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Cross-Impact Analysis with Crowdsourcing for Constructing Consistent Scenarios

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Abstract

Cross-impact analysis is frequently used in scenario-analogous studies to identify critical factors influencing ecological change, strategic planning, technology foresight, resource allocation, risk mitigation, cost optimization, and decision support. Scenarios enable different organizations to comprehend prevailing situations, prepare for probable futures, and mitigate conceivable risks. Unfortunately, cross-impact analysis methods are often criticized for their difficulty in handling complex interactions, cognitive bias, time-intensiveness, heavy reliance on a limited pool of experts, and inconsistency in assigning judgment, which can affect the expected outcomes. This paper introduces a novel method for constructing consistent scenarios that addresses these criticisms and those associated with scenario methods. The method is based on cross-impact analysis and crowdsourcing for constructing consistent scenarios. The cross-impact analysis component of the method is based on advanced impact analysis and cross-impact balance analysis to, respectively, provide a time-efficient reduction in complex interdependent factors and construct consistent scenarios from a set of reduced factors. The crowdsourcing element leverages the cumulative intelligence of a group of experts to help mitigate cognitive bias and transparently give a more inclusive analysis. The method was implemented and validated with a practical case of renewable energy adoption, a vital challenge for socioeconomic progress and climate change resilience. While the method provides a sturdy foundation for writing scenario narratives, the result confirms its robustness for constructing consistent scenarios and suggests that the future of renewable energy adoption can be enhanced through careful cogitation of best-case, base-case, and worst-case scenarios, which include varying states of perceived value, awareness, and perceived support. These findings contribute to a more nuanced understanding of how socio-cognitive and institutional factors interact to influence the pace and direction of sustainable energy transitions.

Keywords: crowdsourcing process; impact analysis; renewable energy; scenario construction; social media

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1. Introduction

Scenario analysis was introduced to address the inherent uncertainty in the human decision-making process by exploring how different future events or factors impact one another to resolve short-term crises and achieve long-term objectives [1]. Scenarios enhance the resilience, innovation, and malleability of organizations [2,3] while the narratives support strategic decision-making, future planning, and mindset shifts [4–6]. The scenario construction methods include the Intuitive Logic Method (ILM), the La Prospective technique, and cross-impact analysis, to explore plausible future outcomes by identifying important driving forces and creating coherent narratives of the possible futures. Specifically, the cross-impact analysis can identify complex interdependencies between different factors to understand their influence on one another and future scenarios [7,8]. Nevertheless, the existing scenario construction methods are still frequently criticized for their focus on probabilistic relationships, time-intensiveness, cognitive bias, and heavy reliance on the subjective judgments of a limited pool of experts [9,10]. The expert groups are frequently dominated by senior decision-makers, who are purposively selected and tend to lack diversification, constraining the scope and inclusivity of the resulting scenarios [9].

This study uniquely applies the advanced impact analysis (ADVIAN®) [11], crowdsourcing process [12], and cross-impact balance (CIB) analysis [8] for the task of constructing consistent scenarios. The ADVIAN® was used for the time-efficient reduction in a large set of complex interdependent factors. The crowdsourcing process was applied to leverage the cumulative intelligence of a group of experts, overcoming cognitive bias and expanding the inclusivity of the constructed scenarios [13,14]. The CIB method was enforced to construct consistent scenarios from the output of a crowdsourcing process [15]. Despite the wide application of crowdsourcing in fields like image classification, language processing, sentiment analysis, idea generation, problem-solving, and opinion collection, crowdsourcing applications are scarce in scenario analysis [12,16–20]. This work uses "X" social media as a crowdsourcing platform to gain valuable insights on factors influencing renewable energy adoption. Social media platforms offer opportunities for multiple applications of crowdsourcing because of their global reach, broad user base, and potent engagement capabilities [21].

Cross-impact data naturally include a list of factors within a system under investigation and qualitative judgments of how a factor impacts certain other factors. This information is often represented as an impact matrix to reflect the strength of a relationship between the factors. Cross-impact data elicitation sources can be categorized into expert elicitation, eliciting data directly from experts, and literature review, extracting data from the existing published monographs [22,23]. The cross-impact analysis process is inherently cumbersome and time-consuming when a large number of factors in a complex system are presented to users for cross-impact assessment, when compared to the case of constructing scenarios with fewer factors. Hence, it is crucial to identify the most critical factors that influence the scenario construction process. This study applies the two data elicitation methods at different stages, leveraging their collective strengths to produce accurate outcomes.

2. Materials and Methods

This section presents the materials used in the study, followed by a description of the crowdsourcing method developed for constructing consistent scenarios. The method is described according to six essential steps.

2.1. Materials Used

The materials used at different stages of this study include Microsoft Excel to record the factors and the relationships that exist between the factors identified from the literature. The ADVIAN® was used to classify the identified interdependent impact factors as driving, driven, and precarious and identify the most critical among the factors [11]. The

CIB method was applied to construct a set of consistent scenarios that heavily depend on a small set of critical factors that are mostly driving and highly uncertain [24]. This study focuses on highly driving and highly precarious factors because they impact the underlying social system to a high degree, are critical, and have the highest degree of uncertainty [25]. In contrast, highly driven factors are reactive and influenced by the system [25,26], and the detailed calculations of the ADVIAN® parameters have been reported in [11,27]. The "X" social media was used as a crowdsourcing platform to recruit the required knowledge experts for the renewable energy adoption study. The platform boasts a large professional user base with over 550 million active users and has witnessed more than 500 million tweets daily [28]. Moreover, more than 90% of its accounts are public and have attracted a large set of participants for research studies [29,30]. In this study, experts were crowdsourced through a tweet that included a link to the developed survey tool (https://github.com/robyn-thompson/RE_Adop_files (accessed on 23 December 2024)), with relevant hashtags posted on the "X" platform to elicit judgments. The inclusion of relevant hashtags can increase reachability and attract a large spectrum of participants [30]. Moreover, "X" users often used hashtags to search, categorize, and highlight pertinent issues for discussion [29]. Ultimately, the ScenarioWizard v4.54 freeware software tool was used to perform the CIB analysis [31] according to the process outlined by Weimer-Jehle [8]. The CIB software (ScenarioWizard version 4.54) and the accompanying user manuals are available for free download at https://www.cross-impact.org/english/CIB_e_ScW.htm (accessed on 1 October 2024).

