to some extent and not satisfied at all).



(a) Distribution of responses based on job classification



(b) Distribution of responses based on years of experience

Figure 3. Distribution of respondents according to job classification and experience years (authors' own work).

Table 3. Description of specified questions opted for the assessment of private partners (authors' own work).

Title	Description
Question A	It aims to understand which one of the five main criteria has the greatest influence on the selection process of private partners alongside the extent of their influence.
Question B-1	Which of the private partners exhibits the highest financial support and to what extent?
Question B-2	Which of the private partners holds the highest technical expertise and to what extent?
Question B-3	Which of the private partners sustains the highest support pertaining to safety and environment, and to what extent?
Question B-4	Which of the private partners has the highest level of managerial expertise and to what extent?
Question B-5	Which of the private partners exhibits the high level of political support?
Question C-1	For private partner A, considering the financial capability with respect to the technical, safety and environment, managerial and political policy. How much are you satisfied with the capability of this private partner in addressing this project?
Question C-2	For private partner A, considering the technical capability with respect to the safety and environment, managerial and political policy. How much are you satisfied with the capability of this private partner in addressing this project?

Table 3. *Cont.*

Title	Description
Question C-3	For private partner A, considering the safety and environment perspective with respect to the managerial and political policy aspects. How much are you satisfied with the capability of this private partner in addressing this project?
Question C-4	For private partner A, considering the managerial perspective with respect political policy aspects. How much are you satisfied with the capability of this private partner in addressing this project?

A sample of the pairwise comparison matrix of financial criteria is delineated in Figure 4. For instance, the expert is asked to specify the degree of importance of equity/debt when compared against foreign financing with respect to their impact on financial criteria.

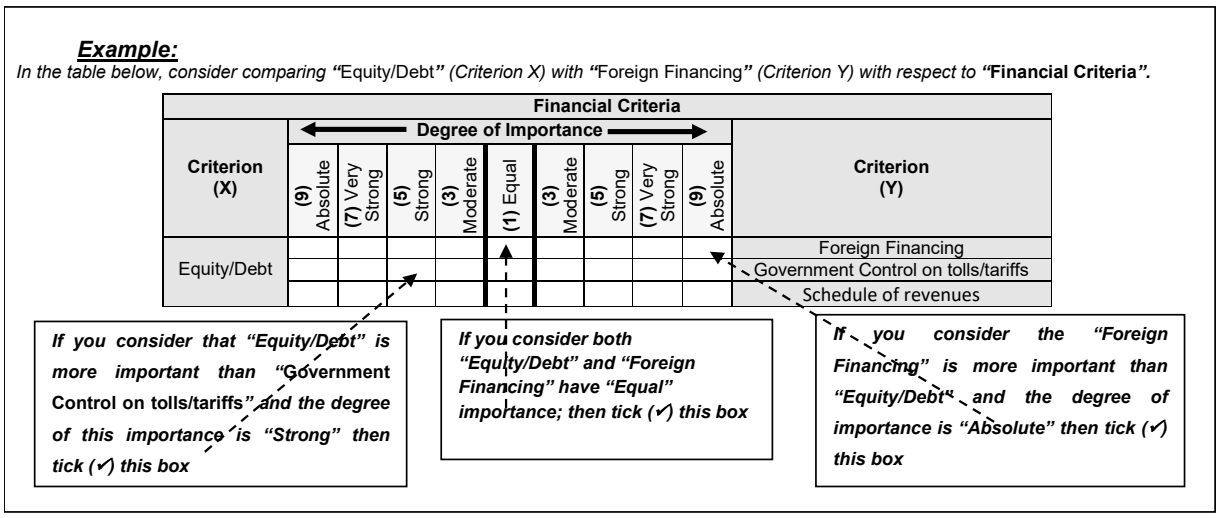


Figure 4. Sample of pairwise comparisons with respect to financial criteria (authors' own work).

Each private partner was evaluated by ten experts against each of the five judging attributes. The experts' evaluation addresses the partner capacity to deliver the best practice of the PPP selection attributes. Tables 4 and 5 explicate a summary of the expert's assessment for private partners A and B in case study I.

Table 4. Experts assessment results for private partner A in case study I (authors' own work).

	Experts Opinions for Private Partner A										
Selection criteria	1	2	3	4	5	6	7	8	9	10	**Average**
Financial	1	2	4	3	1	3	5	3	3	1	2.60
Technical	3	4	4	1	3	4	5	3	2	1	3.00
Safety and Environmental	3	4	3	1	2	3	1	5	2	1	2.50
Managerial	2	3	4	2	4	3	2	3	2	4	2.90
Political	3	2	4	3	1	2	3	4	2	5	2.90

Table 5. Experts assessment results for private partner B in case study I (authors' own work).

Experts Opinions for Private Partner B											
Selection criteria	1	2	3	4	5	6	7	8	9	10	**Average**
Financial	3	4	3	3	5	4	3	3	2	3	3.3
Technical	4	3	4	3	3	2	3	4	4	3	3.3
Safety and Environmental	2	3	4	2	1	5	3	2	4	5	3.1
Managerial	3	4	3	3	2	4	3	4	3	2	3.1
Political	3	4	4	3	2	3	4	2	3	2	3

6. Model Implementation

The developed model is deployed on four real projects from four African countries, namely Ivory Coast, Libya, Tunisia, and Senegal. These projects differ with regard to their type, location, cost and concession period. The variability in the project characteristics plays a role in measuring and verifying the efficaciousness of the developed model. The first case study is a toll bridge located in Ivory Coast, and its cost and concession period are USD 282 million and 30 years, respectively. It is composed of two three-lane carriageways with a total length of 1.5 km. The second case study is a highway in Libya extending for approximately 1700 km. Its cost and concession period are EUR 2033 million and 40 years, respectively. The third case study encompasses upgrading a 270 km highway in Tunisia with cost and concession period of EUR 58.1 million and 30 years, respectively. The fourth case study comprises the construction of 20.4 km toll highway in Senegal with cost and construction period of EUR 64 million and 25 years, respectively.

The developed FANP network is designed to capture multiple levels of dependencies such as dependencies between main selection criteria and overall goal, interdependencies of sub-criteria with each other, and dependencies between sub-criteria and private partners' alternatives. Table 6 demonstrates the fuzzy judgment matrix for the five selection criteria with respect to the overall goal (case study I). In this regard, the linguistic terms and respective fuzzy intervals are used for computing the weights of selection criteria. Based on Chang's extent analysis method, the normalized weights of financial criteria, technical criteria, safety and environment criteria, managerial criteria, and political criteria are 26.6%, 23.2%, 10.9%, 22.7% and 16.6%, respectively. It can be noticed that the highest weight is given to the financial criteria followed by technical criteria. This is a result of the due consideration of the huge impact of equity and debt.

Table 6. Fuzzy judgment matrix of selection criteria for private partners (case study I) (authors' own work).

Goal	C1	C2	C3	C4	C5
C1	(1,1,1)	(3/2,2,5/2)	(1/2,1,3/2)	(1,3/2,2)	(1/2,1,3/2)
C2	(2/5,1/2,2/3)	(1,1,1)	(1,3/2,2)	(1,1,1)	(1/2,1,3/2)
C3	(2/3,1,2)	(1/2,2/3,1)	(1,1,1)	(1/2,2/3,1)	(1,1,1)
C4	(1/2,2/3,1)	(1,1,1)	(1,3/2,2)	(1,1,1)	(3/2,2,5/2)
C5	(2/3,1,2)	(2/3,1,2)	(1,1,1)	(2/5,1/2,2/3)	(1,1,1)

Table 7 explicates the sub-criteria of private partner selection (SC1–SC4). It can be observed that equity/debt (37.41%), construction program and ability to meet its targeted milestone (55.25%) and conformance to laws and regulations (35.79%) are the most important sub-criteria under the financial criteria, technical criteria and safety and environment criteria, respectively. In addition, acceptance of risk transfer (42.1%), and understanding of legal requirements (40%) are found to be the most important sub-criteria under the man-

agerial criteria and political criteria, respectively. The priority weights for the sub-criteria regarding the private partners' alternatives are then determined. The final priorities of the four private partners based on FANP is represented in Table 8. It should be highlighted that herein private partner 1, private partner 2, private partner 3 and private partner 4 are denoted by P1, P2, P3 and P4, respectively. In addition, the terms I, II, III and IV are used to denote case studies I, II, III and IV, respectively. Priority index (PI) is used to reflect the preference of each private partner alternative. It is interfered that P3I is the optimum private partner to deliver this project and then P2I and P1I were ranked in the second and third places, respectively. In this regard, the PI of P3I, P2I and P1I are 0.361, 0.268 and 0.218, respectively.

Table 7. Relative weights of private partner selection sub-criteria (case study I) (authors' own work).

Criteria / Sub Criteria	C1	C2	C3	C4	C5
SC1	37.41%	14.55%	33.33%	22.29%	40%
SC2	32.27%	15.2%	35.79%	42.1%	38.82%
SC3	28.77%	55.25%	30.88%	20%	21.18%
SC4	1.55%	15%	---	15.61%	---

Table 8. Priority vector of private partners based on FANP (case study I) (authors' own work).

Private Partner	Priority Index	Rank
P1I	0.154	4
P2I	0.268	2
P3I	0.361	1
P4I	0.218	3

Table 9 summarizes the weights of the selection criteria of public private partnerships. It can be noticed that technical and financial aspects are the most important in case study I, political aspect occupies the highest rank in case study II. In addition, financial aspect is the most paramount criteria in case studies III and IV.

Table 9. Weights for the selection criteria of public–private partnerships (authors' own work).

Selection Criteria	Case Study I	Case Study II	Case Study III	Case Study IV
C1	35%	27.5%	36.5%	26.6%
C2	35%	25%	20.9%	23.2%
C3	7.5%	6%	19.1%	10.9%
C4	7.5%	10%	21%	22.7%
C5	15%	31.5%	2.5%	16.6%

Table 10 reports the ranking indices and order of private partners based on CoCoSo, WISP, MARCOS, CODAS, WASPAS, TOPSIS and FANP. A closeness coefficient (cc_i) is used to define the ranking order of private partners based on TOPSIS. It is obvious that CoCoSo, WISP, MARCOS and TOPSIS agree on the ranking of four private partners. Although FANP resembles CoCoSo, WISP, MARCOS and TOPSIS on the ranking of first and fourth private partners, it disagrees with them in the ranking of second and third private partners. It can be also observed that significant discrepancies are obtained in the rankings of CODAS and WASPAS. For instance, P1 and P4 are found to be the best private partners according to CODAS and WASPAS, respectively.

Table 10. Ranking of private partners based on the investigated MCDM algorithms (case study I) (authors' own work).

Private Partner	CoCoSo		WISP		MARCOS		CODAS		WASPAS		TOPSIS		FANP	
	K_{ic}	Rank	u_i	Rank	$f(K_i)$	Rank	H_i	Rank	Q_i	Rank	cc_i	Rank	PI	Rank
P1	0	4	0.178	4	0.548	4	0.08	1	0.444	3	0	4	0.154	4
P2	144.779	3	0.202	3	0.624	3	−0.032	3	0.306	4	0.381	3	0.268	2
P3	206.666	1	0.250	1	0.772	1	−0.089	4	0.521	2	1	1	0.361	1
P4	168.711	2	0.216	2	0.667	2	0.040	2	0.604	1	0.554	2	0.218	3

Tables 11–13 report the ranking indices and order of investigated MCDM algorithms for case studies II, III and IV. In case study II, the alternative denoted as "P2II" is chosen as the top priority private partner based on WISP, MARCOS, CODAS, WASPAS, TOPSIS and FANP. Moreover, the aforementioned algorithms provide the exact same rankings of P3II and P1II as the second and third preferred alternatives, respectively. However, CoCoSo obtained comparatively different results yielding P3II and P2II as the first and second preferred alternatives, respectively. It is worth noting that all seven MCDM algorithms appended P1II as the least preferable private partner in delivering the highway project. With regard to case study III, the majority of MCDM algorithms (CoCoSo, WISP, MARCOS and WASPAS) identified P2III as the top priority private partner. Nonetheless, TOPSIS and CODAS selected P3III as the best private partner while FANP determined P1III as the best private partner. It can also be argued that significant disagreements are obtained by the rankings of MCDM algorithms when attempting to deal with case study III when compared against other case studies. With respect to case study IV, it can be seen that all seven MCDM algorithms dictated P3IV, P4IV, P1IV and P5IV as the first, second, third and sixth most preferred private partners, respectively. Additionally, slight discrepancies are encountered in the rankings of P2IV and P6IV.

