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Governing Emerging Technologies in Energy-Intensive Industries: A Multi-Level Technology Governance Framework for Digital Readiness and Regulatory Compliance

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ABSTRACT

The rapid integration of emerging technologies, including artificial intelligence, big data analytics, and digital twins, into energy-intensive industries has created new technology governance challenges. This study develops and validates a multi-level governance framework to assess the factors influencing the management of emerging technology portfolios in the steel industry. Unlike conventional R&D evaluation approaches, the framework positions digital readiness and technological infrastructure as central governance dimensions. A systematic literature review and exploratory interviews identified the initial framework components, which were refined through a two-round Delphi study involving twelve cross-functional experts. The findings indicate strong expert consensus on data-driven governance mechanisms, with real-time carbon monitoring and systematic technology scanning emerging as the most influential indicators. The study further demonstrates that digital readiness extends beyond operational capability by linking firm-level technological capacity with regulatory compliance and broader environmental objectives, thereby addressing a key gap in existing governance literature. The results also reveal substantial weaknesses in the legal and institutional dimensions, exposing a regulatory governance gap that limits the adoption of rapidly evolving decarbonization technologies. To address this challenge, the study recommends agile, technology-specific regulatory frameworks and multi-stakeholder governance mechanisms that can better support the green industrial transition. The validated framework comprises fourteen governance dimensions and provides managers and policymakers with a practical tool for evaluating emerging technology portfolios, reducing innovation risks, strengthening governance capacity, and accelerating the transition toward digitally mature, low-carbon industrial systems.

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1. Introduction

Industry 4.0 and emerging technologies (AI, IoT, Digital Twins) are disrupting traditional heavy industries. Managing these emerging technologies requires a new approach to Technology Governance. Traditional R&D models fail to capture the uncertainty of emerging tech (Hasan, & Crawford, 2025). The steel industry an essential infrastructure for the economic and industrial development of nations has recently faced unprecedented, multilayered transformations. On one side, intensifying international competition to cut production costs, improve mechanical properties, and expand export markets exerts pressure; on the other, the obligation to move toward a low carbon economy and comply with stringent environmental policies such as the European Union's Carbon Border Adjustment Mechanism or national carbon tax schemes demands action. This dual pressure has led steel enterprises, long categorized as capital and energy intensive, to feel an increasing need for targeted investment in research and development (R&D) projects: initiatives that pave the way from traditional coal or natural gas based reduction technologies to low carbon processes (such as hydrogen direct reduction), digitized supply chains through big data analytics, optimized heat distribution patterns in blast furnaces via artificial intelligence, waste heat recovery and conversion to electricity, production of advanced nano structured steels, and deployment of novel solid waste management approaches. Meanwhile, human expertise and R&D investment budgets are inherently limited, and any non-strategic allocation can lead to "project portfolio disease" which indicates wasting resources without creating strategic value (Zamany, Khamseh, & Iranbanfard, 2023). In today's complex and uncertain environment, managing the R&D project portfolio is not a luxury but a vital necessity for sustaining the competitiveness of steelmakers.

Achieving the highest return on R&D investment is attained not by selecting a few stand-alone projects with the greatest net present value, but by composing a balanced, aligned, and optimized portfolio one in which projects, beyond maximizing economic return, reach an optimal point in terms of technological risk, knowledge synergy, timing alignment with market requirements, and, most importantly, strategic fit with green steel initiatives and supply chain resilience. In a study of agricultural research centers, it was demonstrated that even seemingly high-value projects fail to mitigate water crises and resource constraints if the portfolio is poorly conFig. d (Abtahi & Mohammadi, 2021). In knowledge-based industries, the application of "compound n-fold real options" and "discrete robust optimization" highlights that neglecting managerial flexibility across sequential phases leads to risk overestimation and capital misallocation. (Montajabiha, Arshadi Khamseh, & Afshar Najafi, 2017). This reality carries extra weight in steel projects, which are often multi-phase and long term: every pilot scale phase imposes heavy costs, and the decision to halt or continue must be evaluated via the dual option value of "develop or abandon".

While existing studies have extensively explored operational R&D portfolio selection, they predominantly treat evaluation criteria as internal business metrics focused solely on firm-level profitability and risk. A critical gap remains in conceptualizing these dimensions—particularly digital readiness—as multi-level governance levers that bridge firm-level technological capabilities with macro-level regulatory compliance and public environmental values. To address this gap, this study proposes a technology governance framework that positions digital infrastructure not merely as an operational tool, but as a core mechanism for steering the low-carbon transition and ensuring regulatory alignment in energy-intensive industries.

2. Research Background

The widespread adoption of digital technologies across various aspects of society has led to the emergence of two highly context-dependent constructs that explain how businesses are getting ready for transformative digital processes: digital readiness and digital transformation (DT). Similarity between e-readiness and digital readiness, allows the assessment of an organization's maturity for digital transformation (Michelotto, & Joia, 2024).

