Decision Prioritization with MCDM in Post-Disaster Management: A PRISMA-Guided Systematic Review and Bibliometric Mapping

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***Abstract*— Prioritizing post-disaster actions requires balancing multiple, often conflicting criteria. To consolidate scattered evidence, this study reviews decision prioritization with Multi-Criteria Decision-Making (MCDM) in post-disaster management using a PRISMA-guided systematic review and bibliometric mapping. Initial searches returned 18,454 records from Scopus, 47,206 from Google Scholar, 650 from Emerald Insight, 30,975 from ProQuest, and 4,468 from IEEE Xplore. We included English-language articles published between 2014 and 2025—a window chosen to capture the rise of hybrid and fuzzy variants and early integrations with GIS, AI, and big data—that apply MCDM to prioritizing projects, interventions, or sites. We excluded non-English items, duplicates, and incomplete records; screening and eligibility followed PRISMA. We combined SLR procedures with bibliometric analysis in VOSviewer and R-bibliometrix to map co-occurrence. From the pool, 32 studies met the criteria. Distance-based methods (TOPSIS, VIKOR, EDAS) and AHP dominate; hybrid and fuzzy variants are increasing. Objective and mixed weighting are common, while normalization choices and ranking rules vary by context. Validation is uneven: case applications and expert judgment are common, but sensitivity tests and cross-method comparisons are scarce. We connect objectives, weighting and normalization, ranking, and validation, identify method–context fit, and spotlight reporting gaps. We provide method-selection cues and a reporting checklist for practitioners, and a roadmap for standardized validation, transparent parameterization, and integration with GIS, AI, and big data for researchers.**

***Keywords*—Bibliometric Mapping, Decision Prioritization, Multi-Criteria Decision-Making, Post-Disaster Management, PRISMA.**

I. Introduction

In recent decades, the increasing frequency and severity of natural disasters—driven by climate change and urban expansion—have posed serious threats to human lives, infrastructure, and the environment [1-7]. The aftermath of such events often demands complex decision-making processes involving urgent actions and constrained resources [8-12]. Among all disaster phases, the post-disaster recovery stage is particularly critical [13-14]. It requires timely and informed decisions regarding emergency response, humanitarian assistance, and long-term reconstruction [15]. One key challenge in this stage is that decisions must be made under pressure, with multiple conflicting criteria and limited or uncertain data [16-17]. Subjective judgment alone is no longer sufficient; instead, data-driven decision-making becomes essential for minimizing socioeconomic impacts and ensuring fair prioritization of limited resources [18-20]. In this context, decision-makers need structured approaches that support prioritization based on objective assessments [21-23]. MCDM approaches are widely used across various disaster phases—from preparedness to response and recovery [24-26]. These methods can be categorized based on how criteria weights are determined: subjective (e.g., AHP, BWM, ANP), objective (e.g., entropy, CRITIC, DEA), or integrated approaches combining both [27-31]. Similarly, selection models may rely on value-based, distance-based, outranking, or pairwise comparison techniques [25, 32, 33]. Recent advancements have introduced hybrid models such as fuzzy MCDM, and combined weighting method, and multi-expert systems [29, 30, 34]. Within this landscape, decision prioritization selecting and sequencing projects, interventions, sites, or assets under multiple and often conflicting criteria has emerged as a central use case of MCDM in post-disaster management. Prior work spans distance-based approaches (e.g., TOPSIS, VIKOR, EDAS), preference/analytic frameworks (e.g., AHP), and a growing set of hybrid and fuzzy variants, alongside objective and mixed weighting and diverse normalization schemes [29], [30], [34], [35], [36].

However, despite this growing body of research, a key problem remains: there is no unified understanding of how MCDM methods have been applied across post-disaster recovery contexts especially in terms of how they differ in objectives, weighting schemes, normalization techniques, decision models, and evaluation strategies. Most existing reviews focus narrowly on specific sectors or isolated methodological aspects. Previous reviews have either examined specific hazards, conducted bibliometric analyses on disaster logistics without integrating both SLR and bibliometric methods [37-39].