Table 11. Ranking of private partners based on the investigated MCDM algorithms (case study II) (authors' own work).

Private Partner	CoCoSo		WISP		MARCOS		CODAS		WASPAS		TOPSIS		FANP	
	K_{ic}	Rank	u_i	Rank	$f(K_i)$	Rank	H_i	Rank	Q_i	Rank	cc_i	Rank	PI	Rank
P1II	1.414	3	0.208	3	0.602	3	−0.059	3	0.497	3	0.113	3	0.245	3
P2II	2.318	2	0.243	1	0.703	1	0.039	1	0.583	1	0.766	1	0.488	1
P3II	3.135	1	0.223	2	0.646	2	0.019	2	0.534	2	0.313	2	0.267	2

Table 12. Ranking of private partners based on the investigated MCDM algorithms (case study III) (authors' own work).

Private Partner	CoCoSo		WISP		MARCOS		CODAS		WASPAS		TOPSIS		FANP	
	K_{ic}	Rank	u_i	Rank	$f(K_i)$	Rank	H_i	Rank	Q_i	Rank	cc_i	Rank	PI	Rank
P1III	1.165	3	0.235	3	0.645	3	−0.047	3	0.576	3	0.134	3	0.485	1
P2III	14.29	1	0.247	1	0.678	1	0.01	2	0.606	1	0.711	2	0.301	2
P3III	7.690	2	0.245	2	0.672	2	0.036	1	0.601	2	0.712	1	0.214	3

Table 13. Ranking of private partners based on the investigated MCDM algorithms (case study IV) (authors' own work).

Private Partner	CoCoSo		WISP		MARCOS		CODAS		WASPAS		TOPSIS		FANP	
	K_{ic}	Rank	u_i	Rank	$f(K_i)$	Rank	H_i	Rank	Q_i	Rank	cc_i	Rank	PI	Rank
P1IV	3.626	3	0.206	3	0.673	3	0.036	3	0.497	3	0.572	3	0.153	3
P2IV	2.201	5	0.184	5	0.602	5	−0.056	4	0.444	5	0.395	5	0.119	5
P3IV	5.275	1	0.250	1	0.818	1	0.261	1	0.604	1	1	1	0.325	1
P4IV	4.204	2	0.222	2	0.728	2	0.259	2	0.537	2	0.720	2	0.158	2
P5IV	1.134	6	0.163	6	0.535	6	−0.425	6	0.394	6	0.240	6	0.103	6
P6IV	2.991	4	0.191	4	0.624	4	−0.075	5	0.461	4	0.445	4	0.142	4

Tables 14 and 15 elucidate the results of Copeland across the four case studies. It shows the wins, losses, final score and final ranking of each private partner. The consolidated rankings of private partners are determined based on garnering the number of wins and losses of each private partner across the seven investigated MCDM algorithms. It can be seen that P3I is the most superior private partner in case study I with three wins and zero losses while P4I is ranked second with two wins and one loss. It is also indicated that P2II is the best private partner in case study II with two wins and zero losses while P1II is ranked third with two losses and zero wins. P2II outranked the remainder of private partners in case study III with two wins and zero loss. It is also found that P2III is ranked second with one win and one loss. Concerning case study IV, P3IV outperformed other private partners accomplishing five wins and zero losses. In addition to that, P4IV was found to be the second preferred private partner with four wins and one loss.

Table 14. Final rankings of private partners in accordance with Copeland algorithm (case studies I and II) (authors' own work).

Private Partner	Case Study I				Case Study II			
	Wins	Losses	Final Score	Final Rank	Wins	Losses	Final Score	Final Rank
P1	0	3	−3	3	0	2	−2	3
P2	1	2	−1	4	2	0	2	1
P3	3	0	3	1	1	1	0	2
P4	2	1	1	2	---	---	---	---
P5	---	---	---	---	---	---	---	---
P6	---	---	---	---	---	---	---	---

Table 15. Final rankings of private partners in accordance with Copeland algorithm (case studies III and IV) (authors' own work).

Private Partner	Case Study III				Case Study IV			
	Wins	Losses	Final Score	Final Rank	Wins	Losses	Final Score	Final Rank
P1	0	2	−2	3	3	2	1	2
P2	2	0	2	1	1	4	−3	5
P3	1	1	0	2	5	0	5	1
P4	---	---	---	---	4	1	3	3
P5	---	---	---	---	0	5	−5	6
P6	---	---	---	---	2	3	−1	4

Figure 5 reports Spearman's rank correlation coefficients between the investigated seven MCDM models. Figure 6 shows a Kednall tau correlation matrix for the investigated MCDM models. The values stored herein are obtained based on taking the average of the values of Spearman's rank correlation coefficient or Kendall tau rank correlation coefficient over the four case studies. It is observed that a perfect correlation exists between the four MCDM models of HYBD_MCDM, WISP, MAROCS and WPM. In addition to that, high Spearman's correlation and Kendall tau correlation lie between the pairs (HYBD_MCDM, WPM), (WISP, WPM), (MARCOS, WPM) and (WASPAS, WPM). In this context, their Spearman's rank correlation coefficients were 0.9. Furthermore, Kendall tau rank correlation between the aforementioned pairs of MCDM algorithms is 0.833. It is also derived that weak Spearman's correlation are exhibited between the pairs (CoCoSo, CODAS), (CODAS, FANP) and (WASPAS, FANP), whereas their correlation coefficients were equal to 0.286 and −0.014, respectively. In addition to that, their Kendall tau rank correlation values are weak and they correspond to 0.217 and −0.033, respectively.

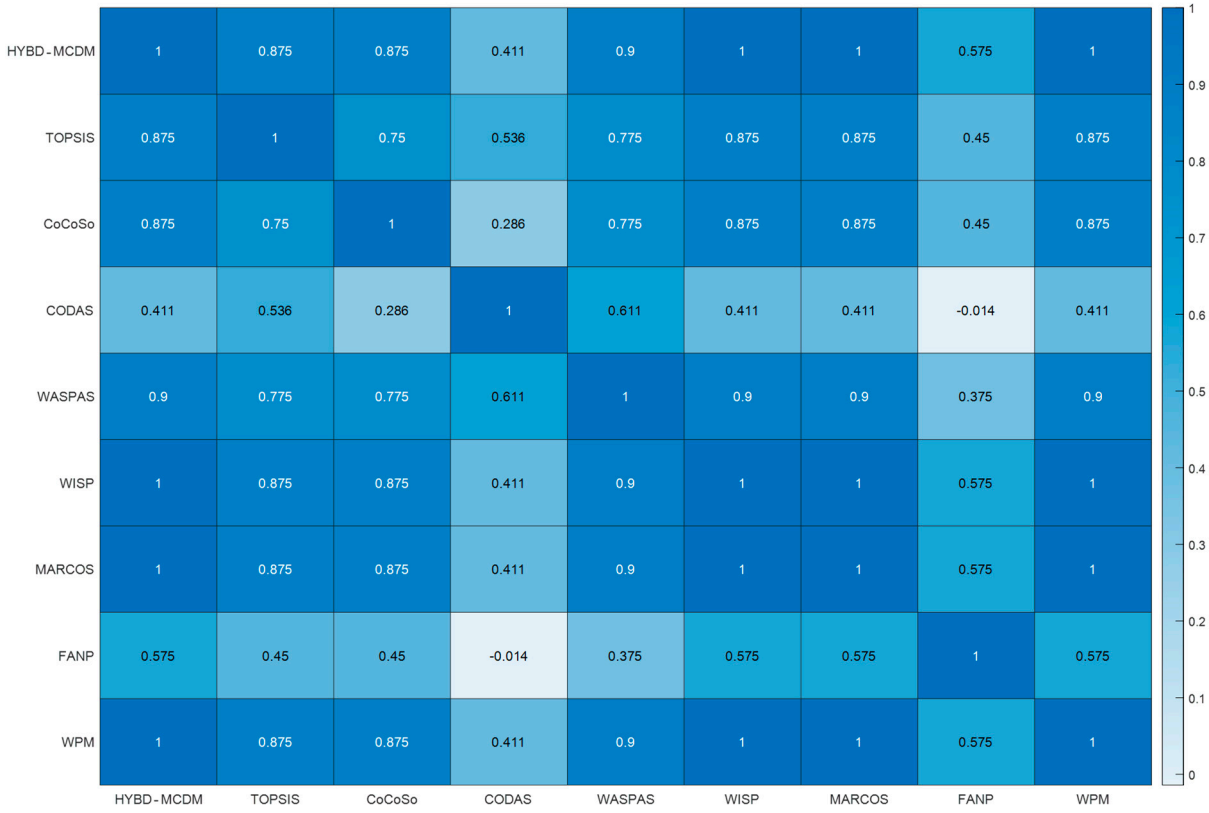


Figure 5. Spearman's rank correlation coefficient between the investigated MCDM models (authors' own work).

On the grand scheme of things, the average Spearman's rank correlation coefficients of the investigated MCDM models are calculated to analyze their reliability (see Table 16). It is shows that the average Spearman's correlation coefficients of HYBD_MCDM, TOPSIS, CoCoSo, CODAS, WASPAS, WISP, MARCOS, FANP and WPM are 0.83, 0.751, 0.72, 0.383, 0.767, 0.83, 0.83, 0.445 and 0.83, respectively. Besides, the average Kendall tau rank correlation coefficients of HYBD_MCDM, TOPSIS, CoCoSo, CODAS, WASPAS, WISP, MARCOS, FANP and WPM are 0.808, 0.704, 0.662, 0.352, 0.704, 0.808, 0.808, 0.444 and 0.808, respectively. This manifests that the developed HYBD_MCDM, WISP, MARCOS and WPM are the most dominant MCDM algorithms in accordance with conformity and consistency with remainder of MCDM algorithms. This paves the way to draw a conclusion that developed HYBD_MCDM, WISP, MARCOS and WPM are highly applicable and can be used as a reference for the selection and evaluation of private partners in infrastructure projects. It

is also noticed that CoCoSo and TOPSIS renders a relatively acceptable agreement with other MCDM models. On the other hand, CODAS and FANP produced rankings that were highly distanced from other MCDM algorithms, which exemplifies their inefficiency in the prioritization of private partners in infrastructure projects.

