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Designing a Systemic Model of Green Technological Innovation in the Steel Industry

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ABSTRACT

The aim of this study is to design a systemic model of green technological innovation in the steel industry. The research was conducted in two phases. In the first phase, using Stafford Beer's approach and the emancipatory paradigm within a framework of team-based integration, the dimensions of the model were identified through seven key processes (initial meeting, agenda setting, topic selection, summarization, and final meeting). This phase adopted a qualitative approach, an applied orientation, an inductive method, and utilized a synchronization protocol tool (structured dialogues and feedback loops). The statistical population consisted of 30 managers, deputies, and consultants from Khuzestan Steel Company, organized into 12 teams.
In the second phase, a five-step process was employed to quantitatively validate the model. This included designing a Likert-scale questionnaire, simple random sampling (113 out of 165 employees with at least a Master's degree based on Morgan's table), data collection, and statistical analysis using SMART PLS software to assess model fit, validity, and reliability. This phase used a deductive approach, quantitative method, and confirmatory factor analysis. Model validity in the first phase was confirmed through alignment with Stafford Beer's approach, and in the second phase through face and content validity methods (CVR and Lawshe's coefficient). Reliability in the first phase was ensured through process robustness and in the second phase through Cronbach's alpha (0.795). Twelve key indicators were identified: energy management, waste management, greenhouse gas reduction, water efficiency, innovation in production processes, green product design, sustainable raw material supply, environmental management, training, investment in research and development, health and safety, and social responsibility. Confirmatory factor analysis showed that all indicators have high validity and are significantly related to green innovation. Waste management (beta coefficient = 0.713) had the strongest effect, and investment in research and development (T = 4.696) played the most significant role. The goodness-of-fit indices (SRMR = 0.05, NFI = 0.92, d-ULS = 0.07, d-G = 0.06, Chi-square = 2.5, GOF = 0.8107) indicated an excellent model-data fit. This model provides an effective tool for implementing green innovations in the steel industry.

Keywords: Systemic model, Green technological innovation, Steel industry, Emancipatory paradigm, Team-based integration

Introduction

The steel industry, as a foundational sector of the global economy, plays a pivotal role in infrastructure development, manufacturing, and economic growth. However, it is also a significant contributor to global greenhouse gas emissions, resource depletion, and environmental degradation. As a result, there is an urgent need for a transformative shift toward sustainable and green practices within this sector. Green technological innovation has emerged as a strategic imperative in addressing these environmental challenges, while simultaneously enhancing industrial competitiveness and resilience [1, 2].

Green technological innovation refers to the development and application of products, processes, and systems that minimize environmental harm while achieving technological and economic goals [3]. In the steel industry, this includes advancements in energy efficiency, waste management, low-carbon production processes, and circular material flows [4]. The move toward green innovation is not only a response to environmental pressures but also a strategic response to evolving regulatory landscapes, stakeholder expectations, and market demands [5, 6]. Given the sector's high carbon intensity and resource consumption, the steel industry has become a key target for national and international green transformation initiatives.

The integration of green technologies within steel production systems necessitates a systemic and multidimensional approach. This includes aligning technological capabilities with environmental objectives, fostering innovation ecosystems, and building organizational capacities that support sustainable practices [7, 8]. A growing body of literature underscores the importance of system-level modeling in capturing the complexities and interdependencies involved in green innovation transitions. Systemic models enable stakeholders to visualize causal relationships, identify leverage points, and simulate the outcomes of policy or technological interventions [9, 10].

One critical factor driving green innovation is the effectiveness of environmental regulations. While traditional command-and-control policies have historically influenced industrial compliance, more recent studies emphasize the importance of well-designed, heterogeneous environmental standards that stimulate innovation without imposing excessive constraints [10, 11]. For instance, differentiated regulatory regimes have been found to produce asymmetric effects on innovation performance, particularly when combined with green financing mechanisms [12, 13]. The role of policy instruments in fostering green transformation is especially pronounced in emerging economies, where regulatory enforcement and market dynamics vary across regions [6, 14].

Equally important are the financial and institutional mechanisms that support green technology development. Green credit, green finance, and public-private investment partnerships are increasingly recognized as catalysts for sustainable industrial innovation [12, 13]. These financial instruments not only reduce the capital constraints that firms face but also signal institutional commitment to low-carbon development pathways. Moreover, organizational innovation, including changes in management practices and leadership styles, plays a decisive role in facilitating green transitions. Transformational and participative leadership approaches have been positively correlated with higher innovation capacity, particularly in complex technological domains such as green steel production [8, 15].