2.2. The Proposed CIACROWDS Method

This work introduces a novel cross-impact analysis crowdsourcing (CIACROWDS) method, which presents six essential steps (Figure 1) for constructing consistent scenarios. The steps are the identification of impact factors, creation of an impact matrix, determination of critical factors, elicitation of expert judgments, creation of a judgment matrix, and the construction of consistent scenarios.

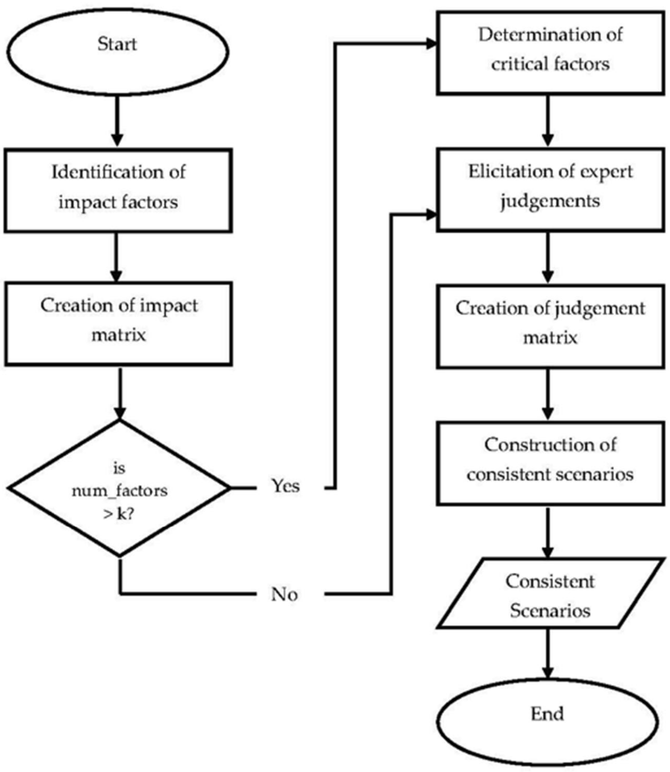

Figure 1. Flowchart for CIACROWDS method.

2.2.1. Identification of Impact Factors

Impact factors are often obtained through human-centered methods such as interviews, group discussions, and workshops, with these being the most prevalently applied in scenario analysis projects [22]. However, these methods have been castigated for their limitations, being time-consuming, labor-intensive, and prone to cognitive bias [32]. Consequently, a less expensive literature review method [33] was applied in Step 1 as a suitable alternative to explore a large set of impact factors and to minimize the heavy burden placed on the end-user to supply the impact factors. The popular protocol of Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [34] was used to discover the relevant research articles. PRISMA protocol was used to guide a systematic literature review conducted on the Web of Science Core Collection (WoSCC) and Scopus databases by employing specific search strategies with inclusion and exclusion criteria (Table 1). The purpose was to identify, analyze, and discover the relevant research articles on factors influencing renewable energy adoption, which is a particular scenario project considered in this work. The search string used to initiate the database exploration is TITLE-ABS-KEY ((factor OR driver) AND "renewable energy" AND "structural equation modeling") AND PUBYEAR > 2013. The initial search yielded 306 entries across the databases, but after applying the inclusion and exclusion criteria, 81 related articles were ultimately selected (Figure 2). The selected articles were analyzed to create a list of n impacting factors serving as input to Step 2 for the creation of the impact matrix, where n is the total number of impact factors within the renewable energy adoption system.

