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MULTI-OBJECTIVE THERMO-ECONOMIC AND SUPPLY CHAIN OPTIMIZATION MODELING FOR HYDROGEN ENERGY INTEGRATION IN SMART FACTORIES

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Abstract

This study examines how multi-objective thermo-economic and supply chain optimization capabilities influence hydrogen energy integration in smart factories operating within Industry 4.0 environments. Using a quantitative, cross-sectional, case-study–based design, the research surveyed 120 respondents across energy, production, maintenance, and supply-chain roles in hydrogen-relevant smart factories. Key constructs measured on Likert's five-point scale indicate that smart factory digitalization (mean 3.65), thermo-economic optimization capability (mean 3.48), and hydrogen supply chain optimization (mean 3.36) are present at moderate-to-high maturity levels, while hydrogen integration performance (mean 3.72) and overall operational/economic performance (mean 3.68) reflect favorable perceived outcomes. Reliability analyses demonstrate strong internal consistency (Cronbach's a ranging from 0.84 to 0.89). Correlation coefficients show statistically significant positive relationships across all constructs, with the strongest association between hydrogen integration performance and operational/economic performance ($r = 0.71$, $p < .01$). Regression modeling confirms that thermo-economic optimization ($\beta = 0.32$, $p < .01$) and supply chain optimization ($\beta = 0.29$, $p < .01$) significantly predict hydrogen integration performance (Adj. $R^2 = .54$), while both capabilities jointly explain substantial variance in operational and economic performance (Adj. $R^2 = .61$). A supporting multi-objective optimization model generates Pareto-optimal scenarios illustrating trade-offs among cost, efficiency, and reliability: a cost-focused configuration achieves 46% exergy efficiency with a disruption risk index of 0.42 at +12% CAPEX, whereas a reliability-focused configuration achieves 55.8% efficiency with risk reduced to 0.17, requiring +31% CAPEX. These quantitative findings reinforce that hydrogen integration success in smart factories depends not only on digital infrastructure but on the coordinated development of exergy-aware thermo-economic routines and resilient hydrogen supply chains. The study thus provides a validated theoretical, empirical, and optimization-based foundation for guiding hydrogen-enabled smart manufacturing and industrial decarbonization strategies.

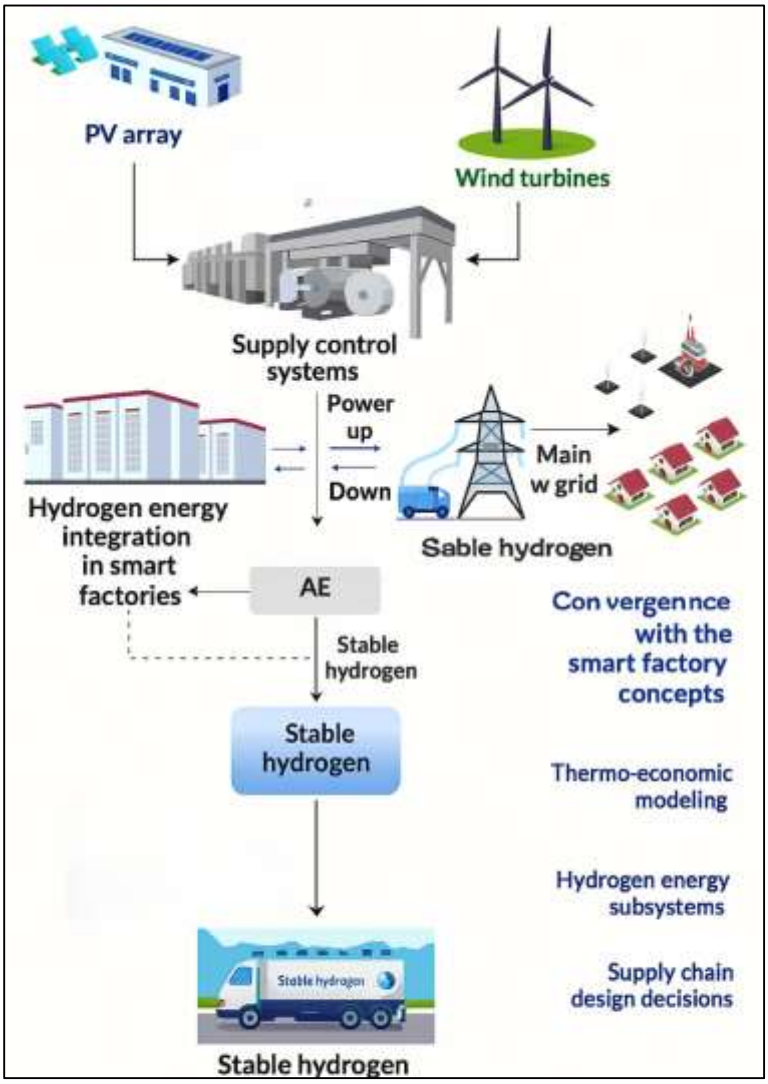
Keywords

Hydrogen energy integration; Smart factories; Thermo-economic optimization; Hydrogen supply chain optimization; multi-objective modeling;