However, no prior review provides an integrated and reproducible account of the full methodological pipeline for

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decision prioritization from objectives through weighting and normalization to ranking and validation while simultaneously offering a structural map of the field. This dual deficit limits method-context fit assessment and constrains auditable prioritization in practice [35-39]. Combining a PRISMA-guided SLR with bibliometric mapping provides complementary value: PRISMA ensures transparent screening and replicable evidence synthesis, while VOSviewer/R-bibliometrix reveal thematic structures, evolution, and influence patterns that are not accessible through narrative synthesis alone [38], [39].

To address this gap, this study explores five core questions concerning the use of MCDM in post-disaster contexts: (1) What are the main objectives of MCDM application? (2) What weighting methods are commonly adopted? (3) Which normalization techniques are used? (4) What decision models are implemented? and (5) How are these methods evaluated or validated?

This study makes three contributions. First, it consolidates decision prioritization with MCDM in post-disaster management by synthesizing objectives, weighting and normalization choices, ranking procedures, and validation practices. Second, it produces a bibliometric map of themes, co-occurrences, and trends that contextualize method selection and reporting. Third, it identifies method–context fit and reporting/validation gaps, offering actionable guidance for researchers and practitioners seeking transparent and auditable prioritization [35-39].

II. Methodology

We conducted a structured search in five digital libraries, namely Scopus, Google Scholar, Emerald Insight, ProQuest, and IEEE Xplore. The search used a three-stage Boolean strategy that is summarized in Table 1. Keyword set A comprised “Multi Criteria Decision Making” or “mcdm”. Keyword set B comprised “Post-Disaster” or “Disaster Recovery”. Keyword set C was “Prioritization”. We first queried each source with set A only, then with A and B, and finally with A, B, and C to focus specifically on decision prioritization in post-disaster contexts. For the first stage (A), the searches returned 18,454 records from Scopus, 47,206 from Google Scholar, 650 from Emerald Insight, 30,975 from ProQuest, and 4,468 from IEEE Xplore. For the second stage (A and B) the returns were 1,107, 4,160, 509, 703, and 877, respectively. For the third stage (A and B and C) the returns were 31, 31, 2, 244, and 10, respectively. Where supported, field restrictions were applied to titles, abstracts, and keywords. Results were exported in BibTeX or CSV formats, merged, and de-duplicated using DOI and title matching.

This study defined explicit eligibility criteria to ensure transparency and reproducibility. Studies were included if they were written in English, published from 2014 to 2025, and applied MCDM to post-disaster decision prioritization, for example prioritizing projects, interventions, sites, assets, or actions. The time window from 2014 to 2025 was selected to capture the emergence of hybrid and fuzzy variants and early integrations with geographic information systems, artificial intelligence, and big-data pipelines. We excluded non-English items, duplicates, records with incomplete metadata, studies that did not apply MCDM, and studies that were not situated in post-disaster contexts.

Semi-automated filtering applied to the A and B and C set yielded 318 unique records. Before screening, we removed 8 duplicates, 32 items flagged as ineligible by automation tools, and 14 records removed for other reasons, leaving 264 records for title and abstract screening. At this stage, 201 records were excluded and 63 reports were sought for retrieval. Four reports could not be retrieved, resulting in 59 full texts assessed for eligibility. We then excluded 24 studies that were not MCDM and 3 that were not post-disaster. In total, 32 studies were included in the review. The selection process is presented in Figure 1 following the PRISMA flow.