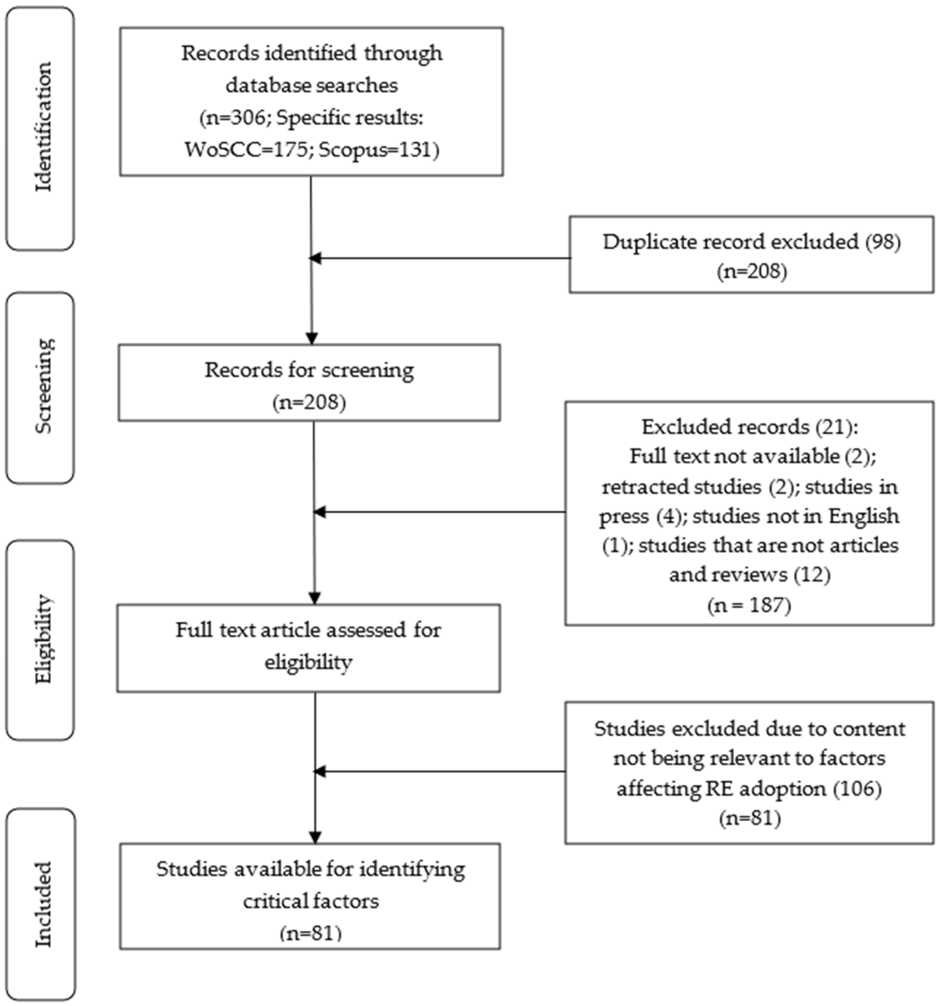

Figure 2. PRISMA flowchart for identifying factors influencing renewable energy adoption.

Table 1. Inclusion and exclusion criteria for identifying factors influencing renewable energy adoption.

ID	Inclusion Criteria	ID	Exclusion Criteria
IC1	Articles published in the English language.	EC1	Articles with no full text available.
IC2	Articles that report certain specific information, such as path coefficients.	EC2	Retracted articles.
IC3	Articles related to certain specific projects or factors impacting on renewable energy adoption.	EC3	Articles marked as "in press".
		EC4	Duplicate records.
		EC5	Articles that are not available in the English language.
		EC6	Gray articles like reviews, newsletters, or conference proceedings.
		EC7	Articles that do not report on certain specific information, such as path coefficients.
		EC8	Articles that do not relate to certain specific projects or factors impacting renewable energy adoption.

2.2.2. Creation of the Impact Matrix

The creation of an impact matrix relies on determining the strengths of the relationships between pairs of interdependent factors. In addition to the criticisms relating to human-centered methods for determining impact strengths, as alluded to in Section 2.1, it is hard to realistically engage humans to supply impact scores for a huge set of factors. Hence, as in Step 1, an alternative literature method was employed to collect relevant secondary data on the impact strengths of the direct relationships between factors. Secondary data from literature can increase the reliability and credibility of the current study and reduce the complexity of collecting data from users multiple times. Moreover, the articles selected in Step 1 were analyzed to determine the direct relationships that exist between pairs of impact factors. The list of factors and impact strengths of direct relationships between pairs of impacting factors was used to create an *nxn* impact matrix. A cell in the matrix denotes the impact strength of a direct relationship between a pair of interdependent factors [35]. For this particular application, these were obtained from the statistical analysis of the structural equation modeling (SEM) technique, but other methods that report on factor relationships can be used. The SEM is a powerful, quantitative tool for testing complex theories and establishing evidence for causal relationships while unveiling the strength of the relationships between system factors [36]. Hence, only published works that applied the SEM method to unveil the relationships between factors and provided the path coefficients to measure the impact strengths of the relationships were selected [37] as specified by the inclusion and exclusion criteria.

The strength and direction of the relationships are reported through the path coefficient in SEM, which assesses the direct or indirect effect within the network of multiple factors. A path coefficient from a factor F_i to a factor F_j quantifies how much a one standard deviation change in F_i is linked to a change in F_j while other factors in the system are controlled. SEM analysis is performed on data gathered from participants, where the structured statements presented to participants were evaluated using a Likert scale. For example, to measure the perceived ease of use of a technology, participants may be presented with a question similar to the following. Please indicate your level of agreement with the following statements regarding the [Name of Software/Technology] on a scale from 1 to 5, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

My interaction with [the system] is clear and understandable [38]. The traditional impact matrix consists of ordinal impact strengths of 0, 1, 2, or 3, representing "no impact", "weak impact", "medium impact", and "strong impact", respectively [25]. This study uses the path coefficients ("β_{ij}" of direct relationships between pairs of factors (*i* and *j*) in the interval [0, 1] to measure the strengths of the relationships. In this scale, 1 indicates a very strong impact, and 0 means a very weak impact. These path coefficients have been empirically validated through SEM in different previous studies without compromising the generalizability of the results [27]. Should several articles include different path coefficients for the same pair of factors, the maximum path coefficient is included in the final impact matrix.

The decision to proceed to Step 3 or Step 4 is made after creating the impact matrix, depending on the number of factors identified in Step 1. This is because a smaller set of critical factors is desirable for constructing scenarios [24]. The CIACROWDS method proceeds to Step 3 for factor reduction, provided the number of identified factors is more than k; otherwise, it branches to Step 4 without factor reduction. The choice of k is guided by literature, where certain authors recently suggested that only five factors should be analyzed [39]. Moreover, it was previously recommended that just seven factors are optimal as the number of judgments to evaluate increases exponentially as the number of factors increases [40]. The developers of the CIB method, who relied on step 6, opine that nine to fifteen factors are optimal for scenario analysis [8]. The present researchers meticulously chose a threshold value of $k = 10$ for further analysis after considering these differing opinions that recommend between 5 and 15 factors. Should there exist 10 factors, for example, then experts would need to provide 90 judgments, which is calculated using the formula $k^2 - k$, because each factor is evaluated for its impact on every other factor, but not on itself, as the diagonal entries. It must be emphasized that, if the number of factors in the system is 10 or less, there will be no need to extract path coefficients and determine critical factors. Some researchers may contend that the extraction of path coefficients during factor identification is a time-wasting exercise. The current researchers believe that if path coefficients are not extracted at the time of factor identification and there are more than ten factors, this would necessitate human experts to provide impact strengths, which would be time and labor-intensive. Moreover, heavy reliance on human experts to collect impact scores can obviously present multiple challenges, such as subjectivity, biases, and inconsistent interpretations of results.

