

# A Technology-Maturity-Based Foresight Portfolio Framework for Smart Seismic Structures: Integrating CRITIC, SWARA-Based Weighting, Fuzzy VIKOR, Borda Analysis, and Monte Carlo Uncertainty Assessment

Shahin Lale Arefi <sup>a\*</sup> , Mahdi Bitarafan <sup>b</sup> 

<sup>a</sup> Department of Civil Engineering, Esfarayen University of Technology, Esfarayen, Iran

<sup>b</sup> International Institute of Earthquake Engineering and Seismology (IIEES), Tehran, Iran

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## ABSTRACT

The rapid development of smart seismic technologies requires structured approaches for selecting foresight methods according to technology maturity. Existing studies mainly address the technical development or performance assessment of individual technologies, while limited attention has been given to maturity-sensitive foresight portfolio design. This study proposes a technology-maturity-based foresight portfolio framework for smart seismic structures. First, scientific and patent-based evidence is screened and coded. The CRITIC method is used to weight evidence indicators and construct weighted maturity profiles, after which technologies are assigned to four planning-oriented maturity/application stages using predefined profile-based classification rules: emerging/research-oriented, developing/technology-readiness, implementation-oriented, and recovery/resilience-oriented. Second, twelve valid expert questionnaires are used to evaluate decision criteria and foresight methods. The criteria are weighted through a SWARA-based procedure, and eight foresight methods are ranked using Fuzzy VIKOR. Third, the overall VIKOR ranking is complemented by a separate tied-rank Borda analysis based on experts' stage-specific portfolio assessments to extract maturity-sensitive foresight portfolios. Robustness is examined using expert agreement and reliability checks, Monte Carlo uncertainty analysis, VIKOR sensitivity analysis, and comparative validation with TOPSIS and PROMETHEE II. The results show that seismic resilience support is the most important criterion. Delphi and technology roadmapping form the most stable overall foresight core, while stage-specific portfolios vary across maturity contexts. The proposed framework supports maturity-sensitive foresight planning for resilient smart seismic infrastructure.

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## 1. Introduction

Earthquakes remain among the most destructive hazards affecting buildings, bridges, lifeline systems, and critical infrastructure. In modern earthquake engineering, infrastructure performance is no longer evaluated only in terms of life safety or collapse prevention. Increasing attention is now given to resilience-oriented objectives, including damage limitation, residual drift control, reparability, reduced downtime, re-occupancy, functional recovery, and lifecycle seismic loss. These objectives require structural systems that can not only resist seismic actions, but also support damage detection, post-earthquake assessment, adaptive

\* Corresponding author.

E-mail address: [sh.arefi@esfarayen.ac.ir](mailto:sh.arefi@esfarayen.ac.ir) (S. Lale Arefi).



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maintenance, and rapid recovery [1].

Smart earthquake-proofing structures are a significant milestone in the resilient paradigm. Such systems feature seismic-proofing technology combined with the ability to monitor, analyze, control, and make decisions based on collected data. Examples of such systems include structural health monitoring systems, smart sensors, IoT seismic monitoring, semi-active control systems, magnetorheological dampers, self-centering systems, base isolation, supplementary damping systems, replaceable fuses, post-earthquake rapid damage assessment systems, and digital twin-based systems. Improvements in IoT-based structural health monitoring and digital twins show that smart infrastructure systems have the potential to improve condition assessment and decision-making [2, 3]. Structural damage detection has emerged as a fundamental component of resilient and intelligent infrastructure systems, as it facilitates the timely identification, localization, and assessment of structural deficiencies, thereby enhancing post-event safety evaluation, informing maintenance strategies, and supporting rapid functional recovery [4, 5].

However, smart seismic technologies do not have the same level of maturity or implementation readiness. Some technologies, such as AI-based damage detection and digital twins, remain strongly research-oriented in many seismic applications. Others, such as structural health monitoring, smart sensors, IoT-based monitoring, and semi-active control devices, show increasing technology-readiness evidence. More established technologies, such as base isolation, supplemental damping devices, and self-centering systems, are closer to engineering implementation. Recovery-oriented solutions, including replaceable fuse systems, rapid damage assessment, and re-occupancy or downtime-reduction tools, are increasingly important for post-earthquake resilience planning. Therefore, planning for smart seismic structures requires not only identifying promising technologies, but also understanding which foresight methods are most appropriate for different maturity contexts.

Technology foresight methods can support this decision-making process by helping engineers, infrastructure owners, and policymakers identify emerging trends, assess technology readiness, evaluate implementation barriers, and plan development pathways. Different foresight methods provide different types of knowledge. Bibliometrics can identify scientific trends and research clusters. Patent analysis can reveal innovation activity, technological maturity, and commercialization signals. Horizon scanning can detect weak signals and early-stage opportunities. Delphi can support structured expert consensus under uncertainty. MACTOR can help analyze stakeholder interests and implementation feasibility. Scenario planning can explore alternative future conditions, while technology roadmapping can translate foresight results into staged implementation pathways. These methods are therefore complementary rather than interchangeable [6, 7].

For this reason, selecting a single “best” foresight method may not be sufficient for smart seismic technology planning. A method that is effective for detecting emerging research trends may not be adequate for assessing implementation feasibility or post-earthquake recovery needs. Similarly, a method suitable for mature engineering technologies may not be appropriate for early-stage digital or data-driven solutions. This suggests that foresight-method selection should be linked to technology maturity. In other words, smart seismic technologies may require maturity-sensitive portfolios of foresight methods instead of a universal single-method solution. To address this need, this study proposes a technology-maturity-based foresight portfolio framework for smart seismic structures. The framework first screens and codes scientific and patent-based evidence and applies the CRITIC method to classify smart seismic technologies into maturity/application stages. Then, expert-based multi-criteria decision analysis is used to evaluate foresight methods with respect to criteria that reflect both foresight capability and seismic engineering relevance. The criteria are weighted through a SWARA-based procedure, and the foresight methods are ranked using Fuzzy VIKOR. A tied-rank Borda analysis is then applied to extract suitable foresight portfolios for each maturity stage. Finally, Monte Carlo uncertainty analysis, VIKOR sensitivity analysis, and comparative validation with TOPSIS and PROMETHEE II are used to examine the robustness of the results.

The proposed framework will consider eight different methods of foresight, including: brainstorming, MACTOR/stakeholder analysis, bibliometrics, patent analysis, Delphi, horizon scanning, scenario planning, and technology roadmapping. Criteria for the decision-making include identification of new scientific and technological trends, weak signal detection, assessment of the technology maturity/ready state, coherence with the objective of seismic resilience, relevance to smart seismic technologies, stakeholder acceptability, long-term uncertainty management, and assistance in planning implementation. Altogether, these criteria allow the framework to connect foresight-method selection with issues relevant for earthquake engineering.

The main contribution of this study is the development of an integrated decision-support framework that links technology maturity, foresight portfolio selection, seismic resilience, and uncertainty analysis. Unlike conventional ranking models that identify one preferred foresight method, the proposed framework determines which combination of methods is more suitable for each maturity stage of smart seismic technologies. This maturity-sensitive perspective helps transform foresight from a generic technology-planning tool into a practical decision-support approach for resilient smart seismic infrastructure.

The remainder of this paper is organized as follows. Section 2 reviews the related work on smart seismic technologies, seismic resilience, technology maturity, foresight methods, and uncertainty-aware decision support. Section 3 presents the research gap and contributions of the study. Section 4 describes the methodology, including CRITIC-based maturity assessment, expert questionnaire design, SWARA-based criteria weighting, Fuzzy VIKOR ranking, tied-rank Borda portfolio extraction, and robustness validation. Section 5 presents and discusses the results, including maturity classification, criteria weights, foresight-method rankings, portfolio recommendations, and practical decision guidelines. Section 6 concludes the paper, and Section 7 discusses limitations and future research directions.

## 2. Related work

This section reviews the literature in three interrelated areas. First, it examines smart seismic technologies and their contribution to resilience-oriented earthquake engineering. Second, it discusses how differences in technological maturity, evidence availability, and implementation readiness create different planning and foresight requirements. Third, it reviews the main foresight methods and uncertainty-aware decision-support approaches relevant to the selection of maturity-sensitive foresight portfolios. The review demonstrates that smart seismic technologies should not be treated as a homogeneous technological domain and that foresight methods should be selected according to the maturity, application context, and strategic purpose of the technologies under consideration.

### 2.1. Smart seismic technologies and resilience-oriented applications

Resilience to earthquakes has become one of the key indicators in the assessment of structural and urban resilience [8]. It is the ability of the system to maintain its essential function and recover from earthquake effects. Earthquake engineering has gradually moved beyond the traditional objectives of strength, ductility, life safety, and collapse prevention toward a broader resilience-oriented perspective. In this perspective, acceptable seismic performance also includes damage limitation, reparability, residual-drift control, reduced downtime, rapid re-occupancy, functional recovery, and the restoration of infrastructure services. Consequently, the performance of buildings and infrastructure is increasingly evaluated not only by their response during an earthquake, but also by the time, resources, and interventions required to restore their intended functionality after the event [9–11]. The NIST-FEMA functional-recovery framework similarly identifies re-occupancy and recovery time as explicit performance objectives for buildings and lifeline systems. Bitarafan et al. [12] studied the importance of selecting appropriate smart structural design scenarios to enhance resilience-oriented seismic performance under future earthquake conditions.

Seismic technologies help achieve these goals by ensuring that structural engineering systems are combined with the technologies of sensing, monitoring, communication, control, data analysis, and engineering decision-making. Major technologies include Structural Health Monitoring (SHM), smart sensors, wireless sensor networks, IoT-based seismic monitoring, and edge computing technology. These technologies provide continuous or event-triggered data about the structural response and condition, allowing one to detect any anomalies, post-earthquake evaluation, schedule maintenance, and rapid engineering decision-making. IoT-based SHM helps combine sensors, communication infrastructure, and data-processing capabilities, while edge computing helps avoid the necessity for full centralization of the process and allows real-time analysis at the site of monitoring [2, 13].

Artificial-intelligence-based damage detection represents a closely related but rapidly developing research direction. Machine-learning and deep-learning models can analyse vibration signals, images, and other monitoring data to identify damage-sensitive patterns that may be difficult to detect through conventional approaches. However, although these methods have demonstrated strong performance in laboratory experiments, benchmark datasets, and numerical applications, their routine use in seismic engineering still depends on the availability of representative training data, model interpretability, uncertainty quantification, and validation under real operating and earthquake conditions [14].

Digital twins extend monitoring and data-driven assessment by linking physical infrastructure to dynamically updated virtual representations. In civil infrastructure, digital twins may combine sensor measurements, inspection records, numerical models, maintenance information, and performance simulations to support condition assessment and lifecycle decision-making. Nevertheless, the literature also identifies unresolved challenges related to semantic interoperability, integration of heterogeneous data, sensor-network representation, model updating, and synchronization between physical and digital systems [3, 15]. Recent bridge applications indicate that digital-twin-based SHM is progressing toward field implementation, although many applications remain project-specific and require broader standardization and validation [16]. A second group of smart seismic technologies is associated with structural response control and seismic protection. This group includes semi-active control systems, magnetorheological dampers, adaptive control strategies, base-isolation systems, and supplemental energy-dissipation devices. Semi-active systems can modify their mechanical properties in response to measured structural behaviour while generally requiring less external energy than fully active systems. Their potential has been demonstrated in structural-control research and full-scale applications, but practical adoption requires attention to reliability, control stability, power availability, maintenance, sensor performance, and fail-safe behaviour [17].

Self-centering and low-damage structural systems provide another important pathway toward seismic resilience. Self-centering systems combine recentering capability with energy dissipation to reduce permanent structural deformation following earthquakes. Reduced residual drift can decrease the probability that an otherwise stable structure is judged economically irreparable and can facilitate inspection, repair, and return to service [18]. Similarly, replaceable fuse mechanisms are intended to concentrate inelastic damage in predefined components that can be inspected and replaced more efficiently than primary structural members. These systems therefore connect structural-response reduction with reparability and post-earthquake recovery objectives [19].

Recent research has increasingly formalized the assessment of downtime and functional recovery. Molina Hutt et al. [20] proposed a probabilistic framework that distinguishes recovery states such as stability, shelter-in-place, re-occupancy, functional recovery, and full recovery. Cook et al. [21] further operationalized functional-recovery assessment by linking component damage states to system-level operation and building-level re-occupancy and functionality. These studies show that recovery is influenced not only by structural damage, but also by damage to non-structural components, utilities, inspection procedures, repair sequencing, labour availability, and other impeding factors. The uncertainty associated with these variables is itself a major decision concern. Kourehpaz et al. [22] demonstrated that assumptions regarding seismic demands, component fragilities, replacement consequences,

and impeding-factor delays can substantially influence loss and recovery-time estimates. More recent downtime-oriented studies have also argued that future seismic design objectives should explicitly address functional disruption in addition to life safety and collapse prevention [23]. Therefore, recovery-oriented smart technologies should be assessed not only in terms of their technical capability, but also according to their potential contribution to reducing inspection time, repair delay, re-occupancy time, and overall functional disruption. Recent applied studies have also highlighted the importance of resilience-oriented assessment and mitigation planning in infrastructure systems under hazard-induced disruption, further emphasizing the need for context-sensitive planning and recovery-oriented decision-making in seismic applications [24, 25].

