

A Robust Grey Multi-Criteria Decision-Making Framework for Prioritization under Uncertainty: Application to Smart Transformation Systems

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Abstract

The digital transformation of scientific-governmental institutions necessitates prioritizing smart solutions under conditions of uncertainty, limited data, and resource constraints. This study develops an integrated Grey Multi-Criteria Decision-Making (Grey MCDM) framework to evaluate and prioritize smart solutions for a national seismological center, explicitly incorporating interval-based data and uncertain expert judgments.

Relevant smart solutions were identified through literature review, expert interviews, and benchmarking, resulting in five executable projects: AI-based seismic event detection, IoT-enabled smart stations, blockchain-based data integrity, cloud-based seismic data management, and a mobile reporting platform. Thirteen technological, organizational, and environmental criteria were defined to support the evaluation process.

To address ambiguity in qualitative assessments and non-deterministic cost and time estimates, the Grey Best-Worst Method was applied to determine criteria weights, while Grey Target Decision-Making was used to rank the alternatives. Robustness was further assessed using interval analysis and Monte Carlo simulation.

The findings indicate that AI-based seismic event detection is the most effective and robust alternative, followed by IoT smart stations and the mobile platform. Sensitivity analysis confirms the stability of rankings, highlighting implementation time, cost, and usability as the most influential criteria. The proposed framework offers a transparent and uncertainty-aware decision support tool for digital transformation planning.

Keywords

Digital Transformation, Smart Systems, Decision-Making Framework, Uncertainty Modelling, Grey MCDM, Grey BWM

1. Introduction

Digital transformation has progressed from a primarily technological shift toward a strategic and organizational phenomenon that reshapes how decisions are made, resources are allocated, and organizational systems evolve over time (Gong & Ribière, 2020; Nadkarni & Prügl, 2020). In complex institutional contexts, particularly scientific–governmental organizations, these decisions are increasingly shaped by large volumes of heterogeneous data, uncertainty, and the need for timely and reliable responses (HosseiniNasab, 2025). Digital transformation in such settings is therefore not simply an operational upgrade; it is a decision-intensive process in which organizations must evaluate competing technological pathways while balancing performance, feasibility, resources, and institutional requirements.

The adoption of digital technologies depends on multiple interrelated factors, including technological readiness, organizational capabilities, and environmental pressures. Although prior research highlights the potential of digital transformation to enhance innovation and organizational performance, implementation is frequently constrained by high investment costs, skill shortages, and resistance to organizational change (Khoshroo and Talari, 2025). These constraints can be particularly consequential in public and data-intensive institutions, where fragmented infrastructures and limited integration mechanisms complicate technology adoption and organizational change (Omrani et al., 2022). Consequently, the central managerial problem is not simply whether a technology should be adopted, but which transformation initiatives should receive priority when organizational resources and information are limited.

Smart transformation represents an advanced stage of digital transformation in which intelligent technologies, including artificial intelligence (AI), the Internet of Things (IoT), and advanced data analytics, are embedded in operational and decision-making processes (Di Giulio & Vecchi, 2021; Verhoef et al., 2021). These technologies can enhance real-time information processing, system adaptability, and organizational coordination. However, their adoption also creates a more complex decision environment because alternative solutions may differ substantially in performance, acquisition cost, implementation time, technological readiness, cybersecurity, usability, and organizational requirements. Selecting among such alternatives consequently requires a structured evaluation approach capable of considering multiple and potentially conflicting dimensions simultaneously.

Seismological centers provide a particularly relevant setting for examining this decision problem. As scientific–governmental institutions responsible for seismic monitoring and hazard assessment, they operate in highly data-intensive environments and face increasing requirements for timely and reliable seismic information (MacCarthy et al., 2020). Emerging technologies such as AI-based seismic detection, IoT-enabled monitoring networks, and cloud-based data platforms offer opportunities to improve monitoring and information processing, but they also involve different levels of investment, technical complexity, infrastructure requirements, and organizational readiness (Khoruzhy et al., 2022; Rosca et al., 2024). The managerial challenge is therefore to determine which initiatives should be prioritized within existing resource and organizational constraints rather than simply identifying which technologies are technologically promising.

Despite the growing literature on digital transformation and smart technologies, important gaps remain in the decision-support perspective. Existing research has largely examined digital transformation at a general organizational level or investigated individual technologies and their potential benefits (Nadkarni & Prügl, 2020; Verhoef et al., 2021). Such approaches provide valuable insights into technology adoption and organizational transformation, but provide less guidance on how competing smart transformation initiatives can be systematically prioritized as a

portfolio of actionable investments. This limitation becomes particularly relevant in scientific and public-sector organizations, where investment decisions must account simultaneously for technological, organizational, financial, and institutional considerations.

Multi-criteria decision-making (MCDM) provides a suitable analytical foundation for such problems because it enables decision-makers to evaluate competing alternatives against multiple, potentially conflicting criteria. Nevertheless, many conventional MCDM approaches rely on precise inputs and deterministic assessments, which may not adequately represent situations in which information is incomplete and expert judgments are inherently approximate (Deepu & Ravi, 2021; Abdelaziz et al., 2025). Grey system theory provides an alternative means of representing such uncertainty by modeling information through grey intervals rather than forcing uncertain judgments into precise values (Chen, 2023). This characteristic is particularly relevant when historical performance data are limited and expert assessments constitute an important source of decision information.

However, the decision-making literature still provides limited integration between smart digital transformation prioritization, interval-based uncertainty modeling, and organizational decision support. In particular, there is limited evidence on frameworks that combine grey MCDM techniques to evaluate a portfolio of implementable smart transformation initiatives in scientific–governmental organizations. This gap is important because technology prioritization in such organizations involves not only comparing expected technological benefits but also explicitly accounting for uncertainty in expert assessments, resource constraints, and implementation feasibility.

To address this gap, this study develops an integrated grey MCDM framework for prioritizing smart transformation initiatives under uncertainty. The framework combines the Grey Best–Worst Method (Grey-BWM) for determining criterion weights with a grey target-based evaluation approach for ranking alternative transformation initiatives. The framework considers technological, organizational, strategic, and environmental criteria, including performance and efficiency, integration, usability, cybersecurity, acquisition and maintenance costs, implementation time, digital resources, strategic alignment, and regulatory considerations. By combining weighting and ranking within a common grey framework, the proposed approach allows uncertain expert judgments to be incorporated throughout the decision process rather than only at a single stage.

The study makes three main contributions. First, it reframes smart digital transformation as a multi-criteria prioritization problem in which alternative technologies are treated as actionable transformation initiatives rather than isolated technological objects. Second, it integrates Grey-BWM and grey target-based evaluation to provide an uncertainty-aware mechanism for weighting criteria and prioritizing competing initiatives when precise information is unavailable. Third, it extends the decision-support perspective to a scientific–governmental setting and demonstrates how grey intervals can provide information not only about alternative rankings but also about variation in expert assessments, thereby supporting more informed and adaptive resource-allocation decisions. The application to the Iranian Seismological Center provides a concrete empirical setting in which these decision challenges can be examined and translated into a phased smart transformation roadmap.

The remainder of the paper is organized as follows. Section 2 reviews the literature on digital transformation, smart technologies, and grey decision-making approaches. Section 3 presents the proposed methodology. Section 4 reports the results and sensitivity analysis. Finally, Section 5 discusses the findings, managerial implications, limitations, and directions for future research.

2. Literature Review

2.1 Digital Transformation in Scientific–Governmental Organizations

Digital transformation is increasingly understood as a strategic and organizational phenomenon rather than a purely technological shift. It involves fundamental changes in structures, processes, and value creation mechanisms, extending from digitization and digitalization toward the transformation of organizational decision-making (Vial, 2019; Verhoef et al., 2021). From a decision perspective, digital transformation reshapes how organizations process information, allocate resources, and respond to environmental complexity.

In scientific–governmental institutions, digital transformation is particularly important because of the data-intensive and high-stakes nature of their operations. These organizations rely on large-scale data infrastructures and require alignment between technological capabilities and organizational processes to support effective decisions. However, fragmented infrastructures, cybersecurity concerns, limited digital capabilities, regulatory complexity, and resource constraints can hinder transformation and reduce the quality and timeliness of decision-making (Desai et al., 2024; Lanamäki et al., 2020).

These challenges become more pronounced in high-risk domains such as crisis management and natural hazard response, where real-time information processing and coordinated decisions are essential. Technologies including artificial intelligence, IoT, social media, and data analytics can support different stages of crisis management, from preparedness to recovery (Fischer-Preßler et al., 2024; Stolerio et al., 2024). However, organizations must evaluate heterogeneous technological capabilities alongside organizational readiness, implementation constraints, data quality, and system integration. Consequently, digital transformation is not merely a technology adoption problem but a multi-criteria prioritization problem under uncertainty, requiring structured decision-support approaches to identify and prioritize the most appropriate transformation alternatives.

2.2 Smart Solutions as a Decision-Oriented Extension of Digital Transformation

Smart transformation is conceptualized as a decision-oriented extension of digital transformation. Unlike traditional digitalization, smart solutions integrate artificial intelligence, IoT, and data analytics to enable adaptive and data-driven decision-making systems (Verhoef et al., 2021).

These solutions are characterized by real-time data processing, interoperability, scalability, and user-centric design. By combining sensing technologies, communication infrastructures, and analytical algorithms, they reduce uncertainty and improve the quality of decisions in complex environments (Wen et al., 2022; Romero et al., 2020). From a managerial perspective, smart solutions transform raw data into actionable insights, thereby supporting evidence-based decision-making.