2.2.3. Determination of Critical Factors

The ADVIAN® method is a useful device to compensate for the limitation of absolute reliance on SEM to unveil critical impact factors. Although SEM can be used to highlight essential factors in a system by examining the path coefficients and statistical significance of direct and indirect effects, the authors acknowledge that not all factor relationships are represented in the selected papers. In addition, the reviewed papers are not exhaustive because it is difficult to compile a complete list of all possible papers. Hence, a relationship that exists in the factor table does not necessarily mean that no relationship exists between the impacting factors. It rather indicates that the selected papers did not report on this relationship, which requires the application of additional tools like ADVIAN® to further expose the potential hidden relationships that SEM does not report on, through the analysis of indirect relationships. Since path coefficient quantifies both strength and direction, it is consistent with impact assessment in CIB. It must be noted that the information obtained from SEM analysis relates to factor relationships, while the factor judgment gathered for CIB analysis (Section 2.2.4) relates to the impact that factor states have on each other.

The CIB analysis can confirm the relationships that are not divulged by the ADVIAN® analysis, providing a strong bedrock for the blending of multiple methods for consistent scenario construction. While the ADVIAN® method classifies factors according to driving, driven, and precarious measures, scenario construction relies on the determination of critical factors that are most driving and highly uncertain. Hence, it is the "driving" and "precarious" factors that will be applied as critical factors for scenario construction. Moreover, a factor is deemed critical if its driving or precarious impact score exceeds a threshold, calculated as two-thirds more than the average standard deviation impact score [26]. The ADVIAN® analysis can be performed manually on the impact matrix computed in Step 1, using the published formulae [27], to determine the critical impact factors. However, a custom-designed software tool was used with code available at: https://github.com/robyn-thompson/ADVIAN-app (accessed on 23 December 2024). The resulting set of critical factors is the output from Step 3 that serves as input to Step 4.

2.2.4. Elicitation of Expert Judgments

The purpose of this step is to elicit judgments using the expert elicitation method to reflect the possible impact that a factor state could have on other factor states [24,41]. This task is not complicated for experts because the judgments elicited pertain to fewer factors with no evaluation of complex and higher-order relationships that may be required for Step 2. This study uses categorical 'low' and 'high' states for each factor, but factor states can generally differ across different applications, like ['low', 'medium', 'high'] for three states. This reasoning complies with the binary state representation used in other CIB studies [15,42,43].

Experts supply judgments through a set of focused questions using methods that suffer from time delays, cognitive bias, and a lack of diversity [44]. Consequently, this study turns to crowdsourcing for the time-efficient recruitment of experts to efficiently provide judgments using a custom online tool. The recruitment of experts for scenario construction can be daunting and often leads to delays [45,46]. This necessitates the application of crowdsourcing through digital platforms, like social media sites, to recruit experts for a scenario construction project. Crowdsourcing can be effectively applied for impact analysis in a consistent scenario construction by leveraging the collective intelligence of a crowd of experts. The approach allows for a more comprehensive and localized understanding of potential impacts, decision-making, and preparedness for random events, especially in complex societal events.

Expert participants were crowdsourced using the "X" social media platform. A tweet with a link to a developed survey tool (https://github.com/robyn-thompson/RE_Adop_files (accessed on 23 December 2024)) was used to elicit judgments. Expert participants who followed the link in the tweet were redirected to the online survey tool to gather judgments on the relationships between each factor state and all other factor states. In contrast to SEM studies, where experts provide data that allows for the analysis of direct relationships between factors, CIB analysis heavily depends on data in the form of judgments of relationships between factor states. These judgments are elicited using the traditional method of a focused question [8], which for this study is in the form: When considering {project x} in the future, if there exists an {x} state of {factor j}, how will that impact a {y} state of {factor k}? An expert can provide an answer by selecting a response, like strong restrictive impact, weak restrictive impact, no significant impact, weak promoting impact, and strong promoting impact. These five qualitative states correspond with numeric values of −2, −1, 0, +1, and +2, respectively.

The online tool first assesses the level of expertise of the participants on the given crowdsourcing challenge to control the quality of responses provided. Previous studies have applied differing criteria to evaluate expertise [47,48]. This study considers a crowdsourcing participant an expert according to the following criteria. At least five years of experience in the field, have authored a book, published an article, or presented at a conference relating to the field, or have in the past three years been invited as a guest speaker to an event related to the field, or leads a corporate team in the field, or is actively involved in policy making in the field, or is a member of a committee in the field, or is a point of contact for the media on matters relating to the field. The participants provided answers to a range of questions to assess whether they can be classified as experts in the field. Only those participants who meet the eligibility criteria are provided with a series of input screens to elicit the judgments of a factor state. The output from Step 4, which is the input to Step 5, is an online table that stores the judgments of each participant.

2.2.5. Creation of Judgment Matrix

A script was run to create a final judgment matrix of all judgments collected from the experts in Step 4. The judgment matrix is needed for constructing consistent scenarios in Step 6. The central tendency statistical measures of the median and arithmetic mean are used to obtain a single judgment for the factor state. The CIACROWDS method uses the median value of all crowdsourcing judgments as the final judgment because the median value is more accurate and less affected by outliers or skewness when compared to the mean. However, the ordinal categorical value closest to the mean of the dataset is used as the final judgment if the number of entries is even, and the arithmetic mean of the middle two entries results in a value that sits between two of the ordinal categories.

