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Digital twin use-case prioritisation for sustainability in smart manufacturing: A multi-criteria decision analytics approach

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ABSTRACT

Manufacturers face growing pressure to invest in digital twins for sustainability and supply chain resilience. Yet, no systematic framework exists to guide the prioritisation of use cases amid competing objectives and practical resource constraints. Digital twins, which integrate real-time sensing, simulation, big data analytics, and artificial intelligence, are among the frontier technologies reshaping industrial production, and their prioritisation is a core socio-economic planning problem of the Industry 4.0 transition. This study addresses this gap by developing an interview-informed multi-criteria decision analysis (MCDA) that prioritises seven recurring digital twin use cases based on sustainability and operational benefits, as well as implementation and scaling burdens. The decision model scores sustainability benefits and feasibility burdens directly. At the same time, implications for supply chain resilience are interpreted ex post through the comparative positioning of the use cases rather than being scored as a separate family of criteria. Drawing on 50 semi-structured expert interviews conducted across 27 countries, the analysis combines qualitative content analysis with a pipeline comprising TOPSIS, VIKOR, and Stochastic Multicriteria Acceptability Analysis (SMAA). Criteria weights derived from interview salience reveal that data readiness, legacy integration, and interoperability effort dominate the prioritisation. The energy and facilities twin ranks first in TOPSIS. In contrast, the supply chain and scenario twin emerge as the VIKOR compromise solution and the most robust first-rank option under interview-centred weight uncertainty (85.6% probability). Sensitivity analysis shows that product passport and circularity twins rise to the top when sustainability benefits are privileged over feasibility burdens. The results yield a prioritisation framework for digital twin investment applicable to manufacturers, industry consortia, and policymakers designing Industry 4.0 roadmaps. Prescriptive implications address both private-sector technology prioritisation and staged implementation, and public policy on digital infrastructure, interoperability standards, and sustainability regulation, with attention to emerging economies.

1. Introduction

Compounding global disruptions, including pandemics, geopolitical realignments, and climate regulation, have made the simultaneous pursuit of operational sustainability and supply chain resilience a central challenge for manufacturing firms and policymakers alike [1–3]. Resilience, understood as the capacity to anticipate, absorb, and recover from disruptions [4,5], now shapes investment decisions and regulatory design across advanced and emerging economies. Concurrently, Industry 4.0 technologies (AI, IoT, blockchain, and digital twins) are transforming how organisations monitor operations, coordinate supply networks, and manage uncertainty [6–8].

Digital twins, defined as dynamic virtual replicas of physical assets or systems that are continuously synchronised with real-time data to support monitoring, simulation, and decision-making [9,10], have attracted particular attention. As a frontier technology that fuses the Internet of Things, big data analytics, simulation, and increasingly artificial intelligence, the digital twin sits at the centre of the Industry 4.0 technology portfolio; deciding which of its use cases to deploy first is therefore emblematic of the broader socio-economic planning challenge of directing frontier technology investment toward sustainability objectives. Applications now span energy management, predictive

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maintenance, quality control, supply chain scenario planning, and product lifecycle traceability [11–13], and recent reviews position digital twins as potentially transformative enablers of both sustainability and resilience in manufacturing [14–16].

Yet a significant gap separates technological potential from deployment reality. The literature remains predominantly technology-centric, concentrating on architectural frameworks and proof-of-concept demonstrations [17–19] rather than the prioritisation problem practitioners face: given limited budgets, heterogeneous legacy systems, and competing objectives, which digital twin use cases should be pursued first? This is inherently a multi-criteria decision problem involving trade-offs between sustainability benefits and implementation burdens that vary across organisational contexts, regulatory environments, and levels of digital maturity [20,21].

Multi-criteria decision analysis (MCDA) offers established methods for such trade-off problems. TOPSIS [22], VIKOR [23], and SMAA [24,25] are widely used in operations research to rank alternatives under conflicting criteria and uncertain preferences [26]. Although applied to technology selection and sustainability assessment in supply chains [27,28], these methods have not been directed at digital twin use-case prioritisation for sustainability-oriented investment decisions with implications for supply chain resilience. Without such a structured approach, organisations risk misallocating resources toward use cases that are technically premature or misaligned with their most pressing needs.

This paper addresses the gap by developing an interview-informed MCDA that ranks seven digital twin use cases against sustainability and performance benefits and implementation burdens. Drawing on 50 expert interviews across 27 countries, it combines qualitative content analysis with a TOPSIS–VIKOR–SMAA pipeline to produce a prioritisation that is empirically grounded and methodologically robust. To set expectations precisely: supply chain resilience is not operationalised as a scored criterion family in the decision model; the resilience implications of the ranked use cases are developed interpretively, ex post, from the comparative positioning of the alternatives. The framework serves as a decision support tool for technology investment prioritisation under uncertainty, relevant to manufacturers, industry consortia, and public policymakers designing Industry 4.0 roadmaps and sustainability regulation.

Four contributions follow. First, the study provides a multi-criteria prioritisation of digital twin use cases for sustainability-oriented investment decisions in smart manufacturing. It discusses the implications of this prioritisation for supply chain resilience. Second, it introduces an interview-informed MCDA methodology that translates practitioner judgement into quantitative scores and salience-based weights, offering a replicable approach where performance data are scarce. Third, it assembles TOPSIS, VIKOR, and SMAA into a replicable decision-analytics pipeline that accounts for method sensitivity, compromise logic, and weight uncertainty, demonstrating how established operations research tools can be combined into an integrated business-analytics workflow for technology investment decisions. Fourth, it derives prescriptive implications for private investment prioritisation and staged implementation, and for public policy on digital infrastructure and sustainability regulation, with attention to emerging economies.

The remainder is organised as follows. Section 2 reviews the literature on digital twins, supply chain resilience, and MCDA-based prioritisation. Section 3 presents the methodology. Section 4 reports results, including sensitivity and robustness analyses. Section 5 discusses the findings in relation to the literature. Section 6 presents conclusions, managerial and policy implications, limitations and directions for future research.

2. Literature review

The digital twin concept, originating in product lifecycle management [9], denotes a virtual replica of a physical entity synchronised through real-time data for monitoring, simulation, and optimisation [10,11]. Systematic reviews document its rapid expansion in manufacturing, with applications in design optimisation, process control, predictive maintenance, quality assurance, scheduling, and energy management [12,13,17]. The enabling technology stack (IoT, cloud computing, machine learning, interoperability standards) varies markedly in maturity across firms, sectors, and countries, producing a highly uneven adoption landscape [16,18,19,29]. Ivanov [30] proposes a seven-element framework for conceptualising digital twins in supply chain and operations management, encompassing technology, people, management, organisation, scope, task, and modelling dimensions. A growing body of work connects digital twins to sustainability: Kamble et al. [14] identify energy optimisation, waste reduction, and lifecycle traceability as primary channels; He and Bai [31] note persistent gaps between conceptual frameworks and empirical deployment; and circular economy applications are explored by Mügge et al. [32], Polimetla et al. [33], and Hirata et al. [34], who use topic modelling to map digital twin research priorities across supply chain management. Reference models by Leng et al. [35] and Lu et al. [36] systematise digital twin architectures and design frameworks for smart manufacturing systems. Nevertheless, the prevailing orientation remains technology-centric: most contributions advance frameworks or demonstrate isolated applications, with limited engagement with the strategic question of prioritising use cases for comparative use under resource and institutional constraints.

Supply chain resilience, the adaptive capability to prepare for, respond to, and recover from disruptions while sustaining performance [4,5,37], has become a central organising concept in operations management, with Wieland and Durach [38] distinguishing engineering resilience (bouncing back) from ecological resilience (adapting forward). Ivanov [39] traces the transformation of supply chain resilience research during the COVID-19 pandemic, documenting a shift toward viability, stress testing, and digital twin-enabled adaptive control. Digital technologies are increasingly positioned as enablers of predictive and prescriptive disruption management [40,41], and the ripple effect literature demonstrates how digital visibility can contain the propagation of disruption through networked structures [2]. Ivanov and Dolgui [15] theorise the digital supply chain twin for real-time risk management; Ivanov [42] extends this to an intelligent digital twin for stress testing and viability; and Ivanov [43] draws on immune-system analogies to propose formal resilience models that combine adaptation and redundancy. Most recently, Ivanov [44] developed conceptual and formal models for the design, adaptation, and control of digital twins within supply chain ecosystems. Applied evidence corroborates the potential: Burgos and Ivanov [45] show resilience improvements in food retail through digital twin simulation; Badakhshan and Ball [46] deploy hybrid modelling for digital twin-based supply chain master planning under disruptions; Maheshwari et al. [47] develop a real-time planning framework for food supply chains; Hossain et al. [48] find significant resilience effects in Bangladeshi manufacturing; Roman et al. [49] review the state of the art of digital twins for supply chain resilience; and Ruel et al. [50] operationalise the concept of supply chain viability. A shared limitation of these contributions is the treatment of the digital twin as a monolithic technology, overlooking the fact that functionally distinct use cases (energy monitoring, scenario planning, product passport traceability, predictive maintenance) entail different data requirements, governance arrangements, and resilience contributions.