In knowledge-intensive organizations, machine learning techniques enhance predictive capabilities, while cloud platforms provide scalable infrastructures for data storage and processing. As a result, organizations become more responsive to dynamic conditions and operational complexities. However, the adoption of smart solutions introduces important trade-offs, as different technologies vary in cost, implementation complexity, and technological maturity. This makes prioritization a central decision problem rather than a purely technical choice.

2.3 Smart Solutions in Seismological Centers

Seismological centers represent a specific class of scientific–governmental organizations where decision-making is highly time-sensitive and data-driven. These centers are responsible for monitoring seismic activity, analyzing signals, and disseminating information for disaster management and public safety (Naserieh et al., 2020). Their operations rely on continuous data flows and require accurate, real-time analysis to support critical decisions.

The seismic monitoring process consists of multiple interconnected stages, including data acquisition, transmission, processing, and dissemination. Each stage involves technological and organizational coordination across distributed systems. Recent advances in intelligent technologies have significantly enhanced these processes. For instance, artificial intelligence and machine learning improve event detection, signal processing, and hazard assessment, while IoT-based sensor networks enable real-time monitoring (Mousavi et al., 2020).

Additional technologies such as cloud computing and blockchain support scalable data management and secure information sharing, addressing challenges related to interoperability and data integrity. Moreover, mobile-based early warning systems extend the reach of seismic information to broader populations (Wang et al., 2022; Yousefi and Tosarkani, 2024).

Despite these advancements, the adoption of smart solutions in seismological centers involves significant challenges. Technologies differ in cost, infrastructure requirements, and implementation complexity, while organizations face constraints related to resources, data quality, and system integration. These factors complicate the evaluation and selection of appropriate technologies, highlighting the need for structured decision-support approaches (Naserieh et al., 2025; Kozłowska et al., 2022).

2.4 Grey Systems Theory

Grey systems theory provides a theoretical foundation for analyzing problems characterized by incomplete, uncertain, or partially known information (Qiao et al., 2025). Positioned between deterministic and stochastic frameworks, it enables the representation of uncertainty through interval grey numbers rather than precise values (Li and Wei, 2018). This feature makes it particularly suitable for decision-making contexts where data is limited or imprecise.

The theory encompasses several methodological tools, including grey numbers for modelling uncertain data, grey prediction models for forecasting with limited information, and grey relational analysis for examining relationships among variables (Li et al., 2024). These tools allow decision-makers to derive meaningful insights despite data constraints.

A key advantage of grey theory is its ability to handle small datasets and incorporate subjective judgments without requiring complex parameterization. In settings where uncertainty primarily reflects incomplete or interval-valued information rather than ambiguity represented through membership functions, grey approaches can provide a parsimonious representation of uncertainty. (Karimi et al., 2024). This makes them particularly relevant for strategic decision-making problems involving emerging technologies.

2.5 Grey Multi-Criteria Decision-Making Approaches

Multi-criteria decision-making (MCDM) methods are widely used to evaluate alternatives involving multiple and often conflicting criteria. Established techniques such as AHP, TOPSIS, ELECTRE, and ANP have been applied in various domains, including technology selection and digital transformation (Maretto et al., 2025; Yu et al., 2021; Ge et al., 2023; Yenugula et al., 2023). These methods provide structured frameworks for comparing alternatives and supporting decision-making.

However, conventional MCDM approaches typically assume precise input data, which limits their applicability in uncertain environments. Fuzzy extensions address some of these limitations but introduce additional complexity through the specification of membership functions and parameters (Alqoud et al., 2025; Zhang et al., 2024).

Grey MCDM approaches offer an effective alternative by incorporating interval-based data into the evaluation process. These methods are capable of handling qualitative assessments, limited historical data, and uncertainty in expert judgments, making them suitable for emerging and complex decision contexts (Liu et al., 2017). Applications of grey decision-making have been reported in areas such as supply chain management, energy systems, and infrastructure planning, demonstrating their flexibility and robustness (Karimi and Ahmadian, 2025).

Despite these developments, a critical gap remains in the literature. Existing studies either examine digital transformation and smart technologies or focus on grey decision-making methods independently. The literature lacks a decision-oriented framework capable of prioritizing heterogeneous smart transformation alternatives under incomplete information (Table 1) while simultaneously accounting for the relative importance of decision criteria and the robustness of resulting priorities.

Table 1. Comparative review of grey decision-making applications and identified research gaps.

Research Domain	Decision/Application Focus	Methodology	Uncertainty Handling	Key Limitation
Digital Transformation & Smart Solutions	AI, IoT, big data, and automated decision-support systems in public institutions	Grey MCDM for data-driven strategies (Devikomathy & Manivannan, 2025)	Grey information	Limited application to scientific–governmental organizations and lack of integrated criteria for seismological contexts (Zhang et al., 2024)
Advanced Manufacturing & Prototyping	Selection of manufacturing and prototyping systems	FAHP–GRA (Moiduddin et al., 2019)	Fuzzy/Grey	Limited integration of real-time data and adaptive decision-making
Energy & Sustainable Infrastructure	Site and technology selection for energy and infrastructure systems	Fuzzy GRA–VIKOR (Zhao & Li, 2016)	Fuzzy/Grey	Limited consideration of national critical infrastructure and disaster-management requirements
Healthcare & Environmental Management	Technology assessment and treatment selection under uncertainty	Fermatean Fuzzy–GRA (Chen et al., 2023)	Fermatean fuzzy	Limited application to proactive risk assessment in public-sector crisis and disaster-management contexts
Supply Chain & Digital Services	Supplier and digital-service selection in multi-stakeholder environments	GRA (Ulutaş et al., 2022)	Grey	Limited application to blockchain-enabled public services and integrated digital-transformation prioritization
This study	Prioritization of smart transformation alternatives in a	Integrated Grey MCDM framework	Grey/interval information	Addresses the gap by integrating technological, organizational, and

	scientific–governmental organization			environmental criteria for smart- transformation prioritization in a high- risk seismological context
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3. Methodology

The objective of this study is to select smart solutions for the Iranian Seismological Center (IRSC) within a digital transformation framework. The research begins with a structured literature review to identify relevant evaluation criteria and technological alternatives, followed by validation through expert judgment. A panel of ten experienced seismology specialists, including Ph.D. holders and senior managers, contributed to ensuring the reliability and contextual relevance of the inputs.

To determine the importance of the criteria under uncertainty, the Grey Best-Worst Method (Grey-BWM) is employed. Subsequently, a grey multi-criteria decision-making approach is applied to evaluate and rank the identified smart technologies. The overall methodology is organized into three sequential phases.

Phase I focuses on problem definition and framework design. Based on literature insights and expert input, the final set of evaluation criteria and feasible alternatives is identified.

Phase II involves weighting the criteria using Grey-BWM. Expert judgments are expressed as interval grey numbers to capture uncertainty and imprecision, resulting in robust criteria weights.

Phase III addresses the evaluation and prioritization of smart solutions. Alternatives are assessed against the weighted criteria using grey numbers, allowing the model to incorporate both quantitative and qualitative uncertainties (Figure 1). This phase produces a reliable ranking of digital transformation initiatives suitable for implementation at IRSC.

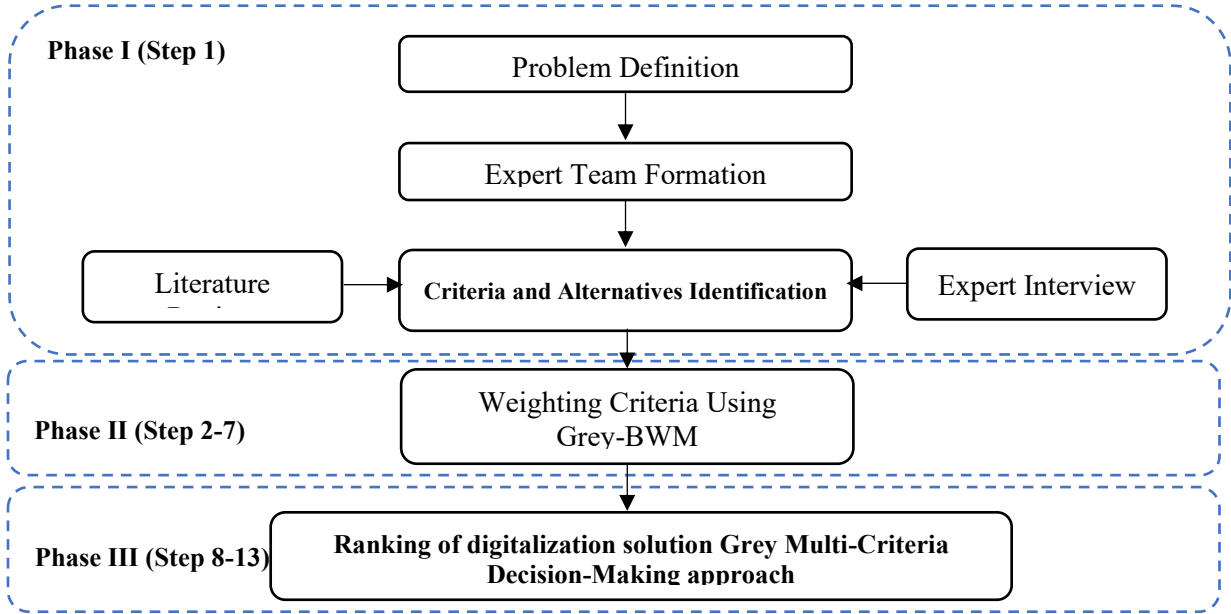


Figure 1. Research flowchart.