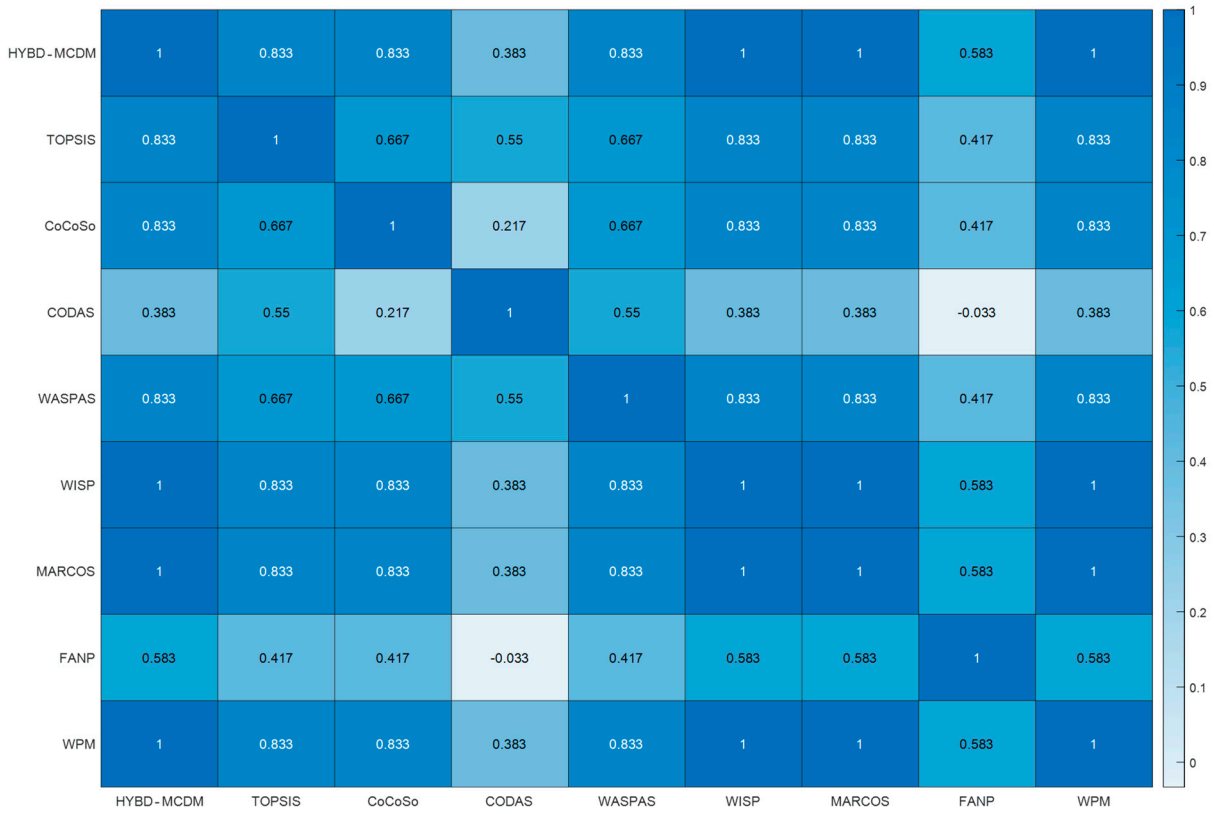


Figure 6. Kendall tau rank correlation coefficient between the investigated MCDM models (authors' own work).

Table 16. Average Spearman's correlation coefficients of MCDM models (authors' own work).

MCDM Model	Average Spearman's Correlation Coefficient
HYBD_MCDM	0.808
TOPSIS	0.704
CoCoSo	0.662
CODAS	0.352
WASPAS	0.704
WISP	0.808
MARCOS	0.808
FANP	0.444
WPM	0.808

An automated tool is programmed using C#.net language to facilitate the implementation of the developed private partner selection model by the users. Figure 7 explicates a visual representation of the capabilities of the developed model. The inputs for the developed automated tool comprise information pertaining to the project and private partners alongside experts' judgments. The outputs involve a priority index and ranking for each respective private partner.

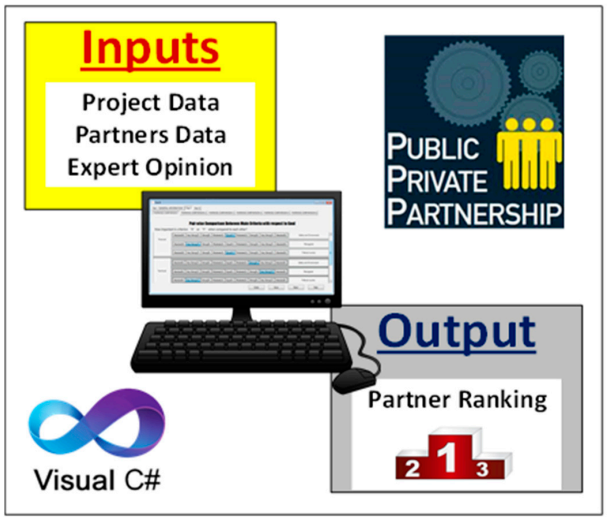
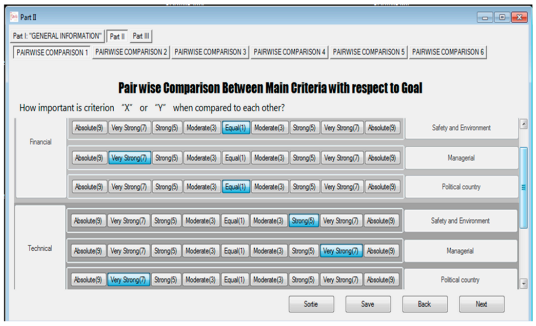
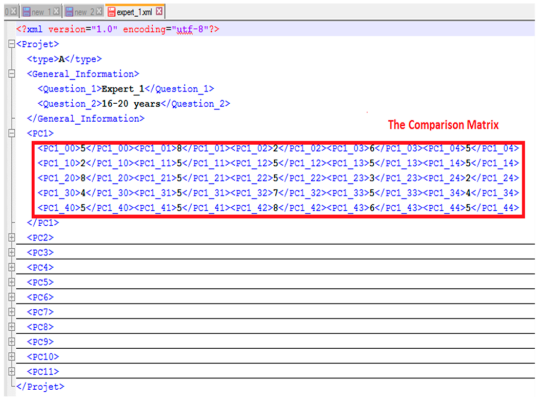


Figure 7. Components of the developed automated platform (authors' own work).

Figure 8a elucidates the interface where the user is asked to demonstrate his preferences towards the private partner selection criteria. The input and processed data are stored in XML format to simplify and expedite their storage, retrieval and management (see Figure 8b). Figure 9 expounds the interface of private partner selection based on ANP. According to the user inputs and experts' judgments, it is found that the private partner B (57.06%) is ranked first followed by private partner C (27.61%) in the second place and then private partner A (15.31%) in the third place.



(a) Interface of pairwise comparisons



(b) Structure of the XML backup file.

Figure 8. Interface of the pairwise comparison entries and structure of XML backup file (authors' own work).

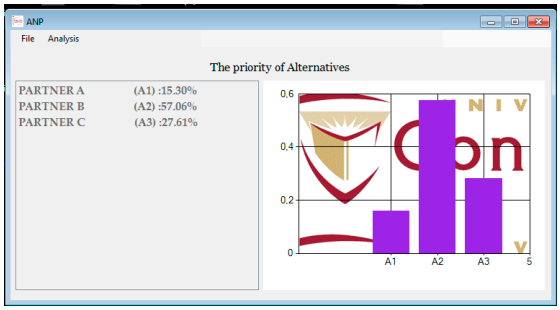


Figure 9. Interface of ranking of private partners based on ANP (authors' own work).

7. Analysis and Discussion

Analytical comparison of criteria weights evinces that different relative importance priorities are retrieved for each case study. For instance, financial and technical aspects (35%) share the same level of importance in case study I (Ivory Coast). The political aspect (31.5%) is ranked first in case study II (Libya), while the financial aspect is regarded as the most prominent criteria in case studies III and IV (Tunisia and Senegal) with 36.5% and 26.6%, respectively. Tables 17–20 expound a comparison between the rankings of the investigated MCDM models. In the first case study, the developed integrated HYBD_MCDM selected private partner "P3I" as the best alternative. This agrees with the majority of MCDM models like TOPSIS, CoCoSo, WISP, MARCOS and WPM, which suggests that "P3I" is the best private partner. WASPAS and FANP produced a slightly different ranking from the consensus ranking of private partners while CODAS determined a completely distinctive ranking. As for the second study, all MCDM algorithms except CoCoSo are consistent in the full ranking of alternatives and simultaneously identifying "P2II" as the optimum private partner. With regard to the third case study, CoCoSo, WASPAS, WISP, MARCOS and WPM conform with the developed HYBD_MCDM model in identifying "P2III" as the best private partner. On the other hand, private partner "P3III" was determined by TOPSIS and CODAS as the best private partner, and FANP appended private partner "P1III" as the best one. With respect to the fourth case study, the most (P3IV) and least (P5IV) preferable private partners do not change rankings no matter what MCDM model is used. Looking into the four case studies and through careful examination of the obtained rankings, it is reasonable to argue that the rankings rendered by the developed HYBD_MCDM are credible and thus it stands as a reliable reference for decision-making in selection of private partners in transportation projects.

Table 17. Comparison of rankings of private partners in case study I (authors' own work).

MCDM Model	Private Partner "P1"	Private Partner "P2"	Private Partner "P3"	Private Partner "P4"
HYBD_MCDM	4	3	1	2
TOPSIS	4	3	1	2
CoCoSo	4	3	1	2
CODAS	1	2	4	3
WASPAS	3	4	2	1
WISP	4	3	1	2
MARCOS	4	3	1	2
FANP	4	2	1	3
WPM	4	3	1	2

Table 18. Comparison of rankings of private partners in case study II (authors' own work).

MCDM Model	Private Partner "P1"	Private Partner "P2"	Private Partner "P3"
HYBD_MCDM	3	1	2
TOPSIS	3	1	2
CoCoSo	3	2	1
CODAS	3	1	2
WASPAS	3	1	2
WISP	3	1	2
MARCOS	3	1	2
FANP	3	1	2
WPM	3	1	2

Table 19. Comparison of rankings of private partners in case study III (authors' own work).

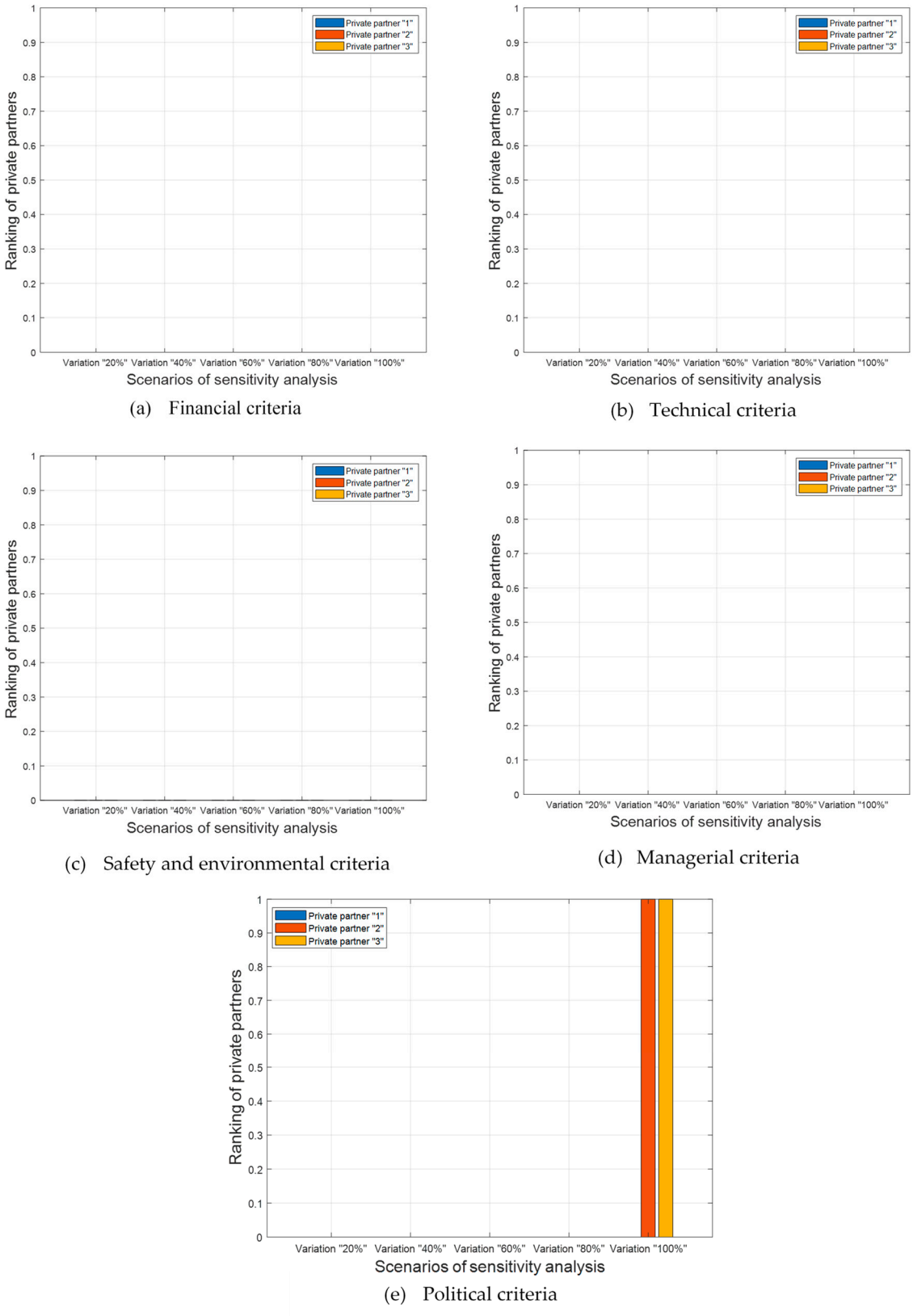
MCDM Model	Private Partner "P1"	Private Partner "P2"	Private Partner "P3"
HYBD_MCDM	3	1	2
TOPSIS	3	2	1
CoCoSo	3	1	2
CODAS	3	2	1
WASPAS	3	1	2
WISP	3	1	2
MARCOS	3	1	2
FANP	1	2	3
WPM	3	1	2

Table 20. Comparison of rankings of private partners in case study IV (authors' own work).