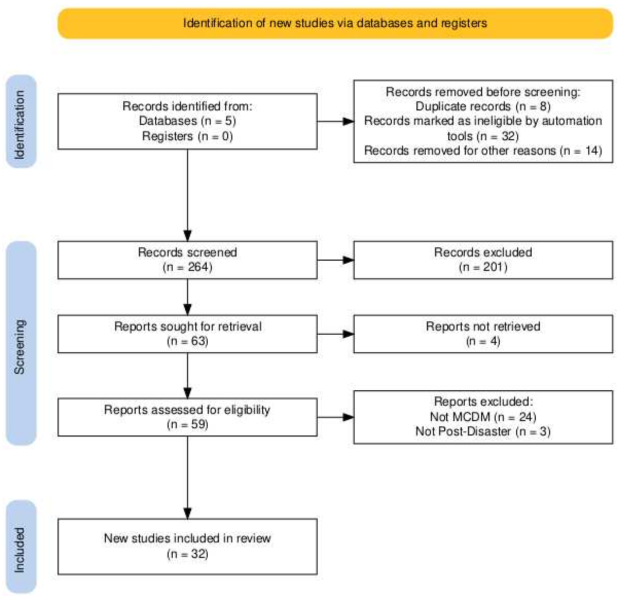

Fig. 1. PRISMA flowchart

To support distinct analytical goals, we organized two datasets. Dataset 1 contained the 59 eligible full texts and was used for bibliometric mapping. Dataset 2 contained the final set of 32 studies and was used for the systematic synthesis. Bibliographic fields such as authors, source, year, and keywords were harmonized. Study descriptors were standardized to capture decision objective and context, disaster type and geography, MCDM method family, weighting strategy, normalization procedure, ranking rule, and validation approach.

Bibliometric analyses were conducted with VOSviewer and R-bibliometrix (Biblioshiny). In VOSviewer we mapped co-occurrence of author keywords and, where available, Keywords Plus. We used full counting, a minimum occurrence threshold of three, normalization by association strength, the

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default VOS layout, and modularity-based clustering. Prior to analysis, we unified common synonyms and spelling variants, for example “MCDM” and “multi-criteria decision-making”. In R-bibliometrix we set the timespan to 2014 to 2025, removed duplicates, analyzed co-word networks and thematic evolution with yearly slices, and reported the leading terms, clusters, and centrality and density statistics. Parameter settings and code snippets are available upon request to facilitate replication.

For the systematic synthesis, we extracted from Dataset 2 the decision objective and context, the MCDM family employed, the weighting strategy used (objective, subjective, or mixed), the normalization and ranking procedures, the validation approach, and the disaster type and geographic setting. Evidence was synthesized narratively and tabulated to compare method–context fit and reporting and validation practices. Because the included studies are heterogeneous and non-interventional, we did not apply formal risk-of-bias tools. Instead, we documented reporting completeness and validation procedures that are relevant for transparent and auditable prioritization.

III. Result and Analysis

A. Bibliometric Analysis

The bibliometric analysis was divided into two main parts: keyword co-occurrence mapping and thematic evolution over time. Using VOSviewer, a co-occurrence network was generated based on keywords that appeared at least twice in the selected documents. A total of 28 keywords were identified, grouped into five thematic clusters.