3.1 Preliminary definitions

A grey number is represented as (Liu et al., 2017):

$$\otimes A \in [\underline{A}, \bar{A}], \quad \underline{A} < \bar{A} \quad (1)$$

For two grey numbers $\otimes A$ and $\otimes B$, the arithmetic operations are defined through equations (2)–(5) (Ghoushchi et al., 2019).

$$\otimes A + \otimes B = [\underline{A} + \underline{B}, \bar{A} + \bar{B}], \quad (2)$$

$$\otimes A - \otimes B = [\underline{A} - \bar{B}, \bar{A} - \underline{B}], \quad (3)$$

$$\otimes A \cdot \otimes B = [\text{Min}\{\underline{A}\underline{B}, \bar{A}\bar{B}, \bar{A}\underline{B}, \underline{A}\bar{B}\}, \text{Max}\{\underline{A}\underline{B}, \bar{A}\bar{B}, \bar{A}\underline{B}, \underline{A}\bar{B}\}], \quad (4)$$

$$\frac{\otimes A}{\otimes B} = \otimes A \cdot \otimes B^{-1} = \left[\text{Min}\left\{\frac{\underline{A}}{\underline{B}}, \frac{\underline{A}}{\bar{B}}, \frac{\bar{A}}{\underline{B}}, \frac{\bar{A}}{\bar{B}}\right\}, \text{Max}\left\{\frac{\underline{A}}{\underline{B}}, \frac{\underline{A}}{\bar{B}}, \frac{\bar{A}}{\underline{B}}, \frac{\bar{A}}{\bar{B}}\right\} \right] \quad (5)$$

If k is a positive scalar, the multiplication of k by a grey number $\otimes A$ is defined as: (Mahmoudi et al., 2020):

$$k \cdot \otimes A \in [k\underline{A}, k\bar{A}] \quad (6)$$

To represent the central point of a grey number, its kernel is:

$$\otimes \hat{A} = \frac{1}{2}(\underline{A} + \bar{A}) \quad (7)$$

The interval length of $\otimes A$ is computed as in (8) (Karimi et al, 2024)

$$L(\otimes A) = \bar{A} - \underline{A} \quad (8)$$

3.2 Research Procedure Steps

Following the research framework defined in Phase I:

Step 1. Identify the evaluation criteria $\{C_1, C_2, \dots, C_n\}$ through literature review and expert consultation.

Given the uncertainty inherent in evaluating digital transformation projects at IRSC, key criteria such as implementation cost and execution time cannot be represented as precise values due to limited historical data. Instead, these parameters are estimated based on expert judgment, resulting in interval-valued data. To ensure consistency, qualitative and semi-quantitative criteria are also expressed in interval form. Accordingly, grey numbers are adopted to capture uncertainty and avoid information loss associated with deterministic representations.

The Grey Best-Worst Method (GBWM) is employed to determine criteria weights under uncertainty. By incorporating grey linguistic variables, GBWM effectively captures imprecise expert judgments and preserves uncertainty throughout the analysis (Abdulaal & Bafail, 2021). This feature makes it particularly suitable for complex decision environments with limited and ambiguous data. Despite its higher computational complexity compared to simpler methods,

GBWM provides stable and reliable results, especially when integrated with MCDM techniques (Ulutaş et al., 2022, Krstić et al, 2025).

In this study, the linear GBWM model proposed by Mahmoudi et al. (2020) is adopted, and the computational procedure is summarized in the subsequent steps.

Table 2. Grey linguistic scales (Mahmoudi et al., 2020).

Linguistic Term	Abbreviation	Grey Number Interval
Equally Important	EI	$[1, 1]$
Weakly Important	WI	$[\frac{2}{3}, \frac{3}{2}]$
Fairly Important	FI	$[\frac{3}{2}, \frac{5}{2}]$
Very Important	VI	$[\frac{5}{2}, \frac{7}{2}]$
Absolutely Important	AI	$[\frac{7}{2}, \frac{9}{2}]$

Step 2. Each of k experts selects the best and worst criteria.

$$\{B^{p1}, B^{p2}, B^{p3}, \dots, B^{pk}\} \text{ , } \{W^{p1}, W^{p2}, W^{p3}, \dots, W^{pk}\} \quad (9)$$

Step 3. Each expert evaluates the preference of the best criterion over all others using the grey linguistic variables in Table 2. Eq (10) represents the Best-to-Others (BO) grey vectors:

$$\begin{aligned} \otimes A_B^{p1} &= (\otimes a_{B1}^{p1}, \otimes a_{B2}^{p1}, \otimes a_{B3}^{p1} \dots \otimes a_{Bn}^{p1}), \\ &\dots \dots \\ \otimes A_B^{pk} &= (\otimes a_{B1}^{pk}, \otimes a_{B2}^{pk}, \otimes a_{B3}^{pk} \dots \otimes a_{Bn}^{pk}). \end{aligned} \quad (10)$$

Step 4. Experts express the preference of all criteria relative to the worst criterion. Eq (11) captures the Others-to-Worst (OW) grey vectors:

$$\begin{aligned} \otimes A_W^{p1} &= (\otimes a_{1W}^{p1}, \otimes a_{2W}^{p1}, \otimes a_{3W}^{p1} \dots \otimes a_{nW}^{p1})^T, \\ &\dots \dots \\ \otimes A_W^{pk} &= (\otimes a_{1W}^{pk}, \otimes a_{2W}^{pk}, \otimes a_{3W}^{pk} \dots \otimes a_{nW}^{pk})^T \end{aligned} \quad (11)$$

Step 5. The optimal weights of the criteria are obtained by solving the Grey BWM optimization model, expressed in Model (12), which incorporates grey-valued inputs throughout the formulation.

$$\min \xi \quad (12)$$

$$\begin{aligned} & \text{s.t.} \\ & \left| \frac{W_B}{W_j} - a_{Bj} \right| \leq \xi, \text{ for all } j, \\ & \left| \frac{W_j}{W_w} - a_{jw} \right| \leq \xi, \text{ for all } j, \\ & \sum_j W_j = 1, \\ & W_j \geq 0, \quad \text{for all } j. \end{aligned}$$

then

$$\min \xi \quad (13)$$

$$\begin{aligned} & \text{s.t.} \\ & \frac{W_B}{W_j} - a_{Bj} \leq \xi \quad \text{for all } j, \\ & -\frac{W_B}{W_j} + a_{Bj} \leq \xi \quad \text{for all } j, \\ & \frac{W_j}{W_w} - a_{jw} \leq \xi \quad \text{for all } j, \\ & -\frac{W_j}{W_w} + a_{jw} \leq \xi \quad \text{for all } j, \\ & \sum_j W_j = 1, \\ & W_j \geq 0, \quad \text{for all } j \end{aligned}$$

by multiplying the constraints of Model (13), the Model (14) is derived as:

$$\min \xi \quad (14)$$

$$\begin{aligned} & \text{s.t.} \\ & W_B - W_j a_{Bj} \leq W_j \xi, \quad \text{for all } j, \\ & -W_B + W_j a_{Bj} \leq W_j \xi, \quad \text{for all } j, \\ & W_j - W_w a_{jw} \leq W_w \xi, \quad \text{for all } j, \\ & -W_j + W_w a_{jw} \leq W_w \xi, \quad \text{for all } j, \\ & \sum_j W_j = 1, \\ & W_j \geq 0, \quad \text{for all } j \end{aligned}$$

Given that Model (14) includes the product of two variables, ξ and W_j , it is inherently nonlinear. To reduce computational complexity, the model is linearized using the McCormick approach.

$$\text{If } x_1 \in [x_1^L, x_1^U], \quad x_2 \in [x_2^L, x_2^U] \quad \text{and} \quad \phi_1 = x_1 x_2 \quad (15)$$

The bilinear term $\phi_1 = x_1 x_2$ in Eq. (15) is linearized via standard reformulation techniques. Given that x_1 and x_2 are continuous and bounded, four linear constraints are introduced (Eqs. 16–19) to replace the product, enabling linear optimization.

$$\phi_1 \geq x_1^L x_2 + x_2^L x_1 - x_1^L x_2^L, \quad (16)$$

$$\phi_1 \geq x_1^U x_2 + x_2^U x_1 - x_1^U x_2^U, \quad (17)$$

$$\phi_1 \leq x_1^L x_2 + x_2^U x_1 - x_1^L x_2^U, \quad (18)$$

$$\phi_1 \leq x_1^U x_2 + x_2^L x_1 - x_1^U x_2^L. \quad (19)$$

The bilinear terms are defined as:

$$\phi_1 = W_j \xi, \phi_2 = W_w \xi, W_j \in [0,1], W_w \in [0,1]. \quad (20)$$

By using Eq. (21), the governing formulation for auxiliary variable ξ is derived in Eq. (22).

$$\text{Consistency Ratio} = \frac{\xi}{\text{Consistency Index}} \quad (21)$$

$$\xi = CI \times CR \quad (22)$$

To ensure acceptable consistency, a threshold A is imposed, restricting the feasible range of CR to $[0, A]$, as formulated in Eq. (23).

$$\xi = [0, CI \times A] CI \geq 0, \quad 0 \leq A \leq 1 \quad (23)$$

By incorporating the definitions in Eqs. (20) and (22), together with constraints (16)– (19), the nonlinear Model (14) is reformulated into the linear grey linear model shown in Eq. (24).