Overall, smart seismic technologies can be organized into three complementary functional domains. The first is monitoring and diagnosis, including SHM, IoT-based monitoring, smart sensors, AI-based damage detection, and digital twins. The second is response control and damage reduction, including base isolation, supplemental damping, semi-active control, magnetorheological dampers, and self-centering systems. The third is repairability and recovery support, including replaceable components, rapid post-earthquake assessment, re-occupancy decision support, and downtime-reduction systems. Although these domains are interdependent, the technologies within them differ substantially in research maturity, validation evidence, field implementation, standardization, and recovery relevance. These differences provide the first justification for adopting a maturity-sensitive foresight framework.

## 2.2. Technology maturity and foresight needs in smart seismic structures

Technology maturity is commonly represented using Technology Readiness Levels or similar stage-based models. Such models are useful for distinguishing conceptual research, laboratory validation, prototype development, and operational deployment. However, maturity cannot always be represented adequately by a single linear scale. Previous research has identified limitations related to system complexity, the validity of readiness assessments, integration between technological components, and the use of readiness levels for planning and review [26]. Accordingly, the maturity categories used for smart seismic technologies should be interpreted as planning-oriented categories rather than formal or universal TRL assignments.

For smart seismic technologies, maturity is multidimensional. Scientific publications indicate research visibility, knowledge development, and experimental validation, while patents can provide complementary information regarding invention activity, technological embodiment, and potential commercialization. Bibliometric and patent information are particularly valuable when historical market data are limited, as is often the case for emerging technologies. Daim et al. [27] demonstrated that combining bibliometric and patent evidence with forecasting approaches can strengthen the analysis of emerging technology trajectories. However, publication or patent activity alone should not be equated with implementation readiness; field validation, engineering standards, interoperability, maintainability, stakeholder acceptance, and recovery contribution must also be considered.

AI-based damage detection and digital twins may be regarded as emerging or research-oriented in many seismic applications. Their scientific visibility has increased rapidly, and their potential for automated diagnosis, predictive maintenance, and lifecycle management is substantial. Nevertheless, many studies continue to rely on laboratory data, numerical simulations, benchmark structures, or project-specific implementations. Their transition into routine seismic design and post-earthquake practice requires reliable data pipelines, validation under changing environmental and operational conditions, interpretable models, professional acceptance, and compatibility with existing engineering procedures [3, 14, 15].

SHM platforms, smart sensors, IoT-based monitoring, edge-computing applications, and semi-active control devices generally represent a developing or technology-readiness-oriented group. These technologies possess stronger experimental, prototype, and application evidence than many fully data-driven solutions. Nevertheless, their readiness differs across structural types and implementation environments. Sensor durability, communication reliability, power requirements, cybersecurity, data management, maintenance, and compatibility with engineering decision processes can influence whether a technically validated system can be adopted at scale [2, 13, 17].

Base isolation, supplemental damping devices, and several self-centering systems are more closely associated with implementation-oriented maturity. These technologies have longer analytical and experimental histories and clearer connections to design practice and structural-performance objectives. However, their implementation still depends on code provisions, constructability, project cost, procurement practices, inspection requirements, maintenance responsibilities, and stakeholder confidence. Consequently, foresight for relatively mature technologies should focus less on detecting scientific novelty and more on understanding adoption barriers, regulatory pathways, market conditions, and staged deployment. Recovery – and resilience – oriented technologies create a different maturity context. Replaceable fuse systems, rapid damage-assessment tools, re-occupancy decision platforms, and downtime-reduction systems are not necessarily less technologically developed than implementation-oriented devices. Instead, they are distinguished by their principal application objective: the restoration of functionality after earthquakes. Their assessment therefore requires evidence related to repair sequencing, inspection, workforce and resource availability, building services, non-structural damage, operational continuity, and acceptable recovery times [11, 20, 21].

These maturity differences create distinct foresight requirements. For emerging technologies, foresight should emphasize scientific mapping, weak-signal detection, research-gap identification, and expert interpretation. For developing technologies, it should incorporate patents, validation evidence, readiness constraints, and pathways from research to application. For implementation-oriented technologies, stakeholder interests, regulation, costs, institutional conditions, and deployment planning become more influential. For recovery-oriented technologies, foresight must additionally consider uncertain damage and recovery scenarios, service-restoration targets, resource constraints, and long-term resilience expectations. The selection of foresight methods

should therefore be related to both technological maturity and the intended decision outcome. Research on foresight-method selection indicates that methods are often chosen on the basis of familiarity or intuition, even though their suitability depends on objectives, available evidence, participation requirements, resources, and uncertainty conditions [28]. Similarly, bibliometric and patent evidence can support the assessment of emerging and developing technologies, but they should be combined with qualitative and participatory methods when implementation, stakeholders, and future uncertainty are important [27].

Accordingly, technology maturity provides a defensible basis for designing foresight portfolios. It does not imply that each technology follows a single fixed development trajectory or that one method corresponds exclusively to one maturity stage. Instead, maturity indicates the dominant types of evidence, uncertainty, actors, and planning questions that the foresight process must address. This interpretation supports the use of complementary portfolios rather than a universal foresight method.

### 2.3. *Foresight methods and uncertainty-aware decision support*

Technology foresight provides structured approaches for anticipating technological change, identifying opportunities and risks, and developing strategic responses under uncertainty. The literature includes a wide range of exploratory, evidential, expert-based, participatory, and planning-oriented methods. Because these methods generate different forms of knowledge, their selection should depend on the problem context, the available information, the maturity of the technology, and the intended use of the foresight outputs. Popper [28] showed that foresight-method selection is itself a methodological problem, while more recent taxonomies confirm the diversity of foresight techniques and the need to align methods with strategic objectives [8, 29].

Bibliometrics is particularly useful for mapping scientific growth, research clusters, influential publications, collaboration networks, and emerging topics. Patent analysis provides a different but complementary view by identifying invention activity, technological claims, assignees, application areas, and possible commercialization signals. The integration of these evidence streams can improve the analysis of emerging technologies, especially when reliable market information is unavailable [27]. For smart seismic technologies, these methods can help distinguish rapidly expanding research areas from technologies showing stronger device-level or application-oriented development.

Delphi is a structured expert-elicitation method that uses iterative questionnaires, controlled feedback, and typically anonymous participation to develop judgments under uncertainty. Its usefulness is particularly strong when empirical evidence is incomplete or when future development depends on multidisciplinary expertise. However, its credibility depends on appropriate expert selection, questionnaire design, feedback procedures, and transparent definitions of agreement or consensus [30]. Delphi is therefore well suited to interpreting uncertain maturity evidence and evaluating the feasibility and resilience contribution of smart seismic technologies.

Horizon scanning focuses on identifying early signals, emerging developments, discontinuities, and potential risks or opportunities. It is particularly relevant for early-stage digital and data-driven technologies whose future applications may not yet be visible in established engineering practice. Recent OECD guidance emphasizes that horizon scanning can support anticipatory technology policy, but also notes challenges related to signal definition, evidence integration, methodological quality, and the translation of scanning results into usable decisions [31].

Scenario planning is used to explore multiple plausible futures rather than predict a single expected outcome. It can incorporate changes in hazard conditions, technology development, regulation, investment, stakeholder expectations, and recovery requirements. Reviews of scenario-planning approaches show that combinations of qualitative and quantitative techniques can improve scenario development, selection, and validation [32]. In smart seismic planning, scenario planning is especially relevant where recovery objectives, resource availability, damage conditions, and acceptable downtime remain uncertain.

MACTOR and related stakeholder-analysis methods focus on actors, objectives, influence relationships, cooperation, and conflict. Such methods become increasingly important when technological performance is no longer the main barrier and implementation depends on infrastructure owners, engineers, contractors, regulators, technology suppliers, insurers, occupants, and emergency-management organizations. Stakeholder analysis can therefore complement technical assessment by identifying institutional constraints, adoption incentives, and potential conflicts affecting implementation. Technology roadmapping links markets, needs, products, systems, technologies, resources, and time horizons within a structured development pathway. It is widely used to support long-term strategic planning and to communicate relationships between evolving needs and technological capabilities [33]. Roadmapping is especially valuable for developing and implementing smart seismic technologies because it can convert scientific, patent, expert, and stakeholder evidence into milestones, responsibilities, validation requirements, and deployment sequences. Brainstorming can provide rapid early-stage idea generation, but its outputs are generally less structured and more dependent on group composition and facilitation. It is therefore more appropriate as a supporting method than as a complete foresight framework. Similarly, no single method can simultaneously provide scientific mapping, weak-signal detection, expert consensus, stakeholder analysis, scenario exploration, and implementation planning. This supports a portfolio perspective in which complementary methods are combined according to the maturity stage and decision need.

The selection and ranking of foresight methods are also affected by uncertainty. Expert judgments are frequently expressed through linguistic assessments, evidence concerning emerging technologies may be incomplete, and alternative criteria may conflict. Fuzzy logic can represent the vagueness of linguistic judgments, while multi-criteria methods can integrate technical, resilience, implementation, stakeholder, and uncertainty-related criteria. SWARA supports stepwise expert weighting, and VIKOR identifies compromise alternatives by balancing overall utility and maximum individual regret. Sensitivity analysis, Monte Carlo simulation,

TOPSIS, and PROMETHEE II can then be used to examine whether the resulting rankings remain stable under alternative assumptions [34–38].

Taken together, the literature provides strong technical knowledge regarding individual smart seismic technologies and a broad range of foresight and decision-support methods. However, the two research streams remain weakly integrated. Existing smart seismic studies primarily examine structural performance, monitoring, control, damage assessment, or recovery, whereas foresight studies generally discuss method selection independently of earthquake-engineering applications. The literature therefore does not clearly explain how foresight methods should be combined for smart seismic technologies at different levels of maturity and application readiness. This gap provides the basis for the maturity-sensitive foresight portfolio framework proposed in this study.

### 3. Research gap and contributions

Previous studies on intelligent seismic structures have focused mainly on the technological innovation and performance analysis of various individual technologies used, including structural health monitoring technology, smart sensors, artificial intelligence-based damage detection, digital twin technology, semi-active control technology, self-centering technology, replaceable fuses technology, and earthquake rehabilitation technologies. All these studies give an insight into how each of these technologies can be employed to reduce the seismic effects, increase monitoring, help in damage detection, and restore functionality. However, these technologies have been considered mainly from a technological perspective, rather than with strategic considerations related to their maturity stages.

In parallel, the technology foresight literature offers several methods for supporting long-term decision-making under uncertainty, such as Delphi, horizon scanning, bibliometrics, patent analysis, scenario planning, stakeholder analysis, and technology roadmapping. Recent studies emphasize that foresight methods should be selected according to the decision context, strategic purpose, and maturity of the technology rather than applied as fixed universal tools [29, 39]. Nevertheless, the direct use of foresight for smart seismic technologies remains limited. More specifically, there is still no clear framework that explains which foresight methods are more suitable for emerging, developing, implementation-oriented, and recovery-oriented smart seismic technologies. This gap is important because each maturity stage creates a different planning need. Emerging technologies require scientific trend analysis and weak-signal detection; developing technologies require readiness assessment, patent evidence, and transition planning; implementation-oriented technologies require stakeholder analysis, feasibility assessment, and deployment pathways; and recovery-oriented technologies require attention to repairability, downtime, re-occupancy, and functional recovery. Recent seismic recovery studies further confirm that functional recovery and re-occupancy should be treated as explicit objectives in resilience-oriented planning rather than secondary outcomes [40].

Therefore, the main gap addressed in this study is the lack of a technology-maturity-based foresight portfolio framework for smart seismic structures. Existing research provides strong technical knowledge on individual smart seismic technologies, and foresight research provides useful planning methods. However, these two streams have not been sufficiently integrated into a decision-support framework that links technology maturity with suitable combinations of foresight methods. To the best of the authors' knowledge, no prior study has developed such a maturity-based foresight portfolio framework specifically for smart seismic structures. To address this gap, this study proposes a maturity-sensitive foresight portfolio framework. Instead of identifying a single best foresight method, the framework treats foresight-method selection as a portfolio design problem. The main contributions of the study are as follows: first, it classifies smart seismic technologies into maturity/application stages using scientific and patent-based evidence; second, it evaluates foresight methods through an SWARA-based weighting and Fuzzy VIKOR decision model; third, it identifies suitable foresight portfolios for each maturity stage; and fourth, it tests the robustness of the results using Monte Carlo uncertainty analysis, VIKOR sensitivity analysis, and comparative validation with alternative multi-criteria decision-making methods. Through these contributions, the study provides a practical decision-support tool for planning resilient smart seismic infrastructure.