The broader Industry 4.0 literature contextualises the conditions under which digital twin investments deliver sustainability and resilience returns. Xu et al. [6] and Liao et al. [8] survey the field and call for empirical studies on implementation barriers and socio-economic impacts. Frank et al. [7] find that adoption follows a staged trajectory in which foundational technologies (sensors, connectivity) precede advanced applications (digital twins, AI), a finding directly relevant to this paper's prioritisation logic. Ghobakhloo [21] maps out Industry 4.0 sustainability opportunities while cautioning that realisation requires strategic alignment rather than technology-led adoption. Luthra and Mangla [20] document eighteen challenges to Industry 4.0 initiatives for supply chain sustainability, spanning organisational, technological, strategic, and legal-ethical dimensions, several of which closely mirror the burden criteria in the present MCDA. Bag et al. [51] link Industry 4.0 to advances in manufacturing capabilities for sustainable development, and Moeuf et al. [52] show that SMEs face disproportionate barriers to adoption. More recently, Jackson et al. [53] propose a capability-based framework for analysing generative AI in supply chain and operations management, and Li et al. [54] demonstrate end-to-end supply chain resilience management using deep learning and explainable AI, illustrating the convergence of frontier analytics with resilience objectives that motivates the present study.

Multi-criteria decision analysis provides the methodological foundation for this study. TOPSIS [22] ranks alternatives by geometric distance to ideal-best and ideal-worst solutions and is among the most widely applied MCDA methods in operations research [26]. VIKOR [23, 55] offers a compromise logic that balances aggregate utility against maximum individual regret. This distinction is analytically consequential when a single bottleneck (e.g., poor data readiness) can block an entire deployment. SMAA [24,25,56] addresses fixed-weight assumptions by exploring the weight space stochastically, producing rank acceptability indices that quantify robustness to preference uncertainty; Pelissari et al. [57] document its growing use in environmental planning and public-sector decision support. These methods have been applied to sustainability-related supply chain decisions [27,28,58] and are complementary to Data Envelopment Analysis, a frontier efficiency method rooted in the socio-economic planning sciences tradition [59,60]. However, MCDA has not been applied to the prioritisation of digital twin use cases for sustainability-oriented investment decisions with implications for supply chain resilience, despite the problem's multi-criteria trade-off structure, stakeholder heterogeneity, and preference uncertainty.

3. Method

3.1. Research design and data

The study adopts a sequential mixed-method design that connects qualitative evidence to a formal multi-criteria decision framework (Fig. 1). The empirical base comprises 50 semi-structured interviews with Industry 4.0 and smart manufacturing experts (researchers, consultants, and practitioners) conducted between June 2024 and June 2025, yielding approximately 48 h of recorded material. Data collection began at the Smart Factory Summit 2024 using purposive sampling to recruit information-rich participants. Then it expanded through snowball sampling, complemented by additional expert interviews at the Smart Factory Summit 2025 (Switzerland). Explicit inclusion criteria governed participant selection at both stages. Eligible participants were required to (i) hold a current professional role as a researcher, consultant, or industry practitioner in Industry 4.0 or smart manufacturing; (ii) have direct professional involvement with the deployment, study, or advisory support of digital manufacturing technologies, including digital twins or closely related Industry 4.0 technologies; and (iii) occupy a senior research, managerial, or advisory position providing first-hand insight into technology adoption and investment decisions. Individuals whose exposure to Industry 4.0 was peripheral (for example, in commercial or general management roles without technology responsibility) and early-career profiles lacking direct project experience were excluded.

Candidates identified through snowball referrals were screened against the same criteria before being invited. The sample reached theoretical saturation. Participants represented 27 countries: Argentina, Australia, Austria, Brazil, Cameroon, China, Croatia, France, Germany, Greece, Hungary, India, Italy, Japan, Kenya, Saudi Arabia, Malaysia, Mexico, Morocco, Serbia, South Korea, Spain, Sweden, Switzerland, Tunisia, the United Arab Emirates, and the United States. The interview guide comprised ten core prompts addressing definitions of Industry 4.0 and smart factories, technology evolution, business and sustainability benefits, SME adoption barriers, skills, future trends, and collaboration versus competition. The guide was intentionally broad and did not include a pre-specified list of digital twin use cases, thereby reducing priming and supporting the elicitation of practitioner-relevant prioritisation dimensions. Standard ethical procedures for qualitative research were followed. Participation was voluntary, and all participants were informed, before the interview, of the purpose of the study, the intended academic use of the data, and their right to withdraw at any time. Informed consent was obtained from each participant, including explicit consent for audio recording. Transcripts were anonymised before analysis, and quotations are reported without identifying attributes.

Transcripts were analysed via thematic analysis [61], supported by MAXQDA software for coding, memoing, and retrieval. Analysis proceeded through repeated close reading, first-cycle coding, and iterative consolidation into second-order themes through research-team discussions until code boundaries stabilised. The goal of this phase was to identify stable decision dimensions that participants use when explaining adoption feasibility and prioritisation, rather than to produce descriptive counts of opinions. The stabilised second-order themes were then translated into the alternative and criterion dictionaries used in the rule-based coding stage reported below.

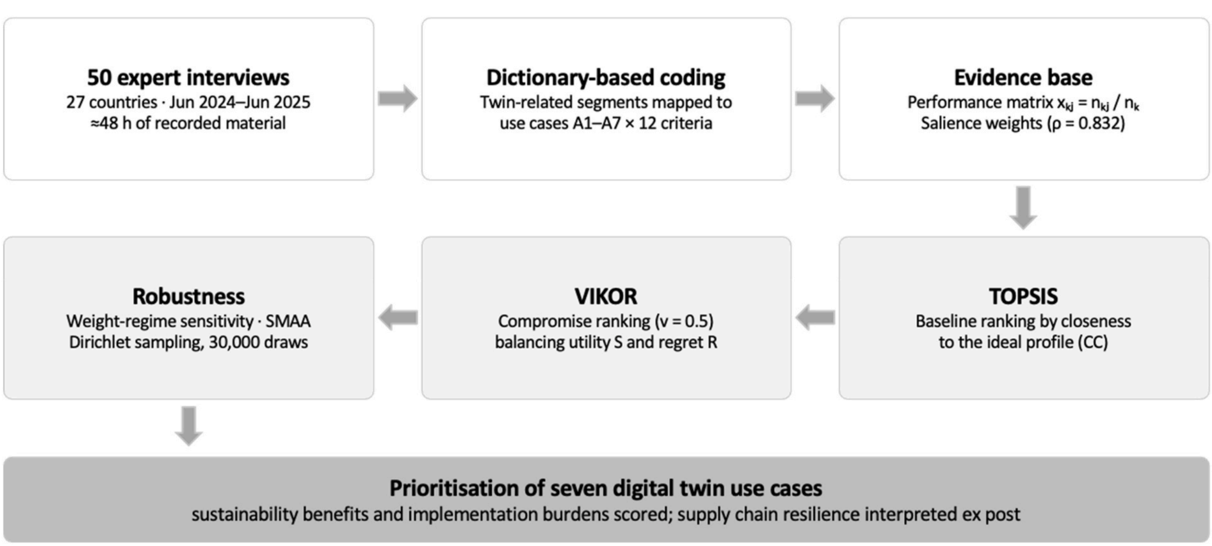

Fig. 1. Methodological pipeline.

3.2. Analytical approach: interview-informed MCDA as a decision support tool

The analysis integrates computer-assisted qualitative content analysis with multi-criteria decision analysis (MCDA), combining qualitative expert insight with formal multi-criteria evaluation to construct a replicable, analytics-based decision-support tool for digital twin investment prioritisation. The objective is to rank recurring digital twin use cases, treated as decision alternatives, by jointly weighing (i) sustainability and performance benefits against (ii) implementation and scaling burdens that interviewees repeatedly identify. MCDA methods are well established in operations research for structuring prioritisation problems characterised by trade-offs rather than a single outcome metric [22–24]. The approach adopted here extends their application to the domain of frontier technology selection for resilient and sustainable supply chains, where decision-makers must balance anticipated sustainability gains against the feasibility of scaling digital infrastructure across heterogeneous industrial environments. A methodological advantage of MCDA over black-box machine learning approaches is its inherent interpretability: every weight, score, and ranking step is transparent and auditable, enabling decision-makers to trace how changes in inputs affect outputs without recourse to post-hoc explainability techniques.