Two experts in user interface design and ten social media users validated the online tool for judgment elicitation and the script for creating the final judgment matrix. The users shared their input data with the researchers so that the data could be used to test the application for accuracy and validity. Improvements were made to the tool, which responded to suggestions by those who performed the pilot testing. The output from Step 5 is a single judgment matrix that serves as input to Step 6.

2.2.6. Construction of Consistent Scenarios

The judgment matrix from Step 5 was uploaded as input to the ScenarioWizard v4.54 freeware software for CIB analysis. The software generated a report of all consistent scenarios, and the output from Step 6 is the list of consistent scenarios for the task under investigation.

3. Results

The CIACROWDS method was validated using a case of renewable energy adoption, which is an important issue for socioeconomic development and climate change adaptation. The last decade has seen a significant drive toward the use of renewables as sustainable energy resources [49]. However, renewable energy adoption has progressed slowly, with a report indicating that just 12.5% of the total energy consumption in 2022 was supplied by renewables, with a 2.5% increase from 2015 [50]. This slow uptake is particularly concerning given the United Nations Sustainable Development Goals (SDGs) of climate action with affordable and clean energy. Renewable energy sources do not produce greenhouse gases, but they improve public health and mitigate global warming. The 2024 report indicates that with just six years remaining to achieve SDGs, only 17% of the goals are on track, and current progress is not at the expected level [51]. Research has explored factors impacting the adoption of renewable energy in the area of focus, such as specific countries, renewable technologies, or different models [52,53]. Global studies of renewable technologies can provide a holistic view of factors influencing the adoption of renewable energy. Moreover, renewable energy adoption scenarios can provide actionable insights for policymakers, help identify common threads across different adoption paths, and serve as a foundation for future policy planning and development. The insights gained can directly contribute to strengthening energy efficiency policies and supporting the attainment of SDGs.

The starting point of the CIACROWDS method is the creation of an impact matrix that requires identifying impact factors and simultaneously determining the strength of the relationships between pairs of impact factors. The impact factor data and the strength of associated relationships through statistical path coefficients were obtained from the published articles that were discovered through the PRISMA protocol. After analyzing and merging factors that referred to the same construct, 36 unique factors that impact the adoption of renewable energy were identified (Table 2). Factor saturation was achieved after reviewing 51 articles. Hence, it will be completely overwhelming to request experts to supply 1260 judgments for the number of factor interactions. Fortunately, the SEM technique becomes essentially useful to collect judgments from published articles, and the ADVIAN® method was used to determine indirect relationships that cannot be easily provided by experts.

Table 2. Factors influencing the adoption of renewable energy.

Factor Code	Factor Name	Factor Code	Factor Name
F1	Perceived performance expectancy	F19	Perceived risk
F2	Perceived ease of use	F20	Moral obligations
F3	Perceived self-efficacy	F21	Access to electricity
F4	Social influence	F22	Personal innovativeness
F5	Awareness	F23	Environmental knowledge
F6	Perceived cost value	F24	Perceived authority support
F7	Attitude	F25	Government policy and propaganda
F8	Geographic and environmental factors	F26	Social media influence
F9	Behavioral intention	F27	Moral norm
F10	Usage behavior	F28	Reason for adoption
F11	Infrastructure readiness	F29	Socio-demographic factors
F12	Financial support	F30	Perceived compatibility
F13	Facilitating conditions	F31	Personal financial commitments
F14	Hedonic motivation	F32	Perceived relevance (usefulness)
F15	Perceived environmental awareness	F33	Trialability
F16	Perceived system quality	F34	Pro-environmental behavior
F17	Perceived trust	F35	Perceived community identity
F18	Perceived satisfaction	F36	Homeownership

Table 3 shows an extract of factors F1 to F10 of the resultant 36 × 36-dimensional impact matrix that records the maximum path coefficient for each relationship between a pair of factors impacting the adoption of renewable energy. The path coefficients were extracted and recorded in an Excel matrix with the independent factor on the rows of the impact matrix, while the dependent factors are on the matrix columns.

Table 3. Extract from the 36 × 36 impact matrix for the renewable energy adoption project.

Factor Code	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
F1	0.000	0.698	0.820	0.620	0.640	0.900	1.000	0.000	0.840	0.000
F2	0.520	0.000	0.000	0.610	0.400	0.319	1.000	0.000	0.700	0.000
F3	0.310	0.000	0.000	0.370	0.446	0.380	0.400	0.000	0.660	0.408
F4	0.610	0.610	0.370	0.000	0.390	0.390	0.596	0.000	0.705	0.363
F5	0.905	0.400	0.000	0.390	0.000	0.370	0.517	0.000	0.900	0.000
F6	0.377	0.319	0.380	0.431	0.370	0.000	1.000	0.000	0.840	0.000
F7	0.530	0.000	0.400	0.400	0.000	0.000	0.000	0.000	1.000	0.000
F8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.520
F10	0.000	0.000	0.000	0.000	0.000	0.000	0.168	0.000	0.000	0.000

Due to more than ten impact factors extracted from the published papers on renewable energy adoption, the ADVIAN® method was applied to the impact matrix to ensure the identification of the most critical factors. The developed automation tool was used to produce all ADVIAN® parameters or measures, with a description of each measure provided in Table 4. The measures are relative direct active sum (RDAS), relative direct passive sum (RDPS), relative indirect active sum (RIAS), relative indirect passive sum (RIPS), criticality (CRI), integration (INT), stability (STA), precarious (PRE), driving (DRI), and driven (DRE) according to the formulae [11,27]. The result of the computation of each measure for a factor is exported to an Excel file (Table 5).