$$\min \otimes \xi \quad (24)$$

$$\begin{aligned} & \text{s.t.} \\ & \otimes W_B - \otimes W_j \otimes a_{Bj} \leq \otimes \phi_1, \quad \text{for all } j, \\ & - \otimes W_B + \otimes W_j \otimes a_{Bj} \leq \otimes \phi_1, \quad \text{for all } j, \\ & \otimes \phi_1 \geq 0, \\ & \otimes \phi_1 \geq \otimes \xi + CI.A. \otimes W_j - CI.A., \\ & \otimes \phi_1 \leq CI.A. \otimes W_j, \\ & \otimes \phi_1 \leq \otimes \xi, \\ & \otimes W_j - \otimes W_w \otimes a_{jw} \leq \otimes \phi_2, \quad \text{for all } j, \\ & - \otimes W_j + \otimes W_w \otimes a_{jw} \leq \otimes \phi_2, \quad \text{for all } j, \\ & \otimes \phi_2 \geq 0, \\ & \otimes \phi_2 \geq \otimes \xi + CI.A. \otimes W_w - CI.A., \\ & \otimes \phi_2 \leq CI.A. \otimes W_w, \\ & \otimes \phi_2 \leq \otimes \xi, \\ & \bar{W}_j - W_j \geq \varepsilon, \quad \text{for all } j, \\ & \sum_j \otimes W_j = [0.8, 1.2], \\ & \otimes W_j \geq 0, \quad \text{for all } j, \quad 0 \leq A \leq 1, \quad CI \geq 0. \end{aligned}$$

Step 6. Derive criteria weights per expert; aggregate via grey geometric mean (Eq. 25), assuming equal expert weights.

$$\otimes W_j = \left(\otimes W_{1j}^{p1 \otimes W_1} \cdot \otimes W_{2j}^{p2 \otimes W_2} \dots \otimes W_{kj}^{pk \otimes W_k} \right)^{\frac{1}{\sum W_k}} \quad (25)$$

Step 7: The derived weights are normalized using Eq. (26).

$$\otimes W_j^* = \left(\frac{\underline{W}_j}{\frac{1}{2} \left[\sum_{j=1}^n \underline{W}_j + \sum_{j=1}^n \bar{W}_j \right]}, \frac{\bar{W}_j}{\frac{1}{2} \left[\sum_{j=1}^n \underline{W}_j + \sum_{j=1}^n \bar{W}_j \right]} \right) \quad (26)$$

In Phase III, the grey target-based multi-criteria decision-making process is applied (Zhang et al., 2024). This method defines a satisfactory range of outcomes rather than a single optimal solution, enabling decision-making under uncertainty.

For multi-criteria problems, the target is represented as an s-dimensional satisfaction region, where each criterion k is defined by an interval $[d_1^{(k)}, d_2^{(k)}]$. The aggregation of these intervals forms a hyperspace, and any solution within this region is considered acceptable.

Step 8:

Let $A = \{a_1, a_2, \dots, a_n\}$ be the set of decision states and $B = \{b_1, b_2, \dots, b_m\}$ the set of alternatives. The value u_{ij}^k (for $i = 1, \dots, n; j = 1, \dots, m$) denotes the performance of the combined situation s_{ij} under criterion k .

$$S = A \times B = \{s_{ij} = (a_i, b_j) | a_i \in A, b_j \in B\} \quad (27)$$

Step 9:

This step determines the nature of each criterion (benefit, cost, or moderate) and defines its corresponding grey target interval. Evaluation is conducted using two approaches: (i) qualitative expert assessment, where alternatives are rated on a 1–9 scale and aggregated into interval values, and (ii) quantitative measurement for objective criteria such as cost and time.

Let $u_{i_0j_0}^k$ denote the threshold value for criterion k .

$$\text{Benefit Criterion: } u_{ij}^k \in [u_{i_0j_0}^k, \max_i \max_j \{u_{ij}^k\}] \quad (28)$$

$$\text{Cost Criterion: } u_{ij}^k \in [\min_i \min_j \{u_{ij}^k\}, u_{i_0j_0}^k] \quad (29)$$

$$\text{Moderate Criterion: } u_{ij}^k \in [A - u_{i_0j_0}^k, A + u_{i_0j_0}^k] \quad (30)$$

Step 10:

The observation effect matrix for criterion k is defined as $U^k = [u_{ij}^k]_{n \times m}$.

Step 11:

The matrix of uniform effect $R^k = [r_{ij}^k]_{n \times m}$ is :

- Benefit Criterion:

$$r_{ij}^k = \frac{u_{ij}^k - u_{i_0j_0}^k}{\max_i \max_j \{u_{ij}^k\} - u_{i_0j_0}^k} \quad (31)$$

- Cost Criterion:

$$r_{ij}^k = \frac{u_{i_0j_0}^k - u_{ij}^k}{u_{i_0j_0}^k - \min_i \min_j \{u_{ij}^k\}} \quad (32)$$

- Moderate effect measure:

$$\circ \text{ Lower effect measure: } r_{ij}^k = \frac{u_{ij}^k - A + u_{i_0j_0}^k}{u_{i_0j_0}^k} \quad (33)$$

$$\circ \text{ Upper effect measure: } r_{ij}^k = \frac{A + u_{i_0j_0}^k - u_{ij}^k}{u_{i_0j_0}^k} \quad (34)$$

Step 12:

Multiply indicator weights (Section 3.3, w_k) by uniform effect matrix to get weighted synthetic effect matrix.

$$R = [r_{ij}]_{n \times m}, \quad r_{ij} = \sum_{k=1}^s r_{ij}^k \cdot w_k \quad (35)$$

Step 13: Ranking and Decision

The r_{ij} are dimensionless, $r_{ij} \in [0,1]$: target achievement (higher better), $r_{ij} \in [-1,0]$: failure. Choose optimal alternative via:

$$\max_{1 \leq j \leq m} \{r_{1j}\} \quad (36)$$

Appendix A presents the pseudocode for the Grey-BWM implementation

4. Results

This study selects smart solution strategies for the IRSC based on operational needs. A panel of 10 senior experts (EX1–EX10) conducted the assessment: three current/former center directors (Ph.D.) and seven senior managers (two Ph.D., five M.Sc.).

The evaluation integrates strategic, performance, and technological criteria to determine optimal implementation sequence for smart technologies, supporting digital transformation decisions.

Phase I, Step 1: Criteria & Alternatives

Key technology selection criteria (Table 3) were extracted from literature (Section 2.3) and expert consultations. Five practical solutions are evaluated. Unlike generic technology assessments, each alternative is a discrete, actionable project with its own budget, timeline, and resources — modular and independent short-term investment options due to organizational constraints. Projects:

- A1: AI-powered automated seismic event detection & location
- A2: IoT-based smart seismological station network
- A3: Blockchain for seismic data integrity & authenticity
- A4: Integrated cloud platform for seismic data storage & processing
- A5: Mobile platform for public reporting & localized early warning

Cost and implementation time are interval-valued (due to uncertainty, vendor choice, infrastructure readiness). Thus, all criteria were grey-interval modeled for scale compatibility. This solution-oriented framing enhances analytical precision and managerial relevance without altering the computational framework.

Table 3. Technology Selection Criteria Aligned with Smart Seismological Center Objectives.

Criterion	Sub-criteria	Nature of Criterion		
		Benefit	Cost	Moderate
Technological	Performance & Efficiency (C1)	✓		
	Ease of Integration with Existing Systems (C2)	✓		
	Usability (C3)	✓		
	Scalability with Growing Needs (C4)	✓		
	Enhanced Cybersecurity (C5)	✓		
	Maintenance Cost (C6)		✓	
Organizational	Technology Acquisition Cost (C7)		✓	
	Implementation Time (C8)			✓
	Availability of Digital Human Resources (C9)	✓		
	Availability of Digital Technical Resources (C10)	✓		
	Strategic Alignment with Organizational Goals (C11)	✓		
	Regulatory Compliance (C12)	✓		
Environmental	Reduced Energy Consumption (C13)	✓		

Phase II: Criteria Weighting Using Grey-BWM.

Step 2: Each DM identified best & worst criteria (Table 2).

Step 3: Each DM evaluated the preference of the most important criterion vs others (Table 2).

Step 4: The expert group assessed the preference of all criteria over the least important criterion (Table 2). Results: Tables 4 & 5.

Step 5: Based on the data collected in Steps 3 and 4 (Tables 5 and 6), linguistic variables are converted into grey numbers. Subsequently, using Model (24), Model (37) is formulated for the first decision-maker (Appendix B).

Step 6: Solve Model (37) via grey LP. Aggregated weights: Table 7. Python (NumPy, pandas, CVXPY, Matplotlib) used. Figure 2 shows expert opinion divergence per criterion.

Step 7: Apply Eq. (25) to individual expert weights → aggregated criterion weights (Table 6). Normalized weights via Eq. (30) (Table 7, Figure 3).

Table 4. Expert evaluations of the most important criterion's preference over other criteria.

Expert	Best Criteria	Criteria												
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
EX1	C1	EI	FI	FI	AI	FI	VI	VI	VI	VI	FI	AI	AI	FI
EX2	C7	WI	VI	FI	AI	FI	FI	EI	VI	FI	FI	AI	AI	FI
EX3	C3	EI	VI	EI	VI	WI	AI	FI	AI	VI	VI	VI	AI	WI
EX4	C1	EI	VI	WI	VI	WI	VI	WI	FI	VI	FI	FI	VI	WI
EX5	C7	WI	AI	AI	WI	FI	VI	EI	AI	VI	VI	AI	AI	FI
EX6	C1	EI	FI	WI	AI	WI	FI	WI	FI	VI	VI	AI	VI	WI
EX7	C3	EI	WI	EI	VI	WI	FI	WI	FI	FI	FI	FI	VI	WI
EX8	C5	WI	VI	FI	AI	EI	VI	VI	VI	AI	AI	FI	FI	AI
EX9	C1	EI	FI	WI	VI	WI	FI	WI	FI	FI	FI	FI	FI	WI
EX10	C3	EI	FI	EI	AI	WI	FI	WI	FI	FI	FI	FI	VI	WI

Table 5. Expert evaluations of the preference of all other criteria over the worst criterion.