The choice of TOPSIS, VIKOR, and SMAA from the broader MCDA toolbox follows from the structure of the prioritisation problem and the nature of the evidence base. TOPSIS [22] provides a transparent, fully compensatory baseline ranking that is well suited to a performance matrix constructed from coded interview evidence. VIKOR [23,55] complements it with a compromise logic that penalises alternatives suffering severe shortfalls on any single criterion, an analytically consequential property in this setting because a single bottleneck, such as poor data readiness, can block an entire deployment. SMAA [24,25,56] then relaxes the fixed-weight assumption by exploring the weight space stochastically, which is appropriate here because the weights are derived from interview salience, an informative but imperfect proxy for stakeholder preferences. Together, the three methods address the principal vulnerabilities of any single deterministic ranking: aggregation logic, compensability, and weight uncertainty [58]. Alternative methods were considered and set aside for identifiable reasons. The Best-Worst Method [62] and the Analytic Network Process [63] are preference-elicitation techniques that require structured pairwise judgements from a live decision panel, whereas the present weights are derived from the salience structure of an existing interview corpus; the ANP would additionally require specifying a network of interdependencies among criteria that the evidence base cannot support. Outranking methods such as PROMETHEE [64] require that preference functions and thresholds be specified for each criterion, introducing analyst degrees of freedom with no empirical anchor in the coded data. Fuzzy variants address imprecision in linguistic judgements elicited directly from experts; in the present design, imprecision enters principally through the weights and is handled explicitly by SMAA's stochastic treatment of the weight space. These alternatives remain attractive in settings where a decision panel is available for direct elicitation, a configuration identified as a future research avenue in Section 6.4.

3.3. Alternatives and criteria

Seven digital twin use cases serve as decision alternatives: (A1) Design and lifecycle twin; (A2) Energy and facilities twin; (A3) Maintenance and asset health twin; (A4) Process performance twin; (A5) Quality and scrap twin; (A6) Supply chain and scenario twin; and (A7) Product passport and circularity twin.

The criteria set comprises 12 dimensions, divided into benefits (to be maximised) and burdens (to be minimised). The six benefit criteria are: emissions impact, energy impact, materials and waste impact, circularity support, reporting and compliance support, and operational performance gains. The six burden criteria are: data readiness effort, standards and connectivity effort, skills and adoption effort, integration with legacy systems, security and data control risk, and cost and investment effort. The framework directly operationalises sustainability benefits and implementation burdens. Supply chain resilience is not introduced as a separate family of criteria in the scoring model; instead, resilience implications are interpreted ex post, particularly for use cases such as A6 that support scenario analysis, visibility, and adaptive coordination. Accordingly, the results should be read as a sustainability-oriented prioritisation with resilience implications, rather than as a direct measure of resilience performance.

3.4. Coding and construction of the evidence base

Because the interviews covered digital twins in relation to smart manufacturing and sustainability, we extracted all passages that explicitly discussed digital twin concepts (for example, 'digital twin', 'twin', and closely related expressions used by participants). These extracted passages constitute the analytical basis for the performance matrix used in the MCDA. Each extracted passage was then coded using two rule-based dictionaries implemented as regular-expression patterns: an alternative dictionary (A1–A7), assigning each segment to one or more digital twin use cases, and a criteria dictionary (12 criteria), assigning the same segment to one or more benefit or burden dimensions. The dictionaries were iteratively refined through manual review of randomly selected coded segments, discussion of ambiguous cases within the research team, and adjustment of keyword patterns until stable coding rules were obtained.

Let S denote the set of twin-related segments. For each segment $s \in S$, define the indicator variable $Isk \in \{0, 1\}$ for whether segment s is coded to alternative k, and $Jsj \in \{0, 1\}$ for whether it is coded to criterion j. Two counts are then computed.

$$n_k = \sum_{s \in S} I_{sk}$$

$$n_{kj} = \sum_{s \in S} I_{sk} J_{sj}$$

The alternative-by-criterion performance score is defined as a conditional share:

$$x_{kj} = \frac{n_{kj}}{n_k}$$

This normalisation ensures that an alternative does not receive inflated scores simply because it is mentioned more frequently in the corpus.

3.5. Criteria weights from interview salience

Criteria weights are derived from interview salience, operationalised as a combination of breadth (coverage across interviews) and intensity (mention frequency within twin-related segments). For each criterion j, interview coverage is defined as:

$$c_j = \sum_{i=1}^{N} \mathbf{1}\left(\exists\, s \in S_i \text{ such that } J_{sj} = 1\right),$$

where S_i denotes the set of twin-related segments in the interview i, and $\mathbf{1}(\cdot)$ is an indicator function. Mention frequency is defined as:

$$f_j = \sum_{s \in S} J_{sj}.$$

To limit the influence of repeated mentions in a small number of segments, intensity is log-scaled and normalised:

$$t_j = \frac{\ln\left(1+f_j\right)}{\max_j \ln\left(1+f_j\right)}.$$

The salience score is then:

$$s_j = c_j + \rho\, t_j,$$

and the final weight is obtained by normalisation:

$$w_j = \frac{s_j}{\sum_j s_j}.$$

In the interview-centred weighting used in this study, ρ it was set to 0.832 so that coverage remains the primary driver of importance while intensity differentiates criteria with similar coverage. The ρ was chosen to be below 1 so that the intensity adjustment (based on log-scaled frequency) remains bounded and cannot outweigh a one-unit change in interview coverage. In this specification, coverage therefore determines the main structure of the weights, while intensity refines weights among criteria with similar coverage.

3.6. TOPSIS ranking (baseline)

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is employed as the baseline MCDA method, ranking alternatives by their proximity to an ideal profile that combines high benefits with low burdens [22].

Given the performance matrix $X = [x\text{kj}]$, TOPSIS first normalises each criterion:

$$r_{kj} = \frac{x_{kj}}{\sqrt{\sum_k x_{kj}^2}}$$

It then applies the criteria weights:

$$v_{kj} = w_j\, r_{kj}$$

The ideal-best and ideal-worst vectors are defined as:

$$A_j^+ = \begin{cases} \max v_{kj}, j \in \text{benefits} \\ \min v_{kj}, j \in \text{burdens} \end{cases}$$

$$A_j^- = \begin{cases} \min v_{kj}, j \in \text{benefits} \\ \max v_{kj}, j \in \text{burdens} \end{cases}$$

Distances to the ideal-best and ideal-worst profiles are computed as:

$$D_k^{\ +} = \sqrt{\sum_j \left(v_{kj} - A_j^+\right)^2}$$

$$D_k^{\ -} = \sqrt{\sum_j \left(v_{kj} - A_j^-\right)^2}$$

The TOPSIS closeness coefficient is:

$$CC_k = \frac{D_k^{\ -}}{D_k^{\ +} + D_k^{\ -}}$$

Alternatives are ranked in descending order of CCk.

3.7. VIKOR compromise ranking

VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) serves as a complementary method that embodies a compromise logic under conflicting criteria [23,55]. Unlike TOPSIS, which measures geometric distance to an ideal point, VIKOR identifies the alternative closest to a compromise solution by balancing aggregate group utility against maximum individual regret.

For each criterion j, define the best and worst reference values. For benefit criteria:

$$f_j^{\ *} = \max\ x_{kj}, f_j^{\ -} = \min\ x_{kj}$$

For burden criteria:

$$f_j^{\ *} = \min\ x_{kj}, f_j^{\ -} = \max\ x_{kj}$$

The normalised gap to the best value is:

$$d_{kj} = \frac{f_j^{\ *} - x_{kj}}{f_j^{\ *} - f_j^{\ -}}$$

Two composite measures are then computed:

$$S_k = \sum_j w_j\, d_{kj}$$

$$R_k = max_j\left(w_j\, d_{kj}\right)$$

Let $S^* = min_\text{k}\, S_\text{k}$, $S- = max_\text{k}\, S_\text{k}$, $R^* = min_\text{k}\, R_\text{k}$, and $R\text{-} = max_\text{k}\, R_\text{k}$. The VIKOR compromise index is:

$$Q_k = v\, \frac{S_k - S^*}{S^- - S^*} + (1 - v)\, \frac{R_k - R^*}{R^- - R^*}$$

The baseline uses $v = 0.5$. Sensitivity checks are performed with $v = 0.25$ and $v = 0.75$.

3.8. Robustness analyses: weight sensitivity and SMAA

Two robustness procedures are applied.