MCDM Model	Private Partner "P1"	Private Partner "P2"	Private Partner "P3"	Private Partner "P4"	Private Partner "P5"	Private Partner "P6"
HYBD_MCDM	3	5	1	2	6	4
TOPSIS	3	5	1	2	6	4
CoCoSo	3	5	1	2	6	4
CODAS	3	4	1	2	6	5
WASPAS	3	5	1	2	6	4
WISP	3	5	1	2	6	4
MARCOS	3	5	1	2	6	4
FANP	3	5	1	2	6	4
WPM	3	5	1	2	6	4

Figures 10–13 demonstrate 100 sensitivity analysis simulation runs over the course of four case studies. In this respect, each of the five PPP selection criteria is varied by 20%, 40%, 60%, 80% and 100%, resulting in 25 sensitivity analysis simulation runs for each case study. By visually inspecting the sensitivity analysis runs, it can be observed that the developed MCDM model is minimally affected by the variations in the weightages of PPP selection criteria exemplifying its robustness. In particular, the rankings of the public private partners are altered in 10 simulation runs (10%) over the entire sensitivity analysis. It is also viewed that political aspect is the most sensitive criteria in selecting

private partners in case study II while managerial aspect is the most sensitive criteria in selecting private partners in case study III. As for case study IV, technical requirements are found to be most the decisive criteria in evaluation of private partners.



(a) Financial criteria

(b) Technical criteria

(c) Safety and environmental criteria

(d) Managerial criteria

(e) Political criteria

Figure 10. Sensitivity analysis of PPP selection criteria in case study I.

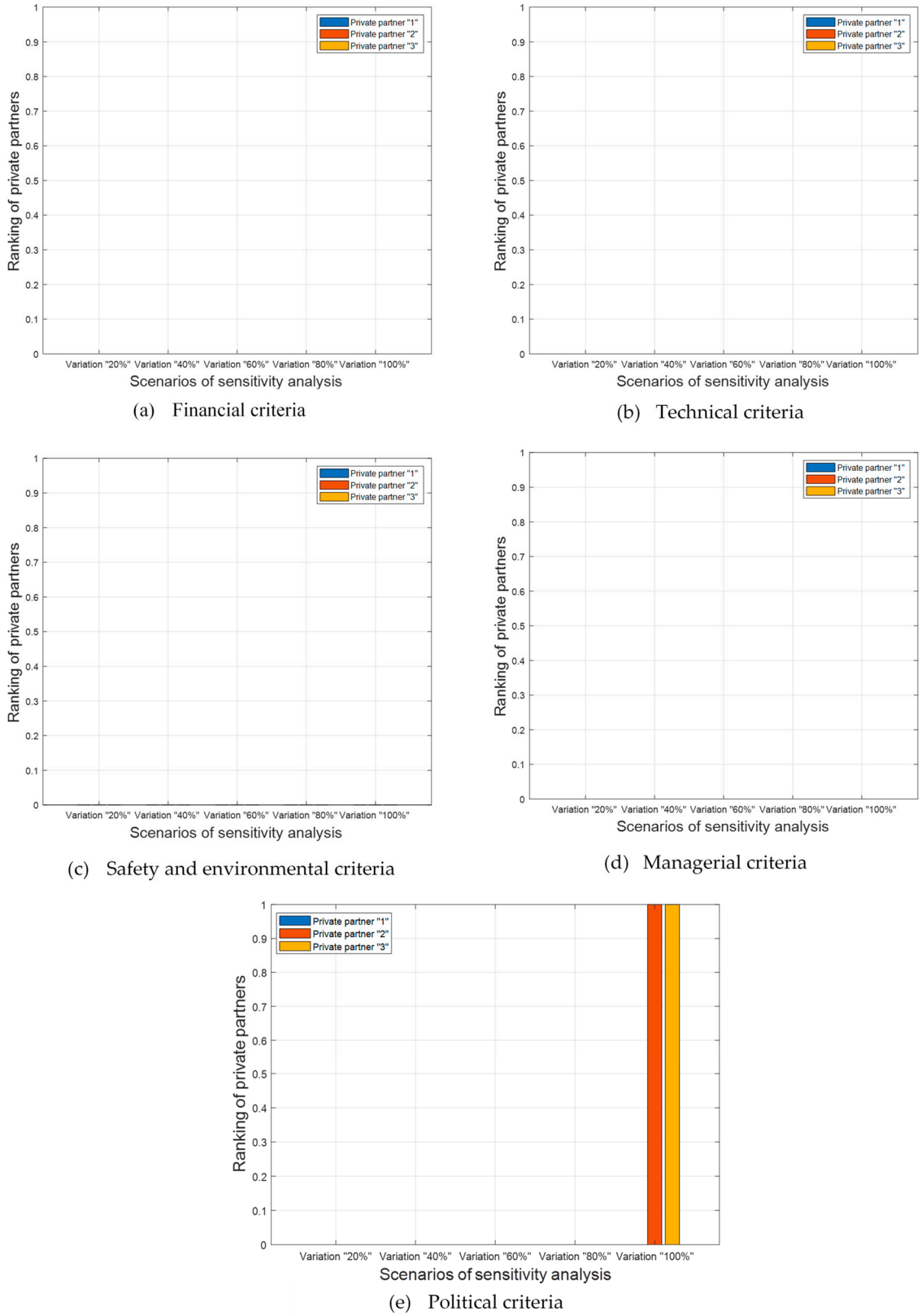


Figure 11. Sensitivity analysis of PPP selection criteria in case study II.

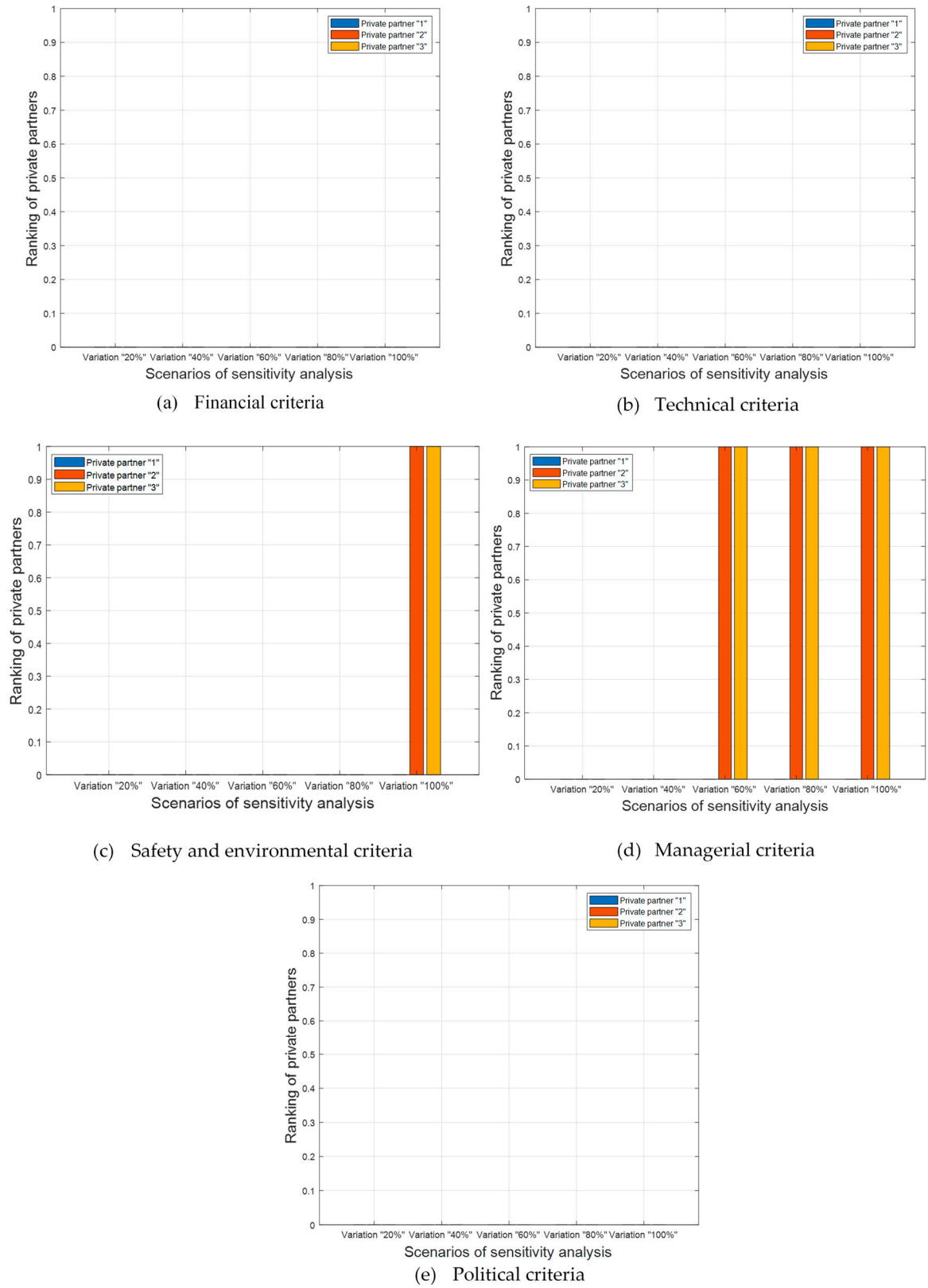


Figure 12. Sensitivity analysis of PPP selection criteria in case study III.