Furthermore, industry-university-research collaborations provide a critical pathway for knowledge transfer, resource sharing, and technological co-development. Strategic alliances between academic institutions and industrial firms create environments conducive to experimentation, prototyping, and adoption of disruptive green technologies [16, 17]. These alliances are particularly beneficial in high-capital industries such as steel, where the costs and risks associated with innovation are substantial. Recent modeling efforts using evolutionary game theory and simulation approaches suggest that firms involved in alliances demonstrate superior performance in green innovation compared to non-aligned counterparts [16].

In parallel, advances in digitalization and data-driven decision-making are transforming how green innovations are developed and deployed. Big data analytics, artificial intelligence, and smart manufacturing systems offer new tools for optimizing energy use, monitoring emissions, and predicting maintenance needs in real-time [18, 19]. These technologies also enable firms to conduct detailed life cycle assessments and generate granular insights into the environmental impact of their operations, which are essential for continuous improvement and compliance reporting. Importantly, the digital transformation of green technology development also enhances organizational agility, enabling firms to rapidly respond to environmental shocks and policy shifts [20].

Amid these advancements, systemic innovation models that integrate technological, organizational, financial, and regulatory dimensions are increasingly seen as essential tools for guiding green transitions in the steel sector. Such models provide a comprehensive framework for understanding the interplay between innovation drivers, barriers, and outcomes. They also offer practical guidance for decision-makers seeking to prioritize investments, design supportive policies, and align internal strategies with sustainability goals [7, 21]. Moreover, they facilitate stakeholder engagement by providing a shared language and conceptual map for exploring complex innovation scenarios.

The development of systemic models also supports the implementation of green hydrogen, carbon capture technologies, and electrification of steelmaking processes—all of which are critical to achieving deep decarbonization in the sector [4, 20]. For example, the integration of green hydrogen in blast furnace operations not only reduces CO_2 emissions but also enhances resilience against energy price volatility. Similarly, the deployment of carbon capture, utilization, and storage (CCUS) technologies is gaining traction as a viable pathway for addressing residual emissions in hard-to-abate industrial activities.

In this context, the current study aims to design and validate a systemic model of green technological innovation tailored to the steel industry. Drawing upon Stafford Beer’s cybernetic framework and the emancipatory paradigm, the model incorporates participatory processes, feedback loops, and multi-level constructs to capture the dynamic and complex nature of green innovation. The two-phase design of the research—qualitative identification and quantitative validation—ensures that the model is both contextually grounded and statistically robust. The identification of twelve key indicators (e.g., energy management, waste reduction, green product design, sustainable raw material supply, environmental management, training, R&D investment, and social responsibility) provides a multidimensional view of green innovation performance.

Notably, the use of partial least squares structural equation modeling (PLS-SEM) allows for the analysis of non-normally distributed data and small to medium sample sizes, making it particularly suitable for real-world organizational research settings [15, 22]. The confirmatory factor analysis results demonstrate high levels of model fit and indicator validity, with waste management and R&D investment showing the strongest impact and significance, respectively. This finding aligns with prior empirical research highlighting the role of waste circularity and research intensity in driving sustainable industrial innovation [1, 9, 17].

In sum, this study contributes to the literature on green innovation in heavy industries by presenting a systemic, empirically tested framework that integrates key technological, organizational, and environmental variables.

Methods and Materials

The present study was conducted with the aim of designing a systemic model of green technological innovation in the steel industry, implemented in two phases. In the first phase, utilizing Stafford Beer's (1990) approach and the spirit of the emancipatory paradigm within a team integration framework, the model dimensions were identified through seven key processes: initial meeting, agenda setting, topic selection, result summarization, and final meeting. This phase followed an applied orientation, an inductive approach, a qualitative methodology, and employed the synchronization protocol tool (including structured dialogues and feedback loops). The statistical population consisted of 30 managers, deputies, and consultants from Khuzestan Steel Company, organized into 12 teams.

In the second phase, for quantitative validation and verification of the model, a five-step process was undertaken, which included designing a Likert-scale questionnaire, defining the statistical population (165 employees of the company with at least a Master's degree), simple random sampling (sample size of 113 based on Morgan's table), data collection, and statistical analysis using SMART PLS software to examine model fit, validity, and reliability. This phase was conducted with an applied orientation, a deductive approach, a quantitative methodology, and a confirmatory factor analysis strategy. The model's validity in the first phase was confirmed by alignment with Stafford Beer's approach, and in the second phase through face and content validity methods (including CVR calculation and Lawshe's coefficient). Additionally, its reliability was ensured in the first phase through the robustness of the processes used and in the second phase via Cronbach's alpha calculation (0.795). Ultimately, the analytical methods used included Stafford Beer's approach in the first phase and factor analysis.