INTRODUCTION

Hydrogen energy integration in smart factories sits at the intersection of industrial engineering, energy systems, and advanced analytics. Smart factories are commonly defined as highly digitized and connected production environments, characterized by cyber-physical systems, pervasive sensing, and data-driven decision-making enabled by Industry 4.0 technologies (Lasi et al., 2014). Within this paradigm, production assets, logistics flows, and energy systems become tightly coupled, transforming the factory into an integrated socio-technical system where operational efficiency, environmental performance, and economic outcomes are monitored and optimized in real time (Zhong et al., 2017). Smart factory frameworks emphasize adaptability, self-optimization, and connectivity across machines, products, and supply networks, linking operational data with strategic planning layers (Mabkhot et al., 2018). At the same time, global decarbonization agendas increasingly focus on hard-to-abate industrial sectors, where process heat, continuous operations, and high reliability requirements create strong demand for low-carbon energy carriers that can be safely and efficiently embedded into complex production systems. Hydrogen, with its high gravimetric energy density and zero direct carbon emissions at the point of use, is frequently positioned as a key secondary energy carrier within these agendas, particularly in energy-intensive manufacturing domains such as chemicals, steel, and advanced materials (Møller et al., 2017). The convergence of smart factory concepts with hydrogen integration creates a compelling context for thermo-economic and supply chain optimization in smart manufacturing environments.

Figure 1: Hydrogen Supply, Conversion, and Storage Pathways within Smart Factory Environments



Hydrogen is widely described as a versatile secondary energy carrier that can be produced from multiple primary resources and then stored, transported, and converted in a variety of end-use technologies (Abdulla & Ibne, 2021; Züttel et al., 2008). In contrast to primary energy sources, hydrogen does not occur freely in nature at industrially relevant scale and therefore requires upstream conversion pathways such as steam methane reforming, coal gasification with carbon management, and water electrolysis powered by renewable electricity (Habibullah & Foysal, 2021; Veneri, 2011). International reviews on hydrogen as an energy carrier emphasize its potential role in mitigating local air pollutants and greenhouse-gas emissions from transport, power, and industrial sectors, while highlighting challenges related to storage density, safety management, infrastructure deployment, and overall cost-competitiveness (Sanjid & Farabe, 2021; Ünal & Kılıç, 2007). In parallel, hydrogen supply chains from production plants to storage terminals, pipelines, trucking, and end-use facilities are increasingly studied using techno-economic and environmental assessment frameworks that account for life-cycle costs, energy use, and environmental burdens across alternative configurations (Sarwar, 2021; Wulf & Kaltschmitt, 2018). These studies provide important international perspectives on how hydrogen may be integrated into regional and cross-border supply networks, but they often remain at macro-system or national scales rather than at the level of individual smart factories (Musfiqur & Saba, 2021; Omar & Rashid, 2021). For manufacturers planning hydrogen adoption, this creates a critical need for analytical models that connect high-level hydrogen value chain design with plant-level energy, cost, and supply chain performance under realistic operating constraints.

Thermo-economic analysis (or exergoeconomic analysis) offers a powerful framework to jointly examine the thermodynamic performance and economic costs of energy systems by combining exergy-based modeling with detailed cost allocation procedures (Abusoglu & Kanoglu, 2009; Redwanul et al., 2021; Tarek & Praveen, 2021). In thermo-economic models, each component of an energy system such as boilers, gas turbines, heat recovery units, and process heaters is represented by its exergy flows as well as investment and operating cost streams, allowing analysts to assign unit costs to thermal products and to locate components that contribute most to overall cost formation (De-León Almaraz et al., 2013; Zaman & Momena, 2021; Rony, 2021). Within conventional power generation, numerous applications show how thermo-economic analysis can guide design and operation choices: for example, reviews of combined heat and power (CHP) systems document how exergy-based cost minimization can improve fuel utilization and cost efficiency simultaneously (Cheng & Ji, 2014; Shaikh & Aditya, 2021). For coal-fired and combined-cycle plants, component-level studies investigate how boiler conditions, turbine inlet temperatures, and auxiliary systems influence both exergy destruction and cost distributions, providing a quantitative basis for design adjustments and retrofit strategies (Sudipto & Mesbaul, 2021; Usón et al., 2009). In more advanced configurations, thermo-economic diagnosis approaches quantify malfunction and dysfunction indices for each component, linking deviations in thermodynamic performance to economic penalties in terms of increased product costs or lost profit opportunities (Zaki, 2021; Xiong et al., 2012). Collectively, this body of work establishes thermo-economic modeling as a mature methodology for analyzing complex energy systems, yet its application to hydrogen-integrated smart factory environments and to multi-objective optimization of factory-level decisions remains comparatively underexplored.