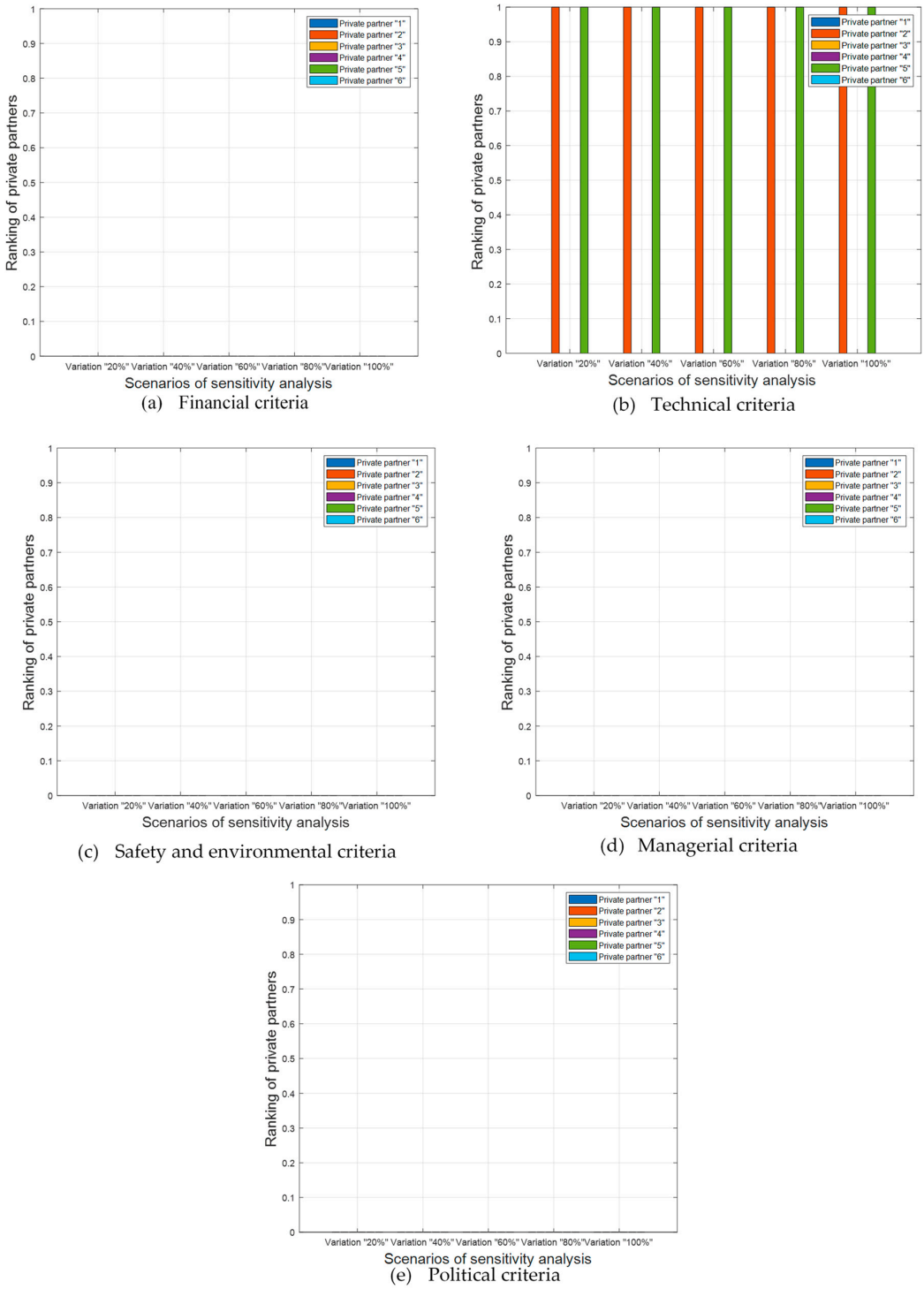


Figure 13. Sensitivity analysis of PPP selection criteria in case study IV.

Figure 14 elucidate a comparison between the investigated MCDM models based on sensitivity analysis runs. It can be viewed that the developed HYBD_MCDM, WASPAS, WISP and MARCOS are the most robust MCDM models. In this respect, the ranking or private partners are varied in 10 sensitivity analysis simulation runs. CoCoSo (12) and WPM (13) come in the second and third places, respectively. It is also noted that TOPSIS and CODAS are the most sensitive MCDM models since they were associated with a ranking change in 29 and 44 sensitivity analysis runs, respectively. In order to better measure the robustness of the developed HBD_MCDM model, the average absolute difference in

ranking (AADR) is incorporated for doing so (see Figure 15). In this context, the AADR is computed by dividing the difference in ranking of private partners by the number of simulation runs multiplied by the number of private partners under consideration. It is inferred that the developed HYBD_MCDM model accomplished AADR of 0.067 demonstrating its superior stability over the remainder of MCDM models. Likewise, WASPAS (0.075), WISP (0.075), MARCOS (0.075) and CoCoSo (0.079) attained low values of AADR, exemplifying their low sensitivity to the variation in weightages of PPP selection criteria. The highest values of AADR are linked with TOPSIS (0.213) and CODAS (0.479) signifying their high influence by weight changes.

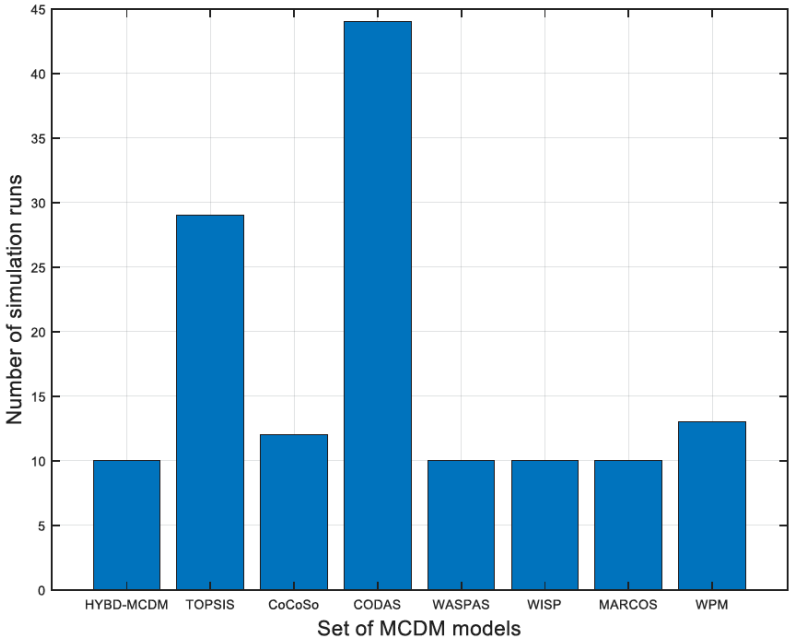


Figure 14. Comparison of sensitivity of MCDM models based on sensitivity analysis runs.

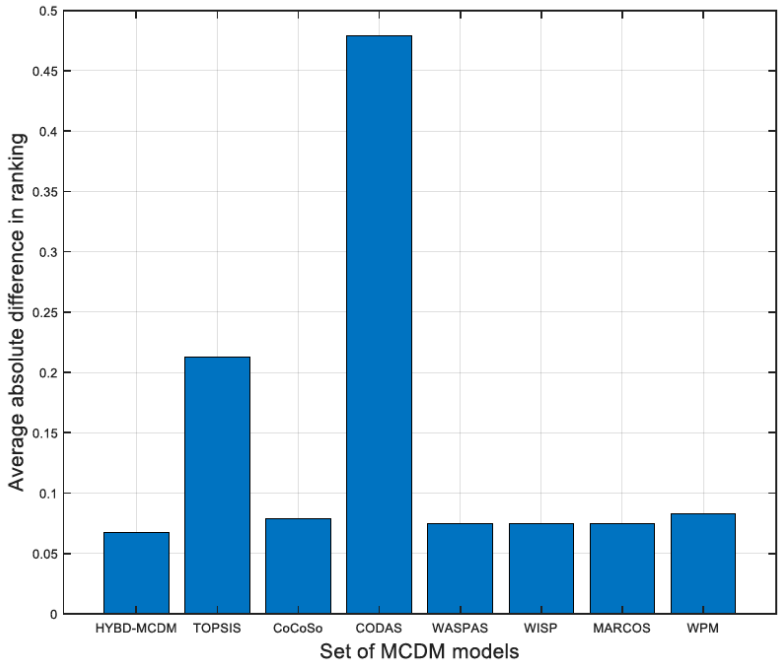


Figure 15. Comparison of sensitivity of MCDM models based on AADR.

8. Conclusions

Several countries have adopted public–private partnerships for capital-intense, strategic and complex infrastructure projects as a paradigm to lessen costs, diminish delays and alleviate economic risks. To this end, this research aimed to study, investigate, and design a two-tier multi-criteria decision-making model for selecting the private partners in PPP infrastructure projects. The first tier encompasses studying and analyzing relative importance weights of selection criteria of private partners capitalizing on fuzzy analytical network process. The second tier is envisioned based on the use of seven MCDM algorithms to prioritize private partners in infrastructure projects and identify the best one among them. These algorithms encompassed CoCoSo, WISP, MARCOS, CODAS, WASPAS, TOPSIS and FANP. Analytical results demonstrated that financial and technical aspects are the most influential factors on the selection of private partners with relative importance weights of 26.6% and 23.2%, respectively. It was also deduced that the sub-criteria of equity/debt (37.41%), construction program and ability to meet its targeted milestone (55.25%) and conformance to laws and regulations (35.79%) highly implicate the selection of private partners.

The analysis of case studies illustrated that different MCDM algorithms induced different rankings of private partners, which necessitates the use of the Copeland algorithm for blending the rankings of the tackled MCDM algorithms. For instance, CODAS and WASPAS failed to solve case study I and CoCoSo was not able to select the correct private partner in case study II. TOPSIS, CODAS and FANP were incapable of accurately finding the optimum private partner in case study III. However, all seven MCDM algorithms agreed on the determination of the best private partner in case study IV. It was also interpreted that notable variations are experienced in the rankings of private partners in the highway case study in Tunisia, when compared against other case studies. The correlation analysis suggested that WISP and MARCOS are highly efficient in the selection of private partners in infrastructure projects. On the contrary, CODAS and FANP failed to appropriately handle the ranking process of private partners, urging not using them in similar application. Some limitations still exist in this study. First, more responses need to be garnered that can aid in further validating the obtained results. Second, the collected data were based on projects only located in Africa. Other questionnaire surveys need to be designed for projects in other continents. Third, potential future research can include other selection criteria like expertise and knowledge of public private partners in similar projects besides the concession period of designated projects. Fourth, the developed model can be tedious and more challenging mostly in the presence of large number of criteria and private partners. The developed model is expected to aid governments by equipping them with an efficient decision support system for evaluating and selecting appropriate private partners and thus guaranteeing the successful delivery of PPP projects. The developed model is characterized by its robustness, generalizability and flexibility, which can facilitate the selection of public–private partners in other construction industries. Another advantage of the developed model is that researchers may opt to compare the results of the developed hybrid MCDM model with their other selection models of private partners. The developed model also pinpoints the factors that significantly influence the selection of private partners in PPP transportation projects. In addition, the procedures adopted in this study can be replicated across different infrastructure projects in developing and developed counties.