### 4. Methodology

This study proposes a maturity-based decision-support framework for selecting foresight portfolios for smart seismic technologies. The framework combines evidence-based maturity assessment, expert-based multi-criteria evaluation, portfolio extraction, and robustness validation. The main objective is to match different smart seismic technology stages with suitable combinations of foresight methods, rather than selecting a single best method for all technologies.

The process begins with the selection of smart seismic technologies that represent the case study and the collection of scientific and patent evidence. The collected evidence is then used to evaluate the level of maturity and application of each selected technology. The weights of the evidential indicators are obtained using the CRITIC method and then used to generate weighted maturity profiles. In the next step, the technologies are categorized into four levels of maturity and application.

In the next stage, decision criteria and foresight methods are defined based on the literature review and twelve valid expert questionnaires. The criteria cover trend identification, weak-signal detection, technology readiness, applicability to smart seismic technologies, seismic resilience support, stakeholder acceptance, long-term uncertainty handling, and implementation planning. Since expert evaluations are expressed through linguistic judgments, fuzzy numbers are used to model the vagueness of the assessments. The criteria are weighted using a SWARA-based procedure, and the foresight methods are ranked using Fuzzy VIKOR. SWARA supports stepwise criterion weighting based on expert judgment, while VIKOR identifies compromise priorities among alternatives under multiple and potentially conflicting criteria [35, 37].

The overall VIKOR ranking was complemented by a separate tied-rank Borda analysis based on experts' stage-specific portfolio assessments. While Fuzzy VIKOR identified the overall compromise priority of foresight methods across the decision criteria, tied-rank Borda analysis was used to extract maturity-sensitive foresight portfolios for each technology stage.

Finally, the robustness of the results is examined through Monte Carlo uncertainty analysis, VIKOR sensitivity analysis, and comparative validation with TOPSIS and PROMETHEE II. This validation stage evaluates whether the proposed rankings and portfolios remain stable under input uncertainty, changes in the VIKOR compromise coefficient, and alternative multi-criteria decision-making methods. The final output is a set of maturity-sensitive foresight portfolios and practical decision guidelines for planning resilient smart seismic infrastructure.

The methodological workflow of the proposed framework is shown in Fig. 1. The process begins with technology identification and evidence collection, followed by CRITIC-based maturity classification. Expert questionnaires are then used to define decision criteria, weight the criteria through SWARA, and rank foresight methods using Fuzzy VIKOR. The overall Fuzzy VIKOR ranking is complemented by a separate tied-rank Borda analysis based on experts' stage-specific portfolio assessments. The Borda analysis is then used to extract maturity-sensitive foresight portfolios for each technology stage. Finally, Monte Carlo analysis, VIKOR sensitivity analysis, and TOPSIS/PROMETHEE II validation are applied to examine the robustness of the results.



**Fig. 1. Methodological workflow of the proposed maturity-based foresight portfolio framework for smart seismic technologies.**

#### 4.1. Evidence-based maturity assessment of smart seismic technologies

This section explains how the maturity/application stages of smart seismic technologies were assessed before selecting foresight portfolios. The purpose of this step was to create a transparent and comparable maturity profile for the selected technologies. The objective was not to conduct a full systematic review, bibliometric analysis, or comprehensive patent-landscaping study. Instead, a structured scientific and patent-based evidence screening was used to support ordinal maturity coding for the CRITIC decision matrix. First, ten representative smart seismic technology groups were identified based on the literature review and the scope of the study. These groups included AI-based damage detection, digital twins, structural health monitoring and advanced smart sensing, smart sensors and IoT-based seismic monitoring, magnetorheological dampers and semi-active control, self-centering systems, base isolation systems, supplemental damping devices, replaceable fuse and low-damage systems, and rapid damage assessment or re-occupancy support tools. These technologies were selected because they represent different functions of smart seismic structures, including monitoring and diagnosis, response control, implementation-oriented seismic protection, and post-earthquake recovery support.

To improve the transparency and reproducibility of the CRITIC-based maturity assessment, a structured evidence screening protocol was applied before constructing the coded maturity matrix. The screening was conducted at the technology-group level. For each technology group, the first twenty most relevant scientific records and the first ten most relevant patent records were screened. Therefore, the evidence base included 200 scientific records and 100 patent records in total.

The scientific sources were selected based on searches around the topic on Google Scholar, while the patent-based sources were selected using Google Patents. The searches were done from the year 1990 to 2026, the latest search being done in July 2026. Keywords related to the technology along with keywords related to seismic and earthquake engineering, structural systems, civil structures, monitoring, sensing, damage detection, response control, damping, isolation, recovery, re-occupancy, and resilience were used. Records were included when they were directly related to seismic, earthquake, structural, civil infrastructure, monitoring, sensing, damage detection, response control, damping, isolation, post-earthquake assessment, reparability, re-occupancy, recovery, or resilience applications. Records were excluded when they were duplicated, unrelated to civil or seismic engineering, focused only on non-structural applications, or did not have a clear connection to smart seismic technologies. The screening protocol is summarized in Table 1.

**Table 1. Evidence screening protocol for CRITIC-based maturity assessment.**

| Item                                  | Description                                                                                                                                                                                                                            |
|---------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Scientific evidence source            | Google Scholar-oriented search and indexed publisher records                                                                                                                                                                           |
| Patent evidence source                | Google Patents                                                                                                                                                                                                                         |
| Search period                         | 1990-2026                                                                                                                                                                                                                              |
| Final search date                     | July 2026                                                                                                                                                                                                                              |
| Number of technology groups           | 10                                                                                                                                                                                                                                     |
| Scientific records screened per group | 20 records                                                                                                                                                                                                                             |
| Patent records screened per group     | 10 records                                                                                                                                                                                                                             |
| Total scientific records screened     | 200 records                                                                                                                                                                                                                            |
| Total patent records screened         | 100 records                                                                                                                                                                                                                            |
| Total evidence records screened       | 300 records                                                                                                                                                                                                                            |
| Screening approach                    | Structured evidence screening for ordinal maturity coding                                                                                                                                                                              |
| Purpose                               | To support CRITIC-based maturity assessment, not to conduct a full systematic review, bibliometric analysis, or patent-landscaping study                                                                                               |
| Inclusion criteria                    | Records related to seismic, earthquake, structural, civil infrastructure, monitoring, sensing, damage detection, response control, damping, isolation, post-earthquake assessment, reparability, recovery, re-occupancy, or resilience |
| Exclusion criteria                    | Duplicate records, unrelated non-civil applications, non-structural records, and records without clear relevance to smart seismic technologies                                                                                         |
| Coding scale                          | Low = 1 ; low-medium = 2 ; medium = 3 ; medium-high = 4 ; high = 5 ; very high = 6                                                                                                                                                     |

Table 2 shows the screening depth for each technology cluster. The organization helped ensure that the same amount of scientific and patent literature was taken into consideration for all the groups regardless of their varying degrees of visibility.

**Table 2. Screening depth by technology group.**

| Technology group                           | Scientific records screened | Patent records screened | Total records screened |
|--------------------------------------------|-----------------------------|-------------------------|------------------------|
| AI-based damage detection                  | 20                          | 10                      | 30                     |
| Digital twins                              | 20                          | 10                      | 30                     |
| SHM/advanced smart sensing                 | 20                          | 10                      | 30                     |
| Smart sensors/IoT-based seismic monitoring | 20                          | 10                      | 30                     |
| MR dampers/semi-active control             | 20                          | 10                      | 30                     |
| Self-centering systems                     | 20                          | 10                      | 30                     |
| Base isolation systems                     | 20                          | 10                      | 30                     |
| Supplemental damping devices               | 20                          | 10                      | 30                     |
| Replaceable fuse/low-damage systems        | 20                          | 10                      | 30                     |
| Rapid damage assessment/re-occupancy tools | 20                          | 10                      | 30                     |
| Total                                      | 200                         | 100                     | 300                    |

After screening, the retained evidence was coded using ten maturity-related indicators: five scientific indicators and five patent-based indicators. The scientific indicators captured research visibility, recent research growth, experimental or validation evidence, implementation or case-study evidence, and recovery/resilience relevance. The patent-based indicators captured patent visibility, seismic/civil patent relevance, device or system maturity, recent patent activity, and recovery/resilience patent signals. These indicators are presented in Table 3.

**Table 3. Evidence-based indicators for maturity assessment of smart seismic technologies.**

| Code | Indicator                             | Evidence source     | Description                                                                                             |
|------|---------------------------------------|---------------------|---------------------------------------------------------------------------------------------------------|
| G1   | Research visibility                   | Scientific evidence | General visibility of the technology in scholarly records                                               |
| G2   | Recent research growth                | Scientific evidence | Recent increase in research attention, especially after 2020                                            |
| G3   | Experimental/validation evidence      | Scientific evidence | Availability of laboratory, numerical, experimental, or validation-based evidence                       |
| G4   | Implementation/case-study evidence    | Scientific evidence | Evidence of real-world application, prototype use, field implementation, or case studies                |
| G5   | Recovery/resilience research evidence | Scientific evidence | Relevance to reparability, downtime reduction, re-occupancy, functional recovery, or seismic resilience |
| P1   | Patent visibility                     | Patent evidence     | General visibility of the technology in patent records                                                  |
| P2   | Seismic/civil patent relevance        | Patent evidence     | Relevance of patent records to seismic, structural, or civil engineering applications                   |
| P3   | Device/system maturity                | Patent evidence     | Evidence of device-level, system-level, or application-oriented technological development               |
| P4   | Recent patent signal                  | Patent evidence     | Recent patent activity indicating continued technological development                                   |
| P5   | Recovery/resilience patent signal     | Patent evidence     | Patent evidence related to repair, rapid assessment, recovery, re-occupancy, or resilience functions    |

The indicators were then rated on an ordinal scale ranging from 1 to 6, where higher numbers indicated more maturity evidence. These scores do not represent a straightforward tally of papers or patents; instead, they represent maturity evidence in ordinal form that was derived from the screening process. Interpretation of this scale is outlined in Table 4.

**Table 4. Interpretation of coding scores.**

| Score | Label       | Interpretation                                                                                       |
|-------|-------------|------------------------------------------------------------------------------------------------------|
| 1     | Low         | Very limited evidence or weak relevance to smart seismic applications                                |
| 2     | Low-medium  | Some evidence exists, but relevance, maturity, or application evidence is limited                    |
| 3     | Medium      | Moderate evidence with partial relevance to seismic or smart infrastructure applications             |
| 4     | Medium-high | Clear evidence of relevance, validation, or development activity                                     |
| 5     | High        | Strong evidence of research, validation, patent relevance, or application potential                  |
| 6     | Very high   | Very strong evidence, high visibility, strong validation, or direct relevance to maturity/resilience |

After the evidence matrix was coded, the CRITIC method was applied to determine the objective weight of each maturity indicator. CRITIC was selected because it considers both the contrast intensity of each indicator and the conflict among indicators. In this study, all indicators were treated as benefit-type indicators, meaning that higher coded values represented stronger maturity-related evidence.

First, the coded decision matrix was normalized using benefit-type normalization, as shown in Eq. 1.

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

where  $x_{ij}$  is the coded value of technology  $i$  under indicator  $j$ , and  $x'_{ij}$  is the normalized value.

Second, the information content of each indicator was calculated as Eq. 2.

$$C_j = \sigma_j \sum_{k=1}^m (1 - r_{jk}) \quad (2)$$

where  $\sigma_j$  is the standard deviation of indicator  $j$ ,  $r_{jk}$  is the correlation coefficient between indicators  $j$  and  $k$ , and  $m$  is the number of indicators.

Finally, the objective weight of each indicator was obtained as Eq. 3.

$$w_j = \frac{C_j}{\sum_{j=1}^m C_j} \quad (3)$$

where  $w_j$  is the CRITIC weight of indicator  $j$ . The weighted maturity score of each technology was then calculated by combining the normalized indicator values with the CRITIC weights, as shown in Eq. 4.

$$M_i = \sum_{j=1}^m w_j x'_{ij} \quad (4)$$

where  $M_i$  is the weighted maturity score of technology  $i$ .

The weighted CRITIC score was used to describe the overall evidence intensity of each technology group. However, the final maturity/application stage was not assigned solely based on a single threshold value of the total CRITIC score. This is because smart seismic technologies may show different maturity patterns. For example, a technology may have strong recent research growth but limited implementation evidence, while another technology may have stronger recovery/resilience evidence even if its overall score is not the highest. Therefore, the final classification was based on a profile-based interpretation of the CRITIC results. In this approach, the weighted score was considered together with the dominant evidence pattern across scientific growth, validation evidence, implementation evidence, patent relevance, device/system maturity, and recovery/resilience signals.

The classification rule was defined as follows. Technologies with strong recent scientific growth but limited implementation and device-level evidence were classified as M1 emerging/research-oriented. Technologies with stronger validation, monitoring, prototype, patent, or technology-readiness signals were classified as M2 developing/technology-readiness. Technologies with stronger implementation, design, deployment, and engineering application evidence were classified as M3 implementation-oriented. Technologies whose dominant evidence profile was related to reparability, re-occupancy, downtime reduction, rapid damage assessment, functional recovery, or resilience were classified as M4 recovery/resilience-oriented. Based on the weighted evidence profiles, the technologies were assigned to four maturity/application stages: emerging/research-oriented, developing/technology-readiness, implementation-oriented, and recovery/resilience-oriented. These stages were not treated as formal Technology Readiness Levels. Instead, they were used as planning-oriented maturity categories designed to support foresight portfolio selection.