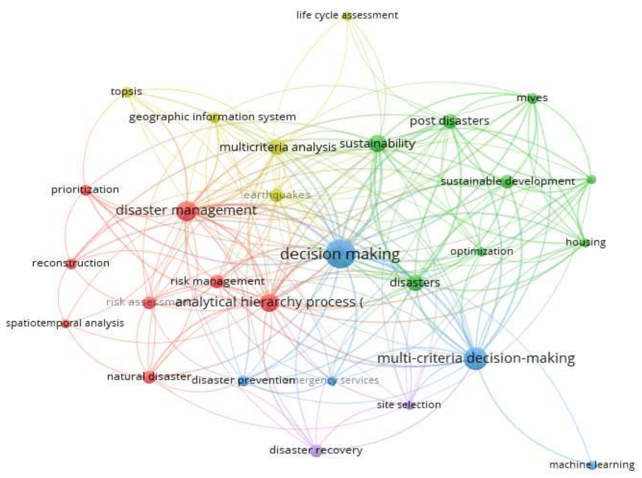

Fig. 2. Co-occurrence mapping

Figure 2 illustrates the resulting keyword visualization. The analysis revealed several dominant terms related to post-disaster MCDM research. “Decision making” appeared most frequently (26 occurrences), followed by “multi-criteria decision-making (MCDM)” (16 times), and “disaster management” (13 times). Keywords such as “analytic hierarchy process (AHP)”, “disaster recovery”, and “prioritization” were also strongly linked, indicating their central role in disaster-related decision-making studies. AHP was the most cited MCDM method (11 mentions), followed by TOPSIS (4 mentions). Although terms like “disaster recovery” (5), “prioritization” (4), and “site selection” (3) appeared less frequently. Most keywords were published between 2020 and 2023, reflecting the rising relevance and currency of the topic.

The map reveals four functional clusters that align with decision-prioritization use cases. The red cluster groups governance and judgment-driven terms around disaster management, analytical hierarchy process, risk management, prioritization, reconstruction, and spatiotemporal analysis. This indicates frequent use of AHP when agencies must structure criteria and reconcile expert judgments before ranking actions. The blue cluster centers on decision making and multi-criteria decision-making, with links to site selection and a peripheral tie to machine learning, which points to MCDM being paired with emerging data-driven pipelines for spatial triage. The green cluster connects post disasters, sustainable development, housing, optimization, and disasters, reflecting reconstruction and housing-focused prioritization where resource allocation and sustainability targets are explicit. The yellow cluster links topsis, geographic information system, earthquake, life cycle assessment, and multicriteria analysis sustainability, suggesting an engineering-oriented stream that couples distance-based ranking with GIS and life-cycle considerations. The central position of decision making and the bridge from prioritization to both AHP and TOPSIS show why method choice tracks context: AHP where expert structuring dominates, TOPSIS where spatial indicators enable rapid, repeatable ranking.

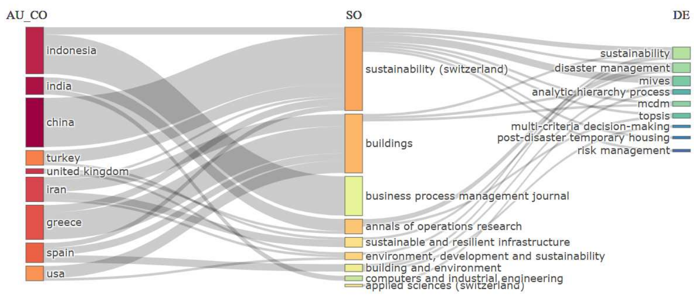

Fig. 3. Three-field plot

Figure 3 presents a three-field plot linking countries, publication sources, and primary keywords. The three-field plot shows that output is concentrated in contributions from Indonesia, India, and China, which flow predominantly into Sustainability (Switzerland) and Buildings. This channeling aligns the field with a sustainability and built-environment framing of post-disaster decision problems. On the keyword side, “sustainability,” “disaster management,” “analytical hierarchy process,” “TOPSIS,” “MCDM/multi-criteria decision-making,” “risk management,” and “post-disaster temporary housing” dominate, while MIVES appears in the same corridor as Buildings, reflecting an engineering and housing-reconstruction orientation. Taken together, these pathways indicate a pragmatic method–context fit: AHP and TOPSIS are frequently selected where criteria structuring and rapid, auditable ranking are required for reconstruction and

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housing decisions, with sustainability targets explicitly in scope. The concentration of sources also implies a topical bias toward built-environment applications; broadening publication venues to operations, logistics, and infrastructure journals would help capture prioritization problems centered on networks, access restoration, and supply resilience, and would encourage cross-method validation beyond case and expert appraisal.