First, a weight-rebalancing sensitivity analysis is conducted by holding the performance matrix X fixed and rescaling the weights to represent different priority regimes. Let B denote the set of benefit criteria and C the set of burden criteria. For a scenario with target shares pB and pC (with $p\text{B} + p\text{C} = 1$), weights are rescaled as:

$$w_j^{(s)} = \begin{cases} w_j \cdot \dfrac{p_B}{\sum_{j\in B} w_j}, j \in B \\[2ex] w_j \cdot \dfrac{p_C}{\sum_{j\in C} w_j}, j \in C \end{cases}$$

Three regimes are tested: sustainability-first (pB, pC) = (0.60, 0.40); feasibility-first (0.30, 0.70); and equal weights $wj(s) = 1/12$.

Second, Stochastic Multicriteria Acceptability Analysis (SMAA) is implemented to assess the robustness of the VIKOR ranking under weight uncertainty [24,25,56,57]. Weight vectors are sampled repeatedly, and VIKOR is recomputed to obtain rank acceptability indices and expected ranks. Two weight distributions are considered. In the interview-centred case, the Dirichlet concentration parameter was set to k = 50. SMAA results are based on 30,000 Monte Carlo draws. The concentration parameter k controls how tightly sampled weights cluster around the baseline salience vector: higher k implies less dispersion; lower k implies greater dispersion. We set k = 50 to represent moderate dispersion around the interview-salience weights; the identity of the most robust first-ranked use case remains unchanged in checks with k between 20 and 100. No fixed random seed was set (the code used the default random state). In the interview-centred case, weights are sampled from a Dirichlet distribution centred on the baseline weight vector w_0, with concentration parameter k:

$$w \sim \text{Dirichlet}(k\, w_0)$$

In the uniform stress test:

$$w \sim \text{Dirichlet}(1)$$

For each Monte Carlo draw, a VIKOR ranking is computed, and rank frequencies are aggregated into P (rank $= r$), P (top 2), P (top 3), and expected rank.

3.9. Interpretive scope

The framework yields prioritisation and robustness results that support prioritisation discussions across contexts shaped by regulatory pressure, resource constraints, and supply chain resilience objectives. It does not estimate the causal effects of digital twins on sustainability outcomes; rather, it translates practitioner judgements into a structured, reproducible analytics pipeline that offers a transferable decision-support tool for diverse institutional and economic environments. It does not model interdependencies, complementarities, or optimal transition paths between use cases and therefore should not be interpreted as a formal sequencing model.

4. Results

4.1. Criteria weights

Table 1 reports the interview-salience criteria weights. Implementation burdens dominate the weight structure: data readiness (22.0%), legacy integration (14.8%), and interoperability effort (13.3%) collectively account for half the total weight, indicating that practitioners treat scaling constraints as decisive in determining whether digital twins can deliver sustainability outcomes. Resilience enters this framing because a twin that cannot be maintained under changing conditions (data disruptions, supplier changes, regulatory updates) cannot deliver sustained sustainability value. One respondent captures this prerequisite logic: *"To create a real digital twin, you should firstly invest in connectivity, real data collection, interoperability, and decide where to store this data."* The salience-based weighting thus reflects an empirical interpretation in which sustainability performance is pursued through the same data infrastructure that enables operational visibility, adaptive response to disruptions, and supply chain coordination.

The concentration of weight on burden criteria aligns with the scale of data integration that interviewees describe as necessary for sustainability transparency: *"they have identified around 300 million data points they need to connect to fulfil scope one, two and three transference."* It is also consistent with the framing of interoperability as a recurring cost driver that limits scalability: *"The interoperability costs are non-conformance costs that never pay off, and that's why we work intensively in the area of Industry 4.0 on standards."* Under this view, the sustainability contribution of digital twins hinges on the organisation's capacity to maintain consistent data and interfaces across complex system landscapes.

Benefit criteria remain salient and indicate the sustainability channels most directly associated with digital twins. Operational performance gains carry the largest benefit weight (6.0%), reflecting a recurring narrative in which measurable performance improvements provide the initial justification for investment, after which sustainability indicators are integrated into the same monitoring and optimisation routines. The energy pathway is particularly concrete, with facility systems described as a major gap: *"But what they are missing is really the facility connectivity … there is also potential for energy management, energy optimisation."* Reporting and compliance support and circularity support also emerge as adoption drivers, consistent with the observation that regulatory requirements shape investment priorities: *"Regulations very strongly drive sustainability. Most companies really try to follow the regulations."* Interviewees additionally connect traceability and product passport requirements to the need for scalable data-sharing infrastructures, warning that *"you can only do that in data space. Otherwise, it's too expensive … The cost will explode."* These signals support an interpretation in which digital twins contribute to sustainable smart manufacturing primarily by enabling auditable measurement and operational control. At the same time, data readiness, connectivity standards, legacy integration, and data governance condition the ability to scale that contribution.

Table 1
Interview-salience criteria weights.

Code	Criterion	Direction	Weight (%)
C1	Data readiness effort	Lower is better	22.0
C4	Integration with legacy systems	Lower is better	14.8
C2	Standards and connectivity effort	Lower is better	13.3
C5	Security and data control risk	Lower is better	9.2
C3	Skills and adoption effort	Lower is better	7.7
C6	Cost and investment effort	Lower is better	6.2
B6	Operational performance gains	Higher is better	6.0
B1	Emissions impact	Higher is better	4.8
B3	Materials and waste impact	Higher is better	4.6
B2	Energy impact	Higher is better	4.5
B5	Reporting and compliance support	Higher is better	3.5
B4	Circularity support	Higher is better	3.3

Note. Weights are reported rounded to 1 decimal place; all computations use the unrounded weight vector. All rankings reported in Section 4 are unchanged when recomputed with the rounded weights.

4.2. Priority ranking of digital twin use cases

Table 2 reports the TOPSIS base-case ranking. The energy and facilities twin (A2) ranks first (CC = 0.6263), followed by the supply chain and scenario twin (A6, CC = 0.6037), the product passport and circularity twin (A7, CC = 0.5767), and the quality and scrap twin (A5, CC = 0.5763). Process performance (A4), design and lifecycle (A1), and maintenance and asset health (A3) rank lower. The ranking reflects how practitioners connect the relevance of sustainability to implementation feasibility under current infrastructure conditions. One respondent notes, *"There are joint objectives between the head of sustainability and the CIO … it also plays into sustainability."* This provides the interpretive frame for the ranking: use cases score higher when they combine sustainability relevance with a feasible pathway toward routine monitoring, disruption response, and decision-making in manufacturing environments.

Interviewees argue that sustainability improvements depend on extending digital visibility beyond the shop floor to facility systems that drive energy consumption, a layer they characterise as a gap in many organisations: *"what they are missing is really the facility connectivity … [there is] huge potential for energy management, energy optimisation."* A6 ranks second because sustainability exposure and operational fragility increasingly lie outside the factory boundary: *"the supply chain is sometimes brittle … people start looking outside of just the factory … into the supply chain."* At the same time, interviewees stress that the feasibility of supply chain twins depends on governance, especially the allocation of information rights across partners: *"who is allowed to see what information."* These two top-ranked use cases are thus closely aligned with the sustainability logic expressed in the interviews: energy management requires facility-level connectivity. In contrast, value-chain sustainability requires scenario capacity and controlled data visibility.

The next tier comprises the product passport and circularity twin (A7, CC = 0.5767) and the quality and scrap twin (A5, CC = 0.5763), which are nearly tied. A7's position is consistent with narratives that treat product passports and traceability as rapidly intensifying compliance and market-access pressures, and that emphasise scalable data-

Table 2
TOPSIS base-case ranking.

Rank	Use case	TOPSIS closeness (CC)
1	A2 — Energy and facilities twin	0.6263
2	A6 — Supply chain and scenario twin	0.6037
3	A7 — Product passport and circularity twin	0.5767
4	A5 — Quality and scrap twin	0.5763
5	A4 — Process performance twin	0.5087
6	A1 — Design and lifecycle twin	0.4671
7	A3 — Maintenance and asset health twin	0.3541

sharing infrastructure as a prerequisite for economically viable implementation. A5 reflects a complementary sustainability pathway centred on material efficiency and defect reduction, supported by evidence that many firms still prioritise real-time visibility for quality control: *"strong demand for optimisation … real-time data … to control the quality."*

The lower-ranked use cases are best understood as more dependent on data foundations that interviewees describe as uneven. For the design and lifecycle twin (A1, CC = 0.4671), the limiting factor is frequently the absence of structured environmental datasets: *"what was missing … [was] the data for your environmental impact … data on processes … materials."* For the maintenance and asset health twin (A3, CC = 0.3541), interviewees highlight inconsistent and unstructured maintenance data: *"customers … do not structure well the data … everybody is doing it differently."* These patterns suggest a prioritisation implication: sustainability-relevant digital twins are prioritised first, where data and connectivity gaps can be closed with manageable effort. In contrast, more data-intensive twins become attractive once common standards and routines are established across plants.