The overarching objective of this research is to develop and empirically examine a structured framework for multi-objective thermo-economic and supply chain optimization in the context of hydrogen energy integration within smart factories, using a quantitative, cross-sectional, case-study–based design. The study is designed to achieve several specific objectives that are closely aligned with this overall aim. First, it seeks to assess the current status of hydrogen energy integration in selected smart factories by documenting existing technological configurations, operational practices, and supply chain arrangements related to hydrogen production, storage, distribution, and on-site utilization. Second, it aims to measure the level of thermo-economic optimization within factory energy systems, with a particular focus on how decision makers manage trade-offs between exergy efficiency, energy cost, equipment utilization, and production reliability when hydrogen is introduced as an energy carrier. Third, the study intends to evaluate the degree of hydrogen supply chain optimization from the perspective of industrial end users, examining how sourcing strategies, logistics choices, inventory policies, and collaboration mechanisms with upstream and downstream partners shape the perceived robustness, flexibility, and cost performance of hydrogen supply. Fourth, it seeks to analyze the relationships among smart factory readiness, thermo-economic optimization practices, hydrogen supply chain optimization, and perceived performance outcomes, using Likert five-point scale survey data analyzed through descriptive statistics, correlation analysis, and regression modeling to test a set of clearly defined hypotheses. Fifth, the research aims to formulate a conceptual multi-objective optimization model that links thermo-economic indicators at the plant level with supply chain performance metrics, identifying key decision variables, objective functions, and constraints that characterize hydrogen-integrated smart factory systems. Finally, the study intends to synthesize empirical findings from the survey-based analysis with insights from the conceptual optimization model in order to produce a coherent, evidence-based description of how hydrogen integration decisions, thermo-economic characteristics, and supply chain configurations interact in real smart manufacturing environments. Through these objectives, the research remains focused on providing a systematic and measurable account of hydrogen energy integration in smart factories that is grounded in observed practices and quantified relationships among well-defined constructs.

LITERATURE REVIEW

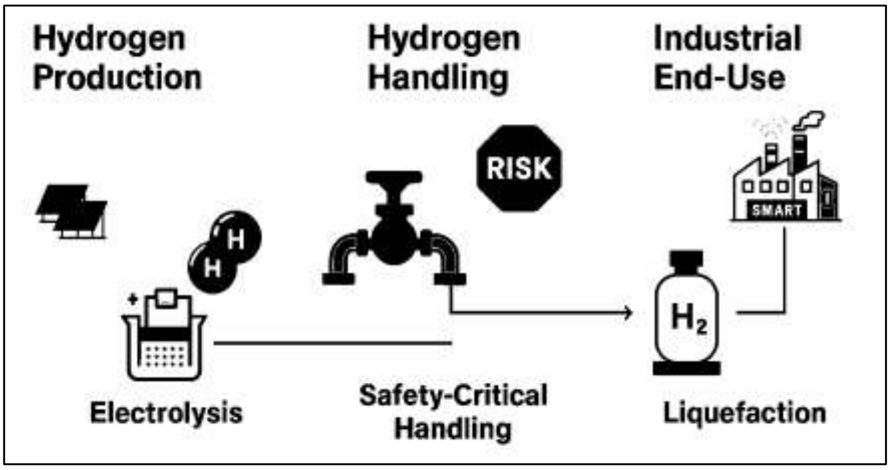
The literature on hydrogen energy integration, thermo-economic analysis, and supply chain optimization in industrial contexts has evolved across multiple streams that intersect directly with the emerging paradigm of smart factories and Industry 4.0. Over the past two decades, researchers have examined hydrogen primarily as a flexible secondary energy carrier and storage medium within wider energy systems, focusing on technical performance, production pathways, and environmental benefits across power, transport, and industrial sectors. Parallel strands of work have advanced thermo-economic and exergoeconomic methods to jointly evaluate the thermodynamic and cost performance of complex energy conversion systems at plant level, emphasizing component-level diagnostics, cost allocation, and identification of improvement opportunities. In another line, operations and logistics scholars have developed optimization-oriented models for hydrogen supply chains that capture strategic decisions on facility locations, transport modes, storage technologies, and capacity sizing under economic and environmental objectives. At the same time, the smart factory and Industry 4.0 literature has highlighted how cyber-physical systems, pervasive sensing, data analytics, and integrated planning architectures are transforming the way manufacturers manage production, energy, and supply networks. Within this multifaceted landscape, there remains a visible fragmentation: many hydrogen studies are conducted at macro or sectoral scales, thermo-economic research tends to focus on stand-alone power or cogeneration systems, and supply chain models frequently treat industrial users as simplified demand nodes rather than embedded, data-rich factory systems. As a consequence, there is limited cumulative understanding of how hydrogen energy, thermo-economic performance, and supply chain design co-evolve within real smart manufacturing environments and how these interdependencies can be captured in multi-objective models that reflect both plant-level and network-level considerations. The present literature review therefore seeks to synthesize and organize these bodies of work in a way that illuminates conceptual and methodological linkages between hydrogen integration, thermo-economic optimization, supply chain design, and smart factory implementation, and to identify specific constructs, relationships, and modeling approaches that will underpin the empirical and analytical components of the current study.