Table 4. Description of ADVIAN® measures.

Measure	Description
Relative direct active sum (RDAS)	The direct active sum of a factor is converted to a relative value out of 100.
Relative direct passive sum (RDPS)	The direct passive sum of a factor is converted to a relative value out of 100.
Relative indirect active sum (RIAS)	The indirect active sum of a factor is converted to a relative value out of 100.
Relative indirect active sum (RIPS)	The indirect passive sum of a factor is converted to a relative value out of 100.
Criticality (CRI)	The strength of the impact that a factor has on other factors, and the strength of impact that other factors have on the factor. Calculated as the geometric mean of the relative indirect active sum and the relative indirect passive sum.
Integration (INT)	A measure of the strength of interrelations that a factor has with other factors. Calculated as the arithmetic mean of the relative indirect active sum and the relative indirect passive sum.
Stability (STA)	A measure of the degree to which a factor stabilizes the system of factors. Calculated by subtracting the harmonic mean of the relative indirect active sum and the relative indirect passive sum from 100.
Precarious (PRE)	A measure of the degree to which a factor influences the system of factors. Calculated as the harmonic mean of criticality and the relative indirect active sum.
Driving (DRI)	A measure of the degree to which a factor can influence other factors without the presence of feedback loops. Calculated as the harmonic mean of 100 minus criticality and the relative indirect active sum.
Driven (DRE)	A measure of the degree to which a factor is influenced by the system of factors. Calculated as the harmonic mean of 100 minus criticality and the relative indirect passive sum.

Table 5. ADVIAN® analysis for the renewable energy adoption project.

	RDAS	RDPS	RIAS	RIPS	CRI	INT	STA	PRE	DRI	DRE
F1	66.74	58.58	76.97	61.18	68.62	69.07	31.83	72.68	49.15	43.81
F2	32.29	30.23	44.36	37.02	40.52	40.69	59.64	42.40	51.37	46.92
F3	22.82	30.48	29.27	40.64	34.49	34.95	65.97	31.77	43.79	51.60
F4	46.44	47.45	59.13	54.95	57.00	57.04	43.04	58.05	50.42	48.61
F5	39.19	27.44	52.17	38.20	44.65	45.19	55.89	48.26	53.74	45.99
F6	34.44	22.30	43.91	38.08	40.89	40.99	59.22	42.37	50.94	47.44
F7	16.45	75.59	22.77	75.01	41.33	48.89	65.06	30.68	36.55	66.34
F8	4.41	4.41	3.01	1.78	2.32	2.40	97.76	2.64	17.16	13.18
F9	6.41	100.00	2.39	100.00	15.45	51.19	95.34	6.07	14.20	91.95
F10	1.02	16.40	0.89	25.20	4.74	13.05	98.28	2.06	9.22	48.99
F11	19.12	8.71	17.69	10.44	13.59	14.07	86.87	15.51	39.10	30.03
F12	12.00	1.57	14.73	2.32	5.84	8.53	95.99	9.28	37.25	14.77

Table 5. *Cont.*

	RDAS	RDPS	RIAS	RIPS	CRI	INT	STA	PRE	DRI	DRE
F13	13.00	10.76	33.87	16.99	23.98	25.43	77.38	28.50	50.74	35.93
F14	18.52	2.30	26.17	5.43	11.91	15.80	91.01	17.66	48.01	21.86
F15	33.71	28.89	48.80	43.84	46.26	46.32	53.81	47.51	51.21	48.54
F16	15.74	1.51	23.08	2.22	7.16	12.65	95.95	12.86	46.29	14.36
F17	5.64	9.11	8.68	2.90	5.02	5.79	95.66	6.60	28.72	16.59
F18	14.83	7.56	17.78	9.14	12.74	13.46	87.93	15.05	39.38	28.24
F19	24.68	27.95	35.15	36.32	35.73	35.74	64.27	35.44	47.53	48.32
F20	15.88	16.08	22.39	21.86	22.12	22.12	77.88	22.25	41.76	41.26
F21	4.24	0.00	2.30	0.00	0.00	1.15	95.39	0.00	15.18	0.00
F22	20.60	15.85	33.04	27.07	29.91	30.06	70.24	31.44	48.13	43.56
F23	21.46	15.88	29.15	26.90	28.00	28.03	72.02	28.57	45.81	44.01
F24	7.39	0.79	6.19	0.28	1.31	3.23	99.47	2.85	24.71	5.25
F25	18.82	4.09	21.10	2.55	7.33	11.82	95.46	12.44	44.22	15.36
F26	6.95	0.00	4.81	0.00	0.00	2.40	90.39	0.00	21.92	0.00
F27	7.55	0.00	7.85	0.00	0.00	3.93	84.30	0.00	28.02	0.00
F28	9.44	7.41	10.85	12.02	11.42	11.43	88.60	11.13	31.00	32.63
F29	1.67	0.00	2.03	0.00	0.00	1.02	95.93	0.00	14.26	0.00
F30	12.07	8.83	16.75	13.69	15.14	15.22	84.93	15.93	37.70	34.08
F31	0.97	0.00	1.24	0.00	0.00	0.62	97.52	0.00	11.14	0.00
F32	14.32	14.01	13.99	29.33	20.26	21.66	81.05	16.84	33.40	48.36
F33	4.53	0.00	0.42	0.00	0.00	0.21	99.16	0.00	6.46	0.00
F34	1.11	0.00	0.98	0.00	0.00	0.49	98.04	0.00	9.89	0.00
F35	0.00	1.74	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00
F36	2.98	0.00	1.41	0.00	0.00	0.70	97.19	0.00	11.86	0.00

Table 6 shows only the relevant ADVIAN® factor classification measures of precarious and driving, which are the measures that impact the adoption of renewable energy. Factors that recorded a measure above the threshold in the categories of precarious (37.605) and driving (49.173) are considered critical. Consequently, six factors, F1, F2, F4, F5, F6, and F15 emerged as highly precarious and six factors, F2, F4, F5, F6, F13, and F15 as significantly driving. Five of these factors, F2, F4, F5, F6, and F15 are both precarious and driving, resulting in seven factors, perceived performance expectancy (F1), perceived ease of use (F2), social influence (F4), awareness (F5), perceived cost value (F6), facilitating conditions (F13), and perceived environmental awareness (F15) being the most driving and uncertain were used for scenario construction.