4.3. Sensitivity analysis of the TOPSIS ranking under alternative priority regimes

The sensitivity analysis examines whether the prioritisation is stable when the decision context shifts between sustainability ambition and implementation feasibility. The interviews describe not a single decision logic but rather diverse settings in which regulation, reporting pressure, and circularity requirements can dominate, as well as settings in which the limiting factor is the capacity to scale a digital twin in complex industrial environments. To capture these contrasts, three weight regimes are tested: sustainability-first (60% benefit/40% burden), feasibility-first (30% benefit/70% burden), and equal weights (all criteria weighted equally) (Table 3).

Under the sustainability-first regime, the ranking shifts toward use cases linked to compliance, traceability, and resource efficiency. The product passport and circularity twin (A7) rises to rank 1 and the quality and scrap twin (A5) to rank 2, indicating that when sustainability outcomes are privileged relative to adoption burdens, traceability and material-efficiency pathways dominate. This ordering is consistent with the view that product passport implementation is both unavoidable and economically viable only with scalable data infrastructures: *"You can only do it in data space. Don't even think of doing this in Excel. The cost will explode."* The energy and facilities twin (A2) remains highly ranked (rank 3), and the supply chain and scenario twin (A6) falls to rank 4, suggesting that in a sustainability-first framing, the compliance and circularity pathway can outweigh cross-firm scenario capability.

Under the feasibility-first regime, the ranking reproduces the base case, with A2 ranked first and A6 ranked second. This reflects the emphasis that many firms continue to face basic infrastructural and integration gaps. The equal-weights regime places A7 first and retains A2 and A5 in the top tier, reinforcing a stable shortlist while showing that the identity of the top-ranked use case depends on whether the decision-maker privileges feasibility constraints or sustainability benefits. Across all regimes, the design and lifecycle twin (A1) and the maintenance and asset health twin (A3) remain persistently disadvantaged due to the interview-documented weaknesses in their data foundations.

Table 3
TOPSIS ranks under alternative weight regimes.

Use case	Base case	Sustainability-first (60/40)	Feasibility-first (30/70)	Equal weights
A1 — Design and lifecycle twin	6	7	6	6
A2 — Energy and facilities twin	1	3	1	2
A3 — Maintenance and asset health twin	7	6	7	7
A4 — Process performance twin	5	5	5	4
A5 — Quality and scrap twin	4	2	4	3
A6 — Supply chain and scenario twin	2	4	2	5
A7 — Product passport and circularity twin	3	1	3	1

4.4. VIKOR compromise ranking under interview-salience weights

The VIKOR results complement TOPSIS by introducing a compromise logic that penalises alternatives with severe shortfalls on any single criterion. Table 4 reports the compromise ranking (v = 0.5).

The supply chain and scenario twin (A6) ranks first (Q = 0.0000), with the lowest aggregate loss (S = 0.3563) and the lowest maximum regret (R = 0.0768). This result aligns with narratives that sustainability, competitiveness, and supply chain resilience increasingly depend on coordination beyond the factory, particularly in the face of supply chain fragility. The relevance of A6's resilience is explicit: interviewees describe supply chain twins as tools for stress-testing sourcing configurations and anticipating the propagation of disruptions across tiers. These capabilities directly support the adaptive recovery and risk management functions emphasised in the supply chain resilience literature [1,39]. The energy and facilities twin (A2) ranks second (Q = 0.3701), consistent with accounts that facility connectivity remains a practical bottleneck for energy optimisation and operational continuity. The product passport and circularity twin (A7) ranks third (Q = 0.6531), reflecting strong relevance under sustainability and compliance narratives but a higher regret profile under feasibility constraints. The maintenance and asset health twin (A3) and the process performance twin (A4) rank lower, consistent with claims of weak data structuring for predictive maintenance and broader harmonization challenges.

The standard VIKOR conditions for identifying a compromise solution are satisfied: the acceptable advantage condition holds because $Q(A'') - Q(A') = 0.3701 > 1/(7-1) = 0.1667$, and the acceptable stability condition holds because A6 is ranked first by both S and R.

4.5. SMAA robustness analysis of the VIKOR ranking

The SMAA analysis extends the VIKOR results by examining the robustness of the ranking to weight uncertainty(see Table 5a and Table 5b). This step is important because the weights are derived from interview salience rather than elicited through a formal preference survey, and the interviews reflect heterogeneous organisational contexts and stakeholder priorities. Two uncertainty regimes are therefore considered: an interview-centred distribution (a Dirichlet centred on the baseline weight vector) and a uniform stress test (a symmetric Dirichlet). The analysis produces rank acceptability indicators that show how often each use case attains particular ranks (Fig. 2).

Under the interview-centred regime, the supply chain and scenario twin (A6) remains strongly dominant, achieving rank 1 in 85.6% of

Table 4
VIKOR compromise ranking (v = 0.5).

Rank	Use case	Q	S	R
1	A6 — Supply chain and scenario twin	0.0000	0.3563	0.0768
2	A2 — Energy and facilities twin	0.3701	0.4452	0.1476
3	A7 — Product passport and circularity twin	0.6531	0.4677	0.2195
4	A1 — Design and lifecycle twin	0.6808	0.5668	0.1885
5	A5 — Quality and scrap twin	0.6830	0.4894	0.2195
6	A3 — Maintenance and asset health twin	0.7692	0.7200	0.1537
7	A4 — Process performance twin	0.7788	0.6263	0.1932

Table 5a
SMAA results — interview-centred weight distribution.

Use case	P (rank = 1)	P (top 2)	P (top 3)	Expected rank
A6 — Supply chain and scenario twin	0.856	0.966	0.976	1.235
A2 — Energy and facilities twin	0.120	0.748	0.789	2.660
A7 — Product passport and circularity twin	0.016	0.143	0.542	3.661
A1 — Design and lifecycle twin	0.003	0.096	0.420	4.005
A5 — Quality and scrap twin	0.005	0.045	0.238	4.215
A4 — Process performance twin	0.000	0.001	0.011	6.026
A3 — Maintenance and asset health twin	0.000	0.001	0.024	6.190

Table 5b
SMAA results — uniform weight distribution (stress test).

Use case	P (rank = 1)	P (top 2)	P (top 3)	Expected rank
A7 — Product passport and circularity twin	0.434	0.641	0.812	2.366
A2 — Energy and facilities twin	0.272	0.472	0.665	2.979
A5 — Quality and scrap twin	0.135	0.512	0.696	2.854
A6 — Supply chain and scenario twin	0.130	0.294	0.558	3.493
A1 — Design and lifecycle twin	0.027	0.061	0.125	5.093
A4 — Process performance twin	0.001	0.013	0.087	5.200
A3 — Maintenance and asset health twin	0.001	0.008	0.057	6.020

simulations and appearing in the top two in 96.6%, with an expected rank of 1.235. The energy and facilities twin (A2) exhibits the second-strongest robustness profile, appearing in the top two in 74.8% of simulations. The product passport and circularity twin (A7) appears in the top three in 54.2% of simulations, indicating frequent competitiveness but greater sensitivity to the weight assigned to feasibility burdens.

Under the uniform stress test, the top position becomes more contested. The product passport and circularity twin (A7) becomes the most frequent rank 1 option (43.4%), consistent with the view that when feasibility burdens are not systematically prioritised, use cases tied to traceability and regulatory compliance rise in prominence. The energy and facilities twin (A2) remains highly competitive (rank 1, 27.2%), indicating that energy-management twins retain their attractiveness across a wide range of preference structures. Across both regimes, the design and lifecycle twin (A1) and the maintenance and asset health twin (A3) remain relatively less competitive, consistent with claims about missing environmental impact data and weakly structured maintenance data.

4.6. *Cross-method synthesis*

Table 6 consolidates the TOPSIS, VIKOR, and SMAA results into a single overview. The energy and facilities twin (A2) and the supply chain and scenario twin (A6) occupy the top positions across methods, while product passport and circularity (A7) and quality and scrap (A5) form a stable second tier. Design and lifecycle (A1) remains generally lower-ranked across methods, while maintenance and asset health (A3) is usually lower-ranked but is sensitive to the VIKOR compromise parameter. The VIKOR compromise parameter sensitivity (Table 7) confirms that the top two positions are stable across v = 0.25, 0.50, and 0.75.