Findings and Results

In this study, the process of designing a systemic model for green technological innovation in the steel industry was carried out using Stafford Beer's (1990) approach to utilize the spirit of the emancipatory paradigm in team integration. In 1990, Stafford Beer, inspired by the emancipatory paradigm, introduced an innovative approach to team integration based on the philosophy of managerial cybernetics. Instead of traditional prescriptive and structured methods, he emphasized that any form of team integration should be grounded in the "liberation" of individuals from the rigid constraints of managerial systems. Beer believed that teams can only function effectively and creatively when a free and flexible space for decision-making and interaction is available. This approach, inspired by the emancipatory paradigm, redefines management from a controlling and mandatory process into an active facilitation of self-organization and the emergence of spontaneous patterns. Therefore, in this view, team integration is the result of spontaneous coordination and genuine member participation, which emerges in a space free from excessive structural controls.

This approach consists of five key stages: initial meeting, agenda setting, topic selection, result summarization, and closing session. In the initial meeting, the project objectives were clearly articulated, participation rules were defined, and a session facilitator was appointed to ensure all members had a shared understanding of the process and goals. In the agenda-setting stage, key topics such as technological solutions, regulatory challenges, economic implications, and environmental impacts were identified and organized into thematic clusters. Timeframes were also established for discussion of each cluster.

During the topic selection stage, each participant prepared a statement or brief presentation on an aspect of green technological innovation. These presentations delved into topics such as carbon capture technologies and the use of renewable energy in the steel industry. The facilitator played a key role in guiding discussions and ensuring clarity in presentations. In the result summarization stage, participants worked in small groups to examine each cluster more closely, aiming to reach consensus or propose innovative solutions based on predetermined rules. The rotation of groups enabled cross-pollination of ideas and enhanced inter-group interactions.

In the final meeting, a spokesperson from each group presented the outcomes of their discussions, and the entire assembly engaged in a discussion on general topics and potential synergies. Key insights and decisions made in various areas were summarized, and the effectiveness of the team convergence method was evaluated. Ultimately, a roadmap for designing and implementing the systemic model of green technological innovation in the steel industry was developed. In this process, 12 independent teams were formed, each focusing on a specific indicator, and overlap of indicators across groups was avoided.

Moreover, in line with the implementation of this approach, a space was created for the expression and examination of both supportive and opposing views. In discussions related to indicators such as “energy management” and “greenhouse gas emission reduction,” diverse perspectives were raised regarding economic challenges and environmental benefits. These views were analyzed through structured discussions facilitated by a moderator, ultimately resulting in consensus-based hybrid solutions with strong argumentative foundations. This process led to the formulation of comprehensive and balanced indicators that accounted for all aspects of the issue and contributed to enhancing the quality and efficiency of the systemic model.

Table 1.

Energy Management Indicator; Derived from Team 1

Conceptual Statement	Indicator Label
Energy efficiency in steel production processes has improved.	Energy Efficiency
The use of renewable energy sources in steel plants has increased.	Renewable Energy
Energy consumption has been optimized.	Energy Consumption Optimization
Technologies for reducing energy consumption have been employed.	Energy Reduction Technologies

In the meetings of Team 1, topics such as energy efficiency, the use of renewable energies, and optimization of energy consumption in the steel industry were discussed. The team explored energy reduction technologies and methods to improve efficiency, aiming to reduce energy usage in steel production processes. In the final meeting, the team presented systematic models for optimizing energy use and incorporating renewable resources.

Table 2.

Waste Management Indicator; Derived from Team 2

Conceptual Statement	Indicator Label
Waste recycling processes have been implemented in steel plants.	Waste Recycling
Waste generation in steel production processes has been minimized.	Waste Reduction
Industrial waste is reused in the production cycle.	Waste Reuse
Hazardous waste management has improved.	Hazardous Waste Management
Advanced waste management technologies have been employed.	Advanced Waste Technologies

Team 2 focused on waste management in the steel industry and addressed topics such as waste recycling, waste reduction, and hazardous waste management. The team ultimately concluded that the use of advanced technologies and improved waste management practices could contribute to reducing environmental impacts. In the final session, solutions were developed for improved waste management and reduced waste generation.

Table 3.

Greenhouse Gas Emissions Reduction Indicator; Derived from Team 3

Conceptual Statement	Indicator Label
Technologies for reducing greenhouse gas emissions have been applied in the steel industry.	Emission Reduction Technologies
Measurement and monitoring of greenhouse gas emissions are conducted.	Emission Monitoring
The volume of greenhouse gas emissions has been reduced.	Emission Reduction
Lower-carbon fuels are used in production processes.	Low-Carbon Fuels

Team 3 examined strategies for reducing greenhouse gas emissions in the steel industry, focusing on emission reduction technologies, emission monitoring, and the use of low-carbon fuels. In summarizing the findings, the team concluded that applying modern technologies and low-carbon fuels could help reduce greenhouse gas emissions. In the final meeting, models for reducing emissions were presented.