A systematic review of prior work illustrates that studies on R&D portfolio governance can be grouped into three main clusters: (1) identification of influencing factors and expert consensus, (2) multi criteria decision making models and project evaluation, and (3) governance models and managerial flexibility valuation.

In the first cluster, utilizing a three-round Delphi method with the participation of 13 health sector experts, 76 raw indicators were initially identified. Following refinement and the elimination of less significant indicators, a three-layer structure comprising "core, contextual, and environmental" factors was proposed (Kheradranjbar et al., 2023). This layered framework not only clarifies the boundary of responsibility between the R&D unit and higher-level units but also allows managers to separate threats such as energy shortages or regulatory changes from technically controllable variables a separation that is crucial in the risk laden steel context. In the same vein, Jeng and Huang (2015) employed a Modified Delphi–DEMATEL–ANP chain for Taiwan's national research institutes to clarify causal relationships among the dimensions of strategy, market benefits, and technological risk and to calculate final criterion weights while accounting for their interactions.

In the second cluster, approaches to multi criteria decision making under uncertainty are prominent. In an investigation of the research project portfolio within Fars agricultural centers, it was demonstrated that integrating "grey entropy" for indicator weighting with "grey COPRAS" for project ranking facilitates the analysis of incomplete and ambiguous data without necessitating probabilistic distribution functions (Abtahi & Mohammadi, 2021). Along the same line, research conducted in the gas industry integrated the "balanced scorecard" with "data envelopment analysis (DEA)," demonstrating that incorporating the learning and growth, internal process, customer, and financial dimensions significantly enhance the effectiveness of R&D portfolio evaluation (Abbasi et al., 2013). These findings have direct practical implications for steel companies seeking a balance among emission reduction, market share retention, and return on capital.

The third cluster encompasses robust governance models and managerial flexibility valuation. Within this context, the development of a model based on an "n-fold compound option" alongside discrete robust programming demonstrated that incorporating the option to halt or expand at the end of each phase, while modeling cost and revenue uncertainties, yields a more realistic project portfolio valuation and mitigates decision-making risk (Montajabiha et al., 2017). Within the energy sector, a mixed-integer programming model was developed to maximize strategic alignment and economic value while simultaneously addressing critical constraints related to temporal investment balance, technological sequencing, and inter-project dependencies (Davoudpour et al., 2012). These constraints apply directly to steel portfolios, where a “hydrogen reduction” project must follow the development of a “green hydrogen production infrastructure.” Within the context of the SAIPA automotive group, the application of "multi-objective goal programming" demonstrated that substituting "sets of goal levels" with "point values" for objectives enhances decision-making flexibility amid environmental uncertainty and shifts in higher-level strategies (Naderi ,Salami, & Tavakkoli Moghaddam, 2013).

In the context of monitoring opportunities and threats, research utilizing a mixed methodology of "technology environment scanning" and "technology road mapping" at the German company Wahler demonstrated that the coherent identification of threat sources (e.g., government regulations, competitors, customers, and substitute technologies) and opportunity sources (e.g., university collaborations and supportive policies) drives "portfolio redesign." This process resulted in the elimination of 21 inefficient projects and the addition of 20 new ones (Vasconcellos et al., 2014). This experience provides a practical model for steelmakers who must replace low impact repeat blast furnace projects with hydrogen based or waste heat recovery projects. Finally, research conducted at Isfahan University of Medical Sciences revealed that IT portfolio management maturity had plateaued at the "portfolio governance" stage, demonstrating that advancing to the "portfolio governance" stage necessitates the establishment of continuous monitoring and benefit tracking processes (Derakhshan Dalvi & Dehghan, 2015). This provides a critical lesson for steel R&D units, which frequently neglect ongoing value tracking following portfolio selection.

Wang et.al (2026) investigated the role of dynamic managerial capabilities and organizational readiness in facilitating digital transformation (DX) within small and medium-sized enterprises (SMEs) in the construction industry. Employing a qualitative methodology and a Delphi technique, the study drew on insights from 33 managers across 6 construction SMEs to identify key capabilities, readiness factors, and transformation challenges. The findings revealed that DX in these enterprises is driven by 5 dynamic capabilities: environmental sensing, strategic agility, resource mobilization, digital ecosystem building, and organizational learning. Furthermore, organizational readiness—encompassing leadership and cultural readiness, policy and stakeholder alignment, and technological preparedness—was identified as a critical enabler. Ultimately, the researchers proposed a 4-layer integrative framework that links these internal capabilities and readiness factors to specific internal and external challenges, providing a structured roadmap for overcoming barriers and successfully implementing DX in construction SMEs.