Author Contributions: Conceptualization, E.M.A., T.Z. and H.E.F.; methodology, E.M.A., T.Z., H.E.F. and O.M.; formal analysis, E.M.A., T.Z., H.E.F. and O.M.; data curation, E.M.A., T.Z., H.E.F., G.A., A.A.-S. and O.M.; investigation, E.M.A., T.Z., H.E.F. and O.M.; resources, E.M.A., T.Z., H.E.F. and O.M.; writing—original draft preparation, E.M.A., T.Z., H.E.F., G.A., A.A.-S. and O.M.; writing—review and editing, E.M.A., T.Z., H.E.F., G.A., A.A.-S. and O.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Some or all data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: The authors extend their appreciation to the Deputyship for Research and Innovation, Ministry of Education in Saudi Arabia for funding this research work through the project no. (IFKSUOR3-497-3).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Veselovsky, M.Y.; Nikolaev, V.I.; Trifonov, V.A. Implementation of Investment Projects in Industry as a Factor of Ensuring the Economic and Spatial Development of Russian Regions. In *International Scientific and Practical Conference Strategy of Development of Regional Ecosystems "Education-Science-Industry" (ISPCR 2021)*; Atlantis Press: Amsterdam, The Netherlands, 2022; pp. 508–514.
2. Jin, X.H. Neurofuzzy decision support system for efficient risk allocation in public-private partnership infrastructure projects. *J. Comput. Civ. Eng.* **2010**, *24*, 525–538. [CrossRef]
3. Wang, L.; Zhou, L.; Xiong, Y.; Yan, D. Effect of promotion pressure and financial burden on investment in public–private partnership infrastructure projects in China. *Asian-Pac. Econ. Lit.* **2019**, *33*, 128–142. [CrossRef]
4. Zhang, X. Critical success factors for public–private partnerships in infrastructure development. *J. Constr. Eng. Manag.* **2005**, *131*, 3–14. [CrossRef]
5. Garvin, M.J.; Cheah, C.Y. Valuation techniques for infrastructure investment decisions. *Constr. Manag. Econ.* **2004**, *22*, 373–383. [CrossRef]
6. Gupta, P.K.; Verma, H. Risk perception in PPP infrastructure project financing in India. *J. Financ. Manag. Prop. Constr.* **2020**, *25*, 347–369. [CrossRef]
7. Zhang, S.; Chan, A.P.; Feng, Y.; Duan, H.; Ke, Y. Critical review on PPP Research–A search from the Chinese and International Journals. *Int. J. Proj. Manag.* **2016**, *34*, 597–612. [CrossRef]
8. Navalersuph, N.; Charoenngam, C. Governance of Public–private partnerships in transportation infrastructure projects based on Thailand's experiences. *Case Stud. Transp. Policy* **2021**, *9*, 1211–1218. [CrossRef]
9. Bayat, F.; Noorzai, E.; Golabchi, M. Identifying the most important public–private partnership risks in Afghanistan's infrastructure projects. *J. Financ. Manag. Prop. Constr.* **2019**, *24*, 309–337. [CrossRef]
10. Aladağ, H.; Işik, Z. The effect of stakeholder-associated risks in mega-engineering projects: A case study of a PPP airport project. *IEEE Trans. Eng. Manag.* **2018**, *67*, 174–186.
11. Zayed, T.; Chang, L.-M. Prototype model for build-operate-transfer risk assessment. *J. Manag. Eng.* **2002**, *18*, 7–16. [CrossRef]
12. Khahro, S.H.; Ali, T.H.; Hassan, S.; Zainun, N.Y.; Javed, Y.; Memon, S.A. Risk severity matrix for sustainable public-private partnership projects in developing countries. *Sustainability* **2021**, *13*, 3292. [CrossRef]
13. Cheng, Z.; Wang, H.; Xiong, W.; Zhu, D.; Cheng, L. Public–private partnership as a driver of sustainable development: Toward a conceptual framework of sustainability-oriented PPP. *Environ. Dev. Sustain.* **2021**, *23*, 1043–1063. [CrossRef]
14. Wang, N.; Ma, M. Public–private partnership as a tool for sustainable development–What literatures say? *Sustain. Dev.* **2021**, *29*, 243–258. [CrossRef]
15. Simon, L.; Jefferies, M.; Davis, P.; Newaz, M.T. Developing a theoretical success factor framework for the tendering phase of social infrastructure PPPs. *Int. J. Constr. Manag.* **2020**, *20*, 613–627. [CrossRef]
16. Sarvari, H.; Valipour, A.; Yahya, N.; Noor, N.M.; Beer, M.; Banaitiene, N. Approaches to risk identification in public–private partnership projects: Malaysian private partners' overview. *Adm. Sci.* **2019**, *9*, 17. [CrossRef]
17. Zhang, X. Concessionaire selection: Methods and criteria. *J. Constr. Eng. Manag.* **2004**, *130*, 235–244. [CrossRef]
18. Wang, Y.; Zhao, Z.J. Performance of public–private partnerships and the influence of contractual arrangements. *Public Perform. Manag. Rev.* **2018**, *41*, 177–200. [CrossRef]
19. Abdel Aziz, A.M. Successful delivery of public-private partnerships for infrastructure development. *J. Constr. Eng. Manag.* **2007**, *133*, 918–931. [CrossRef]
20. Chan, A.P.C.; Ho, D.C.K.; Tam, C.M. Design and build project success factors: Multivariate analysis. *J. Constr. Eng. Manag.* **2001**, *127*, 93–100. [CrossRef]
21. Zhang, X. Improving Concessionaire Selection Protocols in Public/Private Partnered Infrastructure Projects. *J. Constr. Eng. Manag.* **2004**, *130*, 670–679. [CrossRef]
22. Liang, Y.; Jia, H. Key success indicators for PPP projects: Evidence from Hong Kong. *Adv. Civ. Eng.* **2018**, *2018*, 9576496. [CrossRef]
23. Muhammad, Z.; Johar, F. Critical success factors of public–private partnership projects: A comparative analysis of the housing sector between Malaysia and Nigeria. *Int. J. Constr. Manag.* **2019**, *19*, 257–269. [CrossRef]
24. Kavishe, N.; Chileshe, N. Critical success factors in public-private partnerships (PPPs) on affordable housing schemes delivery in Tanzania: A qualitative study. *J. Facil. Manag.* **2019**, *17*, 188–207. [CrossRef]

25. Helmy, R.; Khourshed, N.; Wahba, M.; Bary, A.A.E. Exploring critical success factors for public private partnership case study: The educational sector in Egypt. *J. Open Innov. Technol. Mark. Complex.* **2020**, *6*, 142. [CrossRef]
26. Alteneiji, K.; Alkass, S.; Dabous, S.A. Critical success factors for public–private partnerships in affordable housing in the United Arab Emirates. *Int. J. Hous. Mark. Anal.* **2020**, *13*, 753–768. [CrossRef]
27. Abukeshek, A.K.; Abdella, G.M.; Gunduz, M.; Naji, K. Analysis of Construction Critical Success Factors (CSF) for Public-Private Partnership (PPP) for Sports Infrastructure in Qatar Using Relative Importance Index. In Proceedings of the First Central American and Caribbean International Conference on Industrial Engineering and Operations Management, Port-au-Prince, Haiti, 15–16 June 2021; pp. 1–10.
28. Surachman, E.N.; Handayani, D.; Suhendra, M.; Prabowo, S. Critical success factors on PPP water project in a developing country: Evidence from Indonesia. *J. Asian Financ. Econ. Bus.* **2020**, *7*, 1071–1080. [CrossRef]
29. Adiyanti, N.P.; Fathurrahman, R. Assessing critical success factors for PPP water project in Indonesia: Lessons from West Semarang. *Policy Gov. Rev.* **2021**, *5*, 164–181. [CrossRef]
30. Chourasia, A.S.; Dalei, N.N.; Jha, K. Critical success factors for development of public-private-partnership airports in India. *J. Infrastruct. Policy Dev.* **2021**, *5*, 1259. [CrossRef]
31. Ngullie, N.; Maturi, K.C.; Kalamdhad, A.S.; Laishram, B. Critical success factors for PPP MSW projects–perception of different stakeholder groups in India. *Environ. Chall.* **2021**, *5*, 100379. [CrossRef]
32. Batra, R. A thematic analysis to identify barriers, gaps, and challenges for the implementation of public-private-partnerships in housing. *Habitat Int.* **2021**, *118*, 102454. [CrossRef]
33. Kandawinna, N.; Mallawaarachchi, H.; Vijerathne, D. Successful delivery of Public-Private Partnership (PPP) in the construction projects of Sri Lankan higher education sector. In Proceedings of the 10th World Construction Symposium, Colombo, Sri Lanka, 24–26 June 2022; pp. 782–793.
34. Osei-Kyei, R.; Tam, V.; Ma, M.; Tijani, B. Exploring the challenges in the development of retirement village homes through public-private partnerships. *J. Hous. Built Environ.* **2022**, *37*, 2059–2077. [CrossRef]
35. Othman, K.; Khallaf, R. Identification of the Barriers and Key Success Factors for Renewable Energy Public-Private Partnership Projects: A Continental Analysis. *Buildings* **2022**, *12*, 1511. [CrossRef]
36. Ongel, B.; Tanyer, A.M.; Dikmen, I. A network-based model for the assessment of success in PPP healthcare projects. *Int. J. Constr. Manag.* **2023**, 1–13. [CrossRef]
37. Kukah, A.S.K.; Owusu-Manu, D.G.; Badu, E.; Edwards, D.J. Delphi study for evaluating critical success factors (CSFs) for PPP power projects in Ghana. *J. Facil. Manag.* 2023; *ahead of print*.
38. Zhang, H.; Liu, G.; Han, Q.; Chen, G. Mapping the Barriers of Utilizing Public Private Partnership into Brownfield Remediation Projects in the Public Land Ownership. *Land* **2023**, *12*, 73. [CrossRef]
39. Kien, T.T.; Nguyen, N.M. Factors Affecting the Success of PPP Transport Projects in Vietnam. *Int. J. Sustain. Constr. Eng. Technol.* **2023**, *14*, 69–75.
40. Wang, Y.; Xiao, Z.; Tiong, R.L.; Zhang, L. Data-driven quantification of public–private partnership experience levels under uncertainty with Bayesian hierarchical model. *Appl. Soft Comput.* **2021**, *103*, 107176. [CrossRef]
41. Kowalska-Styczeń, A.; Kravets, P.; Lytvyn, V.; Vysotska, V.; Markiv, O. Game problem of assigning staff to project implementation. *Decis. Mak. Appl. Manag. Eng.* **2023**, *6*, 691–721. [CrossRef]
42. Chikowore, G.; Nhavira, J.D.; Mashonganyika, T.M.; Munhande, C. Disaster management capabilities in Zimbabwe: The context of Africa Agenda 2063. In *Resilience and Sustainability in Urban Africa: Context, Facets and Alternatives in Zimbabwe*; Springer: Singapore, 2021; pp. 37–54.
43. Bolu, C.A.; Abioye, A.; Azeta, J.; Boyo, H.; Onyiagha, G. Regional Peace through Collaborative Engineering driven by the African Union Aspiration 2063. In Proceedings of the 2018 World Engineering Education Forum-Global Engineering Deans Council (WEEF-GEDC), Albuquerque, NM, USA, 12–16 November 2018; pp. 1–6.
44. Akomea-Frimpong, I.; Jin, X.; Osei-Kyei, R.; Kukah, A.S. Public–private partnerships for sustainable infrastructure development in Ghana: A systematic review and recommendations. *Smart Sustain. Built Environ.* **2023**, *12*, 237–257. [CrossRef]
45. Dykes, B.J.; Jones, C.D. Public-private partnerships in Africa: Challenges and opportunities for future management research. *Afr. J. Manag.* **2016**, *2*, 381–393. [CrossRef]
46. Cengiz, A.E.; Aytekin, O.; Ozdemir, I.; Kusan, H.; Cabuk, A. A multi-criteria decision model for construction material supplier selection. *Procedia Eng.* **2017**, *196*, 294–301. [CrossRef]
47. Wang, T.K.; Zhang, Q.; Chong, H.Y.; Wang, X. Integrated supplier selection framework in a resilient construction supply chain: An approach via analytic hierarchy process (AHP) and grey relational analysis (GRA). *Sustainability* **2017**, *9*, 289. [CrossRef]
48. He, X.; Zhang, J. Supplier selection study under the respective of low-carbon supply chain: A hybrid evaluation model based on FA-DEA-AHP. *Sustainability* **2018**, *10*, 564. [CrossRef]
49. Matić, B.; Jovanović, S.; Das, D.K.; Zavadskas, E.K.; Stević, Ž; Sremac, S.; Marinković, M. A new hybrid MCDM model: Sustainable supplier selection in a construction company. *Symmetry* **2019**, *11*, 353. [CrossRef]
50. Yazdani, M.; Wen, Z.; Liao, H.; Banaitis, A.; Turskis, Z. A grey combined compromise solution (CoCoSo-G) method for supplier selection in construction management. *J. Civ. Eng. Manag.* **2019**, *25*, 858–874. [CrossRef]
51. Yazdani, M.; Chatterjee, P.; Pamucar, D.; Abad, M.D. A risk-based integrated decision-making model for green supplier selection: A case study of a construction company in Spain. *Kybernetes* **2020**, *49*, 1229–1252. [CrossRef]