Table 4.

Water Efficiency Indicator; Derived from Team 4

Conceptual Statement	Indicator Label
Water consumption in steel production processes has been optimized.	Water Consumption Optimization
Water recycling has been implemented in steel plants.	Water Recycling
The use of non-potable water sources in production processes has increased.	Non-potable Water Sources
Technologies for reducing water consumption have been employed.	Water Reduction Technologies

Team 4 addressed water efficiency in the steel industry and discussed topics such as optimizing water use, water recycling, and using non-potable water sources. In subsequent meetings, water reduction technologies were reviewed. Ultimately, solutions were proposed for recycling water and reducing water consumption in steel production processes.

Table 5.

Innovation in Production Processes Indicator; Derived from Team 5

Conceptual Statement	Indicator Label
Steel production processes have been updated.	Process Updating
Innovative production techniques have been utilized.	Innovative Production Techniques
Advanced technologies have been used in steel manufacturing.	Advanced Technologies
Production is carried out with higher quality and less waste.	Higher Quality and Less Waste
Production time and cost have been reduced.	Reduced Production Time and Cost

Team 5 worked on innovation in steel production processes, focusing on process updating, the use of innovative techniques, and advanced technologies. In summarizing the findings, the team concluded that innovation could lead to reduced production time and cost and improved product quality. In the final meeting, solutions were proposed for updating processes and reducing production waste.

Table 6.

Green Product Design Indicator; Derived from Team 6

Conceptual Statement	Indicator Label
Products have been designed with minimal environmental impact.	Low Environmental Impact
The use of recycled materials in products has increased.	Recycled Materials
Products have been designed for longer lifespan and recyclability.	Long Lifespan & Recyclability
Product design has reduced resource consumption.	Reduced Resource Consumption

Team 6 focused on green product design in the steel industry, addressing topics such as low environmental impact, use of recycled materials, and designing products for extended lifespan. In the final session, models for green product design and the use of recycled materials were presented. The importance of designing recyclable products was also emphasized.

Table 7.

Sustainable Raw Material Supply Indicator; Derived from Team 7

Conceptual Statement	Indicator Label
Raw materials are supplied through sustainable methods.	Sustainable Supply
Sources of raw material supply have been optimized.	Resource Optimization
Alternative raw materials with lower environmental impact have been used.	Alternative Raw Materials
Supply chain management of raw materials has improved.	Supply Chain Management

Team 7 worked on sustainable raw material supply, focusing on issues such as sustainability, resource optimization, and the use of alternative raw materials. In the final session, strategies for sustainable supply and improved supply chain management were proposed. Using alternative materials and optimizing resources were identified as key solutions.

Table 8.

Environmental Management Indicator; Derived from Team 8

Conceptual Statement	Indicator Label
Environmental management systems have been implemented.	Environmental Management Systems
Monitoring and assessment of environmental impacts have improved.	Monitoring and Assessment
Efforts have been made to reduce the environmental impacts of processes.	Reduced Environmental Impacts
Stricter environmental policies are being enforced.	Strict Environmental Policies

Team 8 focused on environmental management in the steel industry, addressing the implementation of environmental management systems, environmental impact monitoring, and enforcement of strict environmental policies. In the final session, operational models for environmental management and strategies for monitoring and assessment were introduced.

Table 9.

Training and Awareness Indicator; Derived from Team 9

Conceptual Statement	Indicator Label
Employees have been trained in green technologies.	Green Technology Training
Awareness campaigns for reducing resource consumption have been conducted.	Resource Reduction Awareness
Environmental education programs have been held for employees.	Environmental Education Programs
Employees are committed to environmental preservation.	Environmental Commitment

Team 9 focused on training and awareness in the steel industry, emphasizing green technology training, resource conservation awareness, and employee commitment to environmental preservation. In the final session, strategies for training in green technologies and promoting a culture of resource conservation were presented.

Table 10.

Investment in Research and Development Indicator; Derived from Team 10

Conceptual Statement	Indicator Label
Investment in green technology R&D has increased.	Increased Investment
New research projects on green innovation have been initiated.	New Research Projects
Collaborations with universities and research centers are ongoing.	University Collaborations
R&D budgeting has improved.	Improved Budgeting
Research on improving production processes is ongoing.	Process Improvement Research

Team 10 addressed investment in research and development, with a focus on increased funding, new projects, and collaboration with universities. In the final session, solutions were introduced for increasing R&D budgets and enhancing academic partnerships.