		Criteria												
Criteria	Worst Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
EX1	C12	AI	VI	VI	FI	AI	VI	AI	FI	FI	FI	AI	EI	FI
EX2	C11	AI	FI	VI	WI	VI	FI	VI	FI	VI	FI	EI	WI	FI
EX3	C12	VI	FI	AI	FI	AI	FI	VI	FI	FI	FI	FI	EI	VI
EX4	C6	VI	FI	AI	WI	VI	EI	VI	FI	FI	FI	FI	WI	VI
EX5	C4	AI	FI	AI	EI	VI	FI	VI	FI	FI	FI	VI	FI	AI
EX6	C2	VI	EI	VI	EI	VI	FI	AI	VI	VI	FI	WI	WI	AI
EX7	C12	VI	WI	VI	WI	VI	FI	VI	WI	WI	FI	FI	EI	VI
EX8	C11	VI	WI	VI	EI	AI	WI	FI	WI	WI	FI	EI	EI	FI
EX9	C4	VI	WI	VI	EI	AI	FI	VI	WI	VI	VI	WI	WI	VI
EX10	C8	FI	FI	VI	EI	FI	FI	VI	EI	VI	FI	WI	WI	VI

Table 6. Criterion weights: bounds and mean from expert panel.

Criterion	Group Lower	Group Upper	Group Mid
C1	0.09397	0.131638	0.112804
C2	0.05816	0.065701	0.06193
C3	0.097693	0.119799	0.108746
C4	0.046227	0.05091	0.048568
C5	0.105683	0.130542	0.118112
C6	0.060828	0.066793	0.06381
C7	0.095582	0.112047	0.103814
C8	0.057335	0.062555	0.059945
C9	0.058497	0.063307	0.060902
C10	0.064118	0.070259	0.067189
C11	0.053505	0.060249	0.056877
C12	0.030261	0.036774	0.033517
C13	0.096843	0.110727	0.103785

Table 7. Final normalized weights of the criteria.

Criterion	Normalized Lower	Normalized Upper	Normalized Mid
C1	0.09397	0.131638	0.112804
C2	0.05816	0.065701	0.06193
C3	0.097693	0.119799	0.108746
C4	0.046227	0.05091	0.048568
C5	0.105683	0.130542	0.118112
C6	0.060828	0.066793	0.06381
C7	0.095582	0.112047	0.103814
C8	0.057335	0.062555	0.059945
C9	0.058497	0.063307	0.060902
C10	0.064118	0.070259	0.067189
C11	0.053505	0.060249	0.056877
C12	0.030261	0.036774	0.033517
C13	0.096843	0.110727	0.103785

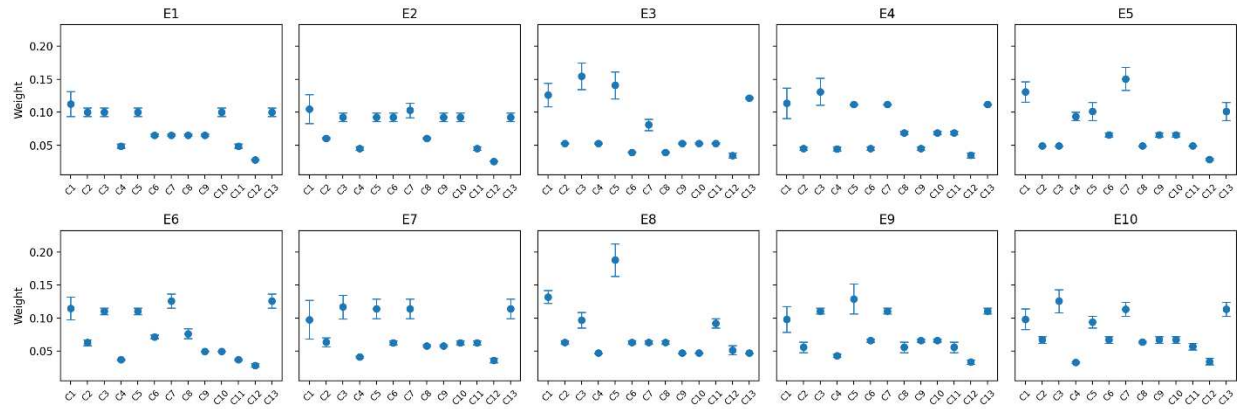


Figure 2. Variation in expert perspectives based on criterion weighting.

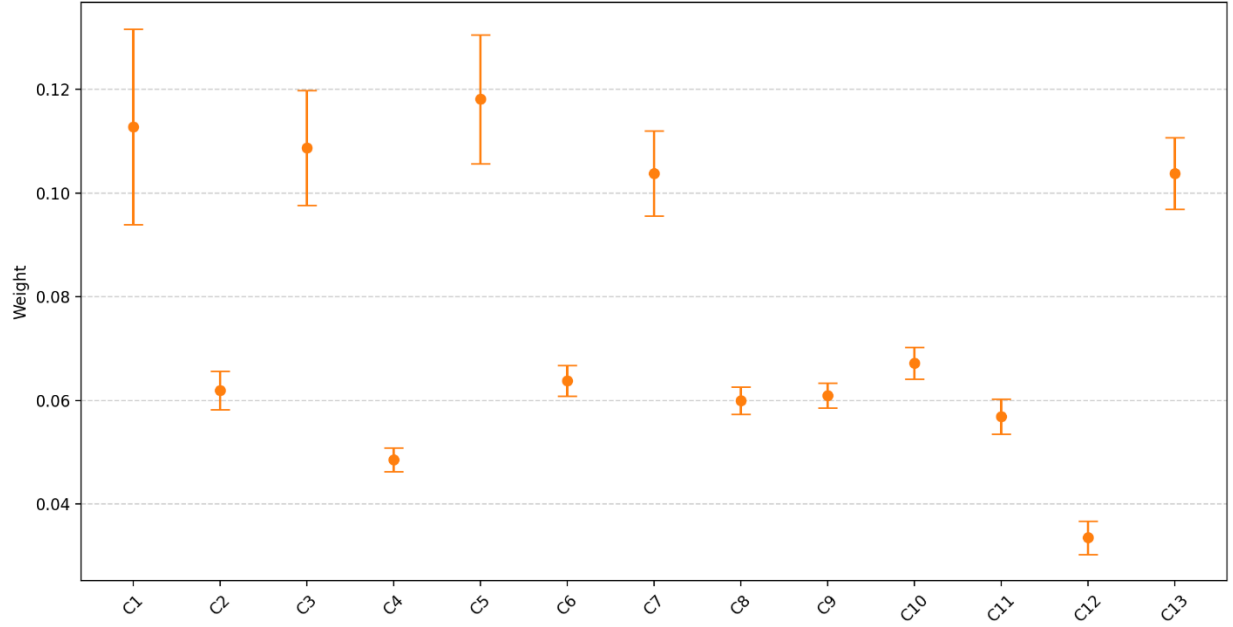


Figure 3. Group-average interval plot of final criterion weights.

The results of the Grey-BWM analysis reveal a clear prioritization structure among the evaluation criteria, reflecting the decision-makers' strategic preferences under uncertainty. The distribution of weights indicates that not all dimensions are equally influential in assessing smart transformation solutions, and a distinct emphasis is placed on risk-sensitive factors.

Among the criteria, cybersecurity and technological readiness emerge as the most influential, underscoring the critical importance of system reliability, data protection, and operational robustness in seismological environments. Given the high-risk and data-intensive nature of such systems, this finding highlights the necessity of minimizing vulnerabilities when adopting advanced digital technologies.

Cost is also assigned a relatively high weight, indicating that financial feasibility remains a key consideration, particularly within resource-constrained public-sector organizations. This suggests that decision-makers adopt a balanced perspective, where economic constraints are considered alongside technical requirements.

In contrast, criteria related to implementation, such as time and required expertise, receive moderate importance. This implies that while operational feasibility is relevant, it is secondary to ensuring long-term system performance and reliability. Similarly, lower-weighted criteria reflect a reduced sensitivity to short-term or less critical factors within the strategic decision context.

From a broader perspective, the weighting pattern indicates a risk-averse decision strategy, where robustness, security, and technological feasibility are prioritized over speed and flexibility. This behavior is consistent with the characteristics of seismological systems, where potential failures can lead to severe societal consequences.

Furthermore, representing the weights as grey intervals rather than precise values allows the model to capture uncertainty in expert judgments, providing a more realistic and flexible assessment framework. This reduces the risk of overconfidence associated with deterministic approaches and enhances the robustness of the decision-making process.

Overall, the results provide a structured and actionable understanding of decision priorities, forming a reliable foundation for the subsequent evaluation and ranking of smart transformation alternatives.

Phase III: Evaluation and Ranking of Smart Solutions.