52. Marzouk, M.; Sabbah, M. AHP-TOPSIS social sustainability approach for selecting supplier in construction supply chain. *Clean. Environ. Syst.* **2021**, *2*, 100034. [CrossRef]
53. Hoseini, S.A.; Fallahpour, A.; Wong, K.Y.; Mahdiyar, A.; Saberi, M.; Durdyev, S. Sustainable supplier selection in construction industry through hybrid fuzzy-based approaches. *Sustainability* **2021**, *13*, 1413. [CrossRef]
54. Dewi, S.K.; Ramadhani, Z.S. An Integrated ANP and MARCOS for Green Supplier Selection: A Case Study on Construction Industry. *J. Tek. Ind.* **2022**, *23*, 133–148.
55. Tushar, Z.N.; Bari, A.M.; Khan, M.A. Circular supplier selection in the construction industry: A sustainability perspective for the emerging economies. *Sustain. Manuf. Serv. Econ.* **2022**, *1*, 100005. [CrossRef]
56. Zhang, X. Paving the way for public–private partnerships in infrastructure development. *J. Constr. Eng. Manag.* **2005**, *131*, 71–80. [CrossRef]
57. El Fathali, H.I. Private Partner Selection and Bankability Assessment of PPP in Infrastructure Projects. Ph.D. Thesis, Concordia University, Montreal, QC, Canada, 2015.
58. Sachs, T.; Tiong, R.; Wang, S.Q. Analysis of political risks and opportunities in public private partnerships (PPP) in China and selected Asian countries: Survey results. *Chin. Manag. Stud.* **2007**, *1*, 126–148. [CrossRef]
59. Wang, W.; Dai, D.S. Research on the concessionaire selection for build-operate-transfer projects. In Proceedings of the 2010 International Conference on Management and Service Science, Wuhan, China, 24–26 August 2010; pp. 1–4.
60. Bashar, T.; Fung, I.W.; Jaillon, L.C.; Wang, D. Major obstacles to public-private partnership (PPP)-financed infrastructure development in China. *Sustainability* **2021**, *13*, 6718. [CrossRef]
61. Cui, C.; Liu, Y.; Hope, A.; Wang, J. Review of studies on the public–private partnerships (PPP) for infrastructure projects. *Int. J. Proj. Manag.* **2018**, *36*, 773–794. [CrossRef]
62. Sharma, C. Determinants of PPP in infrastructure in developing economies. *Transform. Gov. People Process Policy* **2012**, *6*, 149–166. [CrossRef]
63. Meunier, D.; Quinet, E. Tips and Pitfalls in PPP design. *Res. Transp. Econ.* **2010**, *30*, 126–138. [CrossRef]
64. Schaufelberger, J.E.; Wipadapisut, I. Alternate financing strategies for build-operate-transfer projects. *J. Constr. Eng. Manag.* **2003**, *129*, 205–213. [CrossRef]
65. Askar, M.M.; Gab-Allah, A.A. Problems facing parties involved in build, operate, and transport projects in Egypt. *J. Manag. Eng.* **2002**, *18*, 173–178. [CrossRef]
66. Tiong, R.L. CSFs in competitive tendering and negotiation model for BOT projects. *J. Constr. Eng. Manag.* **1996**, *122*, 205–211. [CrossRef]
67. Tiong, R.L.; Alum, J. Evaluation of proposals for BOT projects. *Int. J. Proj. Manag.* **1997**, *15*, 67–72. [CrossRef]
68. Zhao, N.; Ying, F. Method selection: A conceptual framework for public sector PPP selection. *Built Environ. Proj. Asset Manag.* **2019**, *9*, 214–232. [CrossRef]
69. Umar, A.A.; Zawawi, N.A.W.A.; Abdul-Aziz, A.R. Malaysian regulators' ranking of PPP contract governance skills. *Built Environ. Proj. Asset Manag.* **2021**, *11*, 88–102. [CrossRef]
70. Ameyaw, C.; Adjei-Kumi, T.; Owusu-Manu, D.G. Exploring value for money (VfM) assessment methods of public-private partnership projects in Ghana: A theoretical framework. *J. Financ. Manag. Prop. Constr.* **2015**, *20*, 268–285. [CrossRef]
71. Smith, N.J.; Gannon, M. Political risk in light rail transit PPP projects. *Proc. Inst. Civ. Eng. Manag. Procure. Law* **2008**, *161*, 179–185. [CrossRef]
72. Ahadzi, M.; Bowles, G. Public–private partnerships and contract negotiations: An empirical study. *Constr. Manag. Econ.* **2004**, *22*, 967–978. [CrossRef]
73. Hodge, G.A.; Greve, C. Public–private partnerships: An international performance review. *Public Adm. Rev.* **2007**, *67*, 545–558. [CrossRef]
74. Ma, H.; Zeng, S.; Lin, H.; Zeng, R. Impact of public sector on sustainability of public–private partnership projects. *J. Constr. Eng. Manag.* **2020**, *146*, 04019104. [CrossRef]
75. Liu, B.; Shen, J.Q.; Meng, Z.J.; Sun, F.H. A survey on the establishment and application of social capital partner selection system for the new profit PPP project. *KSCE J. Civ. Eng.* **2018**, *22*, 3726–3737. [CrossRef]
76. Sadeghi, A.; Larimian, T. Sustainable electricity generation mix for Iran: A fuzzy analytic network process approach. *Sustain. Energy Technol. Assess.* **2018**, *28*, 30–42. [CrossRef]
77. Abouhamad, M.; Zayed, T. Fuzzy preference programming framework for functional assessment of subway networks. *Algorithms* **2020**, *13*, 220. [CrossRef]
78. Mavi, R.K.; Standing, C. Critical success factors of sustainable project management in construction: A fuzzy DEMATEL-ANP approach. *J. Clean. Prod.* **2018**, *194*, 751–765. [CrossRef]
79. Alani, S.H.N.; Mahjoob, A.M.R. Using AHP to prioritize the corruption risk practices in the Iraqi construction sector. *Asian J. Civ. Eng.* **2021**, *22*, 1281–1299. [CrossRef]
80. Kim, S.Y.; Nguyen, V.T. An AHP framework for evaluating construction supply chain relationships. *KSCE J. Civ. Eng.* **2018**, *22*, 1544–1556. [CrossRef]
81. Rezaei, A.; Tahsili, S. Urban vulnerability assessment using AHP. *Adv. Civ. Eng.* **2018**, *2018*, 2018601. [CrossRef]
82. Attari, M.Y.N.; Beirami, A.A.M.; Ala, A.; Jami, E.N. Resolving the practical factors in the healthcare system management by considering a combine approach of AHP and ANP methods. *Eval. Program Plan.* **2023**, *100*, 102339. [CrossRef] [PubMed]

83. Šmidovnik, T.; Grošelj, P. Solution for Convergence Problem in DEMATEL Method: DEMATEL of Finite Sum of Influences. *Symmetry* **2023**, *15*, 1357. [CrossRef]
84. Aghasafari, H.; Karbasi, A.; Mohammadi, H.; Calisti, R. Determination of the best strategies for development of organic farming: A SWOT–Fuzzy Analytic Network Process approach. *J. Clean. Prod.* **2020**, *277*, 124039. [CrossRef]
85. Yazdani, M.; Abdi, M.R.; Kumar, N.; Keshavarz-Ghorabaee, M.; Chan, F.T. Improved decision model for evaluating risks in construction projects. *J. Constr. Eng. Manag.* **2019**, *145*, 04019024. [CrossRef]
86. Naji, K.K.; Gunduz, M.; Falamarzi, M.H. Assessment of Construction Project Contractor Selection Success Factors considering Their Interconnections. *KSCE J. Civ. Eng.* **2022**, *26*, 3677–3690. [CrossRef]
87. Yücelgazi, F.; Yitmen, I. An ANP model for risk response assessment in large scale bridge projects. *Civ. Eng. Environ. Syst.* **2020**, *37*, 1–27. [CrossRef]
88. Fard, M.B.; Hamidi, D.; Ebadi, M.; Alavi, J.; Mckay, G. Optimum landfill site selection by a hybrid multi-criteria and multi-Agent decision-making method in a temperate and humid climate: BWM-GIS-FAHP-GT. *Sustain. Cities Soc.* **2022**, *79*, 103641. [CrossRef]
89. Agarwal, S.; Singh, A.P. Performance evaluation of textile wastewater treatment techniques using sustainability index: An integrated fuzzy approach of assessment. *J. Clean. Prod.* **2022**, *337*, 130384. [CrossRef]
90. Khoshnava, S.M.; Rostami, R.; Valipour, A.; Ismail, M.; Rahmat, A.R. Rank of green building material criteria based on the three pillars of sustainability using the hybrid multi criteria decision making method. *J. Clean. Prod.* **2018**, *173*, 82–99. [CrossRef]
91. Yadav, D.K.; Barve, A. Prioritization of cyclone preparedness activities in humanitarian supply chains using fuzzy analytical network process. *Nat. Hazards* **2019**, *97*, 683–726. [CrossRef]
92. Heidarie Golafzani, S.; Eslami, A.; Jamshidi Chenari, R.; Hamed Saghaian, M. Optimized selection of axial pile bearing capacity predictive methods based on multi-criteria decision-making (MCDM) models and database approach. *Soft Comput.* **2022**, *26*, 5865–5881. [CrossRef]
93. Firouzi, S.; Allahyari, M.S.; Isazadeh, M.; Nikkhah, A.; Van Haute, S. Hybrid multi-criteria decision-making approach to select appropriate biomass resources for biofuel production. *Sci. Total Environ.* **2021**, *770*, 144449. [CrossRef]
94. Meshram, S.G.; Alvandi, E.; Meshram, C.; Kahya, E.; Fadhil Al-Quraishi, A.M. Application of SAW and TOPSIS in prioritizing watersheds. *Water Resour. Manag.* **2020**, *34*, 715–732. [CrossRef]
95. Jamwal, A.; Agrawal, R.; Sharma, M.; Kumar, V. Review on multi-criteria decision analysis in sustainable manufacturing decision making. *Int. J. Sustain. Eng.* **2021**, *14*, 202–225. [CrossRef]
96. Danesh, D.; Ryan, M.J.; Abbasi, A. Multi-criteria decision-making methods for project portfolio management: A literature review. *Int. J. Manag. Decis. Mak.* **2018**, *17*, 75–94. [CrossRef]
97. Şahin, M. A comprehensive analysis of weighting and multicriteria methods in the context of sustainable energy. *Int. J. Environ. Sci. Technol.* **2021**, *18*, 1591–1616. [CrossRef]
98. Roozbahani, A.; Ebrahimi, E.; Banihabib, M.E. A framework for ground water management based on bayesian network and MCDM techniques. *Water Resour. Manag.* **2018**, *32*, 4985–5005. [CrossRef]
99. Tayal, A.; Gunasekaran, A.; Singh, S.P.; Dubey, R.; Papadopoulos, T. Formulating and solving sustainable stochastic dynamic facility layout problem: A key to sustainable operations. *Ann. Oper. Res.* **2017**, *253*, 621–655. [CrossRef]
100. Koohathongsumrit, N.; Meethom, W. Route selection in multimodal transportation networks: A hybrid multiple criteria decision-making approach. *J. Ind. Prod. Eng.* **2021**, *38*, 171–185. [CrossRef]
101. Karatas, M.; Karacan, I.; Tozan, H. An integrated multi-criteria decision making methodology for health technology assessment. *Eur. J. Ind. Eng.* **2018**, *12*, 504–534. [CrossRef]
102. Sahoo, S.K.; Goswami, S.S. A Comprehensive Review of Multiple Criteria Decision-Making (MCDM) Methods: Advancements, Applications, and Future Directions. *Decis. Mak. Adv.* **2023**, *1*, 25–48. [CrossRef]
103. Phurksaphanrat, B.; Panjavongroj, S. A hybrid method for occupations selection in the bio-circular-green economy project of the national housing authority in Thailand. *Decis. Mak. Appl. Manag. Eng.* **2023**, *6*, 177–200. [CrossRef]
104. Ghoushchi, S.J.; Jalalat, S.M.; Bonab, S.R.; Ghiaci, A.M.; Haseli, G.; Tomaskova, H. Evaluation of wind turbine failure modes using the developed SWARA-CoCoSo methods based on the spherical fuzzy environment. *IEEE Access* **2022**, *10*, 86750–86764. [CrossRef]
105. Deveci, M.; Mishra, A.R.; Gokasar, I.; Rani, P.; Pamucar, D.; Özcan, E. A decision support system for assessing and prioritizing sustainable urban transportation in metaverse. *IEEE Trans. Fuzzy Syst.* **2022**, *31*, 475–484. [CrossRef]
106. Stanujkic, D.; Popovic, G.; Karabasevic, D.; Meidute-Kavaliauskiene, I.; Ulutaş, A. An integrated simple weighted sum product method—WISP. *IEEE Trans. Eng. Manag.* **2021**, *70*, 1933–1944. [CrossRef]
107. Stević, Ž.; Pamučar, D.; Puška, A.; Chatterjee, P. Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to Compromise solution (MARCOS). *Comput. Ind. Eng.* **2020**, *140*, 106231. [CrossRef]
108. Pamucar, D.; Iordache, M.; Deveci, M.; Schitea, D.; Iordache, I. A new hybrid fuzzy multi-criteria decision methodology model for prioritizing the alternatives of the hydrogen bus development: A case study from Romania. *Int. J. Hydrogen Energy* **2021**, *46*, 29616–29637. [CrossRef]
109. Sisto, R.; Fernández-Portillo, L.A.; Yazdani, M.; Estepa-Mohedano, L.; Torkayesh, A.E. Strategic planning of rural areas: Integrating participatory backcasting and multiple criteria decision analysis tools. *Socio-Econ. Plan. Sci.* **2022**, *82*, 101248. [CrossRef]