Table 11.

Health and Safety Promotion Indicator; Derived from Team 11

Conceptual Statement	Indicator Label
Working conditions have improved.	Improved Working Conditions
Safety programs have been implemented for employees.	Safety Programs
A reduction in work-related accidents has been observed.	Reduction in Work Accidents
Workplace hygiene has been enhanced.	Improved Workplace Hygiene

Team 11 worked on improving health and safety in the workplace, focusing on better working conditions, safety initiatives, and reduction of occupational accidents. In the final session, solutions for improving working conditions and minimizing accidents were presented.

Table 12.

Social Responsibility Indicator; Derived from Team 12

Conceptual Statement	Indicator Label
Social and environmental projects are implemented by factories.	Social and Environmental Projects
Interaction with local communities has improved.	Local Community Engagement
Factories participate in corporate social responsibility programs.	CSR Participation
Support is provided for environmental projects.	Support for Environmental Projects
Participation in sustainable development initiatives has increased.	Sustainable Development Participation

Team 12 addressed social responsibility in the steel industry, focusing on social and environmental projects, engagement with local communities, and participation in sustainable development. In the final session, models for social and environmental projects and sustainable development participation were introduced.

In the quantitative section, to select an appropriate software for confirmatory factor analysis (CFA), it was first necessary to determine whether the research data followed a normal distribution.

Table 13.

Kolmogorov–Smirnov Test for Normality of Model Indicators

Model Indicators	Significance Level	Alpha	Test Result
Energy Management	0.0210	0.05	Not Normal
Waste Management	0.0102	0.05	Not Normal
Greenhouse Gas Emissions Reduction	0.0118	0.05	Not Normal
Water Efficiency	0.0159	0.05	Not Normal
Innovation in Production Processes	0.0114	0.05	Not Normal
Green Product Design	0.0229	0.05	Not Normal
Sustainable Raw Material Supply	0.0100	0.05	Not Normal
Environmental Management	0.0154	0.05	Not Normal
Training and Awareness	0.0113	0.05	Not Normal
Investment in Research and Development	0.0160	0.05	Not Normal
Health and Safety Promotion	0.0125	0.05	Not Normal
Social Responsibility	0.0127	0.05	Not Normal

Since the significance levels for all model indicators in the Kolmogorov–Smirnov test are less than 0.05, it is concluded that the data do not follow a normal distribution. Given the non-normality of the data and the sample size of 113, the best choice for confirmatory factor analysis and model fitting is the SmartPLS software. The research model was evaluated in two modes: standardized (Beta) and significance (T-value).

Figure 1.