The compromise nature of the VIKOR result raises a standard robustness question: does the ordering depend on the compromise parameter v? Table 7 and Fig. 3 show that the top two positions are stable across v = 0.25, 0.50, and 0.75, with A6 consistently first and A2 consistently second. Mid-table positions shift, which is analytically informative because it reveals which use cases are more sensitive to whether decision-makers treat a single weak dimension as potentially decisive. Fig. 3 visualises the rank trajectories from both deterministic sensitivity analyses: panel (a) across the four weight regimes and panel (b) across values of the compromise parameter v.

5. Discussion

The interpretation of these findings is anchored in the dynamic capabilities view (DCV) [65,66], which explains performance under rapid technological change through a firm's capacity to sense opportunities, seize them through investment choices, and reconfigure its asset base accordingly. Within this lens, digital twin use-case prioritisation is fundamentally a seizing problem: managers must select among competing technology investments under uncertainty, and the interview-informed MCDA developed here is the kind of structured decision protocol that Teece [66] identifies as a microfoundation of seizing capacity. The burden criteria that dominate the weight structure

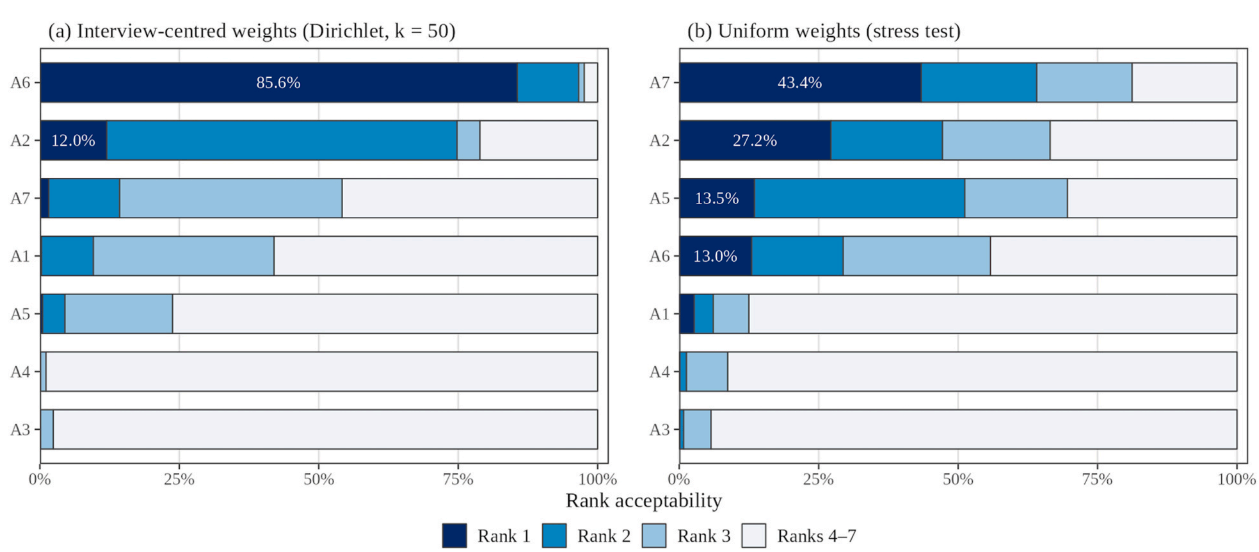

Fig. 2. SMAA rank acceptability indices under interview-centred and uniform weight distributions.

Table 6
Cross-method synthesis of rankings.

Use case	TOPSIS rank	TOPSIS CC	VIKOR rank	VIKOR Q	SMAA E [rank] (interview)	SMAA P (r = 1) (interview)	SMAA E [rank] (uniform)	SMAA P (r = 1) (uniform)
A2	1	0.626	2	0.370	2.660	0.120	2.979	0.272
A6	2	0.604	1	0.000	1.235	0.856	3.493	0.130
A7	3	0.577	3	0.653	3.661	0.016	2.366	0.434
A5	4	0.576	5	0.683	4.215	0.005	2.854	0.135
A4	5	0.509	7	0.779	6.026	0.000	5.200	0.001
A1	6	0.467	4	0.681	4.005	0.003	5.093	0.027
A3	7	0.354	6	0.769	6.190	0.000	6.020	0.001

Table 7
VIKOR sensitivity to the compromise parameter v (rank positions).

Use case	v = 0.25	v = 0.50	v = 0.75
A6 — Supply chain and scenario twin	1	1	1
A2 — Energy and facilities twin	2	2	2
A3 — Maintenance and asset health twin	3	6	7
A1 — Design and lifecycle twin	4	4	5
A4 — Process performance twin	5	7	6
A7 — Product passport and circularity twin	6	3	3
A5 — Quality and scrap twin	7	5	4

correspond, in turn, to the microfoundations of reconfiguration, since data readiness, legacy integration, and interoperability capture how readily a firm can realign existing technical and organisational assets around a new digital capability. The findings are also legible through the Diffusion of Innovations (DOI) framework [67], whose adoption attributes map directly onto the criterion families used in the analysis: the benefit criteria operationalise relative advantage, while the burden criteria capture complexity and compatibility. Read through these complementary lenses, the prioritisation patterns reported below show how capability constraints condition the order in which frontier technologies are absorbed into manufacturing organisations.

The findings of this study advance the understanding of digital twins as sustainability and resilience enablers in smart manufacturing by shifting the analytical lens from technological capability to investment prioritisation under practical constraints. The dominance of burden criteria in the salience-based weight structure, with data readiness (22.0%), legacy integration (14.8%), and interoperability effort (13.3%) collectively accounting for half the total weight, corroborates the proposition advanced by Luthra and Mangla [20] and Ghobakhloo [21] that Industry 4.0 sustainability gains are conditional on deliberate infrastructural alignment rather than technology-led adoption. This finding also extends the digital twin literature, where architectural frameworks and proof-of-concept demonstrations predominate [17,18], by providing empirical evidence that practitioners themselves foreground integration and governance burdens over the sustainability benefits that the technology is intended to deliver. The implication is that the sustainability contribution of digital twins, as conceptualised in the literature [14,31,68], is best understood not as an inherent property of the technology but as an outcome contingent on the organisational and institutional conditions under which the twin is deployed and maintained. In DCV terms, the binding constraint on this contribution is the adopting firm's reconfiguration capacity rather than the technology's intrinsic potential [65,66].

The ranking results also speak to the supply chain resilience literature by decomposing the digital twin into functionally distinct use cases with differentiated resilience implications, addressing a limitation in prior work that treats digital twins as a monolithic category [15,30]. This use-case-level decomposition is the central extension the study offers to the literature: prioritisation judgements, and the capability constraints that drive them, operate at the level of individual use cases rather than at the level of the technology as a whole. Because resilience was not scored as a separate criterion family in the MCDA, these resilience implications should be read as interpretive rather than direct measurement results. The energy and facilities twin ranks first in TOPSIS, consistent with interview accounts that facility connectivity constitutes a limiting layer for sustainability action. Notably, A1 (design and lifecycle) improves from rank 6 in TOPSIS to rank 4 in VIKOR, while A5 (quality and scrap) drops from rank 4 to rank 5; this divergence reflects the regret-minimisation logic of VIKOR, which penalises alternatives with extreme shortfalls on any single criterion and rewards those with more balanced profiles across the benefit-burden space. This finding resonates with the staged adoption logic identified by Frank et al. [7], who observe that foundational technologies precede advanced applications in Industry 4.0 implementation: facility-level energy twins

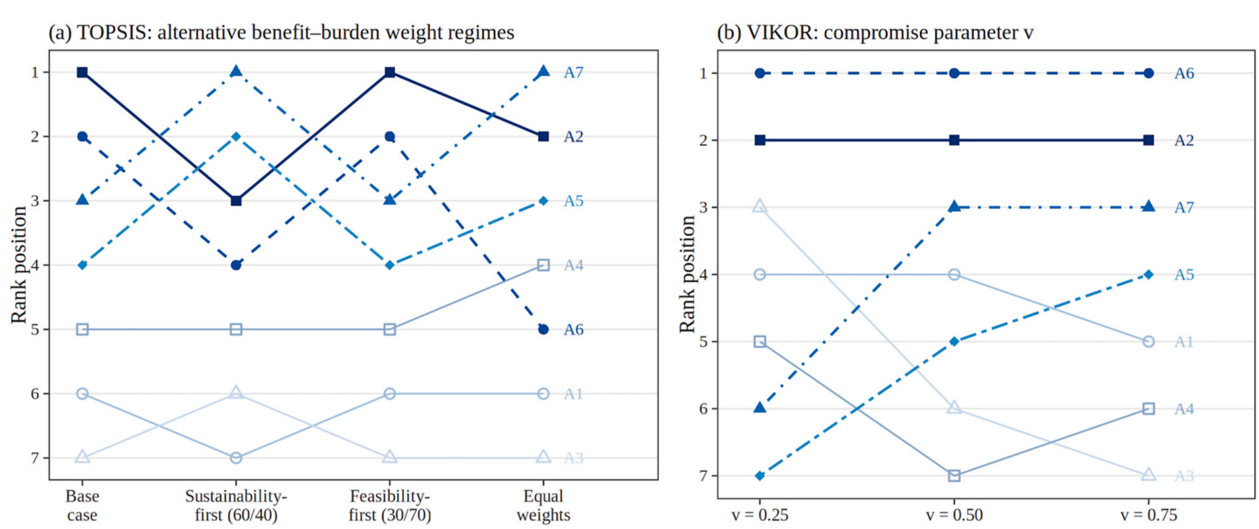

Fig. 3. Sensitivity of digital twin use-case rankings.