Step 8: Define Decision Sets, Alternatives, and Situations

Let $A = \{a_1\}$ be the set of decision states (a single decision context) and $B = \{b_1, b_2, b_3, b_4, b_5\}$ be the set of five smart solution alternatives. The set of decision situations is therefore defined as:

$$S = A \times B = \{s_{ij} = (a_i, b_j) \mid a_i \in A, b_j \in B\} = \{s_{11}, s_{12}, s_{13}, s_{14}, s_{15}\}$$

Step 9: Criterion Characterization and Data Collection

The nature of each criterion is presented in Table 3. Evaluation data were collected using two approaches: qualitative criteria (C1–C5, C9–C13) were assessed by experts on a 1–9 Likert scale, while quantitative criteria, including acquisition cost (C7) and implementation time (C8), were obtained through structured interviews with technology providers. Cost and time estimates were further refined based on expert input, considering system complexity and organizational capacity. Given that expert judgments were expressed in linguistic and approximate terms, all evaluations were converted into interval grey numbers to capture uncertainty and avoid forced precision.

The threshold values $u_{i_0j_0}^k$ are defined as follows; for qualitative criteria, 10e (e= Total expert scores); for C6, 90; for cost (C7), 100,000,000,000 Rials; and for time (C8), 12 months with a ± 6 -month tolerance.

Step 10: Determination of the Observation Effect Matrix

The complete observation effect matrix is presented in Table 8.

Table 8. Observation effect matrix of alternatives based on criteria.

	C1	C2	C3	C4	C5	C6	C7 (million Rial)	C8	C9	C10	C11	C12	C13
A1	90	79	70	90	88	45	70,000	14	58	52	83	89	90
A2	80	81	70	85	50	77	80,000	15	57	63	77	78	80
A3	75	45	50	75	89	66	150,000	18	32	26	54	84	64
A4	87	59	54	81	60	47	210,000	16	28	25	58	71	52
A5	73	73	88	80	59	58	60,000	18	41	33	60	72	54
threshold values	10	10	10	10	10	100	100,000	12	10	10	10	10	10

Step 11: The matrix of uniform effect was calculated using Eqs. (31)– (34), as presented in Table 9.

Step 12: Weighted synthetic effect matrix = criteria weights (Table 7) $\times$ uniform effect matrix (Table 9). Results: Table 10.

Step 13: Based on the data in Table 10 and applying Eq. (35), the synthetic effect vector for each alternative is calculated, leading to the final ranking.

$$R = [0.969, 0.833, 0.688, 0.375, 0.830]$$

Since all values $r_{11}, r_{12}, r_{13}, r_{14}, r_{15} > 0$, all evaluated alternatives satisfy the defined grey target. The final ranking is determined by maximizing the synthetic effect value:

$$\max_{1 \leq j \leq 5} \{r_{1j}\} = r_{11} = 0.969$$

Consequently, Alternative A1 (AI-based system) is identified as the highest priority for organizational smart transformation. The complete ranking order is:

1. A1: AI-based system ($r_{11} = 0.969$)
2. A2: IoT-based solution ($r_{12} = 0.833$)
3. A5: Mobile application platform ($r_{15} = 0.830$)
4. A3: Blockchain system ($r_{13} = 0.688$)
5. A4: Cloud computing platform ($r_{14} = 0.375$)

It should be noted that the statement all alternatives satisfy the grey target refers to the synthetic effect values ($r_{1j} > 0$), which represent the weighted aggregation of criteria, rather than the performance of each individual criterion. As shown in Table 9, some alternatives (e.g., A3 and A4) exhibit negative scores for C7 (Acquisition Cost) due to exceeding the predefined threshold. However, these are compensated by strong performance in other criteria (e.g., C5 and C1), resulting in positive overall synthetic effects.

This highlights a key property of the grey target method. it allows for compensatory trade-offs between criteria, where weaknesses in one dimension can be offset by strengths in others, provided the aggregated performance remains within the acceptable multi-dimensional hyperspace.

Table 9. The matrix of uniform effect of alternatives based on criteria.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	1.000	0.972	0.769	1.000	0.987	1.000	0.750	1.667	0.960	0.792	1.000	1.000	1.000
A2	0.875	1.000	0.769	0.938	0.506	0.418	0.500	1.750	1.000	1.000	0.918	0.861	0.875
A3	0.813	0.493	0.513	0.813	1.000	0.618	-1.250	2.000	0.440	0.302	0.603	0.937	0.675
A4	0.963	0.690	0.564	0.888	0.633	0.964	-2.750	1.833	0.360	0.283	0.658	0.772	0.525
A5	0.788	0.887	1.000	0.875	0.620	0.764	1.000	2.000	0.620	0.434	0.685	0.785	0.550

Table 10. Weighted matrix of synthetic effect of alternatives.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	0.113	0.060	0.084	0.049	0.117	0.064	0.078	0.100	0.058	0.053	0.057	0.034	0.104
A2	0.099	0.062	0.084	0.046	0.060	0.027	0.052	0.105	0.061	0.067	0.052	0.029	0.091
A3	0.092	0.031	0.056	0.039	0.118	0.039	-0.130	0.120	0.027	0.020	0.034	0.031	0.070
A4	0.109	0.043	0.061	0.043	0.075	0.061	-0.285	0.110	0.022	0.019	0.037	0.026	0.054
A5	0.089	0.055	0.109	0.042	0.073	0.049	0.104	0.120	0.038	0.029	0.039	0.026	0.057

The results of the grey target-based evaluation provide a clear prioritization among the proposed smart transformation alternatives. Based on the computed synthetic effect values, all alternatives achieve positive scores, indicating that they satisfy the predefined grey target and are feasible under the considered multi-criteria decision framework. However, a significant differentiation is observed in their overall performance levels.

Among the evaluated options, A1 (AI-powered seismic detection system) achieves the highest synthetic effect value (0.969), making it the most preferred alternative. This superior performance can be attributed to its strong alignment with the most influential criteria identified earlier, particularly performance efficiency (C1) and cybersecurity (C5). The results suggest that AI-based solutions provide substantial improvements in real-time data processing, accuracy, and system reliability, which are critical in seismological applications.

The second and third positions are occupied by A2 (IoT-based infrastructure) (0.833) and A5 (mobile platform) (0.830), respectively. The close proximity of their scores indicates comparable performance levels, although with different strengths. A2 demonstrates balanced performance across technical and organizational criteria, particularly in system integration and resource availability. In contrast, A5 shows strong performance in usability (C3) and cost efficiency (C7), making it an attractive option for enhancing user interaction and public engagement.

A3 (blockchain-based system) ranks fourth (0.688), despite achieving the highest score in cybersecurity (C5). Its lower overall ranking is primarily due to its poor performance in cost (C7) and resource-related criteria (C9 and C10), reflecting the high implementation complexity and infrastructure requirements associated with blockchain technologies.

Finally, A4 (cloud computing platform) is ranked last (0.375), mainly due to its significantly high acquisition cost and relatively weak performance in several organizational criteria. The negative impact of cost (C7), as reflected in the uniform effect matrix, substantially reduces its overall synthetic score despite moderate technical capabilities.

An important observation is that some alternatives (particularly A3 and A4) exhibit negative values in specific criteria, especially cost. However, due to the compensatory nature of the grey target method, these weaknesses are partially offset by strengths in other dimensions. This highlights the flexibility of the approach in capturing trade-offs among conflicting criteria and avoiding overly restrictive decision rules.

From a strategic perspective, the ranking results reinforce the findings of the weighting phase, emphasizing that solutions aligned with system performance, security, and operational reliability are prioritized over those with high cost or implementation complexity. The results also suggest

that decision-makers favor scalable and immediately impactful technologies, such as AI and IoT, over more infrastructure-intensive solutions like blockchain and cloud platforms. Overall, the findings provide a robust decision-support basis for prioritizing digital transformation investments in seismological systems. The proposed framework not only ranks alternatives but also reveals the underlying trade-offs, enabling policymakers to make informed and risk-aware decisions under uncertainty.

4.3 Sensitivity Analysis

To evaluate the stability and reliability of the obtained results, a sensitivity analysis was conducted using Monte Carlo simulation over 5,000 iterations (Cui et al, 2023). Figure 4 demonstrates a high degree of conformity between the baseline scores and the simulation averages. This alignment indicates that realistic variations in criterion weights do not significantly alter the overall ranking structure, confirming the model's internal robustness. Furthermore, Figure 4 visualizes the distribution of alternative scores under uncertainty. The highly concentrated distribution for Alternative A1, along with the minimal gap between its baseline and simulated average score, underscores its remarkable stability against weighting fluctuations. In contrast, the broader score distributions for Alternatives A3 and A5 reveal their higher sensitivity to weight changes and lower predictability.

Table 11 presents the probability of each alternative achieving different ranks. Based on these results, Alternative A1 holds the first rank with a 68.2% probability, demonstrating the highest stability among all options. Alternative A4, with a 25.8% probability for the first rank and a 58.9% probability for the second, is identified as a reliable backup option. Conversely, Alternative A3 did not achieve the first or second rank in any simulation iteration, reinforcing its lower priority. The high probability of Alternative A2 occupying the third rank positions it as a complementary, middle-ground solution.

The Tornado diagram in Figure 5 identifies criteria C8 (Implementation Time), C7 (Acquisition Cost), and C3 (Usability) as the most sensitive to weight changes. Consequently, more precise estimation of these criteria's importance is crucial for subsequent decision-making stages. Finally, the correlation matrix in Figure 6 shows that Alternatives A1, A3, and A4 exhibit similar behavioral patterns in response to weight changes, with their fluctuations being positively correlated. In contrast, Alternative A5 displays more independent behavior, showing weak correlation with the others.

These collective findings confirm that the model's final ranking is stable and reliable against uncertainties in criterion weights. Alternative A1 not only performs best in the baseline scenario but also maintains its superior performance across a significant portion of the uncertainty space. Therefore, a combined strategy prioritizing AI, Cloud computing, and IoT solutions presents an optimal, low-risk pathway for the smart transformation of the IRSC.