In this framework, emerging/research-oriented technologies are those with strong scientific potential and recent research growth but limited large-scale implementation evidence. Developing/technology-readiness technologies show stronger evidence of validation, prototype development, patent activity, monitoring applications, or increasing readiness signals. Implementation-oriented technologies are closer to engineering deployment and are associated with feasibility, stakeholder acceptance, practical

application, and design or retrofit relevance. Recovery/resilience-oriented technologies are mainly linked to repairability, downtime reduction, re-occupancy, rapid damage assessment, and post-earthquake functional recovery.

This evidence-based maturity structure provides the foundation for linking each smart seismic technology stage with suitable foresight methods. Therefore, the CRITIC-based maturity assessment does not only classify technologies, but also supports the main logic of the study: foresight methods should be selected and combined according to the maturity and application context of smart seismic technologies.

#### 4.2. Expert questionnaire survey and decision criteria

After defining the maturity/application stages of smart seismic technologies, an expert questionnaire survey was conducted to evaluate the suitability of foresight methods. The expert-based stage was designed to capture judgments on three aspects: the relative importance of decision criteria, the performance of foresight methods under these criteria, and the suitability of foresight-method portfolios for different technology maturity stages.

Twelve validated expert questionnaires have been used for the analysis. Each expert held a doctorate degree in civil engineering in the fields of structural engineering and earthquake engineering. This kind of expertise was relevant for the research area under investigation, particularly in relation to seismic performance, smart structural systems, structural health monitoring, seismic resilience, and engineering decision-making. For confidentiality purposes, no names or institutions are listed.

The questionnaire consisted of three main analytical parts. In the first part, the experts ranked the decision criteria and provided comparative judgments for SWARA-based criteria weighting. In the second part, they evaluated the performance of eight foresight methods with respect to the decision criteria using linguistic ratings. In the third part, they assessed suitable foresight-method portfolios for each maturity/application stage. This part allowed tied ranks, meaning that more than one foresight method could be assigned to the same importance level when experts considered them equally relevant.

Eight decision criteria have been set in order to evaluate foresight approaches for use in smart seismic technology planning (Table 5). These decision criteria have been selected with a view to meeting both the general requirements for foresight approaches and special requirements of smart seismic buildings.

**Table 5. Decision criteria used for evaluating foresight methods.**

| Code | Criterion                                       | Description                                                                                                   |
|------|-------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| C1   | Emerging trend identification                   | Ability to identify emerging scientific and technological trends                                              |
| C2   | Weak signal detection                           | Ability to detect weak signals and disruptive future changes                                                  |
| C3   | Technology maturity and readiness assessment    | Ability to assess technology maturity, readiness, and development potential                                   |
| C4   | Applicability to smart seismic technologies     | Suitability for smart seismic systems and earthquake engineering applications                                 |
| C5   | Seismic resilience support                      | Ability to support damage reduction, repairability, downtime reduction, re-occupancy, and functional recovery |
| C6   | Stakeholder acceptance and practical usability  | Ability to consider stakeholder acceptance, usability, and implementation feasibility                         |
| C7   | Long-term uncertainty handling                  | Ability to address long-term technological and contextual uncertainty                                         |
| C8   | Implementation planning and roadmapping support | Ability to support staged implementation, planning, and technology roadmapping                                |

The foresight alternatives included eight methods commonly used in technology foresight, innovation planning, and strategic decision support (Table 6). These methods were selected because they represent complementary foresight functions, ranging from scientific trend analysis and patent-based innovation tracking to expert consensus, weak-signal detection, stakeholder analysis, scenario exploration, and implementation planning.

**Table 6. Foresight methods evaluated in the expert questionnaire.**

| Code | Foresight method            | Main role in the framework                                                        |
|------|-----------------------------|-----------------------------------------------------------------------------------|
| A1   | Brainstorming               | Generating ideas and exploring early expert insights                              |
| A2   | MACTOR/stakeholder analysis | Evaluating actor interests, conflicts, and implementation feasibility             |
| A3   | Bibliometrics               | Identifying scientific trends and emerging research domains                       |
| A4   | Patent analysis             | Assessing innovation activity and technology development signals                  |
| A5   | Delphi method               | Building structured expert consensus under uncertainty                            |
| A6   | Horizon scanning            | Detecting weak signals and emerging changes                                       |
| A7   | Scenario planning           | Exploring alternative future conditions and uncertainty                           |
| A8   | Technology roadmapping      | Translating foresight results into staged development and implementation pathways |

For the performance evaluation of foresight methods, a five-level linguistic scale was used: very low (VL), low (L), medium (M), high (H), and very high (VH). These linguistic ratings were converted into fuzzy numbers in the Fuzzy VIKOR analysis. This allowed the study to model the vagueness of expert judgments while ranking foresight methods across multiple criteria.

The portfolio assessment part of the questionnaire was designed to provide assistance for making decisions taking into consideration the level of maturity. In contrast to forcing the experts to define a single approach at every level of maturity, the tied-

rank design made it possible to select combinations of approaches that have different weights. The above-mentioned approach is consistent with the main goal of the research, which is developing foresight portfolios in accordance with different levels of maturity of the technology under consideration.

#### 4.3. SWARA-based criteria weighting

After defining the decision criteria, the SWARA method was applied to determine their relative weights based on expert judgments. SWARA was selected because it allows experts to express the importance of criteria in a stepwise and interpretable manner, making it suitable for decision problems where expert knowledge plays a central role [35]. SWARA's appropriateness for developing the framework for weighting expert judgments has been proven in many previous studies carried out by the researchers [41–44]. In this study, the method was used to weight the eight criteria  $C_1 - C_8$ , which represent the main requirements for selecting foresight methods for smart seismic technology planning.

According to the questionnaire, the criteria were ranked by experts according to their level of importance, starting with the most important. Further on, for every subsequent criterion, which was ranked starting with the second one, the expert stated the importance ratio coefficient  $s_j$ , which reflected the relative importance of criterion  $j$  compared to criterion  $j - 1$ .

For each expert, the SWARA procedure was implemented in three steps. First, the coefficient  $k_j$  was calculated as Eq. 5.

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \quad (5)$$

where  $s_j$  is the comparative importance coefficient assigned by the expert. Second, the recalculated weight  $q_j$  was obtained as Eq. 6.

$$q_j = \begin{cases} 1, & j = 1 \\ \frac{q_{j-1}}{k_j}, & j > 1 \end{cases} \quad (6)$$

Finally, the normalized criterion weight  $w_j$  was calculated as Eq. 7.

$$w_j = \frac{q_j}{\sum_{j=1}^n q_j} \quad (7)$$

where  $n$  is the number of criteria. This procedure was applied separately to the responses of the twelve experts. The individual weights were then aggregated by averaging the corresponding criterion weights across experts and normalizing them to obtain the final SWARA-based criterion weights.

The resulting weights reflect the collective expert judgment regarding the relative importance of the criteria. These weights were subsequently used as input for the Fuzzy VIKOR analysis to rank the foresight methods. In this way, the SWARA-based weighting step connects expert judgment on decision priorities with the later evaluation of foresight alternatives.

#### 4.4. Fuzzy VIKOR ranking of foresight methods

After obtaining the SWARA-based criterion weights, the foresight methods were ranked using the Fuzzy VIKOR method. VIKOR was selected because it identifies compromise solutions among alternatives evaluated under multiple and potentially conflicting criteria [36]. In this study, the alternatives were the eight foresight methods  $A_1 - A_8$ , and the criteria were the eight decision criteria  $C_1 - C_8$ .

Since expert assessments could be represented linguistically, the fuzzy scale was used due to the natural vagueness of such assessments. The linguistic terms have been converted into triangular fuzzy numbers as shown in Table 7.

**Table 7. Linguistic scale used for Fuzzy VIKOR evaluation.**

| Linguistic term | Code | Triangular fuzzy number |
|-----------------|------|-------------------------|
| Very low        | VL   | (0.00 , 0.00 , 0.25)    |
| Low             | L    | (0.00 , 0.25 , 0.50)    |
| Medium          | M    | (0.25 , 0.50 , 0.75)    |
| High            | H    | (0.50 , 0.75 , 1.00)    |
| Very high       | VH   | (0.75 , 1.00 , 1.00)    |

In every foresight approach, the linguistic evaluation results provided by the twelve experts were first transformed into triangular fuzzy numbers. After that, the aggregated fuzzy values were calculated for each alternative on each criterion based on the evaluations of the experts. Assume that a triangular fuzzy number is represented as  $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ . The aggregated fuzzy value was determined by Eq. 8.

$$x_{ij} = \left( \frac{1}{p} \sum_{e=1}^p l_{ij}^e, \frac{1}{p} \sum_{e=1}^p m_{ij}^e, \frac{1}{p} \sum_{e=1}^p u_{ij}^e \right) \quad (8)$$

where  $p$  is the number of experts, and  $l$ ,  $m$ , and  $u$  represent the lower, middle, and upper values of the triangular fuzzy number.

To apply VIKOR, the aggregated fuzzy ratings were defuzzified into crisp scores. The centroid method was used (Eq. 9).

$$x_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3} \quad (9)$$

where  $x_{ij}$  is the defuzzified performance score of foresight method  $i$  under criterion  $j$ . Since all criteria in this study were benefit-type criteria, higher values indicated better performance.

Next, the best and worst values for each criterion were identified as shown in Eqs. 10 and 11.

$$f_j^* = \max_i x_{ij} \quad (10)$$

$$f_j^- = \min_i x_{ij} \quad (11)$$

where  $f_j^*$  and  $f_j^-$  represent the best and worst performance values under criterion  $j$ , respectively.

The VIKOR utility measure  $S_i$  and regret measure  $R_i$  were then calculated for each foresight method, using Eqs. 12 and 13.

$$S_i = \sum_{j=1}^n w_j \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \quad (12)$$

$$R_i = \max_j \left[ w_j \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \right] \quad (13)$$

where  $w_j$  is the SWARA-based weight of criterion  $j$ . The  $S_i$  value represents the overall distance of an alternative from the ideal solution, while  $R_i$  represents the maximum individual regret across criteria.

Finally, the VIKOR compromise index  $Q_i$  was computed as Eq. 14.

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \quad (14)$$

where:

$$S^* = \min_i S_i, \quad S^- = \max_i S_i \quad (15)$$

The parameter  $v$  refers to the weighting given to the majority utility approach, while the parameter  $1 - v$  indicates the weighting given to the individual regret approach. For the main study,  $v = 0.5$  was used to balance the two attitudes towards decision making. The lower  $Q_i$  values indicate better performance in compromising. Therefore, the foresight techniques were sorted according to their  $Q_i$  values.

Fuzzy VIKOR methodology produced a ranking of the foresight methods with respect to all the criteria used in decision making. This ranking was not considered the final outcome of the study. It only acted as an interim outcome, which was combined later with the Borda ranking of ties to produce foresight portfolios suitable for different stages of smart earthquake technology development.

#### 4.5. Tied-rank Borda portfolio extraction

After the overall ranking of foresight methods was obtained through Fuzzy VIKOR, a tied-rank Borda analysis was applied to identify suitable foresight portfolios for each maturity/application stage. This step was necessary because the objective of the study was not to recommend a single foresight method for all smart seismic technologies. Instead, the aim was to determine which combinations of foresight methods are more suitable for emerging, developing, implementation-oriented, and recovery/resilience-oriented technologies.

The questionnaire included a portfolio assessment part where the relevancy of eight foresight methods for each level of maturity was assessed by experts. Experts were allowed to assign tied ranks where several methods could be ranked the same in terms of their appropriateness because it was considered appropriate in this case, as foresight methods are usually complementary rather than competitive. The scoring scheme used in the tied-rank Borda analysis is shown in Table 8.

**Table 8. Scoring scheme for tied-rank Borda portfolio extraction.**

| Expert-assigned level | Interpretation                | Borda score |
|-----------------------|-------------------------------|-------------|
| Rank 1                | Essential method              | 3           |
| Rank 2                | Supporting method             | 2           |
| Rank 3                | Optional method               | 1           |
| Not selected          | Not included in the portfolio | 0           |

For each maturity stage, the Borda score of foresight method  $i$  was calculated by aggregating the scores assigned by the twelve experts, as shown in Eq. 16.

$$B_{im} = \sum_{p=1}^{e=12} b_{ime} \quad (16)$$

where  $B_{im}$  is the total Borda score of foresight method  $i$  for maturity stage  $m$ ,  $b_{ime}$  is the score assigned by expert  $e$ , and  $p$  is the number of experts. To support comparison across stages, the average Borda score was also calculated as Eq. 17.

$$\bar{B}_{im} = \frac{B_{im}}{p} \quad (17)$$

A higher Borda score indicates stronger expert support for including a method in the foresight portfolio of a given maturity stage. Methods with the highest scores were selected as the recommended portfolio for that stage.