Beta Values in the Model

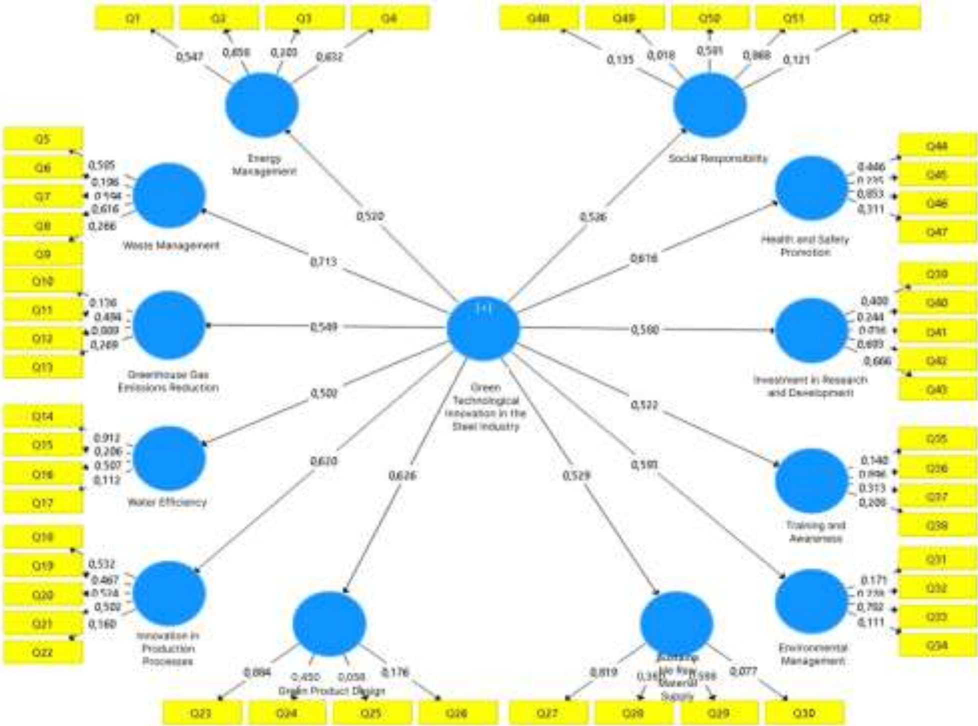
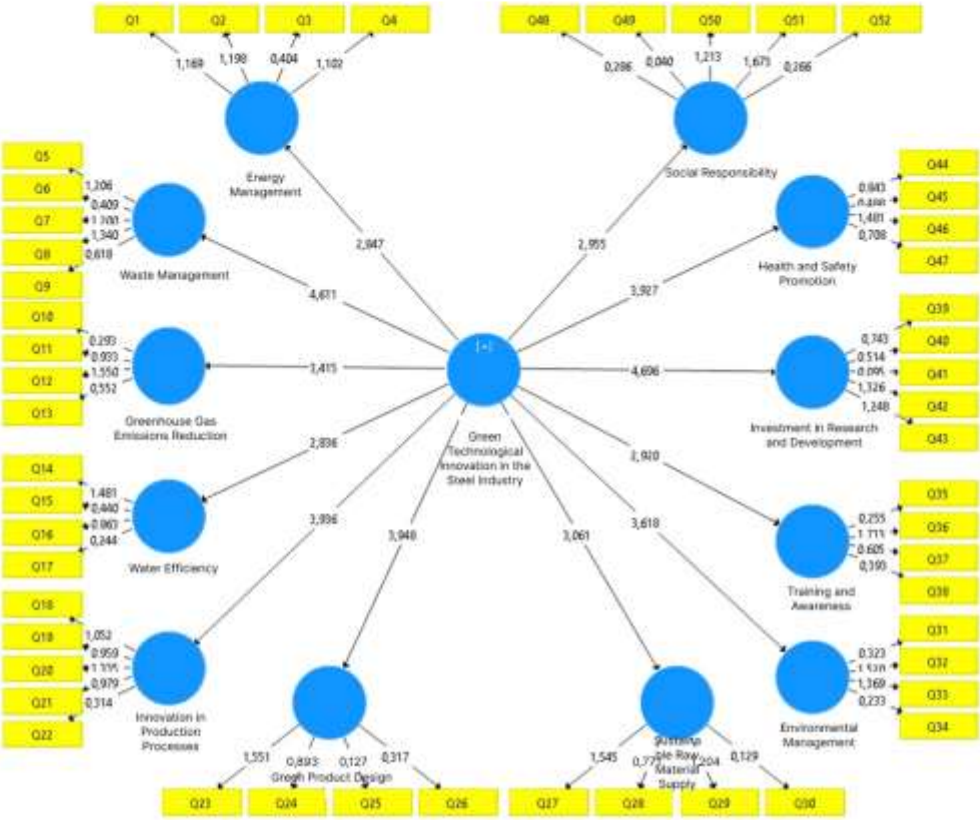


Figure 2.

T-values in the Model



In confirmatory factor analysis without a dependent variable, a second-order reflective construct is used, which integrates the first-order variables (12 main indicators) in a hierarchical structure. In this method, each first-order variable is connected to its sub-indicators and then linked to the second-order variable. This approach reduces model complexity, increases analytical precision, and enables assessment of how first-order variables are influenced by the model's core concept.

Table 14.

Beta and T-value Analysis

Relationship of Indicators with Core Concept	Impact Intensity (β)	T-value	Significance Level	Result
Energy Management	0.520	2.847	P < 0.01	Confirmed
Waste Management	0.713	4.611	P < 0.01	Confirmed
Greenhouse Gas Emission Reduction	0.549	3.415	P < 0.01	Confirmed
Water Efficiency	0.502	2.836	P < 0.01	Confirmed
Innovation in Production Processes	0.620	3.936	P < 0.01	Confirmed
Green Product Design	0.626	3.948	P < 0.01	Confirmed
Sustainable Raw Material Supply	0.529	3.061	P < 0.01	Confirmed
Environmental Management	0.593	3.618	P < 0.01	Confirmed
Training and Awareness	0.522	2.920	P < 0.01	Confirmed
Investment in R&D	0.580	4.696	P < 0.01	Confirmed
Health and Safety Promotion	0.616	3.927	P < 0.01	Confirmed
Social Responsibility	0.526	2.955	P < 0.01	Confirmed