Table 11. Alternative ranking probability and stability from Monte Carlo simulation.

Alternative	Probability Rank 1	Probability Rank 2	Probability Rank 3	Robustness level
A1_AI	0.682	0.261	0.041	Very robust
A4_Cloud	0.258	0.589	0.123	Robust
A2_IoT	0.041	0.108	0.452	Relatively robust
A5_Mobile	0.019	0.042	0.284	Relatively robust
A3_Blockchain	0.000	0.000	0.100	Robust

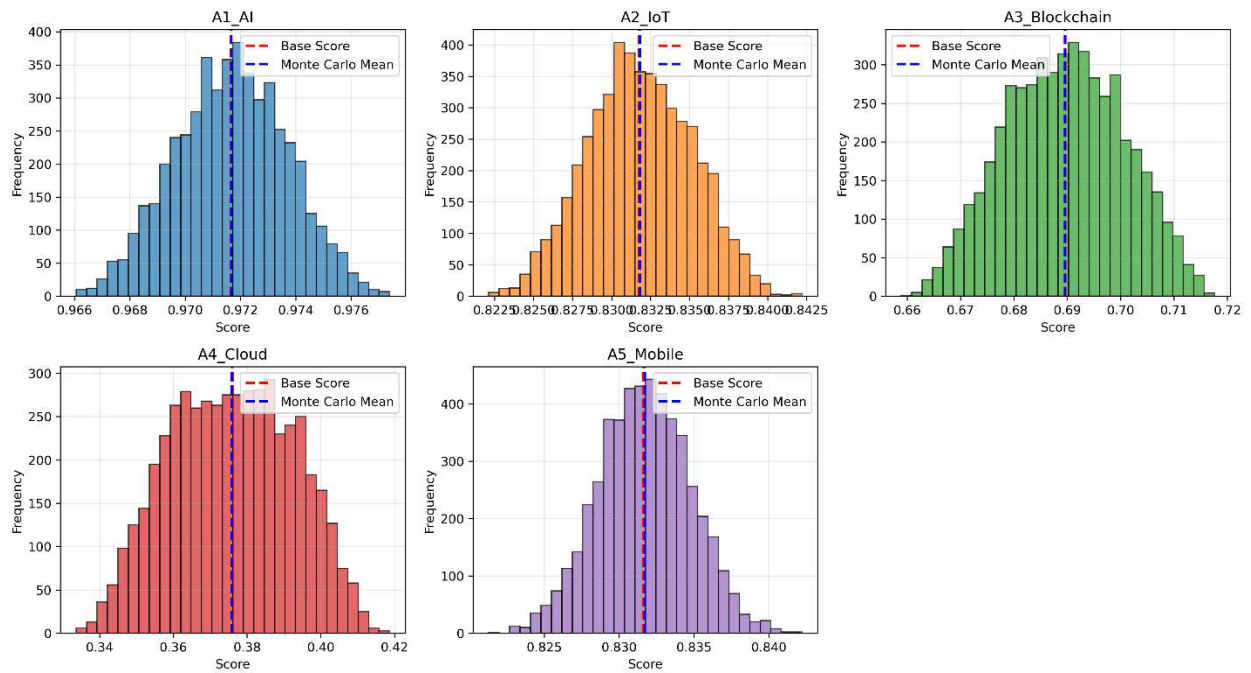


Figure 4. Score Distribution in Monte Carlo Simulation.

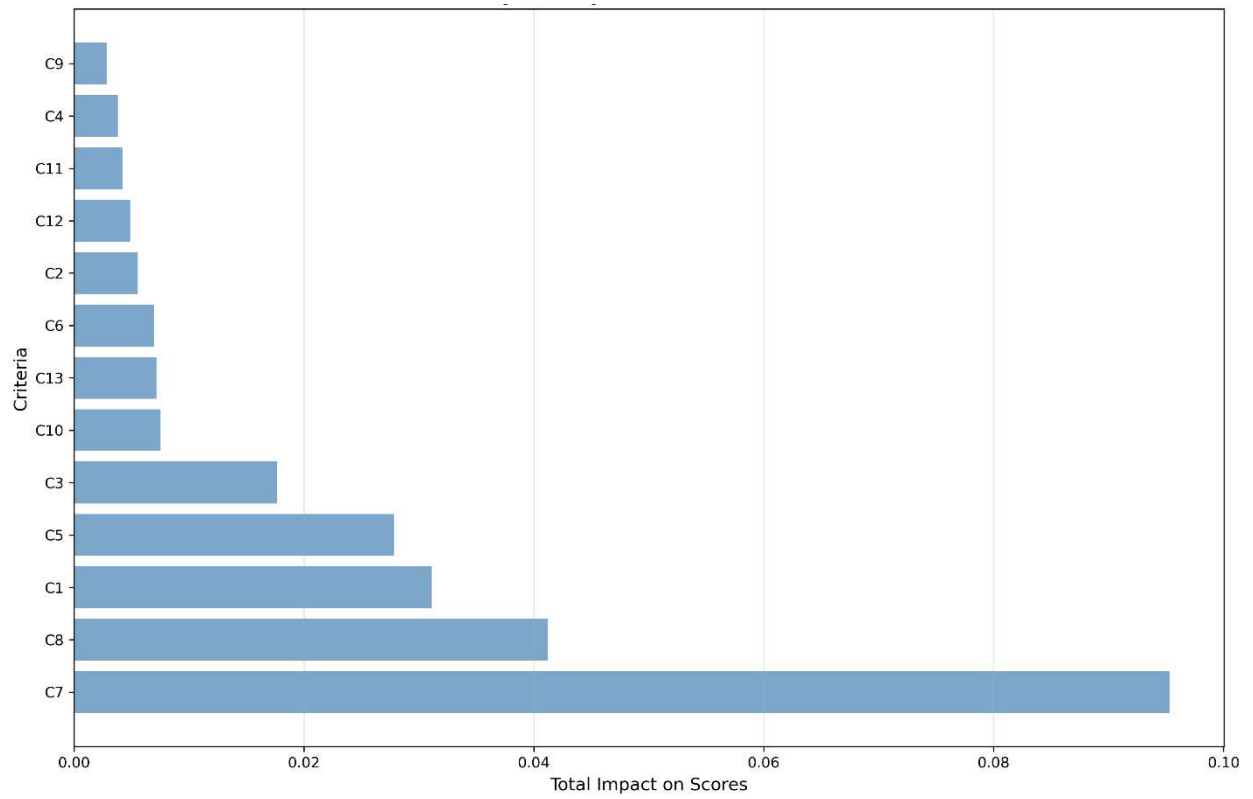


Figure 5. Tornado Analysis: Impact of Criteria on Final Score.

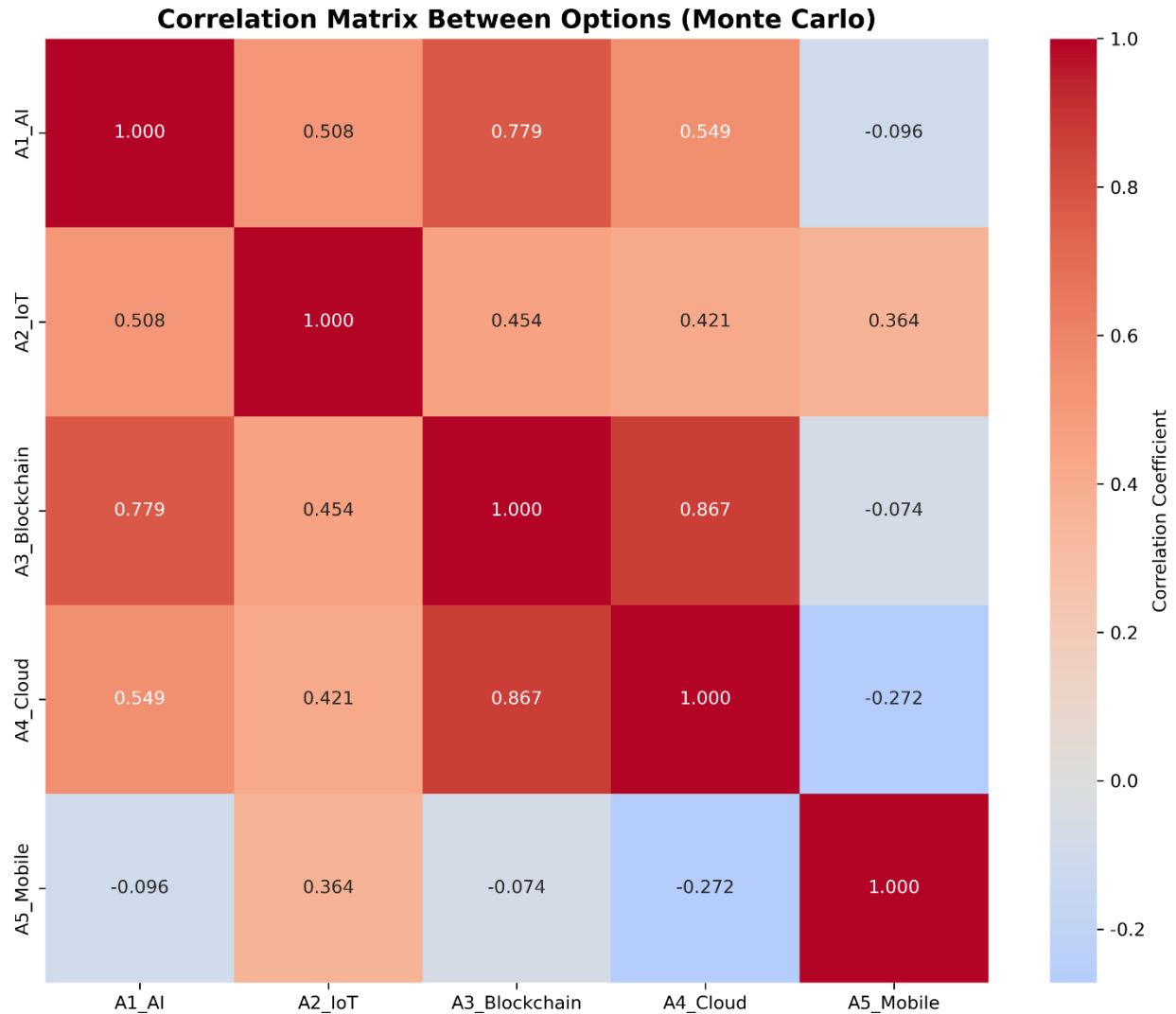


Figure 6. Correlation matrix Between alternatives across 5,000 Monte Carlo scenarios.