Hydrogen Energy Integration in Smart Factory Systems

Hydrogen is increasingly recognized as a pivotal energy carrier in low-carbon industrial energy systems, particularly where continuous high-temperature heat, feedstock flexibility, and deep decarbonization are required. From an energy-systems modeling perspective, hydrogen emerges as a strategic complement to electrification, enabling temporal decoupling between renewable generation and industrial demand through large-scale storage, sector coupling, and fuel substitution in "hard-to-abate" sectors such as steel, chemicals, and refining (Hanley et al., 2018). In this broader context, smart factories can be conceptualized as cyber-physical production environments that not only consume hydrogen as a fuel or feedstock but also interact dynamically with regional hydrogen infrastructures via flexible demand response, on-site electrolysis, and integrated cogeneration. At the plant level, hydrogen use must be coordinated with other energy carriers electricity, steam, natural gas, compressed air so that production scheduling, load shifting, and process control jointly minimize operating cost and emissions while respecting process constraints. At the supply-side, industrial hydrogen production technologies principally steam methane reforming, partial oxidation, and biomass or waste gasification remain dominant and are closely intertwined with CO_2 management strategies, such as pre-combustion capture and utilization routes, which directly shape the thermo-economic performance of hydrogen-enabled manufacturing systems (Behroozsarand et al., 2010; Hozyfa, 2022; Amin, 2022). Within smart factory environments, therefore, hydrogen is not a stand-alone decarbonization option; it must be modeled as part of a multi-energy, multi-process infrastructure in which the timing, location, and quality (pressure, purity, temperature) of hydrogen flows are matched against dynamic production requirements and external market signals (Arman & Kamrul, 2022; Mohaiminul & Muzahidul, 2022).

A second foundational stream of work relevant for hydrogen integration in smart factories concerns hydrogen management and network optimization in industrial processing plants, particularly refineries, where hydrogen has long been treated as a constrained shared utility rather than an unlimited commodity. Hydrogen network design and retrofit studies show that individual process units hydrotreaters, hydrocrackers, reformers, and other hydrogen sinks and sources are coupled by complex recycle and purification loops in which pressure, purity, and flowrate constraints determine both feasible operating windows and overall energy efficiency (Elsherif et al., 2015; Omar & Ibne, 2022; Sanjid & Zayadul, 2022). This perspective is highly relevant for smart manufacturing environments that plan to introduce hydrogen for high-temperature furnaces, reduction processes, or on-site fuel cells, because it highlights the need for integrated mass-exchange and pinch-based targeting approaches that treat hydrogen as a networked resource. By representing hydrogen sources, sinks, and purification units (e.g., pressure-swing adsorption, membranes) within unified superstructure models, prior studies demonstrate that significant reductions in fresh hydrogen demand and flaring can be achieved through systematic reallocation and blending of internal streams, even before new production capacity is added (Hasan, 2022; Mominul et al., 2022). Translating these insights into smart factories implies that the hydrogen sub-system production, storage, purification, buffering, and distribution to end-use equipment should be co-optimized with production scheduling, maintenance planning, and real-time control (Rabiul & Praveen, 2022; Farabe, 2022). Such co-optimization creates a methodological bridge between traditional hydrogen network management and Industry 4.0 concepts such as digital twins, edge sensing, and predictive analytics, which can continuously monitor hydrogen quality and availability and feed into multi-objective thermo-economic optimization frameworks (Roy, 2022; Rahman & Abdul, 2022).

Figure 2: Hydrogen Production, Safety-Critical Handling, and Liquefaction Pathways



A third body of literature relevant to hydrogen integration in smart factories addresses safety-critical handling of hydrogen and the thermo-economic characteristics of hydrogen liquefaction and storage at industrial scale (Razia, 2022; Zaki, 2022; Kanti & Shaikat, 2022). Comprehensive risk-analysis frameworks for hydrogen production and distribution plants develop quantitative risk assessment