represent a comparatively contained integration scope that can serve as a platform for subsequent, more data-intensive deployments. This sequencing also mirrors the DOI framework, in which complexity and compatibility govern the order of adoption as much as relative advantage does [67]. The supply chain and scenario twin emerges as the VIKOR compromise solution and the most robust first-rank option under interview-centred weight uncertainty (85.6%), a result that extends the conceptual work of Ivanov [42,44] on digital supply chain twins for stress-testing and viability by providing practitioner-grounded evidence on the conditions under which such twins are prioritised in practice. The resilience value identified by respondents, namely the capacity to model disruption scenarios and test alternative sourcing configurations, aligns with the theoretical framing of resilience as adaptive capability [4,38] rather than merely the ability to restore a pre-disruption state. This adaptive reading is congruent with the DCV, in which resilience rests on the sensing and reconfiguring capacities that allow firms to redeploy resources as disruptions unfold [65,66].

The sensitivity and SMAA analyses reveal that the identity of the top-ranked use case is not fixed but varies systematically with the decision context, a finding that carries substantive implications for how digital twin prioritisation should be framed in both research and practice. When sustainability benefits are privileged over feasibility burdens, product passport and circularity twins dominate, consistent with the regulatory pressure narrative that interviewees articulate and that the broader literature associates with the EU Digital Product Passport and the Corporate Sustainability Reporting Directive [32,33]. The uniform-weight SMAA stress test, in which product passport twins achieve rank 1 in 43.4% of simulations, suggests that this use case becomes the modal priority whenever feasibility burdens are not systematically weighted above sustainability benefits. Conversely, under a feasibility-first regime, the ranking reverts to the base case with energy and facilities twins dominant, confirming that the prioritisation is sensitive to the stakeholder perspective adopted. This context-dependence is precisely what makes the SMAA framework valuable [24,25,57] for technology investment decisions characterised by heterogeneous stakeholder preferences, and distinguishes the present approach from deterministic rankings that implicitly assume a single, agreed-upon weighting.

The lower-ranked use cases, design and lifecycle (A1) and maintenance and asset health (A3), should not be interpreted as irrelevant to sustainability or resilience but rather as more dependent on data foundations that the interviews describe as uneven and weakly harmonised across plants. This interpretation is consistent with the barriers identified in the Industry 4.0 adoption literature, including data quality deficits, skills gaps, and the disproportionate integration costs faced by SMEs [51,52]. A staged prioritisation implication follows: energy and facilities, supply chain and scenario, product passport and circularity, and quality and scrap twins constitute a robust shortlist of early priorities under current conditions, while design and lifecycle and maintenance and asset health twins become increasingly competitive as common data standards, governance arrangements, and cross-plant harmonization mature. This is a practical staging logic rather than a formally optimised sequence, because interdependencies between use cases were not modelled. Viewed through the DCV, however, this staging describes a capability-building trajectory: early, lower-burden twins develop the data foundations and integration routines on which the seizing of later, more demanding use cases depends [66].

To delineate the contribution precisely, the findings divide into those that corroborate prior claims and those that extend or refine them. Three results corroborate the literature: the dominance of integration and governance burdens confirms the propositions of Luthra and Mangla [20] and Ghobakhloo [21]; the staged adoption pattern confirms Frank et al. [7]; and the vulnerability of data-intensive use cases to weak data foundations is consistent with the documented barriers facing SMEs [51,52]. Three results go beyond corroboration. First, the study decomposes the digital twin construct into seven functionally distinct use cases and shows that prioritisation, and the capability constraints driving it, operate at this level rather than at the level of the technology as a whole, a granularity absent from prior assessments [15,30]. Second, it converts practitioner salience into formal criterion weights, offering an interview-informed route to MCDA prioritisation in settings where quantitative performance data are scarce. Third, it demonstrates that the identity of the top-ranked use case is conditional on the weighting regime, refining deterministic accounts of technology prioritisation by establishing that robustness analysis, rather than a point ranking, is the appropriate output for investment guidance.

6. Conclusion, implications, limitations and future research

6.1. Concluding remarks

This study developed an interview-informed multi-criteria decision analysis to prioritise seven digital twin use cases for sustainability-oriented investment decisions in smart manufacturing, and to discuss the implications of these priorities for supply chain resilience. Drawing on 50 expert interviews across 27 countries and integrating TOPSIS, VIKOR, and SMAA into a unified analytics pipeline, the analysis produced a robust prioritisation grounded in practitioner experience. The energy and facilities twin emerged as the TOPSIS front-runner, the supply chain and scenario twin as the VIKOR compromise solution with the strongest robustness profile (85.6% probability of rank 1 under interview-centred weight uncertainty), and the product passport and circularity twin as the dominant choice when sustainability benefits are privileged over feasibility burdens. Across all methods, data readiness, legacy integration, and interoperability effort were identified as the dominant constraints conditioning whether digital twins can deliver sustained sustainability value. The study contributes a systematic, multi-criteria prioritisation of digital twin use cases for sustainability-oriented decision support, links the resulting priorities to debates in the supply chain resilience and MCDA literatures, and offers a replicable interview-informed methodology for contexts where quantitative performance data remain scarce.

Looking forward, three avenues appear most pressing beyond the methodological extensions. First, the dynamic capabilities generate testable propositions: if data readiness and integration routines index reconfiguration capacity, then observed adoption sequences across firms should covary with measurable capability indicators, and longitudinal designs could treat use-case sequencing as an observable trace of capability building. Second, the convergence of digital twins with generative and agentic artificial intelligence is likely to reshape both sides of the decision model, as AI-assisted data contextualisation and model maintenance lower the very integration burdens that currently dominate the weight structure; future research should examine how this shifting feasibility frontier alters the prioritisation and whether it compresses the staging logic identified here. Third, as shared data spaces and product passport regimes move from design to enforcement, quasi-experimental evaluations of their effects on SME twin adoption would connect the prioritisation framework to causal evidence on policy effectiveness, closing the loop between private investment sequencing and public infrastructure provision.

6.2. Managerial implications

The results yield a prioritisation framework and a staged implementation logic that can be operationalised based on data and integration maturity. For organisations at an early adoption stage, the energy and facilities twin (A2) constitutes the recommended entry point: it ranks first in TOPSIS under both the base-case and feasibility-first regimes and combines meaningful sustainability impact with contained, single-site integration scope. The supply chain and scenario twin (A6), as the compromise-optimal alternative and the most robust first-rank option under preference uncertainty (85.6%), is the priority for organisations balancing sustainability, resilience, and feasibility; however, its feasibility depends on cross-firm data governance. A practical staging principle follows: begin with use cases whose data requirements can be met within existing infrastructure (A2, A5), extend to those requiring cross-firm governance (A6, A7), and defer data-intensive twins (A1, A3) until foundational standards are established.

These recommendations should be differentiated by firm size. Large multinational manufacturers typically command the data engineering resources, supplier leverage, and internal integration capacity to pursue the supply chain and scenario twin (A6) and the product passport and circularity twin (A7) early, and can act as anchor firms in shared data-space initiatives, internalising part of the cross-firm governance burden that these use cases impose on their supply networks. For small and medium-sized enterprises, which face disproportionate adoption barriers in data quality, skills, and integration costs [51,52], the staging logic is more binding: the energy and facilities twin (A2) and the quality and scrap twin (A5) constitute the realistic entry points, since both deliver measurable returns within a single site and largely within existing infrastructure. SME participation in the higher-order twins (A6, A7) is best pursued through industry consortia and shared platforms that mutualise integration costs, rather than through standalone deployment, and large firms and policymakers can accelerate this participation by extending data-space onboarding support to smaller supply chain partners.