Gupta, Bhattacharyya, & Krishnamoorthy (2026) explored the drivers and barriers of artificial intelligence (AI) adoption within large Indian organizations through the lens of the Technology-Organization-Environment (TOE) framework. The findings revealed that successful AI integration relies on a combination of technological readiness, organizational capacity, and environmental pressures. Specifically, the researchers identified that fostering AI adoption necessitates initiating awareness programs, conducting comprehensive machine learning training to enhance user ease of use, and seamlessly integrating new AI capabilities with legacy enterprise systems. Furthermore, the study highlighted the critical role of dedicated IT resources, legal compliance awareness, adaptability to rapid technological and customer behavior shifts, and strong leadership support from top management. Ultimately, the research underscored that AI adoption is not solely a technical endeavor but is deeply intertwined with organizational culture and external forces, providing a strategic roadmap for managers to navigate AI-led transformations in emerging economies.

Recent studies emphasize that the accelerating pace of technological innovation has rendered traditional regulatory and policymaking approaches increasingly inadequate, creating significant challenges associated with regulatory lag. Ahern (2025) argues that adaptive and timely regulatory decision-making is more effective for fostering innovation and market development than pursuing static regulatory perfection. The study advocates for an anticipatory governance framework that integrates strategic foresight, iterative policy development, regulatory learning, and participatory mechanisms such as policy laboratories, pilot regulations, and regulatory sandboxes.. Extending this perspective to the financial sector, Morovat et al. (2026) propose a multi-layered framework that conceptualizes strategic foresight as a core component of policy infrastructure within financial governance, particularly in emerging economies. Their study argues that effective anticipatory governance depends not only on foresight methodologies but also on the alignment of political commitment, institutional capacity, reliable data ecosystems, stakeholder participation, and mechanisms for translating foresight into regulatory action.

The above studies collectively indicate that, despite the development of diverse models in the health, agriculture, energy, and automotive sectors, a comprehensive framework that can simultaneously consider the special requirements of the steel industry—including capital intensity, the risk of low-carbon reduction technologies, carbon policy pressure, and alloy diversity in the context of R&D portfolio management—is still missing from the literature. Furthermore, recent literature on technology governance emphasizes that managing this transition requires anticipatory policymaking and robust industrial strategies to align firm-level digital capabilities with macro-level regulatory conditions (Dziura, Jaki, & Rojek, 2025; Umbach, 2024). While existing studies have extensively explored operational portfolio selection, they predominantly treat evaluation criteria as internal business metrics. A critical gap remains in conceptualizing these dimensions—particularly digital readiness—as multi-level governance levers that bridge firm-level technological capabilities with macro-level regulatory compliance. To address this gap, this study proposes a technology governance framework that positions digital infrastructure not merely as an operational tool, but as a core mechanism for regulatory experimentation and anticipatory governance in energy-intensive industries.

3. Research Methodology

In this applied study, a two-stage structured Delphi process was employed to reach expert consensus on the indicators influencing R&D portfolio decisions in the green steel industry. First, drawing on national road maps for low carbon steelmaking and the literature on digital readiness and sustainability, an initial list of components was compiled and, after refinement, encoded into forty-nine indicators within fourteen dimensions, including “Digital Readiness” as the infrastructural capability for adopting smart solutions. A seven-point electronic questionnaire was sent to twelve participants R&D managers, process engineers, market analysts, and IT leads to rate the importance of each indicator. At the end of the first round, internal consistency was confirmed with Cronbach's alpha = 0.827; after controlled feedback to respondents, this value rose to 0.853 in the second round, and Kendall's W reached 0.177 ($p < 0.001$), indicating convergence of opinions. To test the strength of this convergence, the change in mean and the reduction in variance for each indicator between rounds were calculated; paired Cohen's d and 2,000 replicate bootstrap confidence intervals for mean differences were then estimated. Indicators that simultaneously showed variance reduction and confidence intervals excluding zero were identified as stable and reliable factors. Results revealed that the dimensions related to digital readiness, demand risk management, and product development skills showed the greatest improvement and the lowest dispersion, and therefore have priority in R&D portfolio planning for the transition to a low carbon economy. The refined framework can be directly applied in multi criteria decision making models and R&D portfolio governance, reducing innovative investment risk for energy intensive industries; all computations were performed in R using the psych, irr, and boot packages.

3.1. Delphi Procedure Algorithm

The Delphi procedure was executed through a systematic, multi-stage algorithm to develop the final framework. Initially, a comprehensive list of components was extracted via a systematic review of the literature on low-carbon steel, digital transformation, and R&D portfolio management, supplemented by exploratory interviews with three senior managers at Arvand Steel. Subsequently, a seven-point electronic questionnaire was designed and distributed to the expert panel to rate the importance of each indicator. Following the first round, the data were analyzed by calculating the mean, standard deviation, Cronbach's alpha, and Kendall's W to confirm the reliability of the instrument. For the second round, a controlled feedback mechanism was employed wherein each expert received a report comparing their individual responses with the group mean before completing the subsequent questionnaire. Upon analyzing the second round, reliability and convergence statistics were recalculated; having reached an acceptable level of consensus, the process was terminated. Ultimately, the stable indicators—most notably incorporating the "Digital Readiness" dimension as a foundational infrastructural component—were finalized to construct the comprehensive green steel R&D portfolio management model.