5. Discussion and Conclusion

The findings demonstrate that A1, the AI-powered seismic event detection and localization system, is the highest-priority smart transformation initiative for the IRSC, achieving the highest synthetic effect value (0.969). This result is consistent with the weighting analysis, in which performance and efficiency (C1), cybersecurity (C5), usability (C3), and acquisition cost (C7) emerged among the most influential evaluation criteria. The strong performance of A1 across these dimensions indicates that AI-based seismic analytics can provide a relatively strong balance between operational performance and organizational feasibility. Moreover, A1 maintained its first position in 68.2% of the simulated scenarios, providing evidence that its priority is not solely dependent on a single set of expert judgments. Nevertheless, this result should be interpreted as evidence of ranking stability within the specified uncertainty and sensitivity settings rather than as a guarantee of implementation success.

The ranking of the remaining alternatives provides further insight into the structure of the transformation decision. A2 (IoT-based smart stations) ranks second with a synthetic effect of 0.833, while A5 (mobile platform) follows closely with a value of 0.830. The small difference between these alternatives suggests that their relative priority is comparatively sensitive to the underlying evaluation conditions. A2 provides particular value through improved data acquisition, monitoring, and integration capabilities, whereas A5 performs strongly in usability and acquisition cost. Consequently, the two alternatives should not necessarily be regarded as mutually exclusive investments. Rather, their complementary characteristics provide a basis for sequential or partially parallel implementation depending on available resources and organizational priorities.

In contrast, A3 (blockchain-based data integrity system) ranks fourth (0.688), despite its strong performance on cybersecurity (C5). Its relatively weak performance on acquisition cost and digital resource availability reduces its aggregate performance. A4 (cloud-based seismic data platform) obtains the lowest score (0.375), primarily because of its substantial acquisition cost and weaker performance on several organizational and resource-related criteria. These results do not imply that blockchain or cloud technologies are unsuitable for seismological applications. Instead, they indicate that, under the criteria, thresholds, and organizational conditions considered in this study, their immediate priority is lower than that of the other alternatives. This distinction is important because technology prioritization is context-dependent and should not be interpreted as a general technological superiority ranking.

An important implication of the results is therefore that the ranking should be interpreted as a transformation roadmap rather than a single-technology selection problem. A1 can constitute the initial priority because it directly strengthens the analytical capability of the seismological system. A2 can subsequently strengthen the sensing and data-acquisition layer, while A5 can improve public accessibility and communication. Cloud infrastructure and blockchain capabilities can then be introduced when the organizational, financial, and technical conditions required for their effective deployment become more favorable. Such sequencing allows the organization to distribute investment over time and progressively develop the technological and organizational capabilities required for an integrated smart seismological system.

The weighting results provide an additional perspective on this prioritization. Cybersecurity (C5), performance and efficiency (C1), and usability (C3) receive the highest mean weights, whereas regulatory compliance (C12) and scalability (C4) receive comparatively lower weights. This pattern suggests that experts place greater emphasis on operational effectiveness, system security, and practical usability than on factors associated with longer-term expansion or regulatory considerations. The relatively high weight assigned to acquisition cost (C7) further indicates that technological performance cannot be considered independently of financial feasibility in a resource-constrained public organization. The results therefore support a balanced decision logic in which technical benefits must be evaluated together with implementation feasibility and organizational constraints.

The grey representation of criterion weights provides an additional form of information that is not available from conventional crisp weighting approaches. The interval width reflects differences in expert judgments and therefore provides an indication of the degree of consensus surrounding each criterion. For example, C5 has an interval of approximately [0.1057, 0.1305], with a width of 0.0248, indicating greater variation in expert assessments of the importance of cybersecurity. In contrast, C12 has a substantially narrower interval of approximately [0.0303, 0.0368], with a width of 0.0065. The latter indicates greater agreement among the experts regarding its relative importance. Thus, the grey framework does not only produce a ranking of criteria and alternatives;

it also provides decision-makers with information about where expert consensus is strong and where additional investigation or deliberation may be warranted.

This feature has direct managerial implications. Managers responsible for digital transformation can use the proposed framework to distinguish between a priority signal and a confidence signal. A criterion with a high weight but a relatively wide interval may deserve additional data collection, expert consultation, or targeted sensitivity analysis before substantial resources are committed. Conversely, a criterion with a stable interval and a consistent influence on the ranking can provide greater confidence in resource-allocation decisions. This makes the framework potentially useful not only for selecting technologies but also for identifying areas in which the organization's knowledge base remains uncertain.

From an implementation perspective, the results suggest that digital transformation should be managed as a portfolio of interconnected initiatives rather than as a one-time technology adoption decision. Prioritizing A1 does not imply postponing all other technologies indefinitely. Instead, the findings support a phased strategy in which analytical intelligence, sensing infrastructure, and user-facing capabilities are progressively integrated. Such sequencing can reduce the organizational burden of simultaneous technological change, allow lessons from early projects to inform subsequent investments, and provide opportunities to revise priorities as information about technology performance and organizational readiness improves.

Three practical recommendations follow from these findings. First, IRSC management should prioritize the development or acquisition of AI-based seismic detection and localization capabilities as an initial transformation initiative. Second, IoT-based station modernization and mobile information services should be considered complementary components of subsequent transformation stages, particularly where they can be integrated with the analytical capabilities developed through A1. Third, acquisition cost, implementation time, usability, cybersecurity, and organizational resource availability should be monitored throughout implementation because changes in these factors may alter the relative attractiveness of competing projects. Consequently, technology selection should be treated as an adaptive decision process rather than a fixed decision made independently of implementation experience.

The findings also have broader implications beyond the specific case of the IRSC. Scientific and governmental organizations frequently operate with limited historical data, heterogeneous expert knowledge, resource constraints, and technologies whose performance and implementation requirements are difficult to estimate precisely. In such settings, the combination of grey uncertainty representation and multi-criteria evaluation can provide a structured means of transforming qualitative organizational knowledge into actionable priorities. The proposed approach can therefore potentially be adapted to other data-intensive public institutions facing comparable technology-selection and digital-transformation decisions, although such transferability requires recalibration of the criteria, thresholds, alternatives, and expert assessments for each organizational context.

Despite these contributions, several limitations should be acknowledged. First, the analysis relies on the judgments of a panel of ten experts. Although the panel included senior managers and current or former directors with relevant organizational experience, expert-based assessment remains inherently subjective. Second, the alternatives and criteria were evaluated within the specific technological and organizational context of the IRSC; consequently, the resulting ranking should not be generalized directly to other seismological institutions or geographic settings. Third, the analysis represents uncertainty through grey intervals within predefined ranges, but does not explicitly incorporate dynamic cost-benefit relationships, implementation risks, or changes in

organizational conditions over time. Finally, the current analysis evaluates alternative priorities before large-scale implementation and therefore does not provide empirical evidence of the realized operational benefits of the selected technologies.

These limitations provide several directions for future research. Future studies could develop multi-objective decision models that jointly consider cost, operational risk, sustainability, implementation time, and technological performance. Longitudinal models could also examine how criterion weights and alternative priorities evolve as organizational capabilities mature and technologies become more widely adopted. In addition, operational data collected from seismic networks could be incorporated to complement expert judgments and reduce dependence on subjective assessments. Pilot implementation of the highest-ranked alternatives would provide an important basis for validating the predicted benefits and testing whether the proposed ranking remains consistent with observed performance. Finally, future research could investigate an integrated AI–IoT architecture in which intelligent seismic analytics, smart sensing infrastructure, and public-facing early-warning services operate as interconnected components of a broader digital transformation strategy.

Overall, this study contributes an uncertainty-aware decision-support framework for prioritizing smart transformation initiatives in a data-intensive scientific-governmental institution. Its contribution lies not only in identifying A1 as the highest-priority alternative, but also in showing how grey interval information can expose differences in expert consensus and how multi-criteria evaluation can translate these uncertain judgments into a phased transformation roadmap. The findings demonstrate that effective digital transformation in seismological systems is not simply a matter of adopting the most advanced technology; rather, it requires aligning technological capability with security, usability, cost, organizational readiness, and implementation feasibility. By integrating these considerations into a transparent decision process, the proposed framework provides a practical basis for more informed and adaptive technology investment decisions.

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Data Availability Statement

All data generated or analyzed during this study are included in the manuscript. Python codes that support the findings of this study are available from the corresponding author upon request.

Compliance with Ethical Standards

This study involved expert questionnaires and interviews. No sensitive personal data were collected. All participants gave informed consent. Formal ethics approval was not required due to the non-sensitive, survey-based nature of the research. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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