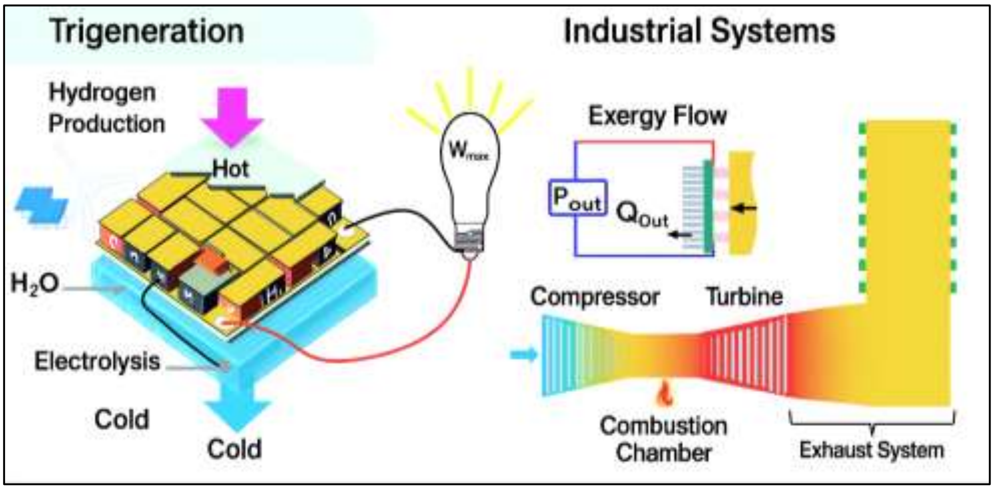
(QRA) models that integrate hazard identification (HAZOP), event tree analysis, and consequence modeling for jet fires, flash fires, and vapor cloud explosions, thereby providing structured procedures for evaluating individual and societal risk around hydrogen facilities (Mohammadfam & Zarei, 2015). These risk-based approaches are essential when smart factories introduce high-pressure hydrogen pipelines, storage vessels, or fueling interfaces inside densely instrumented industrial spaces, because the spatial layout of process equipment, sensors, and human–machine interfaces must respect exclusion zones derived from probabilistic accident scenarios. In parallel, research on the design and optimization of hydrogen liquefaction processes characterizes liquefaction as one of the most energy-intensive industrial operations and documents how alternative refrigeration cycles, mixed-refrigerant schemes, and process integration strategies can reduce specific energy consumption and improve exergy efficiency (Mohammadfam & Zarei, 2015). For smart factories that either receive liquefied hydrogen or consider on-site liquefaction as part of their supply chain, these insights directly affect the thermo-economic parameters underlying optimization models, including specific energy use, capital intensity, and feasible operating windows for storage and regasification. Together, safety-oriented risk modeling and thermo-economic liquefaction research provide crucial boundary conditions and parameter ranges for multi-objective optimization models that aim to integrate hydrogen into factory-scale energy systems without compromising safety, reliability, or cost performance.

Thermo-Economic Optimization in Industrial and Trigeneration Energy Systems

Thermo-economic optimization has emerged as a core analytical lens for industrial energy systems, because it explicitly couples thermodynamic performance with cost formation in a single decision framework. Rather than evaluating plants only in terms of first-law efficiency or levelized cost, thermo-economic analysis uses exergy as the "currency" that links irreversibilities to both capital and operating expenditures, allowing designers to localize where improvements generate the greatest economic returns. In combined cycle power plants, for example, a multi-objective optimization model was developed that simultaneously maximized exergy efficiency, minimized total cost rate, and reduced CO_2 emissions, demonstrating how supplementary firing or changes in gas-turbine conditions shift the trade-off surface between environmental impact and system cost (Ahmadi et al., 2011). Similarly, a thermoeconomic framework applied to a biomass-fired steam-turbine trigeneration plant showed that exergy-based costing can reveal the real cost burden of each configuration under changing fuel prices and operating hours, which is not evident from simple energy balances (Lian et al., 2010). Together, such studies establish that thermo-economic optimization is not a purely theoretical construct but a practical decision tool for complex industrial energy systems, especially where multiple products (electricity, heat, cooling) and fluctuating load profiles coexist. In the context of smart factories pursuing hydrogen integration, these insights are particularly important because they indicate how exergy-cost metrics can be extended to hydrogen production, storage, and utilization subsystems, so that the added thermo-economic complexity of hydrogen does not undermine overall plant profitability.

A significant strand of thermo-economic research focuses specifically on trigeneration architectures, which are highly relevant to smart factories aiming to satisfy electricity, process heat, space conditioning, and possibly hydrogen compression or conditioning from a unified energy hub. Investigations of three trigeneration configurations based on organic Rankine cycles (ORCs) supplied by solid oxide fuel cell (SOFC), biomass, and solar heat sources formulated thermoeconomic objective functions that minimize cost per unit of exergy for combined cooling, heating, and power (Al-Sulaiman et al., 2013). Their results underline how different primary energy carriers and integration schemes redistribute both exergy destruction and cost shares among subsystems, with the solar-driven trigeneration system exhibiting the lowest exergy-based product cost despite lower exergy efficiency, due to zero fuel cost and avoided emissions. In a complementary study, an SOFC-driven trigeneration system was optimized using a multi-objective evolutionary algorithm, with trigeneration exergy efficiency and total product unit cost as competing objectives (Sadeghi et al., 2015). The Pareto-front solutions revealed that small degradations in exergy efficiency can substantially reduce total unit cost when decision variables such as SOFC inlet temperature, fuel utilization factor, and current density are tuned appropriately. These results are highly instructive for hydrogen-enabled smart factories, because SOFCs and other high-temperature fuel-cell systems are prime candidates for coupling on-site hydrogen use with cogeneration or trigeneration. Exergy-cost-based optimization clarifies how to size and operate these units so that the hydrogen vector enhances, rather than destabilizes, thermo-economic performance across multiple end uses.