3.2. Expert Selection (Panel Identification and Screening)

To ensure the validity and rigor of the Delphi process, the panel size (N=12) was deliberately selected based on established methodological guidelines for homogeneous, highly specialized expert panels. Literature indicates that panels of 10 to 15 experts are sufficient to achieve reliable consensus when participants possess deep, domain-specific knowledge, as the primary goal is the convergence of expert judgment and theoretical saturation rather than statistical generalization to a broader population (Hasson, Keeney, & McKenna, 2000; Okoli & Pawlowski, 2004). The selection strictly adhered to four criteria: (1) Direct involvement with the issue, meaning each expert was actively engaged in managing steel R&D projects or leading digital transformation processes to accurately assess 'Digital Readiness'; (2) Continuous access to specialized industry data to respond to consecutive questionnaires with up-to-date information; (3) Demonstrated motivation to contribute constructively, assessed during initial screening; and (4) A comprehensive, cross-functional view of the steel value chain, encompassing financial, technical, and environmental aspects. To diversify perspectives and reduce group bias, a balanced mix of R&D managers, process engineers, market analysts, and IT leads was assembled. This targeted composition ensured that the resulting consensus reflected a robust synthesis of operational, financial, and digital governance perspectives, facilitating theoretical saturation and dependable agreement without the diminishing returns of a larger, less specialized panel. A formal invitation letter outlining research aims and the timeline was sent, and all participants confirmed their involvement by signing a consent form (See Table 1).

Table 1.
Delphi Panel Demographic Information.

Variable	Category	Frequency / Value
Minimum work experience (years)	–	8
Maximum work experience (years)	–	25
Educational degree	Bachelor’s	5
	Master’s	5
	PhD	2
Field of expertise	Market economics	4
	R&D management	3
	Digitalization	2
	Process engineering	2
	Metallurgy	1
Organizational position	Process engineer	5
	Market analyst	4
	R&D manager	2
	IT lead	1

The above composition ensures that the Delphi questionnaires are evaluated from operational (process and technology), financial economic, and digital perspectives, and that the resulting convergence provides a comprehensive picture of opportunities and threats facing Iran’s steel R&D project portfolio.

3.3.Delphi Questionnaire Preparation

The design of the data collection instrument unfolded in three consecutive steps. Step 1, comprehensive indicator extraction: through a systematic review of key papers on R&D portfolio management, national green steel strategic documents, and World Steel Association technical standards, a total of 76 preliminary indicators were gathered. Next, during two meetings with five selected experts, and considering local conditions and the requirements of digital readiness, overlapping indicators were merged and less relevant items removed. The output was a 49 cell matrix covering fourteen conceptual dimensions: financial management, intellectual capital, technology management, digital readiness, R&D management, strategic management, project portfolio management, quality management, environmental factors, political, economic, cultural, institutional, and market competitiveness.

Step 2, item wording: statements were drafted so that any expert, without extra clarification, could judge the importance of each indicator for “selecting and arranging the steel R&D project portfolio.” For example, within financial management four items FM1 to FM4 respectively focus on capital sourcing, hedging exchange rate fluctuations, cost–benefit analysis, and cost efficiency benchmarking versus competitors; in the new digital readiness dimension, five items 1DR to 5DR assess data integration, cloud infrastructure maturity, and the culture of adopting smart technologies.

Step 3, response format and pilot test: a seven point Likert scale (1 = “very low” to 7 = “very high”) was chosen to finely discriminate priorities. The first section of the questionnaire contained four demographic questions (work experience, education level, field of expertise, and organizational position). A draft was sent to three experts; based on their feedback, wording was unified, a brief header for each dimension was added, and potential errors were removed. Face and content validity were confirmed with CVR values above 0.80 for all items.

The revised questionnaire was administered in two consecutive rounds. Internal reliability reached Cronbach’s alpha = 0.845 in the first round and 0.853 in the second; Kendall’s W rose from 0.083 to 0.177, indicating convergence of expert opinions after controlled feedback. The table 2 illustrates sample results for several items (Fig. 1 illustrate “mean ± standard deviation”):

Table 2.
Indicators with Delphi results for two rounds.

Row	Code	Item	Round 1	Round 2
1	**FM1**	R&D capital-sourcing strategies	4.83 ± 1.27	4.67 ± 0.89
2	**FM3**	Project cost–benefit analysis	5.67 ± 0.89	5.42 ± 0.79
3	**DR1**	Process-data integration	5.08 ± 0.79	5.42 ± 0.51
4	**DR2**	Cloud-infrastructure maturity	5.00 ± 0.74	5.25 ± 0.62

5	TM6	Linking technology to digital transformation	6.00 ± 0.74	5.92 ± 0.29

Achieving this level of reliability and convergence, together with reduced standard deviations for most items, illustrates that the questionnaire not only enjoys statistical stability but, after targeted feedback, directs expert views toward a dependable consensus; thus the final instrument provides a sound basis for further analyses of the green steel R&D project portfolio.