The tied-rank Borda analysis complements the Fuzzy VIKOR ranking. While VIKOR provides an overall compromise ranking of foresight methods across all criteria, Borda analysis captures the stage-specific suitability of methods. This distinction is important because a method may not be highly ranked in the overall VIKOR result but may still be highly relevant for a specific maturity stage. For example, bibliometrics and patent analysis may be especially useful for emerging or developing technologies, even if expert consensus methods or roadmapping methods show stronger overall performance.

Therefore, the Borda step converts expert judgments into maturity-sensitive foresight portfolios. These portfolios provide the main practical output of the framework by linking each technology maturity stage with a suitable combination of foresight methods.

#### 4.6. Expert agreement, reliability, and robustness analyses

To strengthen the credibility of the expert-based decision process, this study included both statistical checks of expert responses and robustness analyses of the ranking results. Since the proposed framework relies on judgments from twelve experts, it was necessary to examine whether the expert inputs showed an acceptable level of agreement and internal consistency before interpreting the final SWARA, Fuzzy VIKOR, and Borda results. Therefore, expert agreement, questionnaire reliability, uncertainty analysis, sensitivity analysis, and comparative validation were considered as complementary validation steps.

In the first step, Kendall's coefficient of concordance was used to assess the degree of agreement between the experts in their rankings. The use of Kendall's  $W$  is justified since it can be used to test the consistency of multiple experts' rankings of the same items. The measure was used to test the rankings of SWARA criteria and the maturity stage portfolio. Kendall's  $W$  scale ranges between 0 and 1, where a value closer to 1 shows a higher degree of agreement between experts. Statistical significance of Kendall's  $W$  was also tested.

Second, Cronbach's alpha was calculated as a supplementary reliability indicator for the linguistic evaluation matrix used in the Fuzzy VIKOR analysis. While Kendall's  $W$  evaluates agreement among experts in ranking-based tasks, Cronbach's alpha assesses the internal consistency of questionnaire responses. In this study, Cronbach's alpha was used to examine whether the expert ratings across the foresight-method evaluation matrix were sufficiently consistent for multi-criteria analysis.

Once the agreement of the experts was verified and the questionnaire validated, an uncertainty analysis using the Monte Carlo method was carried out to test the robustness of the results in light of the uncertainty associated with the expert opinion and linguistic evaluation. The simulation was run 10,000 times. During each of those times, the expert answers were resampled, and the linguistic evaluations were randomly altered within their corresponding fuzzy intervals. After that, the criterion weights based on SWARA and the ranking indicators based on VIKOR were calculated again. With the help of this procedure, the probabilities of each foresight technique remaining in the lead (for example, having ranks 1, 2, or 3) could be estimated.

Sensitivity analysis was then performed on the VIKOR compromise coefficient. In the main analysis, the coefficient was set to 0.50 to balance the majority utility strategy and the individual regret strategy. To test whether the ranking structure was sensitive to different decision attitudes, the analysis was repeated using values of 0.25, 0.50, and 0.75. This step helped determine whether the priority order of foresight methods changed when greater emphasis was placed on either group utility or individual regret.

Finally, the comparative validation was done using TOPSIS and PROMETHEE II. Both techniques have been used because each one represents a different logic of multi-criteria decision making. TOPSIS uses the proximity of the alternatives to the ideal and anti-ideal solutions to rank them, while PROMETHEE II provides a comprehensive ranking on the basis of preference flow [36, 38]. The rankings from both these techniques have been compared to the ranking provided by Fuzzy VIKOR for evaluating that if the results depend on any one decision-making method.

Through these checks, the study evaluates both the reliability of expert-based inputs and the robustness of the final decision results. Kendall's  $W$  and Cronbach's alpha support the credibility of the questionnaire-based judgments, while Monte Carlo simulation, VIKOR sensitivity analysis, TOPSIS, PROMETHEE II, and Spearman correlation assess the stability and external consistency of the ranking and portfolio outputs. Therefore, this validation structure strengthens the reliability of the proposed maturity-sensitive foresight portfolio framework.

## 5. Results and discussion

This section presents and discusses the results of the proposed maturity-based foresight portfolio framework. The results are organized according to the methodological workflow of the study, moving from evidence-based technology maturity assessment to expert-based foresight evaluation, portfolio extraction, and robustness validation. First, the CRITIC results are reported to show how smart seismic technologies were classified into maturity/application stages. Second, the SWARA-based criterion weights are presented to identify the most influential factors in selecting foresight methods. Third, the Fuzzy VIKOR ranking is discussed to determine the overall priority of foresight methods across the decision criteria. Fourth, the tied-rank Borda results are used to extract maturity-sensitive foresight portfolios for each technology stage. Finally, Monte Carlo uncertainty analysis, VIKOR sensitivity analysis, and comparative validation with TOPSIS and PROMETHEE II are discussed to evaluate the robustness of the findings.

The purpose of this section is not only to report numerical results, but also to interpret their implications for smart seismic

technology planning. In particular, the discussion focuses on how different maturity stages create different foresight needs. Emerging technologies require methods that can identify scientific trends and weak signals; developing technologies require tools for assessing readiness and innovation potential; implementation-oriented technologies require stakeholder and deployment analysis; and recovery-oriented technologies require methods that can address reparability, downtime reduction, re-occupancy, and functional recovery. Therefore, the results are interpreted with respect to the main objective of the study: developing maturity-sensitive foresight portfolios rather than selecting a single universal foresight method.

### 5.1. CRITIC-based maturity assessment results

The CRITIC-based maturity assessment was conducted using the coded ordinal evidence matrix developed from the structured screening of 200 scientific records and 100 patent records. Therefore, the maturity results should be interpreted as evidence-based ordinal maturity profiles rather than as direct publication counts or patent counts. The purpose of this analysis was to identify the relative maturity/application profile of smart seismic technology groups and to classify them into planning-oriented maturity stages for foresight portfolio selection.

The CRITIC method was applied to ten maturity-related indicators, including five scientific indicators and five patent-based indicators. The scientific indicators captured research visibility, recent research growth, experimental or validation evidence, implementation or case-study evidence, and recovery/resilience research evidence. The patent-based indicators captured patent visibility, seismic/civil patent relevance, device or system maturity, recent patent activity, and recovery/resilience patent signals. Since CRITIC assigns higher weights to indicators with greater contrast and lower redundancy, the resulting weights indicate which evidence dimensions provided the most useful information for distinguishing the maturity profiles of smart seismic technologies (Table 9).

**Table 9. CRITIC weights of evidence-based maturity indicators.**

| Rank | Code | Indicator                             | Evidence source     | CRITIC weight |
|------|------|---------------------------------------|---------------------|---------------|
| 1    | G2   | Recent research growth                | Scientific evidence | 0.234         |
| 2    | P5   | Recovery/resilience patent signal     | Patent evidence     | 0.130         |
| 3    | G5   | Recovery/resilience research evidence | Scientific evidence | 0.116         |
| 4    | G1   | Research visibility                   | Scientific evidence | 0.093         |
| 5    | G3   | Experimental/validation evidence      | Scientific evidence | 0.085         |
| 6    | P2   | Seismic/civil patent relevance        | Patent evidence     | 0.075         |
| 7    | P4   | Recent patent signal                  | Patent evidence     | 0.072         |
| 8    | P1   | Patent visibility                     | Patent evidence     | 0.070         |
| 9    | P3   | Device/system maturity                | Patent evidence     | 0.064         |
| 10   | G4   | Implementation/case-study evidence    | Scientific evidence | 0.062         |

The highest weight was assigned to recent research growth ( $G2 = 0.234$ ). This indicates that recent growth in scientific attention was the most informative indicator for distinguishing the maturity profiles of smart seismic technologies. This result is reasonable because several smart seismic technologies, such as AI-based damage detection, digital twins, advanced sensing systems, and IoT-based seismic monitoring, are characterized by rapid research development. Strong recent research growth does not necessarily mean that a technology is fully mature or widely implemented, but it is an important signal for identifying emerging and developing technology areas that require foresight attention.

The second and third highest weights were assigned to recovery/resilience patent signal ( $P5 = 0.130$ ) and recovery/resilience research evidence ( $G5 = 0.116$ ). These results show that resilience-oriented evidence played an important role in the maturity assessment. In the context of smart seismic structures, maturity should not be evaluated only through general research visibility or technical development. It should also consider whether a technology supports reparability, downtime reduction, rapid damage assessment, re-occupancy, functional recovery, and post-earthquake resilience. Therefore, the relatively high weights of  $P5$  and  $G5$  confirm that recovery and resilience functions are central to the maturity classification of smart seismic technologies.

Research visibility ( $G1 = 0.093$ ) and experimental/validation evidence ( $G3 = 0.085$ ) also received meaningful weights. These indicators helped distinguish technologies with broad scholarly attention and stronger validation evidence from technologies that remain more conceptual or early-stage. Patent-related indicators also contributed to the applied and innovation-oriented side of the maturity assessment. Seismic/civil patent relevance, recent patent signal, patent visibility, and device/system maturity helped identify whether a technology showed evidence of practical embodiment, device-level development, system-level design, or application-oriented innovation.

The lowest CRITIC weight was assigned to implementation/case-study evidence ( $G4 = 0.062$ ). This does not mean that implementation evidence is unimportant. Rather, it indicates that, within the coded evidence matrix, this indicator provided less independent contrast than indicators such as recent research growth and recovery/resilience signals. In practical interpretation, implementation evidence remains important for identifying technologies that are closer to engineering deployment, but it should be considered together with validation evidence, patent relevance, device maturity, and resilience-related signals.

Although weighted CRITIC scores were calculated for all technology groups, the final maturity/application classification was

not based only on a fixed numerical threshold. The classification was profile-based. In other words, the weighted score was used to describe the overall evidence intensity of each technology group, while the final stage assignment was determined by the dominant evidence pattern across research growth, validation evidence, implementation evidence, patent relevance, device/system maturity, and recovery/resilience signals. This distinction is important because smart seismic technologies may show different maturity patterns. For example, digital twins may show strong recent research growth and future potential while still having limited routine implementation in seismic engineering practice. Conversely, recovery-oriented tools may be classified as recovery/resilience-oriented because their dominant evidence profile is linked to repairability, re-occupancy, downtime reduction, and functional recovery.

Table 10 clarifies that the maturity/application classification was not threshold-based. A higher weighted CRITIC score indicates stronger overall evidence intensity, but it does not automatically place a technology in a later maturity stage. Instead, each technology was assigned to a stage according to its dominant evidence profile. This profile-based interpretation is suitable for smart seismic technologies because some technologies are mainly research-intensive, some are readiness-oriented, some are closer to engineering implementation, and others are primarily linked to post-earthquake recovery and resilience objectives.

**Table 10. Profile-based classification of smart seismic technologies using CRITIC results.**

| Technology group                           | Weighted CRITIC score | Dominant evidence profile                                                                                      | Classification rule                                                                   | Final stage                         |
|--------------------------------------------|-----------------------|----------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|-------------------------------------|
| AI-based damage detection                  | 0.328                 | High recent research growth; limited implementation and device maturity                                        | Strong scientific emergence but limited deployment evidence                           | M1. Emerging/research-oriented      |
| Digital twins                              | 0.401                 | High recent research growth and recent patent signal; limited field implementation in seismic practice         | Strong research and future potential, but limited routine seismic implementation      | M1. Emerging/research-oriented      |
| SHM/advanced smart sensing                 | 0.504                 | Strong research visibility, validation evidence, patent relevance, and monitoring applications                 | Stronger validation and technology-readiness signals                                  | M2. Developing/technology-readiness |
| Smart sensors/IoT-based seismic monitoring | 0.599                 | Strong recent research growth, validation, monitoring applications, and patent activity                        | Strong technology-readiness and monitoring-application profile                        | M2. Developing/technology-readiness |
| MR dampers/semi-active control             | 0.270                 | Strong validation, patent relevance, and device/system maturity                                                | Device-level and control-system readiness, but requiring broader application planning | M2. Developing/technology-readiness |
| Self-centering systems                     | 0.331                 | Strong validation and implementation relevance; direct connection to seismic design and residual drift control | Engineering application and deployment-oriented evidence                              | M3. Implementation-oriented         |
| Base isolation systems                     | 0.446                 | Very strong validation and implementation/case-study evidence                                                  | Established engineering application and deployment relevance                          | M3. Implementation-oriented         |
| Supplemental damping devices               | 0.561                 | Strong validation, patent relevance, device maturity, and implementation evidence                              | Strong implementation-oriented seismic protection profile                             | M3. Implementation-oriented         |
| Replaceable fuse/low-damage systems        | 0.395                 | Very strong recovery/resilience research evidence and strong recovery patent signal                            | Dominant repairability and low-damage recovery function                               | M4. Recovery/resilience-oriented    |
| Rapid damage assessment/re-occupancy tools | 0.527                 | Very strong recovery/resilience research and patent signals                                                    | Dominant post-earthquake assessment, re-occupancy, and functional recovery profile    | M4. Recovery/resilience-oriented    |

Based on this profile-based interpretation, the selected smart seismic technologies were classified into four maturity/application stages (Table 11). These stages were not treated as formal technology readiness levels, but as planning-oriented categories designed to support maturity-sensitive foresight portfolio selection.