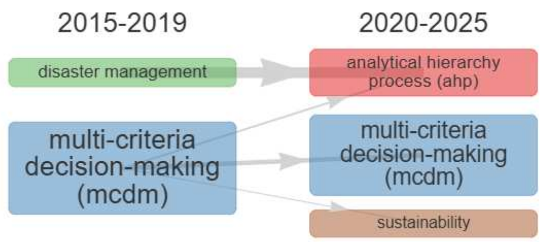

Fig. 4. Thematic evolution

Thematic evolution analysis (Figure 4) compares two time periods: 2015–2019 and 2020–2025. The shift from a broad “disaster management” focus to the anchors “analytical hierarchy process,” “MCDM,” and “sustainability” reflects a move from scoping problems to structuring defensible choices. As recovery governance matured, agencies needed traceable reasoning for why projects or sites were prioritized. That pressure elevates AHP because it exposes criteria hierarchies and trade-offs, while the persistent “MCDM” node signals consolidation around a core toolkit that accommodates varied ranking logics and data regimes. The rise of “sustainability” shows that prioritization now embeds long-horizon objectives, expanding the value model and increasing dependence on transparent weighting and normalization. Methodologically, pick AHP or related preference-analytic designs when stakeholder alignment and explicit criteria structuring are central.

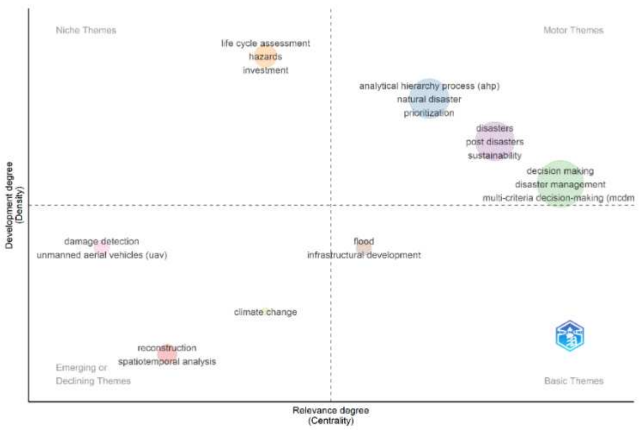

Fig. 5. The thematic map

The thematic map (Figure 5) classifies research themes based on two dimensions: centrality (relevance) and density (development stage). The map separates a mature core from specialized and still-forming strands. Motor themes cluster around analytical hierarchy process, prioritization, natural disasters, and sustainability, which signals a shift toward defensible, criteria-structured decision making under recovery mandates. Basic themes such as decision making, disaster management, and multi-criteria decision-making form the shared vocabulary that many studies rely on; they are central but less internally developed because they spread across diverse applications. Niche themes like life-cycle assessment, hazards, and investment show deep technical development with weaker links to the broader literature; without bridges to prioritization use cases they risk remaining siloed. Emerging or declining items such as reconstruction, spatiotemporal analysis, and climate change sit at low centrality, reflecting fragmented terminology and new data modalities rather than lack of importance. Flood and infrastructural development near the axes suggest applied subfields that are consolidating but not yet fully integrated.

B. Systematic Literature Review Findings

This section presents the findings of the systematic literature review (SLR), structured around five research questions (RQs), highlighting the methods and objectives explored in each study.

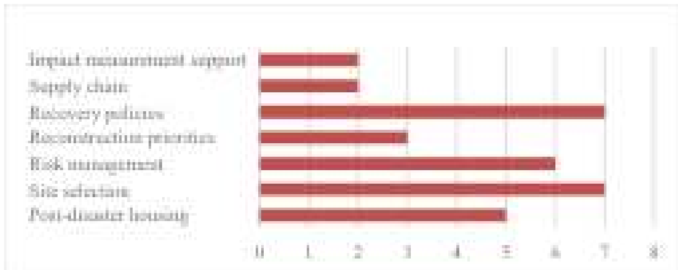

Fig. 6. MCDM topic objectives

RQ1: What are the main objectives of applying MCDM in post-disaster contexts? Across the 32 studies, the most frequent objects are site selection and recovery policies (seven studies each), reflecting early-recovery decisions about where to intervene and which rules or directives to adopt. Risk management appears in six studies, likely because part of this topic is treated within technical hazard literatures. Post-disaster housing and reconstruction priorities occupy a middle tier, indicating a shift from initial location and policy choices toward medium-term rebuilding agendas. Impact measurement support and supply chain are least represented, marking underexplored objects.