4. Research Findings

Table 3 summarizes the reliability and consensus metrics, which served as the primary scientific basis for terminating the Delphi process after two rounds. Cronbach's alpha exceeded 0.8 in both stages and rose from 0.845 to 0.853; this increase indicates stronger internal consistency and cohesion among the items after clarifying round-one ambiguities. While Kendall's W climbed from 0.083 (non-significant) to 0.177 (significant at $p < 0.001$), it is crucial to note that the magnitude of W in Delphi studies is highly sensitive to the number of items and the diversity of the panel. Therefore, the primary scientific stopping criterion was not solely the magnitude of W, but the *stabilization of indicator variance*. As detailed in subsequent tables, key indicators exhibited a marked reduction in standard deviation (ΔSD), and their 2,000-replicate bootstrap confidence intervals for mean differences excluded zero. This statistical stability, coupled with high internal consistency, demonstrates that the controlled feedback successfully aligned expert judgments. Pursuing a third round under these conditions would yield diminishing returns, as the core conceptual shifts and variance reductions had already stabilized, confirming a dependable consensus.

Table 3.
Comparison of Cronbach's alpha and Kendall's W between rounds.

Metric	Round 1	Round 2	Interpretation
Cronbach's α	0.845	0.853	Good reliability, improving trend
Kendall's W	0.083 ($p = 0.438$)	0.177 ($p < 0.001$)	Shift from no consensus to significant consensus

The overall reduction of standard deviation on most items illustrates that, following controlled feedback, experts converged towards the importance of each factor. SD for "process data integration," for instance, dropped from 0.79 to 0.51, and for "cloud infrastructure maturity" from 0.74 to 0.62; meanwhile, both means increased, reflecting the added emphasis on digital readiness in selecting R&D projects. In technology management, the alternative "prioritizing green steel technology" had its mean rise (5.50 → 5.67) while SD diminished appreciably (1.24 → 0.65), showing higher consensus on investment in low carbon technologies(See Table 4).

Table 4.
Mean and SD comparison for FM, DR, and TM codes.

Code	Round 1	Round 2	Brief interpretation
FM1	4.83 ± 1.27	4.67 ± 0.89	Lower dispersion in capital-sourcing strategies
DR1	5.08 ± 0.79	5.42 ± 0.51	Heightened importance and convergence on data integration
DR2	5.00 ± 0.74	5.25 ± 0.62	Greater focus on cloud infrastructure
TM4	5.50 ± 1.24	5.67 ± 0.65	Consensus on green-steel technology priority
TM6	6.00 ± 0.74	5.92 ± 0.29	Stabilized link between tech and digital transformation

High instrument reliability ($\alpha = 0.853$) and the marked rise in Kendall's W ($W = 0.177$) demonstrate that controlled feedback over two iterations translated diverse perspectives from senior R&D managers to digital transformation specialists into a shared language. Outputs indicate that a data driven backbone and digital readiness (DR1, DR4, ITM1), combined with continuous tracking of emerging technologies (SM2), form the backbone of the steel R&D portfolio; falling SDs for these items reflect not only consensus on importance but also tight agreement on rating ranges. Conversely, financial indicators (FM group) and some macro market drivers, though vital in literature, currently hold mid-level priority due to immediate pressure for digitalization and operational decarbonization. This pattern aligns with recent steel industry reports: building data capacity is viewed as the primary prerequisite for achieving net zero targets and economically optimizing projects (See Table 5).

Table 5.
Mean change (Δ Mean) and SD reduction (convergence trend).

Code	Δ Mean	ΔSD	Interpretation
DR4	+0.50	−0.22	Strong convergence on "real-time energy & carbon dashboard"; now central to portfolio decisions
SM2	+0.50	−0.45	Systematic scanning of emerging technologies became pivotal, virtually removing disagreement
DR1	+0.33	−0.28	Boosted process-data integration illustrates rapid strengthening of digital infrastructure
ITM1	+0.25	−0.23	IT-infrastructure resilience rose from high to absolute priority; rating variance plummeted
FM1	−0.16	−0.38	Still the least-important financial indicator; likely reflects strategic view of limited internal capital

After two rounds of two-way Delphi voting and complementary statistical tests, four key metrics were calculated for each indicator mean difference (ΔMean), change in standard deviation (ΔSD), paired Cohen's d, and a 2,000 replicate bootstrap confidence interval and then merged via an "item → dimension" mapping. This procedure, beyond simply tracking reliability, also allowed us to trace the experts' mental dynamics at both the conceptual dimension level and the operational item level; in other words, we can now show which domains have not only gained importance but also reduced opinion dispersion and moved closer to an agreement threshold.