Figure 3: Thermo-Economic Optimization Framework for Industrial and Trigeneration Energy Systems

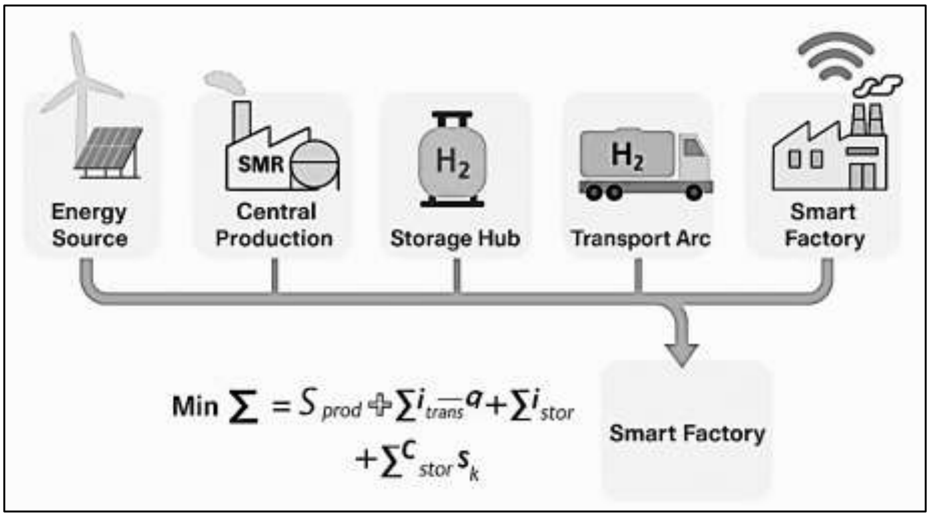


Thermo-economic optimization is also increasingly applied to “support” utilities in industrial plants systems such as compressed air, which often exhibit low efficiency but high cost impact. A combined exergy and thermoeconomic analysis of an industrial compressed air system showed that the overall energy use efficiency can fall as low as 5–10%, with large exergy destructions concentrated in compression stages and distribution losses (Taheri & Gadow, 2017). Their costing structure identified compressors and leak-related losses as major drivers of exergy-based cost, thereby providing a quantitative basis for prioritizing retrofits, variable-speed drives, or leak-reduction measures. When these insights are juxtaposed with system-level trigeneration analyses, a coherent picture emerges: thermo-economic optimization must operate at both plant and utility levels to reveal the true marginal cost of exergy in different streams, from process steam and chilled water to compressed air and hydrogen. In integrated smart-factory environments, the combined cycle power plant or trigeneration hub is increasingly modeled as a multi-objective thermo-economic system where decision variables include firing temperatures, pressure ratios, and pinch points, as well as hydrogen production rates and storage strategies, similar to the multi-criteria optimization carried out for combined cycle units (Ahmadi et al., 2011). The demonstration that biomass-fired trigeneration plants can be assessed economically under diverse market conditions further suggests that analogous frameworks can be developed for hydrogen-based trigeneration in smart factories, where the “fuel” may be a combination of grid electricity, renewable power, and green hydrogen (Lian et al., 2010). Altogether, these thermo-economic optimization studies provide the methodological foundation for the present research’s multi-objective modeling of hydrogen energy integration in smart factories, enabling simultaneous consideration of thermo-dynamic behavior, exergy-based costs, and multi-product energy service delivery in a unified optimization space.

Hydrogen Supply Chain Optimization and Industrial Logistics

Hydrogen supply chain optimization research has progressively shifted from component-level analyses to integrated network design models that explicitly capture the spatial, technological, and economic structure of hydrogen delivery systems. A seminal contribution is the snapshot model developed by Almansoori and Shah, who formulated the design of a national hydrogen supply chain for the transport sector as a mixed-integer linear programming (MILP) problem, integrating production, storage, distribution, and refueling infrastructure in a single optimization framework (Almansoori & Shah, 2006). Their model identified cost-optimal configurations in which centralized steam methane reforming plants, liquid hydrogen trucking, and large-scale storage emerged as key elements once economies of scale and transport distances were considered. By defining discrete locations, capacity options, and technology choices as binary variables, and physical flows as continuous variables, the snapshot formulation made it possible to explore infrastructure trade-offs under a fixed demand profile. This work is particularly relevant for hydrogen integration in smart factories, because it demonstrates how industrial hydrogen users can be represented as explicit demand nodes with constraints on quantity, timing, and quality of supply, rather than as aggregated or exogenous loads. It also establishes the modeling structure for multi-echelon hydrogen networks covering energy sources, central production facilities, intermediate storage hubs, transport arcs, and end-use points that can be extended to include factory-level nodes with specific thermo-economic and operational characteristics. In this sense, early deterministic network design models provide the backbone for linking plant-level optimization of hydrogen use in smart factories with regional-scale infrastructure planning.