In statistical analysis, the Beta coefficient (β) represents the intensity of the impact of an independent variable on the dependent variable. Values between 0 and 1 are generally considered acceptable, with values closer to 1 indicating stronger influence. The T-value assesses statistical significance, and values greater than 1.96 (at 95% confidence level) confirm the significance of the indicators. The table presents the impact intensity (β) and T-value for the relationship between core concepts and the systemic model indicators, covering 12 key indicators—all of which were statistically significant at $P < 0.01$. Indicators such as Energy Management (β=0.520, T=2.847), Waste Management (β=0.713, T=4.611), Greenhouse Gas Emission Reduction (β=0.549, T=3.415), Water Efficiency (β=0.502, T=2.836), Innovation in Production Processes (β=0.620, T=3.936), Green Product Design (β=0.626, T=3.948), Sustainable Raw Material Supply (β=0.529, T=3.061), Environmental Management (β=0.593, T=3.618), Training and Awareness (β=0.522, T=2.920), Investment in R&D (β=0.580, T=4.696), Health and Safety Promotion (β=0.616, T=3.927), and Social Responsibility (β=0.526, T=2.955) were all confirmed as significant contributors to the model. The strongest effect was observed for Waste Management (β=0.713), and the highest significance was observed for Investment in R&D (T=4.696).

Table 15.

Model Goodness-of-Fit Indices

Value	Index
0.05	SRMR
0.92	NFI
0.07	d-ULS
0.06	d-G
2.5	χ^2/df

Table 15 presents various model fit indices. The SRMR (Standardized Root Mean Square Residual), which measures the discrepancy between observed and predicted correlation matrices, is 0.05—below the acceptable threshold of 0.08—indicating good model fit. The NFI (Normed Fit Index), which assesses the degree to which the proposed model matches the data, has a value of 0.92, exceeding the acceptable level of 0.90, indicating a well-fitting model. The d-ULS (Unweighted Least Squares Discrepancy) value of 0.07 is below 0.08, further confirming a good model fit. Similarly, the d-G index, which operates like d-ULS, has a value of 0.06—also under the 0.08 threshold—supporting model compatibility. Finally, the χ^2/df (chi-square divided by degrees of freedom) index, used to assess model fit, is 2.5. Values less than 3 typically indicate good fit, confirming the adequacy of the proposed model.

Additionally, the Goodness of Fit (GOF) index is a criterion that evaluates the structural model's compatibility with actual data, indicating how well the model explains the dataset. This index is calculated using the average communality and the coefficient of determination (R^2). Values above 0.36 are considered strong fits. In this study, the GOF value was calculated at 0.8107, demonstrating excellent and acceptable overall model fit.

Discussion and Conclusion

The findings of the present study provide compelling empirical support for the systemic model of green technological innovation in the steel industry. Using a dual-phase research design, the study identified twelve core indicators representing critical dimensions of green innovation—ranging from energy management and waste reduction to investment in R&D and social responsibility. Confirmatory factor analysis using SmartPLS revealed that all twelve indicators had statistically significant and positive relationships with the overarching construct of green technological innovation. Among them, *waste management* exhibited the strongest standardized path coefficient ($\beta = 0.713$), while *investment in research and development* yielded the highest statistical significance ($T = 4.696$). The model demonstrated excellent goodness-of-fit metrics (e.g., SRMR = 0.05, NFI = 0.92, GOF = 0.8107), confirming the robustness of the proposed framework.

These results underscore the foundational role of *waste management* in driving green innovation within the steel sector. This aligns with prior findings that emphasize how waste recycling, hazardous material control, and closed-loop production significantly contribute to green productivity gains in energy-intensive industries [1, 4]. The high impact of waste management in this study indicates that minimizing material losses and implementing circular economy practices are not only environmentally beneficial but also strategically significant for innovation-led competitiveness. This finding is consistent with the broader literature asserting that sustainable production practices offer dual environmental and operational performance advantages [5, 9].

The second major highlight—the significance of *R&D investment*—also resonates with the growing scholarly consensus on the catalytic role of research and innovation in achieving green transformation. As evidenced by [13] and [12], firms that commit substantial resources to green R&D are more likely to develop breakthrough technologies such as green hydrogen, electrification methods, and low-carbon steelmaking processes. These investments not only enhance technological capabilities but also reinforce long-term strategic positioning in the face of evolving environmental standards and consumer expectations. The high T-value associated with R&D investment in this study indicates its robust explanatory power in modeling systemic innovation trajectories.