Expert judgments were elicited through an online survey distributed by an "X" tweet. The tweet requested assistance with the study, provided the link to the survey tool, and included hashtags relevant to the study context. In a two-week timeframe, 31 respondents who clicked on the link in the tweet qualified for inclusion in the study. However, only 14 respondents completed the online survey. A possible reason for the 55% dropout can be the substantial time required to assess the seven-factor judgment matrix, the complexity, and the cognitive demand of the survey. It is a positive endeavor that about 45% of the expert respondents participated in this study to provide judgment scores on renewable energy adoption. According to [54], 10–15 experts are a satisfactory number of expert participants, while the authors [55] believe that seven experts are sufficient for expert participant studies. The researcher received private messages from several social media users who expressed interest in the study and confirmed their participation. This engagement highlighted the diverse geographic distribution of participants, representing regions such as the USA, Egypt, Spain, Iran, the UK, South Africa, Australia, China, Greece, Kenya, and Pakistan. Additionally, the diversity extended to the professional backgrounds of participants, which included fields such as engineering, academia, council governance, data protection, artificial intelligence, mining, energy, information technology, and law. This broad representation underscores the inclusivity, reach, interest, and participant diversity achieved through crowdsourcing, ensuring a rich and varied set of perspectives has contributed to the study.

Table 6. ADVIAN classification of factors impacting renewable energy adoption.

Factor Code	Precarious	Driving	Factor Code	Precarious	Driving
F1	72.676	49.146	F19	35.439	47.529
F2	42.398	51.366	F20	22.253	41.755
F3	31.769	43.787	F21	0.000	15.179
F4	58.055	50.422	F22	31.435	48.125
F5	48.263	53.741	F23	28.572	45.812
F6	42.369	50.945	F24	2.851	24.706
F7	30.677	36.552	F25	12.437	44.223
F8	2.642	17.160	F26	0.000	21.925
F9	6.071	14.204	F27	0.000	28.020
F10	2.058	9.222	F28	11.128	30.997
F11	15.508	39.102	F29	0.000	14.262
F12	9.279	37.246	F30	15.927	37.704
F13	28.500	50.738	F31	0.000	11.142
F14	17.657	48.010	F32	16.835	33.403
F15	47.513	51.215	F33	0.000	6.463
F16	12.857	46.293	F34	0.000	9.888
F17	6.599	28.717	F35	0.000	0.000
F18	15.051	39.383	F36	0.000	11.862
Threshold	37.605	49.173		37.605	49.173

Once all judgments had been gathered through the online survey tool, a script was executed, resulting in the creation of the judgment matrix. The judgment matrix is the input to the fourth step of the CIACROWDS method (Table 7), to identify consistent scenarios using CIB analysis. There is the possibility of inconsistency between the SEM results and expert evaluation because of the contextual nature of socio-economic factors and the subjectivity inherent in human judgment. This makes it important to examine the relationship between factor states using the CIB analysis to complement the SEM analysis of factor relationships, which is an important contribution of the current work.

Table 7. Judgment matrix for the renewable energy adoption project.

Factor		F1		F2		F4		F5		F6		F13		F15	
State		High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
F1	High	0	0	1	−1	2	−2	2	−2	2	−2	2	−2	1	−1
	Low	0	0	−1	1	−1	1	−1	1	0	0	−1	1	−1	1
F2	High	2	−2	0	0	2	−2	1	−1	1	−1	2	−2	1	−1
	Low	−1	1	0	0	−1	1	−1	1	−1	1	−1	1	0	0
F4	High	1	−1	2	−2	0	0	2	−2	1	−1	2	−2	2	−2
	Low	−1	1	−1	1	0	0	−1	1	0	0	−1	1	−1	1
F5	High	1	−1	1	−1	1	−1	0	0	1	−1	1	−1	2	−2
	Low	−1	1	−1	1	0	0	0	0	−1	1	−1	1	−1	1
F6	High	2	−2	1	−1	2	−2	1	−1	0	0	2	−2	1	−1
	Low	−1	1	−1	1	−1	1	−1	1	0	0	−1	1	−1	1
F13	High	1	−1	1	−1	1	−1	2	−2	1	−1	0	0	2	−2
	Low	−1	1	−1	1	−1	1	−1	1	−1	1	0	0	−1	1
F15	High	1	−1	1	−1	1	−1	2	−2	1	−1	1	−1	0	0
	Low	−1	1	−1	1	−1	1	−1	1	−1	1	−1	1	0	0

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The CIB analysis of the judgment matrix using the ScenarioWizard software tool generated two consistent scenarios. The optimal number of scenarios is between three and five [56], while Finlay [57] suggested that three is the ideal number. Hence, additional scenarios were generated by lowering the consistency threshold [42] to two. The difference between the chosen impact value and the highest possible impact value is no more than two, with one additional scenario created to bring the total to three consistent scenarios, where they promote renewable energy (RE) adoption, moderate RE adoption, or restrict RE adoption (Table 8).