**Table 11. CRITIC-based maturity/application classification of smart seismic technologies.**

| Maturity stage                      | Technology examples                                                                                                   | Main maturity interpretation                                                                            |
|-------------------------------------|-----------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------|
| M1. emerging/research-oriented      | AI-based damage detection; Digital twins                                                                              | Strong research potential and rapid scientific growth, but limited large-scale implementation evidence  |
| M2. developing/technology-readiness | Advanced smart sensing; SHM; Smart sensors/IoT-based seismic monitoring; MR dampers/semi-active control               | Increasing validation, prototype development, monitoring applications, and technology-readiness signals |
| M3. implementation-oriented         | Self-centering systems; Base isolation systems; Supplemental damping devices                                          | Closer to engineering application, supported by stronger performance evidence and deployment relevance  |
| M4. recovery/resilience-oriented    | Replaceable fuse/low-damage systems; Rapid post-earthquake damage assessment; Re-occupancy/downtime reduction systems | Directly related to repairability, downtime reduction, re-occupancy, and functional recovery            |

The classification shows that smart seismic technologies do not follow a single maturity pathway. AI-based damage detection and digital twins were classified as emerging/research-oriented technologies because they show strong scientific potential and rapid research growth, but still require broader validation, standardization, and integration into routine seismic engineering practice. These technologies are important for future smart infrastructure systems, but their widespread implementation in seismic applications remains developing.

Structural health monitoring, advanced smart sensing, IoT-based seismic monitoring, and MR dampers/semi-active control were classified as developing/technology-readiness technologies. These technologies have stronger validation evidence, monitoring applications, prototype development, and patent-related signals than purely emerging technologies. However, they still require further integration into design practice, infrastructure management systems, and long-term implementation frameworks.

Self-centering systems, base isolation systems, and supplemental damping devices were classified as implementation-oriented technologies. These technologies are more directly connected to seismic response reduction, performance-based design, and engineering deployment. Their maturity profiles are supported by stronger experimental, analytical, and application-oriented evidence. However, their future adoption still depends on factors such as cost, constructability, maintenance requirements, code acceptance, and stakeholder confidence.

Replaceable fuse and low-damage systems, rapid post-earthquake damage assessment tools, and re-occupancy or downtime-reduction systems were classified as recovery/resilience-oriented technologies. These technologies are directly linked to post-earthquake reparability, downtime reduction, re-occupancy decisions, and functional recovery. Their maturity profile is therefore not defined only by technical readiness, but also by their contribution to resilience-oriented performance objectives.

Overall, the CRITIC results provide the evidence-based foundation for the subsequent expert-based foresight analysis. The maturity classification shows that different smart seismic technologies require different foresight needs. Emerging technologies require methods that can identify scientific trends and weak signals. Developing technologies require tools for assessing readiness, patent evidence, and transition pathways. Implementation-oriented technologies require stakeholder and deployment analysis. Recovery/resilience-oriented technologies require methods that can address uncertain post-earthquake conditions, reparability, downtime reduction, re-occupancy, and functional recovery. Therefore, the CRITIC-based maturity assessment supports the main logic of this study: foresight methods should be selected and combined according to the maturity and application context of smart seismic technologies.

## 5.2. SWARA-based criteria weights

After defining the maturity stages of smart seismic technologies, the SWARA-based weighting procedure was applied to determine the relative importance of the eight decision criteria (Table 12). The results reflect the collective judgment of the twelve experts regarding which criteria are most important for selecting foresight methods in the context of smart seismic technology planning.

**Table 12. Final SWARA-based weights of decision criteria.**

| Rank | Code | Criterion                                       | Final weight |
|------|------|-------------------------------------------------|--------------|
| 1    | C5   | Seismic resilience support                      | 0.181        |
| 2    | C8   | Implementation planning and roadmapping support | 0.151        |
| 3    | C4   | Applicability to smart seismic technologies     | 0.145        |
| 4    | C3   | Technology maturity and readiness assessment    | 0.141        |
| 5    | C6   | Stakeholder acceptance and practical usability  | 0.117        |
| 6    | C7   | Long-term uncertainty handling                  | 0.095        |
| 7    | C1   | Emerging trend identification                   | 0.088        |
| 8    | C2   | Weak signal detection                           | 0.082        |

The highest weight was assigned to seismic resilience support ( $C5 = 0.181$ ). This result indicates that experts considered the ability of a foresight method to support resilience-oriented objectives as the most important selection criterion. In the context of smart seismic structures, this means that foresight methods should not only identify promising technologies, but also help evaluate how these technologies contribute to damage reduction, reparability, downtime reduction, re-occupancy, and functional recovery. This finding is consistent with the broader shift in earthquake engineering from life-safety-based performance toward resilience-oriented planning.

The second most important criterion was implementation planning and roadmapping support ( $C8 = 0.151$ ). This shows that experts valued foresight methods that can translate technological possibilities into staged development and deployment pathways. For smart seismic technologies, this is particularly important because many solutions require long-term coordination among researchers, engineers, infrastructure owners, technology developers, and regulatory bodies. A foresight method that only identifies future opportunities is therefore less useful unless it can also support practical planning and implementation.

The third and fourth criteria were applicability to smart seismic technologies ( $C4 = 0.145$ ) and technology maturity and readiness assessment ( $C3 = 0.141$ ). Their high weights show that foresight-method selection should be closely connected to the engineering characteristics and maturity status of the technologies being assessed. In other words, a suitable foresight method must be capable of addressing the specific requirements of smart seismic systems, such as sensing, monitoring, control, post-earthquake assessment, and recovery support. At the same time, it should help distinguish between technologies that are still research-oriented and those that are closer to engineering implementation.

Stakeholder acceptance and practical usability ( $C6 = 0.117$ ) also received a relatively important weight. This result highlights that the adoption of smart seismic technologies depends not only on technical performance, but also on institutional acceptance, usability, cost, maintenance requirements, and compatibility with real engineering practice. This is especially relevant for implementation-oriented technologies, where deployment feasibility and stakeholder confidence may strongly influence future adoption.

The criteria related to long-term uncertainty handling ( $C7 = 0.095$ ), emerging trend identification ( $C1 = 0.088$ ), and weak signal

detection ( $C2 = 0.082$ ) received lower but still meaningful weights. These criteria are particularly relevant when it comes to nascent technologies where scientific progress takes place quickly and where future paths are unpredictable. The relatively low weight that is given to these criteria does not mean that identifying trends and picking up weak signals is less important but simply that experts focus more on their role in building resilience and implementation.

Overall, the SWARA results show that foresight-method selection for smart seismic technologies should be guided primarily by resilience relevance, implementation support, engineering applicability, and technology maturity assessment. This weighting pattern supports the central logic of the study: foresight portfolios should be selected not only to identify future technologies, but also to support their practical development and contribution to resilient seismic infrastructure.

### 5.3. Fuzzy VIKOR ranking of foresight methods

After obtaining the SWARA-based criterion weights, the eight foresight methods were evaluated using the Fuzzy VIKOR method (Table 13). The main purpose of this step was to identify the overall compromise priority of foresight methods across all decision criteria. The VIKOR compromise coefficient was set to  $v = 0.50$ , giving equal importance to the group utility measure  $S$  and the individual regret measure  $R$  [36].

**Table 13. Fuzzy VIKOR ranking of foresight methods.**

| Rank | Code | Foresight method            | S     | R     | Q     |
|------|------|-----------------------------|-------|-------|-------|
| 1    | A5   | Delphi method               | 0.265 | 0.062 | 0.047 |
| 2    | A8   | Technology roadmapping      | 0.210 | 0.082 | 0.083 |
| 3    | A7   | Scenario planning           | 0.407 | 0.145 | 0.517 |
| 4    | A6   | Horizon scanning            | 0.530 | 0.145 | 0.621 |
| 5    | A2   | MACTOR/stakeholder analysis | 0.590 | 0.145 | 0.672 |
| 6    | A1   | Brainstorming               | 0.736 | 0.145 | 0.796 |
| 7    | A4   | Patent analysis             | 0.673 | 0.167 | 0.836 |
| 8    | A3   | Bibliometrics               | 0.798 | 0.181 | 1.000 |

The results reveal that the Delphi method (A5) reaches the optimal compromise position in relation to all criteria, which is proven by the smallest  $Q$  value. It proves that the Delphi technique works effectively on all selected criteria mainly because of the ability to generate a consistent solution amidst uncertainty. This feature becomes especially significant in the field of intelligent seismic technology as it is dominated by uncertainty. This research finding shows how effective Delphi is in decision-making based on the criteria that have been applied using weights. This is because Delphi is very effective in creating consensus among experts in cases of uncertainty. This is important since, in the area of smart seismic technologies, many technologies operate on incomplete data and uncertain development.

Technology roadmapping (A8) ranked second and showed the lowest  $S$  value among all methods. This suggests that roadmapping performs strongly from the perspective of overall group utility. Its high ranking is consistent with the importance assigned to implementation planning, technology readiness, and practical deployment in the SWARA results. For smart seismic technologies, roadmapping is particularly valuable because it can translate future-oriented insights into staged development pathways, milestones, and implementation plans. The difference between Delphi and technology roadmapping approaches is small compared to the gap between the latter two. Thus, the result can be viewed as not suggesting that the Delphi approach is sufficient on its own. Instead, a combination of both the Delphi and technology roadmapping approaches is considered to form a solid core of foresight planning. The Delphi approach is more efficient in reaching expert agreement and reducing uncertainties, while the technology roadmapping approach allows for easier implementation of the decisions made.

Scenario planning (A7) was ranked third in the list. This is because scenario planning is very vital, especially when it comes to analyzing different future situations. It is important, especially in technology that involves recovery after earthquakes, reducing downtime, and re-occupancy. While scenario planning was not ranked above Delphi and roadmapping in the list, it is still an essential factor when there is a high level of uncertainty about future hazards.

Methods such as horizon scanning (A6) and MACTOR/stakeholder analysis (A2) obtained middle positions in the overall ranking. Horizon scanning is useful for detecting weak signals and emerging changes, while MACTOR is more relevant for analyzing stakeholder interests and implementation feasibility. Their middle ranking suggests that these methods may be more stage-specific than universally dominant. In other words, they may not be the strongest methods across all criteria, but they can be highly relevant for particular maturity stages. Patent analysis (A4) and bibliometrics (A3) received lower overall VIKOR rankings. This does not mean that they are unimportant. Their lower position reflects the fact that the overall expert-weighted criteria gave stronger priority to resilience support, implementation planning, and practical usability. However, bibliometrics and patent analysis remain essential for specific maturity contexts. Bibliometrics is particularly useful for emerging technologies, where scientific trend identification is needed, while Patent Analysis is important for developing technologies, where innovation activity and technology-readiness signals must be assessed.

Overall, the Fuzzy VIKOR results indicate that Delphi, technology roadmapping, and scenario planning have the strongest overall compromise performance. However, the ranking also confirms that no single foresight method can address all maturity

stages of smart seismic technologies. Therefore, the VIKOR results were used as an intermediate prioritization step, while the final maturity-sensitive foresight portfolios were extracted through the tied-rank Borda analysis in the next section.

#### 5.4. Maturity-sensitive portfolio results using tied-rank Borda analysis

The Fuzzy VIKOR results provided the overall ranking of foresight methods, but the main objective of this study was to identify suitable foresight portfolios for different maturity stages of smart seismic technologies. For this reason, tied-rank Borda analysis was applied to the maturity-stage portfolio assessments provided by the experts. This step allowed more than one method to be assigned to the same importance level, reflecting the fact that foresight methods are complementary rather than mutually exclusive (Table 14).