110. Raheja, S.; Obaidat, M.S.; Kumar, M.; Sadoun, B.; Bhushan, S. A hybrid MCDM framework and simulation analysis for the assessment of worst polluted cities. *Simul. Model. Pract. Theory* **2022**, *118*, 102540. [CrossRef]
111. Ghoushchi, S.J.; Garg, H.; Bonab, S.R.; Rahimi, A. An integrated SWARA-CODAS decision-making algorithm with spherical fuzzy information for clean energy barriers evaluation. *Expert Syst. Appl.* **2023**, *223*, 119884. [CrossRef]
112. Chaudhary, N.; Singh, S.; Garg, M.P.; Garg, H.K.; Sharma, S.; Li, C.; Tag Eldin, E.M.; El-Khatib, S. Parametric optimisation of friction-stir-spot-welded Al 6061-T6 incorporated with silicon carbide using a hybrid WASPAS–Taguchi technique. *Materials* **2022**, *15*, 6427. [CrossRef]
113. Liu, P.; Saha, A.; Mishra, A.R.; Rani, P.; Dutta, D.; Baidya, J. A BCF–CRITIC–WASPAS method for green supplier selection with cross-entropy and Archimedean aggregation operators. *J. Ambient. Intell. Humaniz. Comput.* **2022**, *14*, 11909–11933. [CrossRef]
114. Alam, K.A.; Ahmed, R.; Butt, F.S.; Kim, S.G.; Ko, K.M. An uncertainty-aware integrated fuzzy AHP-WASPAS model to evaluate public cloud computing services. *Procedia Comput. Sci.* **2018**, *130*, 504–509. [CrossRef]
115. Can, G.F. An intutionistic approach based on failure mode and effect analysis for prioritizing corrective and preventive strategies. *Hum. Factors Ergon. Manuf. Serv. Ind.* **2018**, *28*, 130–147. [CrossRef]
116. Aytekin, A.; Görçün, Ö.F.; Ecer, F.; Pamucar, D.; Karamaşa, Ç. Evaluation of the pharmaceutical distribution and warehousing companies through an integrated Fermatean fuzzy entropy-WASPAS approach. *Kybernetes* **2022**, 1–32. [CrossRef]
117. Slebi-Acevedo, C.J.; Pascual-Muñoz, P.; Lastra-González, P.; Castro-Fresno, D. Multi-response optimization of porous asphalt mixtures reinforced with aramid and polyolefin fibers employing the CRITIC-TOPSIS based on Taguchi methodology. *Materials* **2019**, *12*, 3789. [CrossRef]
118. Dutta, B.; Dao, S.D.; Martínez, L.; Goh, M. An evolutionary strategic weight manipulation approach for multi-attribute decision making: TOPSIS method. *Int. J. Approx. Reason.* **2021**, *129*, 64–83. [CrossRef]
119. Peng, C.; Du, H.; Liao, T.W. A research on the cutting database system based on machining features and TOPSIS. *Robot. Comput. -Integr. Manuf.* **2017**, *43*, 96–104. [CrossRef]
120. Panda, M.; Jagadev, A.K. TOPSIS in multi-criteria decision making: A survey. In Proceedings of the 2018 2nd International Conference on Data Science and Business Analytics (ICDSBA), Changsha, China, 21–23 September 2018; pp. 51–54.
121. Sheikh, V.; Izanloo, R. Assessment of low impact development stormwater management alternatives in the city of Bojnord, Iran. *Urban Water J.* **2021**, *18*, 449–464. [CrossRef]
122. Sayadinia, S.; Beheshtinia, M.A. Proposing a new hybrid multi-criteria decision-making approach for road maintenance prioritization. *Int. J. Qual. Reliab. Manag.* **2021**, *38*, 1661–1679. [CrossRef]
123. Zavadskas, E.K.; Cavallaro, F.; Podvezko, V.; Ubarte, I.; Kaklauskas, A. MCDM assessment of a healthy and safe built environment according to sustainable development principles: A practical neighborhood approach in Vilnius. *Sustainability* **2017**, *9*, 702. [CrossRef]
124. Soni, A.; Chakraborty, S.; Das, P.K.; Saha, A.K. Materials selection of reinforced sustainable composites by recycling waste plastics and agro-waste: An integrated multi-criteria decision making approach. *Constr. Build. Mater.* **2022**, *348*, 128608. [CrossRef]
125. Ghosh, B.; Mukhopadhyay, S. Erosion susceptibility mapping of sub-watersheds for management prioritization using MCDM-based ensemble approach. *Arab. J. Geosci.* **2021**, *14*, 36. [CrossRef]
126. Madhu, P.; Dhanalakshmi, C.S.; Mathew, M. Multi-criteria decision-making in the selection of a suitable biomass material for maximum bio-oil yield during pyrolysis. *Fuel* **2020**, *277*, 118109. [CrossRef]
127. Wu, B.; Lu, M.; Huang, W.; Lan, Y.; Wu, Y.; Huang, Z. A case study on the construction optimization decision scheme of urban subway tunnel based on the TOPSIS method. *KSCE J. Civ. Eng.* **2020**, *24*, 3488–3500. [CrossRef]
128. Mohseni, S.; Baghizadeh, K.; Pahl, J. Evaluating Barriers and Drivers to Sustainable Food Supply Chains. *Math. Probl. Eng.* **2022**, *2022*, 4486132. [CrossRef]
129. Chang, D.Y. Applications of the extent analysis method on fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [CrossRef]
130. Yariyan, P.; Zabihi, H.; Wolf, I.D.; Karami, M.; Amiriyan, S. Earthquake risk assessment using an integrated Fuzzy Analytic Hierarchy Process with Artificial Neural Networks based on GIS: A case study of Sanandaj in Iran. *Int. J. Disaster Risk Reduct.* **2020**, *50*, 101705. [CrossRef]
131. Shokouhyar, S.; Ataafarin, B.; Tavassoli, E. Investigation and measurement of effective factors of information technology solutions on customer relationship management with fuzzy logic approach. *Int. J. Intell. Enterp.* **2017**, *4*, 243–260. [CrossRef]
132. Ertay, T.; Akyol, D.E.; Araz, C. An integrated fuzzy approach for determining engineering characteristics in concrete industry. *Appl. Artif. Intell.* **2011**, *25*, 305–327. [CrossRef]
133. Mediouni, A.; Zufferey, N.; Subramanian, N.; Cheikhrouhou, N. Fit between humanitarian professionals and project requirements: Hybrid group decision procedure to reduce uncertainty in decision-making. *Ann. Oper. Res.* **2019**, *283*, 471–496. [CrossRef]
134. Bulgurcu, B.; Nakiboglu, G. An extent analysis of 3PL provider selection criteria: A case on Turkey cement sector. *Cogent Bus. Manag.* **2018**, *5*, 1–17. [CrossRef]
135. Im, K.; Cho, H. A systematic approach for developing a new business model using morphological analysis and integrated fuzzy approach. *Expert Syst. Appl.* **2013**, *40*, 4463–4477. [CrossRef]
136. Janjua, S.; Hassan, I. Fuzzy AHP-TOPSIS multi-criteria decision analysis applied to the Indus Reservoir system in Pakistan. *Water Supply* **2020**, *20*, 1933–1949. [CrossRef]
137. Faisal, M.N.; Al Subaie, A.A.; Sabir, L.B.; Sharif, K.J. PMBOK, IPMA and fuzzy-AHP based novel framework for leadership competencies development in megaprojects. *Benchmarking Int. J.* 2022; *ahead of print*.

138. Hawari, A.; Alkadour, F.; Elmasry, M.; Zayed, T. Condition assessment model for sewer pipelines using fuzzy-based evidential reasoning. *Aust. J. Civ. Eng.* **2018**, *16*, 23–37. [CrossRef]
139. Elshaboury, N. Prioritizing risk events of a large hydroelectric project using fuzzy analytic hierarchy process. *J. Proj. Manag.* **2021**, *6*, 107–120. [CrossRef]
140. Badida, P.; Janakiraman, S.; Jayaprakash, J. Occupational health and safety risk assessment using a fuzzy multi-criteria approach in a hospital in Chennai, India. *Int. J. Occup. Saf. Ergon.* **2022**, *29*, 1047–1056. [CrossRef]
141. Kelleci, O.; Aydemir, D.; Altuntas, E.; Oztel, A.; Kurt, R.; Yorur, H.; Istek, A. Thermoplastic composites of polypropylene/biopolymer blends and wood flour: Parameter optimization with fuzzy-grey relational analysis. *Polym. Polym. Compos.* **2022**, *30*, 09673911221100968. [CrossRef]
142. Kahraman, C.; Ertay, T.; Büyüközkan, G. A fuzzy optimization model for QFD planning process using analytic network approach. *Eur. J. Oper. Res.* **2006**, *171*, 390–411. [CrossRef]
143. Saaty, T.L. Fundamentals of the analytic network process—Dependence and feedback in decision-making with a single network. *J. Syst. Sci. Syst. Eng.* **2004**, *13*, 129–157. [CrossRef]
144. Yazdani, M.; Zarate, P.; Zavadskas, E.K.; Turskis, Z. A Combined Compromise Solution (CoCoSo) method for multi-criteria decision-making problems. *Manag. Decis.* **2018**, *57*, 2501–2519. [CrossRef]
145. Keshavarz Ghorabaee, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. A new combinative distance-based assessment (CODAS) method for multi-criteria decision-making. *Econ. Comput. Econ. Cybern. Stud. Res.* **2016**, *50*, 25–44.
146. Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J.; Zakarevicius, A. Optimization of Weighted Aggregated Sum Product Assessment. *Elektron. Ir Elektrotechnika* **2012**, *122*, 3–6. [CrossRef]
147. Hwang, C.L.; Yoon, K. Methods for multiple attribute decision making. In *Multiple Attribute Decision Making: Methods and Applications a State-of-the-Art Survey*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
148. Gupta, P.; Bharat, A. Developing sustainable development Index as a tool for appropriate urban land take. *Environ. Dev. Sustain.* **2022**, *24*, 13378–13406. [CrossRef]
149. Eldrandaly, K.A. Exploring multi-criteria decision strategies in GIS with linguistic quantifiers: An extension of the analytical network process using ordered weighted averaging operators. *Int. J. Geogr. Inf. Sci.* **2013**, *27*, 2455–2482. [CrossRef]
150. Chen, Y.; Yu, J.; Khan, S. Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. *Environ. Model. Softw.* **2010**, *25*, 1582–1591. [CrossRef]

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