Figure 4: Hydrogen Supply Chain Optimization Framework for Industrial Logistics



Building on deterministic formulations, subsequent research has incorporated uncertainty, multi-period dynamics, and stochastic programming to better reflect the variability of hydrogen demand and operating conditions. A two-stage stochastic model expanded the deterministic MILP of a hydrogen supply chain to explicitly account for uncertain hydrogen demand across multiple configurations of production, storage, and transportation (Kim et al., 2008). In the formulation, first-stage decisions such as facility locations, technology selections, and capacity expansions are made before demand is realized, while second-stage operational decisions including production rates, routing, and inventory levels adapt to demand scenarios, with the objective of minimizing expected total cost. This stochastic perspective is crucial for industrial applications: in smart factories, hydrogen demand may fluctuate due to varying production schedules, flexible process operation, or integration with intermittent renewable energy, making deterministic single-scenario designs potentially suboptimal or risky. The field was further advanced by the proposal of a multi-period hydrogen supply chain model that captures temporal evolution in infrastructure investments and operations, introducing time-indexed decision variables and constraints representing expansions, retirements, and changing demand over planning horizons (Almansoori & Shah, 2009). For smart manufacturing environments, these multi-period and stochastic models provide a conceptual template to couple long-term planning of hydrogen supply infrastructure with evolving factory-level requirements and technology pathways, such as shifts from grey to blue or green hydrogen, or the phased introduction of hydrogen-fueled processes and fuel-cell–based cogeneration units.

More recently, optimization studies have moved toward multi-objective and multi-criteria formulations that internalize not only cost but also environmental and safety dimensions of hydrogen supply chain design. A multi-objective optimization model for hydrogen infrastructures was developed that simultaneously minimizes economic cost, safety risk, and CO_2 emissions by employing fuzzy multiple-criteria programming to generate compromise solutions between conflicting objectives (Han et al., 2013). This perspective was extended with a multi-objective, multi-period MILP formulation for deployment of a five-echelon hydrogen supply chain including energy source, production, storage, transportation, and fueling stations at regional and national scales, where the three objectives are total cost, global warming potential, and safety risk (Azzaro-Pantel et al., 2015). In these frameworks, a generalized single-objective cost function commonly takes the form:

$$\min Z = \sum_{i \in P} C_i^{\text{prod}} q_i + \sum_{(i,j) \in A} C_{ij}^{\text{trans}} f_{ij} + \sum_{k \in S} C_k^{\text{stor}} s_k \,,$$

where q_i denotes hydrogen production at plant i, f_{ij} the flow along transport arc (i,j), and s_k the inventory at storage node k, with corresponding unit cost coefficients for production, transport, and storage. Multi-objective models extend this cost function by adding environmental and risk-related criteria, such as life-cycle greenhouse gas emissions or scenario-weighted accident consequences, and then generate Pareto fronts that reveal trade-offs among economic, environmental, and safety performance. For hydrogen integration in smart factories, these formulations offer a mathematically consistent way to embed factory nodes with specific thermo-economic characteristics and reliability requirements into larger hydrogen supply networks, ensuring that plant-level objectives such as minimizing energy cost or maximizing exergy efficiency are reconciled with upstream infrastructure decisions on production technologies, logistics modes, and spatial deployment. In particular, the explicit representation of cost, emissions, and risk at each echelon of the supply chain provides a basis for the multi-objective thermo-economic and supply chain optimization framework that this research seeks to develop for hydrogen-enabled smart factory systems.