Table 8. Scenarios generated for the renewable energy adoption project.

Scenario	Best-Case Scenario	Base-Case Scenario	Worst-Case Scenario
Perceived Performance Expectancy	High	Low	Low
Perceived Ease of Use	High	Low	Low
Social Influence	High	Low	Low
Awareness	High	High	Low
Perceived Cost Value	High	High	Low
Facilitating Conditions	High	Low	Low
Perceived Environmental Awareness	High	High	Low
Scenario Property	Promote RE Adoption	Moderate RE adoption	Restrict RE Adoption

4. Conclusions

This section concludes the paper by summarizing the main points in three categories, which are discussion of results, limitations, future work, and ethical considerations.

4.1. Discussion of Results

Table 8 shows the consistent scenarios with the rows presenting the critical factors for RE adoption. The scenario labels ‘Best-case’, ‘Base-case’, and ‘Worst-case’ are based on the promoting, moderating, or restricting factor states. The principle of relatedness was applied to reduce the seven factors to three factors. The principle refers to object grouping based on their meaningful connections, similarities, or contextual relationships [58]. Hence, the seven factors can be grouped into three constructs according to their conceptual connections and functional similarities in the context of technology adoption models. The first can be named perceived value, which includes perceived performance expectancy, perceived ease of use, and perceived cost value. The factors are related because they influence whether individuals, businesses, and government organizations see renewable energy as a viable investment based on effort, usability, and cost savings. The second is awareness, which includes awareness, social influence, and perceived environmental awareness. These factors affect public opinion and the motivation to adopt renewable energy technologies. The perceived support includes facilitating conditions and perceived ease of use. Both these factors influence how easily users of renewable energy can transition to new technology, given the support in place and resources available.

The ‘best-case’ scenario is characterized by high perceived value, high awareness, and high perceived support. This scenario can enhance the adoption of renewable energy technology and greatly increase the chances of attaining some of the SDGs. This scenario portrays an idealistic but possibly unrealistic future. In contrast, the ‘worst-case’ scenario has low states for all impact factors. This scenario would not promote renewable energy adoption but would hinder progress. This is also not a realistic scenario and would impede the attainment of the SDGs. The ‘base-case’ scenario has a mixture of high and low states for the impact factors. The construct states for this scenario are low for perceived value and perceived support, while awareness is high when considering the individual factors in Table 8. The scenario with a mixture of states can provide a more realistic view of the future and offer decision-makers useful insights into renewable energy adoption issues and areas that need intervention strategies to enhance and accelerate its use. The constructed scenarios meet the study objective of providing a crowdsourcing cross-impact analysis method for constructing consistent scenarios based on advanced impact analysis, crowdsourcing process, and cross-impact balance analysis to resolve the inherent limitations of the cross-impact analysis method. Moreover, scenario narratives are not the focus of this paper because it is the method employed for the construction of consistent scenarios that is the focus. The scenarios constructed, therefore, form a solid foundation for a team of subject matter specialists to develop the narratives associated with each scenario [59].

4.2. Limitations and Future Work

This study has demonstrated the successful implementation of ADVIAN® for time-efficient data reduction in interdependent factors, crowdsourcing for time-efficient recruitment of expert participants for the study, and CIB for consistent scenario construction. However, a potential limitation of this study is that the application chosen to demonstrate the method results in scenarios of all high states and of all low states. While this may be predictable, this is just a demonstration of the method, which can easily be applied to other complex topics in different application domains.

While the number of participants that met the inclusion criteria is reported, it would have been prudent to record and report on the number of crowdsourced participants who followed the link but did not meet the inclusion criteria, as this could provide additional valuable data on the effectiveness of using 'X' for crowdsourcing. Moreover, while the method itself is time-efficient, the time invested by participants may be high. Further work could compare the overall time invested by participants using other methods compared to the time invested using this method. Due to the process of crowdsourcing being used and the anonymity of participants, the geographic location of expert participants was not gathered. The judgments obtained from participants may be regionally influenced, which deserves further investigation in another study.

The current method relies on studies that have applied SEM analysis to factors and reported on the path coefficients. This may limit the first steps of the method to only those fields that have attracted many research publications and would be more difficult to apply to emerging fields. In this case, factors could be identified in the same manner, but relationships between factors could be obtained using the CIMgen method [23] through the crowdsourcing process. Future work could explore the application of crowdsourcing for developing the narratives for the constructed scenarios.

4.3. Ethical Considerations

Ethical considerations are generally needed for studies that use data mined from "X" tweets for research purposes [60]. The current study does not use data from "X"; instead, the study collects data from the voluntary participants through the online survey. The online survey sought informed consent, which has become a common practice in online studies [61]. Moreover, the link to the survey does not collect any personal data from participants, but only the judgment data that is stored in a repository. No minors were involved in the study, as the letter of information and consent indicates that participants should be 18 years or older. Participation in this study is entirely voluntary, with participants electing to click on the link to the survey tool if they wish. Participant anonymity is guaranteed, as no personal information relating to the participant is gathered because the information is irrelevant to this study. Hence, no data protection regulation has been violated in this study. The online survey was used to quantify relationships between pairs of impacting factors. The participants were presented with a link to the letter of information and consent, ensuring that informed consent was obtained. Acknowledgment of this was gained through the selection to proceed with the survey. The participant can exit the survey at any stage without their data being stored. Ethical clearance for this study was obtained from the educational institution of the researcher, Ethical Clearance number IREC 067/24.

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Abbreviations

The following abbreviations are used in this manuscript:

ADVIAN®	Advanced Impact Analysis
CIB	Cross-impact Balance
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
SEM	Structural Equation Modeling
SDG	Sustainable Development Goals

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