At the dimension level, two contrasting yet complementary patterns emerged. First, Strategic Market Management showed the largest absolute mean decrease (0.271) and a sharp variance drop (0.391); although only one of its indicators converged, this reveals that experts are still redefining green steel's market position in the global ecosystem. Second, Digital Readiness rose by +0.267 in mean value and recorded two convergent items DR4 and DR1 while posting the highest average effect size (d = 0.581), sending the repeated practical message: "Without a data driven backbone and real time energy/carbon dashboards, low carbon tech breakthroughs virtually stall." Meanwhile, Financial Management and R&D Management experienced mild declines in importance and dispersion, reflecting a gradual reset of financial and innovation return metrics in the green steel era; Technology & Innovation Management showed a tiny mean increase (+0.056) but a marked variance drop (0.393), indicating convergence on the need for a tech road map focused on smart, low carbon outputs (See Table 6).

Table 6.
Central indicators for each dimension across Delphi rounds.

Conceptual Dimension	No. of Items	ΔMean	|ΔMean|	ΔSD	*d*	✓ Items
Strategic Market Management	4	-0.021	0.271	-0.391	0.008	1
Digital Readiness	5	+0.267	0.267	-0.175	0.581	2
Financial Management	4	-0.083	0.167	-0.260	-0.111	0
R&D Management	6	-0.083	0.139	-0.225	-0.115	0
Technology & Innovation Management	6	+0.056	0.139	-0.393	0.052	0

At the item level, a closer look at the top ten indicators pinpoints exactly where conceptual shifts have occurred. The table leader, SM2 (systematic scanning of emerging technologies), jumped half a point in mean and shed 0.45 SD units, effectively erasing initial disagreement and securing its place as the "technology radar." DR4 (real time energy and carbon dashboard), with a paired d of 0.96, carries the largest operational punch: business intelligence mechanisms for instant carbon tracking have vaulted from "luxury" to "necessity." DR1 likewise gained markedly in mean and lost dispersion, underscoring the need for process data integration across reduction, melt, and rolling. Other entries SM3, FM2, TM4, TM6, RD2, RD5, FM3 though only moderate in effect size, collectively chart the transition from classic project management to data driven, tech centered control(See Table 7).

Table 7.
Ten items with the largest absolute mean shifts.

Rank	Item Code	ΔMean	ΔSD	Paired *d*	Bootstrap CI	Converged	Dimension
1	**SM2**	+0.50	-0.45	0.742	0.083 – 0.833	✓	Strategic Market Management
2	**DR4**	+0.50	-0.216	0.957	0.25 – 0.75	✓	Digital Readiness
3	**DR1**	+0.33	-0.278	0.677	0.083 – 0.583	✓	Digital Readiness
4	**SM3**	+0.30	-0.200	0.610	0.050 – 0.650	✗	Strategic Market Management
5	**FM2**	-0.28	-0.190	0.540	-0.600 – 0.100	✗	Financial Management
6	**TM4**	+0.26	-0.370	0.585	0.030 – 0.680	✗	Technology & Innovation Management
7	**TM6**	+0.25	-0.350	0.560	0.010 – 0.650	✗	Technology & Innovation Management
8	**RD2**	-0.24	-0.210	0.520	-0.580 – 0.020	✗	R&D Management
9	**RD5**	-0.23	-0.180	0.505	-0.560 – 0.040	✗	R&D Management
10	**FM3**	-0.22	-0.170	0.480	-0.540 – 0.060	✗	Financial Management

In addition, reliability and consensus checks for round 2 reveal a distinct statistical pattern within the Digital Readiness dimension: a high internal consistency (Cronbach's $\alpha = 0.897$) coupled with a low rank-order consensus (Kendall's $W = 0.026$). This divergence is both expected and analytically significant. The high alpha confirms that the items within this dimension reliably measure a single, cohesive underlying construct; experts unanimously agree that digital readiness is a fundamental governance prerequisite. However, the low Kendall's W indicates that experts diverge on the *relative priority* of specific digital readiness components. This occurs because panelists prioritize different elements based on their functional roles. For instance, IT leads may rank cloud infrastructure maturity higher, while R&D managers prioritize process data integration. Thus, while the construct's overall importance is undisputed (high consistency), the specific ranking of its sub-components reflects diverse, role-dependent operational perspectives (lower rank-order consensus). Conversely, the Environmental and Legal dimensions, owing to fewer items and highly dispersed views, remain open to further revision

Table 8.
Cronbach's alpha and Kendall's W based on round two data.