6.3. Policy implications

The dominance of burden criteria in the weight structure signals that the sustainability return on digital twin investments is conditioned by upstream public investments in interoperability standards, data governance, and workforce capability. Public programmes supporting industrial energy efficiency could target digital twin pilot funding at facility-level energy visibility as a high-return first step. The rise of product passport twins under sustainability-first and uniform-weight regimes reflects the increasing salience of traceability requirements (EU Digital Product Passport, CSRD), but economically viable implementation requires shared data spaces (e.g., Catena-X, GAIA-X) that reduce per-firm compliance costs, particularly for SMEs in emerging economies. The prioritisation logic is especially relevant in developing contexts, where policymakers can use the framework to allocate scarce public resources toward use cases with the highest expected sustainability and resilience return per unit of infrastructural investment.

Two caveats scope these implications. First, the regulatory and infrastructural instruments cited above (Catena-X, GAIA-X, the CSRD, and the EU Digital Product Passport) anchor the discussion in the European context from which they originate, whereas the interview sample spans 27 countries; the European instruments should therefore be read as illustrative of a general mechanism, namely public provision of interoperability standards and shared data spaces, rather than as the only available template. Second, comparable mechanisms exist or are emerging in other regions: Japan's Society 5.0 agenda and China's industrial internet platform programmes pursue analogous data-infrastructure objectives; the Smart Industry Readiness Index, developed in Singapore and now applied internationally, provides a maturity-assessment instrument that complements the prioritisation framework proposed here; Manufacturing USA institutes such as CESMII perform a comparable shared-infrastructure function for smart manufacturing in the United States; and the African Union's Digital Transformation Strategy offers a continental framing for the digital infrastructure investments on which twin adoption in African manufacturing depends.

6.4. Limitations and future research

Several limitations warrant acknowledgement. First, the MCDA operationalises sustainability benefits and implementation burdens directly, while supply chain resilience is interpreted through the use cases rather than scored as a distinct criterion family. Future research should incorporate explicit resilience criteria and test how their inclusion changes the ranking. Second, although all 50 interviews were retained in the qualitative dataset, the performance matrix is constructed from a subset of twin-related segments extracted from the full interview corpus; fine-grained differences among mid-ranked alternatives should therefore be interpreted with caution. Third, the recruitment strategy may introduce selection bias: participants recruited through Smart Factory Summit attendance and subsequent snowball referrals are embedded in professional networks oriented toward Industry 4.0, and may hold systematically more favourable views of digital twin feasibility, or operate at higher levels of digital maturity, than practitioners outside these networks. The prioritisation should accordingly be read as reflecting the judgement of engaged, network-connected experts rather than of the manufacturing population at large, and replication with samples drawn from outside these professional circuits would test the boundary conditions of the findings. The MCDA rests on interview-derived salience measures rather than quantitative performance data; future research could complement it with Data Envelopment Analysis to benchmark input-output efficiency across implementations. Although the sample spans 27 countries, the analysis does not formally disaggregate by region; stratification by income group or regulatory environment would yield context-specific guidance. The weights are derived from a single interview wave, and longitudinal replication with updated data or Delphi elicitation would strengthen temporal validity. Finally, the study does not model interdependencies between use cases; network-based or simulation-augmented MCDA extensions could capture prioritisation synergies and produce more granular investment roadmaps.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Claude and Grammarly to improve the language. The authors reviewed and edited the output as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Adel Ben Youssef: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Adelina Zeqiri:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sama Mbang:** Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Conflict-of-interest statements

- The authors did not receive support from any organization for the submitted work.
- The authors have no relevant financial or non-financial interests to disclose.
- The authors have no competing interests to declare that are relevant to the content of this article.

Appendix A. Criteria and alternatives glossary

Table A.1
Criteria definitions

Code	Label	Direction	Description
B1	Emissions impact	Higher is better	Extent to which the digital twin helps measure and reduce GHG emissions (scope 1–3 where relevant).
B2	Energy impact	Higher is better	Extent to which the digital twin helps reduce energy consumption or improve energy management.
B3	Materials and waste impact	Higher is better	Extent to which the digital twin helps reduce scrap, defects, rework, and material losses.
B4	Circularity support	Higher is better	Extent to which the digital twin supports reuse, repair, remanufacturing, recycling, and longer product life.
B5	Reporting and compliance support	Higher is better	Extent to which the digital twin helps produce auditable sustainability data and meet reporting or customer requirements.
B6	Operational performance gains	Higher is better	Extent to which the digital twin improves throughput, downtime, lead times, and quality performance.
C1	Data readiness effort	Lower is better	Effort needed to obtain reliable data (quality, consistency, ownership, governance).
C2	Standards and connectivity effort	Lower is better	Difficulty of connecting systems and exchanging data smoothly across vendors and platforms.
C3	Skills and adoption effort	Lower is better	Effort to build capabilities and embed twin-based routines in day-to-day decisions.
C4	Integration with legacy systems	Lower is better	Difficulty of implementing and maintaining twins in older, heterogeneous industrial environments.
C5	Security and data control risk	Lower is better	Risk from cybersecurity exposure and concerns about sensitive data access and control.
C6	Cost and investment effort	Lower is better	Total cost to build, run, and maintain the twin (capital expenditure and ongoing costs).

Table A.2
Alternative definitions

Code	Label	Description
A1	Design and lifecycle twin	Using a twin for eco-design choices and lifecycle impact analysis across the product lifecycle.
A2	Energy and facilities twin	Using a twin to monitor and optimise energy use across facilities, utilities, and production support systems.
A3	Maintenance and asset health twin	Using a twin to monitor asset condition and predict failures, reducing downtime and resource waste.
A4	Process performance twin	Using a twin to improve process stability, throughput, and operational control on the shop floor.
A5	Quality and scrap twin	Using a twin to reduce defects, rework, and scrap through improved monitoring and quality control.
A6	Supply chain and scenario twin	Using a twin to model the supply chain and test scenarios for disruptions, emissions, and resilience.
A7	Product passport and circularity twin	Using a twin to support traceability, product passport requirements, and circularity actions such as repair, reuse, and recovery.

Appendix B. Interview participant profile

Table B.1
Interview participant profile (N = 50)

No.	Type	Country	No.	Type	Country	No.	Type	Country
1	R	Croatia	18	P	Morocco	35	R	Argentina
2	R	Germany	19	C	Brazil	36	R	Argentina
3	R and C	Mexico	20	C	Brazil	37	R	UAE
4	P	France	21	P	Germany	38	R	Spain
5	P	Tunisia	22	C and P	Cameroon	39	R	Japan
6	P	Malaysia	23	P	India	40	R	Australia
7	P	Malaysia	24	P	Switzerland	41	P	India
8	C and P	Saudi Arabia	25	C and P	Switzerland	42	R	China
9	P	Switzerland	26	R	United States	43	P	Austria
10	P	Switzerland	27	R	Sweden	44	P	Germany
11	P	Switzerland	28	R	Brazil	45	P	Switzerland
12	C	Brazil	29	R	Brazil	46	R	India
13	R	South Korea	30	R	Germany	47	P	Mexico
14	P	Greece	31	R	Hungary	48	C and P	Austria
15	P	Switzerland	32	R	Switzerland	49	P	Malaysia
16	P	Morocco	33	R	Serbia	50	R and C	Germany
17	P	Kenya	34	R	Italy			

Note: R = researcher/academic; P = practitioner/industry professional; C = consultant/advisory. Interviews were conducted between June 2024 and June 2025.

Appendix C. Performance matrix

Table C1a
Performance matrix for benefit criteria (higher is better)

Use case	n_k	B1	B2	B3	B4	B5	B6
A1	17	0.059	0.059	0.059	0.059	0.000	0.059
A2	4	0.250	0.750	0.750	0.250	0.000	0.000
A3	4	0.000	0.000	0.250	0.000	0.000	0.250
A4	5	0.000	0.200	0.200	0.000	0.000	0.200
A5	3	0.333	0.333	0.667	0.000	0.333	0.333
A6	9	0.222	0.111	0.111	0.222	0.111	0.111
A7	3	0.667	0.333	0.333	0.667	0.667	0.333

Table C1b
Performance matrix for burden criteria (lower is better)

Use case	n_k	C1	C2	C3	C4	C5	C6
A1	17	0.588	0.294	0.059	0.294	0.059	0.000
A2	4	0.250	0.250	0.000	0.500	0.250	0.000
A3	4	0.500	0.750	0.000	0.500	0.250	0.250
A4	5	0.600	0.200	0.000	0.400	0.400	0.000
A5	3	0.667	0.000	0.000	0.333	0.333	0.333
A6	9	0.111	0.111	0.111	0.222	0.222	0.111
A7	3	0.667	0.000	0.000	0.333	0.333	0.667

Data availability

The data that has been used is confidential.

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