The distribution shows a phase bias toward location triage and governance, while impact measurement and logistics remain thinly covered. Future work should elevate these two objects by linking recovery performance indicators to decision priorities and by modeling networked supply constraints across places and time. Studies should also trace how the dominant objects change over the recovery cycle, clarifying when and why priorities move from siting and policy to housing, reconstruction, and risk control.

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Fig. 7. MCDM Weighted Method

RQ2: What weighting methods are used in post-disaster MCDM studies? Across the 32 studies, AHP is the dominant weighting technique (11 studies; [20, 25, 30, 32], [38–44]), which is consistent with problems that require an explicit criteria hierarchy and traceable trade-offs. Expert judgment without a formal algorithm appears in 5 studies, indicating continued reliance on domain panels but also a risk of uneven documentation. BWM is used in 4 studies, typically to reduce comparison burden and improve consistency. ANP and Fuzzy AHP each occur in 2 studies, the former when criteria are interdependent and the latter when judgments are linguistic or imprecise. DEMATEL is reported in 2 studies, mainly to uncover causal influence among criteria before weighting. A Combine category (3 studies) mixes subjective schemes with objective or fuzzy treatments, and an Another Method category (3 studies) groups miscellaneous or under-reported approaches. Less frequent techniques include SWARA, BORDA, and CILOS (each once).

Overall, the portfolio skews toward subjective and preference-analytic weighting, with objective schemes only sporadically and sometimes implicitly reported under combined or miscellaneous labels. When using AHP, report the criteria hierarchy, pairwise matrices, the aggregation rule, and the consistency ratio threshold used for acceptance. For BWM, include the reference best and worst criteria, the comparison vectors, and the linear programming model and solution. For ANP, document the network structure and the supermatrix convergence settings. For Fuzzy AHP, state the membership functions, fuzzification and defuzzification procedures. For DEMATEL, provide the thresholding rule and the total relation matrix. Studies that rely on expert judgment should describe the elicitation protocol, panel composition, and inter-rater agreement, and justify how qualitative inputs were converted to numeric weights. For combined or miscellaneous approaches, make the fusion formula explicit and place weights on a common ratio scale so they are comparable across criteria.

RQ3: What normalization techniques are applied in MCDM-based post-disaster decision-making? Across the reviewed studies, normalization aligns with the logic of the underlying model rather than author preference. Vector normalization is most common (11 studies), typically paired with distance-based procedures such as TOPSIS, VIKOR, and COCOSO, because it preserves geometric relationships needed for Euclidean [18], [19], [27], [32]. Linear (min–max) normalization appears in 4 studies, mainly with additive or value-aggregation models such as COPRAS, MABAC, and WASPAS, where proportional scaling supports compensatory summation [3], [18], [32], [33]. Reference-based difference normalization is rare (2 studies) and used where the model measures deviation from a target or mean, as in VIKOR/EDAS [15], [40]. In short, distance models favor vector scaling; additive models favor linear scaling; deviation models use reference-based transforms [36].

RQ4: Which MCDM methods are used to assess impacts and determine priorities in post-disaster response?

TABLE 1. MCDM METHODS AND RESPECTIVE NORMALIZATION TECHNIQUES

Method	Articles	Normalization Technique
TOPSIS, PROMETHEE, ELECTRE, CODAS	15	Vector normalization
EDAS	3	Deviasi dari rata-rata
WASPAS, MAIRCA, MABAC, EAMR, COCOSO, COPRAS	7	Linear normalization
VIKOR	2	Reference-based difference normalization