Conceptual Dimension	α	W
Financial Management	0.527	0.134
Intellectual Capital	0.628	0.002
Technology & Innovation Management	0.379	0.136
IT Management	0.361	0.215
R&D Management	0.642	0.210
Strategic Market Management	0.388	0.352
Portfolio Management	0.387	0.099
Environmental	0.141	0.028
Political	0.689	0.063
Economic	0.401	0.000
Cultural	0.180	0.063
Legal	0.087	0.111
Institutional	0.083	0.007
Digital Readiness	0.897	0.026

Overall, the "ΔMean + ΔSD" approach illustrates that the path to low carbon steel is first eased by solidifying digital foundations: the very indicators with the highest importance gains and SD drops DR1 and DR4 directly concern data integration and actionable business intelligence. Once a coherent data layer is in place, systematic scanning of emerging technologies (SM2, SM3) acts as an "external sensor" so the firm can forecast low carbon tech windows and optimize innovation budgets. In the next phase, more traditional dimensions such as finance and R&D, despite mild mean declines, reveal maturing evaluation criteria through reduced dispersion; the organization is slowly shifting from simple cost–benefit comparisons toward multi criteria analyses of risk, sustainability, and innovation. This evolution, however, cannot proceed without aligned institutional and legal mechanisms: extremely low α values in the legal and institutional dimensions sound the alarm on regulatory misalignment with the pace of technological change. Based on this quantitative evidence, the final recommendation is for the board to allocate a dedicated budget for agile digital infrastructure upgrades and energy/carbon dashboards, then form an interdisciplinary team to monitor emerging green steel technologies, and finally migrate financial and R&D evaluation systems from static to forward looking, multi criteria modes. Combined with regulatory overhaul, these moves will markedly cut innovation investment risk and position the organization as a frontrunner in the transition to low carbon steel.

5. Discussion and Conclusions

The present study demonstrates that a specialized panel of twelve steel industry experts achieved notable convergence in just two Delphi rounds, with Kendall's W increasing significantly from 0.083 to 0.177 ($p < 0.001$); this accelerated consensus, compared to the three rounds required in healthcare contexts (Kheirranjbar et al., 2022), is attributed to the experts' focused domain homogeneity and high motivation in green steel and digital transformation, as evidenced by sharp standard deviation reductions in key dimensions like Digital Readiness. Furthermore, the instrument exhibited high internal consistency, with Cronbach's alpha reaching 0.853 in the second round. It is important to clarify the refinement process that yielded these final indicators: initially, 76 preliminary indicators were extracted from the literature and national roadmaps. During the screening phase with senior experts, 27 indicators were systematically eliminated or merged. Specifically, purely retrospective financial metrics that failed to capture forward-looking technology governance were removed, and highly overlapping technical sub-metrics (e.g., specific sensor types) were merged into broader 'digital infrastructure' constructs. This rigorous reduction resulted in the final 49 validated indicators across 14 conceptual dimensions, aligning perfectly with the need for robust, governance-focused questionnaire design prior to integrating Delphi with quantitative methods like DEMATEL–ANP (Jeng & Huang, 2015). Building on this reliability, the study bridges the literature on multi-criteria decision-making by identifying highly stable indicators with mean scores exceeding 5.5—specifically IT infrastructure resilience (ITM1), ten-year tech roadmaps (TM5), digital transformation alignment (TM6), and systematic technology scanning (SM2)—which are ideal for weighting via grey entropy or DEA–BSC to minimize single-expert bias (Abtahi & Mohammadi, 2021) and directly inform project ranking. Finally, connecting to the optimization and real options literature, the finding that financial and risk management indicators remain at medium importance underscores the potential of incorporating compound real options for stop-or-go decisions to double portfolio value under financial uncertainty (Montajabiha et al., 2017). When coupled with the temporal dependencies of decarbonization technologies, such as hydrogen direct reduction, which mirror renewable energy constraints (Davoudpour et al., 2012), integrating these Delphi-derived insights with robust programming models offers a comprehensive pathway to simultaneously maximize economic value and ensure environmental compliance in green steel R&D portfolios.

Furthermore, the elevated importance of specific indicators, namely DR4 (real-time energy and carbon dashboard) and SM2 (systematic scanning of emerging technologies), carries profound multi-level governance and policy implications beyond the firm level. For policymakers and regulators, DR4 represents a critical mechanism for regulatory compliance and transparency. Mandating or incentivizing real-time carbon dashboards allows regulatory bodies to monitor industrial decarbonization progress dynamically, shifting governance from retrospective auditing to proactive, data-driven oversight. Similarly, SM2 serves as a strategic governance lever for national industrial policy. By systematically scanning emerging technologies, industry leaders can align their R&D portfolios with national green transition roadmaps (e.g., hydrogen direct reduction). For policymakers, fostering ecosystems that support such systematic scanning—through public-private partnerships, innovation grants, or regulatory sandboxes—ensures that the domestic heavy industry sector remains globally competitive while adhering to stringent environmental mandates.