**Table 14. Recommended maturity-sensitive foresight portfolios.**

| Maturity stage                      | Technology examples                                                                                                   | Recommended foresight portfolio                              |
|-------------------------------------|-----------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------|
| M1. Emerging/research-oriented      | AI-based damage detection; Digital twins                                                                              | Bibliometrics + horizon scanning + Delphi                    |
| M2. Developing/technology-readiness | Advanced smart sensing; SHM; Smart sensors/IoT-based seismic monitoring; MR dampers/semi-active control               | Patent analysis + Delphi + technology roadmapping            |
| M3. Implementation-oriented         | Self-centering systems; Base isolation systems; Supplemental damping devices                                          | MACTOR + technology roadmapping + Delphi                     |
| M4. Recovery/resilience-oriented    | Replaceable fuse/low-damage systems; Rapid post-earthquake damage assessment; Re-occupancy/downtime reduction systems | Technology roadmapping + MACTOR + Delphi + scenario planning |

The suggested portfolio for M1, which is represented by emergence and research types of technology, includes bibliometrics, horizon scanning, and Delphi. Such a combination is suitable for use because, as mentioned above, technologies of emergence require methods that can help to spot scientific trends, identify weak signals, and verify future directions through the opinion of experts. Bibliometrics enables scientific mapping, while horizon scanning enables the identification of signals of changes and disruptions. For M2 developing/technology-readiness technologies, the recommended portfolio includes patent analysis, Delphi, and technology roadmapping. This stage requires a stronger focus on innovation activity, technology readiness, and transition from research to application. Patent analysis helps identify invention-oriented and commercialization signals, Delphi supports expert interpretation of uncertain readiness evidence, and technology roadmapping translates these findings into development milestones and application pathways. For M3 implementation-oriented technologies, the recommended portfolio consists of MACTOR, technology roadmapping, and Delphi. Technologies in this stage are closer to engineering deployment; therefore, the main challenge is no longer only identifying future opportunities, but also understanding stakeholder interests, implementation constraints, and practical feasibility. MACTOR is useful for analyzing actors and institutional conditions, roadmapping supports staged deployment, and Delphi helps refine expert-based priorities.

For M4 recovery/resilience-oriented technologies, the recommended portfolio includes technology roadmapping, MACTOR, Delphi, and scenario planning. This is the most complex portfolio because recovery-oriented technologies must address post-earthquake uncertainty, repairability, downtime reduction, re-occupancy, and functional recovery. Scenario Planning is particularly important at this stage because post-earthquake recovery depends on uncertain future conditions, including hazard intensity, damage distribution, resource availability, and recovery expectations. These results show that the most suitable foresight methods change across technology maturity stages. Bibliometrics and patent analysis are not the highest-ranked methods in the overall VIKOR results, but they become essential in specific maturity contexts. This confirms that relying only on a single overall ranking could lead to incomplete recommendations. The tied-rank Borda results therefore provide the main practical contribution of the study by translating expert judgments into stage-specific foresight portfolios for smart seismic technology planning.

#### 5.5. Robustness and validation results

To examine the credibility and stability of the results, this section reports four complementary checks: expert agreement and questionnaire reliability, Monte Carlo uncertainty analysis, VIKOR sensitivity analysis, and comparative validation using TOPSIS and PROMETHEE II. The first check evaluates whether the expert-based inputs were sufficiently consistent for multi-criteria analysis. The remaining checks examine whether the ranking of foresight methods and the resulting maturity-sensitive portfolios remain stable under input uncertainty, changes in the VIKOR compromise coefficient, and alternative decision-making models.

Together, these analyses provide a broader validation structure for the proposed framework. Rather than relying only on the main Fuzzy VIKOR and Borda outputs, the study evaluates the reliability of the expert judgments, the robustness of the rankings, and the consistency of the results across different analytical assumptions. This helps determine whether the final foresight portfolios can be considered dependable for maturity-sensitive smart seismic technology planning.

##### 5.5.1. Expert agreement and questionnaire reliability

Before interpreting the robustness analyses, the reliability of the expert-based inputs was examined using Kendall's coefficient of concordance and Cronbach's alpha. This step was added to determine whether the judgments provided by the twelve experts showed an acceptable level of agreement and internal consistency. Kendall's W was used for ranking-based parts of the questionnaire, while Cronbach's alpha was applied to the linguistic evaluation matrix used in the Fuzzy VIKOR analysis.

From the results (Table 15), it can be seen that the reliability of the expert inputs is enough for the subsequent analysis. The

value of Kendall's W coefficient for the criteria prioritization from the SWARA approach was 0.862 and was statistically significant ( $\chi^2 = 42.238$ ,  $P < 0.001$ ). It shows that criteria prioritization was not random, and experts agreed. Thus, the reliability of criteria weightings used in the SWARA approach is justified.

The derived foresight-method rankings also showed a very strong level of agreement among experts, with Kendall's W equal to 0.949 ( $P < 0.001$ ). This suggests that the experts had highly consistent views regarding the relative performance of the foresight methods across the decision criteria. In addition, Cronbach's alpha for the 64-item linguistic evaluation matrix was 0.790, indicating acceptable internal consistency of the questionnaire responses used for the Fuzzy VIKOR analysis.

For the maturity-stage portfolio assessments, Kendall's W values were 0.864 for M1, 0.851 for M2, 0.889 for M3, and 0.787 for M4. These values indicate strong agreement across all maturity stages. Therefore, the stage-specific portfolio recommendations were not based on highly dispersed or inconsistent expert judgments. Overall, these statistical checks provide additional support for the reliability of the expert-based inputs used in the SWARA weighting, Fuzzy VIKOR ranking, and tied-rank Borda portfolio extraction.

**Table 15. Expert agreement and questionnaire reliability results.**

| Reliability check | Data used                            | Result  | Interpretation                      |
|-------------------|--------------------------------------|---------|-------------------------------------|
| Kendall's W       | SWARA criteria rankings              | 0.862   | Strong expert agreement             |
| Chi-square        | SWARA criteria rankings              | 42.238  | Statistically significant           |
| P-value           | SWARA criteria rankings              | < 0.001 | Non-random agreement                |
| Kendall's W       | Derived foresight-method rankings    | 0.949   | Very strong expert agreement        |
| P-value           | Derived foresight-method rankings    | < 0.001 | Statistically significant agreement |
| Cronbach's alpha  | 64-item linguistic evaluation matrix | 0.790   | Acceptable internal consistency     |
| Kendall's W       | M1 portfolio assessment              | 0.864   | Strong expert agreement             |
| Kendall's W       | M2 portfolio assessment              | 0.851   | Strong expert agreement             |
| Kendall's W       | M3 portfolio assessment              | 0.889   | Strong expert agreement             |
| Kendall's W       | M4 portfolio assessment              | 0.787   | Strong expert agreement             |

### 5.5.2. Monte Carlo uncertainty analysis

A simulation using Monte Carlo analysis involving 10,000 repetitions was conducted for evaluating the effect of uncertainties in experts' evaluations and linguistic assessment (Table 16). In each repetition, the response of the experts was randomly generated, and the linguistic assessment was varied according to the corresponding fuzzy set. The new values of the VIKOR criteria were calculated to find out the probability of dominance.

**Table 16. Monte Carlo uncertainty analysis of foresight-method rankings.**

| Method                          | Mean Q | 95% uncertainty interval | P (Rank 1) | P (Top 2) | P (Top 3) |
|---------------------------------|--------|--------------------------|------------|-----------|-----------|
| A5. Delphi method               | 0.028  | 0.000-0.087              | 88.65%     | 99.99%    | 100%      |
| A8. Technology roadmapping      | 0.102  | 0.001-0.182              | 11.34%     | 99.78%    | 100%      |
| A7. Scenario planning           | 0.394  | 0.187-0.588              | 0.01%      | 0.23%     | 77.59%    |
| A2. MACTOR/stakeholder analysis | 0.546  | 0.360-0.736              | 0%         | 0%        | 13.58%    |
| A6. Horizon scanning            | 0.553  | 0.387-0.707              | 0%         | 0%        | 8.73%     |
| A1. Brainstorming               | 0.780  | 0.668-0.896              | 0%         | 0%        | 0%        |
| A4. Patent analysis             | 0.800  | 0.573-0.955              | 0%         | 0%        | 0.10%     |
| A3. Bibliometrics               | 0.982  | 0.882-1.000              | 0%         | 0%        | 0%        |

The Monte Carlo results confirm the robustness of the leading methods. Delphi had the highest probability of being ranked first, while technology roadmapping was almost always placed within the top two. Scenario planning was not usually ranked first, but it had a high probability of remaining within the top three. This indicates that Delphi and technology roadmapping form the most stable overall foresight core, while scenario planning plays an important supporting role under uncertainty.

The simulation also shows that the lower global ranking of bibliometrics and patent analysis is stable in the overall VIKOR results. However, this does not reduce their stage-specific relevance. As shown in the Borda portfolio results, bibliometrics remains essential for emerging technologies, and patent analysis remains essential for developing/technology-readiness stages.

### 5.5.3. VIKOR sensitivity analysis

Sensitivity analysis was performed by changing the VIKOR compromise coefficient  $v$ . The main analysis used  $v = 0.50$ , while two additional settings,  $v = 0.25$  and  $v = 0.75$ , were tested to examine whether the ranking changed under different decision attitudes (Table 17).

Ranking was quite stable across the three values for  $v$ . The main difference was that Delphi and technology roadmapping interchanged places when  $v = 0.75$ . This result shows that Delphi produces better results in the case when individual regret is more

valuable, while technology roadmapping dominates in the case when the weight of majority utility increases. The stable ranking in third place of scenario planning serves to support its role as a reliable assisting technique.

**Table 17. VIKOR sensitivity analysis under different compromise coefficients.**

| Method                          | Rank at $v = 0.25$ | Rank at $v = 0.50$ | Rank at $v = 0.75$ |
|---------------------------------|--------------------|--------------------|--------------------|
| A5. Delphi method               | 1                  | 1                  | 2                  |
| A8. Technology roadmapping      | 2                  | 2                  | 1                  |
| A7. Scenario planning           | 3                  | 3                  | 3                  |
| A6. Horizon scanning            | 4                  | 4                  | 4                  |
| A2. MACTOR/stakeholder analysis | 5                  | 5                  | 5                  |
| A1. Brainstorming               | 6                  | 6                  | 7                  |
| A4. Patent analysis             | 7                  | 7                  | 6                  |
| A3. Bibliometrics               | 8                  | 8                  | 8                  |

#### 5.5.4. Comparative validation with TOPSIS and PROMETHEE II

For the evaluation of dependence of the findings on the VIKOR approach, the ranking has been compared to the rankings based on the use of TOPSIS and PROMETHEE II approaches. These approaches are built on different logic: TOPSIS uses distances from ideal and anti-ideal solutions, while PROMETHEE II utilizes preference flows.

The comparative results show a consistent ranking structure across the three methods (Table 18). Delphi and technology roadmapping remained the two leading methods, although their order changed between VIKOR and the comparative methods. Scenario planning remained third in all methods, confirming its stable intermediate position. Bibliometrics remained last in the overall ranking, which again suggests that its role is not as a universal foresight method, but as a stage-specific method for emerging technologies.

**Table 18. Comparative validation of foresight-method rankings.**

| Method                          | VIKOR $v = 0.50$ | TOPSIS | PROMETHEE II |
|---------------------------------|------------------|--------|--------------|
| A8. Technology roadmapping      | 2                | 1      | 1            |
| A5. Delphi method               | 1                | 2      | 2            |
| A7. Scenario planning           | 3                | 3      | 3            |
| A2. MACTOR/stakeholder analysis | 5                | 4      | 5            |
| A6. Horizon scanning            | 4                | 6      | 4            |
| A4. Patent analysis             | 7                | 5      | 6            |
| A1. Brainstorming               | 6                | 7      | 7            |
| A3. Bibliometrics               | 8                | 8      | 8            |

Spearman's rank correlation was used to quantify ranking agreement (Table 19).

**Table 19. Spearman rank correlation for robustness validation.**

| Comparison                            | Spearman correlation |
|---------------------------------------|----------------------|
| VIKOR $v = 0.50$ vs. VIKOR $v = 0.25$ | 1.000                |
| VIKOR $v = 0.50$ vs. VIKOR $v = 0.75$ | 0.952                |
| VIKOR $v = 0.50$ vs. TOPSIS           | 0.857                |
| VIKOR $v = 0.50$ vs. PROMETHEE II     | 0.952                |

The high correlation values indicate that the main ranking pattern is not strongly dependent on a single decision model. Therefore, the validation results strengthen confidence in the robustness of the proposed framework. Overall, the analyses confirm that the final maturity-sensitive foresight portfolios are supported not only by the main Fuzzy VIKOR and Borda results, but also by uncertainty simulation, sensitivity testing, and comparative multi-criteria validation.

#### 5.6. Decision guideline and practical implications

Based on the CRITIC maturity classification, SWARA-based criterion weights, Fuzzy VIKOR ranking, and tied-rank Borda portfolio results, a practical decision guideline was developed for selecting foresight portfolios for smart seismic technologies. The guideline connects each maturity/application stage with its main decision need and the most suitable combination of foresight methods (Table 20).

The guideline shows that foresight planning for smart seismic technologies should be adjusted to the maturity and application context of each technology group. For emerging technologies, the main task is not immediate deployment, but understanding the direction of scientific development and identifying early signals of future change. Therefore, bibliometrics, horizon scanning, and

Delphi are most suitable because they combine research trend mapping, weak-signal detection, and expert interpretation.

For developing technologies, the key issue is the transition from research to application. At this stage, patent analysis becomes important because it can reveal innovation activity and technology-readiness signals. However, patent evidence alone is not sufficient. Delphi is needed to interpret uncertain evidence, while technology roadmapping helps translate readiness signals into development milestones and implementation pathways.

For implementation-oriented technologies, the main challenge is practical deployment. Technologies such as self-centering systems, base isolation, and supplemental damping devices are technically more mature, but their adoption depends on stakeholder acceptance, design practice, cost, maintenance, and regulatory conditions. Therefore, MACTOR, technology roadmapping, and Delphi form a suitable portfolio for analyzing actors, planning implementation, and refining priorities.