Table 1 maps methods to the normalization they require. Distance-based procedures (TOPSIS dan CODAS) account for 15 applications and almost uniformly use vector normalization. EDAS appears in 3 studies and adopts mean-deviation scaling, consistent with its deviation-from-average scoring. Additive and mixed value-aggregation models (WASPAS, MAIRCA, MABAC, EAMR, COCOSO, COPRAS) use linear normalization in 7 studies. VIKOR uses reference-based difference normalization in 2 studies. Counts reflect papers that report a normalization step; methods used primarily for weighting (for example AHP, ANP) are not tallied here. This alignment is structural: distance models need geometry-preserving scaling, additive models need proportional scaling, and deviation models normalize against a reference set [36]. Authors should name the exact variant and give the equation used, specify benefit or cost direction, state how zeros and negative values were handled, and clarify whether weights were applied before or after normalization (examples include [3], [15], [18], [32], [33], [40], [41]). To meet reproducibility expectations, re-estimate rankings with a plausible alternative normalization consistent with the method family and report rank stability (for example, Spearman correlation). This avoids hidden rank reversals and addresses the reviewers' request for interpretive, method-aware reporting.

RQ5: How are MCDM results evaluated or validated in post-disaster studies? Across the 32 papers we recorded 79 validation events, with many studies using more than one approach. The modal practices are real-world case applications (22) and expert or stakeholder appraisal (18), which strengthen contextual credibility but do little to test result stability. Internal checks (14) are mostly method-specific coherence tests such as AHP consistency

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ratios; these address reliability of judgments, not robustness of rankings. Comparative analyses against alternative MCDM or machine-learning baselines are present in 12 instances, and sensitivity or stability analyses in 8, indicating that robustness is underused relative to its importance in prioritization tasks. Rank aggregation (5) appears as an ensemble tactic to reconcile multiple models, but its adoption is limited and often under-documented.

This studi propose a minimum validation protocol that treats prioritization results as hypotheses to be stress-tested rather than merely illustrated. First, ensure full parameter transparency by reporting all weights, normalization choices, and method-specific settings (for example, the VIKOR v parameter and the distance norm). Second, test within-model robustness through one-way and, where feasible, global sensitivity analyses on key levers such as weights, normalization, and tie-breaking; summarize stability using rank correlation (Spearman or Kendall), top-k overlap, and swap counts. Third, conduct cross-method triangulation by comparing the primary model with at least one credible alternative from a different family and report agreement metrics. Fourth, seek external validation by replicating the analysis on a second site, hazard, or time slice when data permit. Finally, when rank aggregation is used, harmonize scores to a common scale, state the aggregation rule (such as Borda or Copeland), and report uncertainty bands.

Key findings are clear. Bibliometrics show AHP, MCDM, and sustainability as motor themes, with output concentrated in built-environment venues; Indonesia, India, and China dominate contributions. In the SLR, site selection and recovery policies are the most studied objects; risk management, housing, and reconstruction are mid-tier; impact measurement and supply chains are underexplored. AHP leads weighting; BWM and expert judgment appear selectively. Normalization follows model logic: vector for distance-based, linear for additive, and reference-based for deviation models. Validation is skewed to case application and expert appraisal, with sensitivity and cross-method checks still scarce. Practically, use distance-based models for rapid, indicator-rich triage and preference-analytic designs for policy alignment; adopt standardized reporting and robustness tests to make rankings auditable, and expand work on impact measurement and logistics to close persistent gaps.

IV. Conclusion

From 32 studies, the picture is clear: MCDM in post-disaster work is used chiefly to decide where to act and which policies to advance. Weighting is led by AHP; other schemes appear but far less often. Normalization tracks the model class-vector with distance-based families, linear with additive models, and reference-based with deviation models. Bibliometric signals point to growing ties with sustainability and the built environment, while impact measurement and logistics/supply chains remain thinly studied.

What follows for practice is straightforward. Match the tool to the task: distance-based families for fast, metric-driven screening; preference models (e.g., AHP/ANP) when criteria must be structured and negotiated; hybrid or fuzzy designs when evidence is uncertain, ideally anchored in GIS. For credibility, at minimum state all settings, probe sensitivity, cross-check with one alternative method, and replicate when data allow. Doing so turns rankings into auditable, defensible priorities and shows exactly where future work should expand—on impact metrics and supply-chain constraints.

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