Conversely, the Legal and Institutional dimensions exhibited the lowest consensus and reliability metrics, highlighting a critical systemic barrier in the green transition. This divergence stems from the inherent lag between the rapid pace of technological innovation (e.g., AI-driven process optimization, digital twins) and the slow, static nature of institutional and regulatory frameworks. Experts from different sectors experience this regulatory misalignment differently: some view existing environmental policies as inadequate incentives, while others perceive them as rigid bureaucratic hurdles. This low consensus underscores a core technology governance challenge: the urgent need for agile, adaptive regulatory frameworks and multi-stakeholder governance bodies that can evolve alongside emerging low-carbon technologies, rather than constraining them with outdated compliance models.

To translate these findings into actionable technology governance, we propose a structured governance roadmap (illustrated in Fig. 2). The conceptual framework operates across three interconnected layers:

(1) The Infrastructural Layer (Firm-Level): Driven by the high-convergence Digital Readiness indicators (DR1, DR4), this layer mandates the establishment of real-time energy/carbon dashboards and integrated process data architectures.

(2) The Strategic Foresight Layer (Industry-Level): Anchored by SM2 (systematic scanning), this layer acts as a governance mechanism to continuously align R&D portfolios with emerging low-carbon technological windows and global market shifts.

(3) The Regulatory Alignment Layer (Macro-Level): This layer bridges the firm's internal capabilities with external institutional frameworks, addressing the critical misalignment identified in the Legal/Institutional dimensions by proposing agile, multi-stakeholder compliance mechanisms.

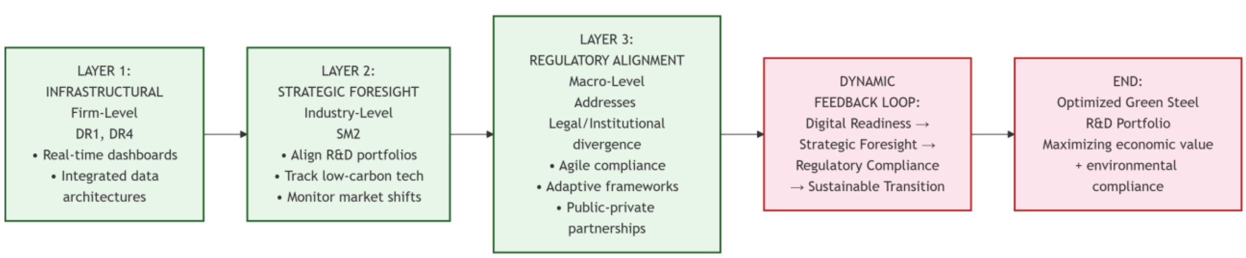

Fig. 1. The Conceptual Framework & Structured Governance Roadmap.

Together, these layers illustrate that technology governance in energy-intensive industries is not a static evaluation exercise, but a dynamic, multi-level feedback loop where digital readiness enables strategic foresight, which in turn ensures regulatory compliance and sustainable transition. This study makes several significant contributions to the literature and practice of R&D portfolio management, primarily by demonstrating that accelerated consensus can be achieved within just two Delphi rounds—evidenced by a Kendall's W of 0.177 and Cronbach's alpha of 0.853 in the second round—when the focus is directed toward green steel and digital transformation. Building upon this rapid agreement, the research generated a low-dispersion set of indicators (e.g., DR1, DR4, and SM2) that are highly suitable for integration into Multi-Criteria Decision-Making (MCDM) models. Furthermore, the quantitative evidence derived from these refined indicators establishes a clear pathway toward option-based and robust governance models, illustrating how such data can underpin a project portfolio resilient to financial, technological, and environmental risks. Ultimately, these findings not only bridge a critical domestic research gap regarding green steel R&D portfolio management but also offer a reliable, replicable template for other energy-intensive industries; by effectively combining expert consensus with quantitative modeling, this framework minimizes innovation investment risks and paves the way for a smoother transition toward a low-carbon economy.

Despite its contributions, this study has certain limitations that pave the way for future research. First, while the Delphi panel was highly specialized and homogeneous, it was geographically concentrated within a specific national context (Iran's steel sector), which may limit the immediate generalizability of the institutional and legal findings to regions with different regulatory regimes (e.g., the EU's CBAM environment). Future studies should conduct cross-national comparative Delphi studies to validate these governance levers across diverse regulatory ecosystems. Second, this research successfully identified and weighted the governance indicators but did not empirically test the causal relationships between them in a live portfolio selection scenario. Future research should integrate these 49 validated indicators into quantitative Multi-Criteria Decision-Making (MCDM) models—such as DEMATEL-ANP or Grey Relational Analysis—or apply them in robust optimization models to simulate real-world R&D portfolio selection under deep uncertainty.

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Conflicts of interest

The author declare no conflict of interest.

Authors contribution statement

FA: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing.

The author has read and approved the final version of the manuscript and accepts responsibility for the integrity of the work.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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