For recovery/resilience-oriented technologies, foresight must address post-earthquake uncertainty. Repairability, downtime reduction, re-occupancy, and functional recovery depend on uncertain damage scenarios, resource availability, inspection capacity, and recovery expectations. For this reason, scenario planning is added to the portfolio together with technology roadmapping, MACTOR, and Delphi. This combination supports both strategic planning and adaptive decision-making for post-earthquake recovery.

Overall, the decision guideline demonstrates the practical value of treating foresight-method selection as a portfolio design problem. A single method cannot adequately support all stages of smart seismic technology development. Instead, maturity-sensitive portfolios provide a more flexible and context-specific basis for research planning, technology development, implementation strategy, and resilience-oriented infrastructure decision-making.

**Table 20. Decision guideline for selecting maturity-sensitive foresight portfolios for smart seismic technologies.**

| Maturity stage                      | CRITIC-based smart seismic technologies                                                                               | Main decision need                                                                                  | Recommended foresight portfolio                              | Practical guideline                                                                                                                                   |
|-------------------------------------|-----------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|--------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|
| M1. Emerging/research-oriented      | AI-based damage detection; Digital twins                                                                              | Identifying scientific trends, weak signals, and future research directions                         | Bibliometrics + horizon scanning + Delphi                    | Avoid premature implementation decisions; First map scientific development and weak signals, then validate future directions through expert consensus |
| M2. Developing/technology-readiness | Advanced smart sensing; SHM; Smart sensors/IoT-based seismic monitoring; MR dampers/semi-active control               | Assessing readiness, patent activity, development feasibility, and transition to application        | Patent analysis + Delphi + technology roadmapping            | Evaluate innovation and readiness signals, interpret them through expert judgment, and translate them into a staged development roadmap               |
| M3. Implementation-oriented         | Self-centering systems; Base isolation systems; Supplemental damping devices                                          | Evaluating implementation feasibility, stakeholder acceptance, maintenance, and deployment pathways | MACTOR + technology roadmapping + Delphi                     | Analyze stakeholder roles and constraints, define implementation milestones, and refine deployment priorities through expert consensus                |
| M4. Recovery/resilience-oriented    | Replaceable fuse/low-damage systems; Rapid post-earthquake damage assessment; Re-occupancy/downtime reduction systems | Addressing repairability, downtime reduction, re-occupancy, and functional recovery                 | technology roadmapping + MACTOR + Delphi + scenario planning | Combine roadmap planning, stakeholder analysis, expert consensus, and alternative recovery scenarios to support post-earthquake functionality         |

## 6. Conclusions

This study proposed a technology-maturity-based foresight portfolio framework for smart seismic structures. The framework was developed to address the need for a structured decision-support approach that links the maturity level of smart seismic technologies with suitable combinations of foresight methods. Instead of treating foresight-method selection as the choice of a single best method, the study conceptualized foresight as a portfolio design problem in which different maturity stages require different combinations of evidence-based, expert-based, stakeholder-oriented, and planning-oriented methods.

The first stage of the analysis used scientific and patent-based evidence and the CRITIC method to weight maturity indicators and construct weighted maturity profiles. Based on predefined profile-based classification rules, the selected smart seismic technologies were then assigned to four maturity/application stages. The results showed that smart seismic technologies differ considerably in their maturity profiles. AI-based damage detection and digital twins were classified as emerging/research-oriented technologies, while SHM, smart sensors, IoT-based seismic monitoring, and semi-active control systems were positioned as developing/technology-readiness technologies. Self-centering systems, base isolation, and supplemental damping devices were classified as implementation-oriented technologies, whereas replaceable fuse systems, rapid damage assessment tools, and re-occupancy or downtime-reduction systems were classified as recovery/resilience-oriented technologies. This classification confirms that smart seismic technologies should not be planned through a single uniform foresight approach.

The SWARA-based weighting results showed that seismic resilience support was the most important criterion for selecting foresight methods. This indicates that foresight planning for smart seismic technologies should not focus only on technological novelty or research visibility, but should also consider repairability, downtime reduction, re-occupancy, and functional recovery. Implementation planning, applicability to smart seismic technologies, and technology maturity assessment were also among the most influential criteria, showing that practical deployment and engineering relevance are central to foresight-method selection in

this domain.

The Fuzzy VIKOR results indicated that Delphi and Technology Roadmapping form the strongest overall foresight core. Delphi is particularly useful for developing structured expert consensus under uncertainty, while Technology Roadmapping helps translate foresight results into staged development and implementation pathways. Scenario Planning also showed an important supporting role, especially where future recovery conditions and long-term uncertainty must be considered. However, the results also demonstrated that no single foresight method is sufficient for all technology maturity stages.

The tied-rank Borda analysis provided the main portfolio-based output of the study. For emerging/research-oriented technologies, Bibliometrics, Horizon Scanning, and Delphi were identified as the most suitable portfolio because they support scientific trend mapping, weak-signal detection, and expert interpretation. For developing/technology-readiness technologies, Patent Analysis, Delphi, and Technology Roadmapping were recommended because this stage requires innovation evidence, readiness assessment, and transition planning. For implementation-oriented technologies, MACTOR, Technology Roadmapping, and Delphi were more appropriate because stakeholder acceptance, feasibility, and deployment pathways become central. For recovery/resilience-oriented technologies, the recommended portfolio included Technology Roadmapping, MACTOR, Delphi, and Scenario Planning, reflecting the need to address post-earthquake uncertainty, reparability, downtime reduction, re-occupancy, and functional recovery.

The robustness and validation analyses strengthened the reliability of these findings. Expert agreement and questionnaire reliability checks showed that the expert-based inputs were sufficiently consistent for multi-criteria analysis. Monte Carlo uncertainty analysis confirmed that Delphi and Technology Roadmapping remained the most stable overall foresight methods, while VIKOR sensitivity analysis and comparative validation with TOPSIS and PROMETHEE II showed that the main ranking structure was not dependent on a single decision-making method. These results support the credibility of the proposed maturity-sensitive foresight portfolios.

The main contribution of this study is the integration of technology maturity assessment and foresight portfolio selection for smart seismic structures. The proposed framework advances existing foresight and resilience planning studies by connecting scientific and patent-based maturity evidence, expert-based multi-criteria evaluation, portfolio extraction, and robustness validation in a single decision-support process. In practical terms, the framework can help engineers, infrastructure owners, policymakers, and resilience planners select foresight methods according to the maturity and application context of smart seismic technologies. This is particularly useful for long-term planning of resilient infrastructure, where emerging technologies, implementation constraints, stakeholder interests, and post-earthquake recovery requirements must be considered together.

Overall, the findings show that maturity-sensitive foresight portfolios provide a more flexible and context-specific basis for smart seismic technology planning than a single-method ranking approach. By linking foresight methods to technology maturity stages, the proposed framework supports more informed decisions about research prioritization, technology development, implementation pathways, and resilience-oriented infrastructure planning.

## Statements & declarations

### *Author contributions*

**Shahin Lale Arefi:** Investigation, Formal analysis, Data curation, Methodology, Validation, Resources, Writing - Review & Editing.

**Mahdi Bitarafan:** Conceptualization, Investigation, Methodology, Formal analysis, Project administration, Resources, Writing - Original Draft.

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### *Data availability*

The data presented in this study will be available on interested request from the corresponding author.

### *Declarations*

The authors declare no conflict of interest.

## Appendix A. Coded evidence matrix used for CRITIC analysis

Table A.1 shows the coded evidence matrix used in the maturity assessment based on the CRITIC methodology. These values represent ordinal maturity ratings that have been generated based on the screening of evidence from scientific and patent sources. They are not directly derived from counts of publications or patents. Instead, they are coded ratings of the following aspects: research visibility, concurrent growth of research, evidence of validation, evidence of implementation, patent visibility, seismic/civil patents relevance, maturity of devices/systems, current patent activity, and resilience indicators.

**Table A.1. Coded evidence matrix used for CRITIC-based maturity assessment.**

| Technology group                           | G1 | G2 | G3 | G4 | G5 | P1 | P2 | P3 | P4 | P5 |
|--------------------------------------------|----|----|----|----|----|----|----|----|----|----|
| AI-based damage detection                  | 5  | 6  | 4  | 2  | 3  | 3  | 3  | 2  | 4  | 2  |
| Digital twins                              | 5  | 6  | 3  | 2  | 3  | 3  | 2  | 3  | 5  | 3  |
| SHM/advanced smart sensing                 | 6  | 5  | 5  | 4  | 4  | 5  | 5  | 4  | 4  | 3  |
| Smart sensors/IoT-based seismic monitoring | 5  | 6  | 4  | 4  | 4  | 5  | 4  | 4  | 5  | 3  |
| MR dampers/semi-active control             | 5  | 4  | 5  | 3  | 3  | 5  | 5  | 5  | 4  | 2  |
| Self-centering systems                     | 5  | 4  | 5  | 4  | 4  | 4  | 4  | 4  | 4  | 4  |
| Base isolation systems                     | 6  | 4  | 6  | 6  | 4  | 5  | 5  | 6  | 4  | 2  |
| Supplemental damping devices               | 6  | 4  | 6  | 5  | 4  | 6  | 6  | 5  | 5  | 3  |
| Replaceable fuse/low-damage systems        | 4  | 4  | 5  | 3  | 6  | 4  | 4  | 5  | 4  | 5  |
| Rapid damage assessment/re-occupancy tools | 5  | 5  | 4  | 3  | 6  | 4  | 3  | 4  | 4  | 6  |

**Note.** G1 = research visibility; G2 = recent research growth; G3 = experimental/validation evidence; G4 = implementation/case-study evidence; G5 = recovery/resilience research evidence; P1 = patent visibility; P2 = seismic/civil patent relevance; P3 = device/system maturity; P4 = recent patent signal; P5 = recovery/resilience patent signal.

The coding scale used in this matrix was as follows: 1 = low, 2 = low-medium, 3 = medium, 4 = medium-high, 5 = high, and 6 = very high. Higher values indicate stronger maturity-related evidence for the corresponding indicator.

## Appendix B. Search strings and screening depth used for evidence coding

The search strings and screening depth used for the structured evidence screening are reported in Table B.1. The purpose of this appendix is to improve the transparency of the CRITIC-based maturity assessment by showing how the scientific and patent-based evidence was identified for each technology group. The screening was conducted at the technology-group level. For each group, the first twenty most relevant scientific records and the first ten most relevant patent records were screened.

**Table B.1. Search strings and screening depth used for evidence coding.**

| Technology group                           | Scientific search string                                                                                   | Patent search string                                                                                        | Scientific records screened | Patent records screened |
|--------------------------------------------|------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|-----------------------------|-------------------------|
| AI-based damage detection                  | "AI-based damage detection" OR "machine learning damage detection" AND earthquake AND structure OR seismic | "earthquake damage detection" OR "seismic damage detection" AND artificial intelligence OR machine learning | 20                          | 10                      |
| Digital twins                              | "digital twin" AND civil infrastructure AND earthquake OR seismic                                          | "digital twin" AND structure AND seismic OR earthquake                                                      | 20                          | 10                      |
| SHM/advanced smart sensing                 | "structural health monitoring" AND earthquake OR seismic AND smart sensing                                 | "structural health monitoring" AND seismic OR earthquake AND sensor                                         | 20                          | 10                      |
| Smart sensors/IoT-based seismic monitoring | "IoT-based seismic monitoring" OR "smart sensor" AND earthquake AND structure                              | "IoT" AND earthquake monitoring AND structural sensor OR seismic sensor                                     | 20                          | 10                      |
| MR dampers/semi-active control             | "magnetorheological damper" AND seismic OR "semi-active control" AND earthquake                            | "magnetorheological damper" AND seismic control OR earthquake control                                       | 20                          | 10                      |
| Self-centering systems                     | "self-centering system" AND seismic OR earthquake-resistant structure                                      | "self-centering" AND seismic structure OR earthquake-resistant structure                                    | 20                          | 10                      |
| Base isolation systems                     | "base isolation" AND seismic AND building OR bridge                                                        | "base isolation" AND earthquake OR seismic isolation AND structure                                          | 20                          | 10                      |
| Supplemental damping devices               | "supplemental damping" AND seismic OR earthquake engineering                                               | "damping device" AND seismic OR earthquake AND structure                                                    | 20                          | 10                      |
| Replaceable fuse/low-damage systems        | "replaceable fuse" AND seismic OR "low-damage system" AND earthquake                                       | "replaceable fuse" AND seismic OR earthquake-resistant structure                                            | 20                          | 10                      |
| Rapid damage assessment/re-occupancy tools | "rapid damage assessment" AND earthquake OR "re-occupancy" AND seismic resilience                          | "post-earthquake damage assessment" OR re-occupancy AND structure OR building                               | 20                          | 10                      |
| Total                                      | —                                                                                                          | —                                                                                                           | 200                         | 100                     |

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