Similarly, the importance of *green product design* and *innovation in production processes* was substantiated by their high path coefficients ($\beta = 0.626$ and $\beta = 0.620$, respectively). These dimensions suggest that process efficiency and eco-design are core building blocks of a sustainable steel industry. Previous studies have argued that green design strategies—such as using recyclable materials and improving energy efficiency—are integral to reducing the product life-cycle environmental footprint [3, 15]. Moreover, technological upgrades in production lines (e.g., adopting smart systems and precision metallurgy) enable firms to reduce emissions, optimize inputs, and minimize downtime [18, 19].

The findings related to *environmental management* (β = 0.593), *energy management* (β = 0.520), and *water efficiency* (β = 0.502) further support the notion that operational excellence in resource stewardship is crucial for successful green innovation. These results are coherent with studies emphasizing the role of environmental management systems (EMS) in embedding sustainability principles across industrial operations [6, 7]. The empirical significance of these indicators in this study validates prior research that shows how rigorous EMS practices, when aligned with environmental KPIs, contribute to reducing the ecological footprint of high-emission industries [14].

Furthermore, the dimensions of *training and awareness*, *social responsibility*, and *health and safety*—while often overlooked in purely technological models—emerged as statistically significant in this study. This underscores the socio-organizational facets of green innovation, as suggested by [8], who emphasized that human capital development, organizational culture, and ethical leadership are key enablers of innovation adoption. The significance of *training and awareness* confirms the need to align employee mindsets and competencies with green transformation goals, while *social responsibility* reflects the growing importance of stakeholder engagement and legitimacy in green transitions [6, 21].

A noteworthy dimension validated by this study is *sustainable raw material supply* (β = 0.529), reflecting the upstream importance of green procurement and responsible sourcing. The steel industry is heavily dependent on resource extraction, which makes it vulnerable to environmental criticism and regulatory scrutiny. Integrating sustainability principles in raw material acquisition—such as the use of low-carbon inputs, recycled metals, and traceable sourcing—can enhance environmental performance and supply chain resilience [2, 20]. The study confirms that proactive sourcing strategies are a fundamental component of the systemic model.

Overall, the results provide empirical backing to the systemic nature of green innovation, as posited in theoretical works on technological transitions and systems thinking [3, 17]. The multidimensional approach of the model—capturing organizational, technological, environmental, and social dimensions—mirrors the complex interplay of factors involved in green industrial transformation. As [11] and [16] assert, a systems approach is vital for addressing path dependencies, coordinating multi-actor efforts, and sustaining long-term innovation momentum.

Moreover, the application of confirmatory factor analysis and the use of PLS-SEM techniques in this study are methodologically significant. Given the non-normality of the dataset, PLS was an appropriate choice that allowed for robust estimation under small-to-medium sample conditions. This aligns with recent methodological advancements in sustainability research, where hybrid models and reflective constructs are increasingly being used to explore latent relationships [13, 22].

Despite its contributions, the present study is not without limitations. First, the sample size, while adequate for PLS-SEM, was drawn from a single geographic and industrial context—specifically the Iranian steel sector. This may limit the generalizability of the findings to other countries or sectors with differing regulatory, economic, and technological conditions. Second, the study's cross-sectional design does not account for the dynamic evolution of green innovation over time. Innovation is inherently a temporal process, and longitudinal studies would be better positioned to capture causal trajectories and feedback effects. Finally, while the model integrated multiple dimensions of innovation, it may have omitted other relevant factors such as digital infrastructure maturity, policy volatility, and market dynamics that could influence green innovation outcomes.

Future studies could address these limitations by expanding the model to other industrial sectors such as cement, aluminum, or chemicals to assess the transferability of the framework. Comparative analyses across countries with differing institutional arrangements and regulatory intensities could also yield insightful cross-cultural findings. Additionally, longitudinal designs employing panel data or system dynamics modeling could uncover deeper insights into the temporal dynamics of innovation adoption and diffusion. It would also be valuable to integrate external shocks—such as carbon pricing policies, raw material scarcity, or geopolitical disruptions—into the model to assess systemic resilience. Moreover, incorporating qualitative insights from stakeholders through mixed-method approaches can provide richer context and validation to quantitative findings.

Practitioners in the steel industry can use the validated systemic model as a diagnostic and planning tool for green transformation initiatives. By identifying key performance indicators across technical, environmental, and organizational domains, firms can prioritize investments and monitor progress more effectively. Policymakers should consider designing integrated regulatory and financial frameworks that incentivize systemic innovation rather than isolated compliance. Training programs aimed at upskilling the workforce in green technologies and sustainability literacy should be institutionalized. Cross-sector partnerships, especially with academic and research institutions, should be encouraged to foster co-innovation and reduce the costs and risks associated with R&D. Lastly, embedding environmental stewardship and social responsibility into core business strategies will be critical for building stakeholder trust and long-term competitiveness in a rapidly decarbonizing world.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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