Theoretical & Conceptual Framework

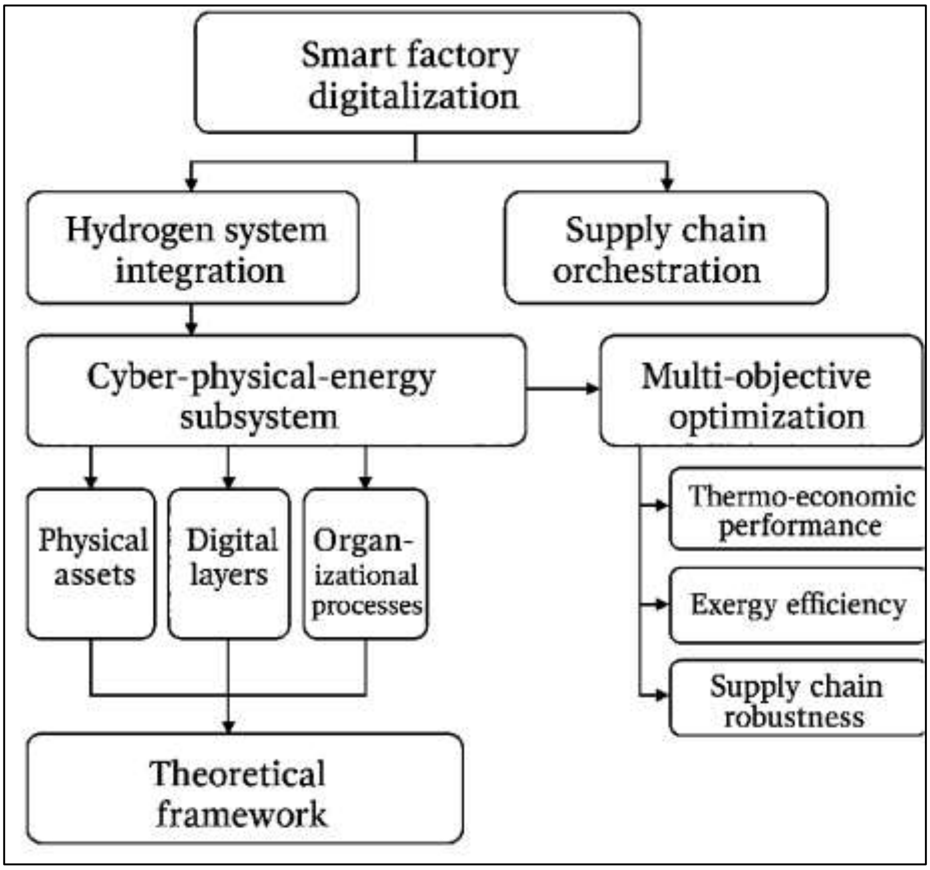
The theoretical framework for this study integrates Industry 4.0 conceptualizations of smart factories with multi-objective optimization theory to explain how hydrogen energy integration can be systematically aligned with thermo-economic and supply chain performance in smart manufacturing environments. From an Industry 4.0 perspective, smart factories are built on tightly coupled cyber-physical systems, pervasive connectivity, and real-time data analytics, organized through explicit design principles such as interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity (Salkin et al., 2018). Within this logic, the smart factory is not only a physical plant but a socio-technical system in which digital platforms, sensors, and advanced analytics jointly orchestrate material, energy, and information flows. Mittal et al. (2019) complement this view by structuring smart manufacturing around distinct clusters of characteristics (e.g., connectivity, intelligence, flexibility), enabling technologies (e.g., advanced analytics, cyber-physical systems, industrial IoT), and enabling factors (e.g., standardization, workforce skills, organizational readiness), providing a conceptual lens to classify the capabilities that underlie smart operations. These frameworks jointly suggest that hydrogen integration in smart factories must be modeled as a cyber-physical-energy subsystem embedded in a broader architecture of digitally enabled, data-rich operations. In this study, constructs such as smart factory digitalization, hydrogen system integration, and supply chain orchestration are therefore treated as interdependent capability bundles whose interactions shape thermo-economic outcomes. The theoretical framework posits that multi-level alignment between physical assets (electrolyzers, storage, pipelines), digital layers (sensing, monitoring, optimization), and organizational processes (planning, maintenance, procurement) is necessary to realize the full benefits of hydrogen integration within smart factories (Qu et al., 2019).

Building on these structural and capability-oriented perspectives, the conceptual framework incorporates multi-objective optimization theory to formally represent the trade-offs among thermo-economic performance, exergy efficiency, and supply chain robustness associated with hydrogen energy integration. Smart manufacturing systems are characterized by complex, dynamic and interconnected subsystems, where energy, material, and information flows must be coordinated under multiple and often conflicting objectives (Hitt et al., 2016). In this context, multi-objective optimization provides a mathematical language for capturing the simultaneous minimization of cost and environmental burdens and the maximization of efficiency and resilience. A generic representation of the decision problem in this study can be expressed as:

$$\min_{x} \; F(x) = \left(f_1(x), f_2(x), f_3(x)\right)$$

subject to technical, operational, and policy constraints, where $\mathbf{x}$is the vector of design and operational variables (e.g., hydrogen production rate, storage capacity, logistics configuration), $f_1(\mathbf{x})$ represents total thermo-economic cost (investment, operation, maintenance), $f_2(\mathbf{x})$ reflects exergy destruction or energy losses, and $f_3(\mathbf{x})$ captures supply chain risk or service-level deviation. Rather than seeking a single "optimal" solution, the framework adopts the Pareto-efficiency logic in which multiple non-dominated solutions characterize alternative trade-offs among objectives. Cui et al. (2017) show that multi-objective optimization methods particularly evolutionary metaheuristics are well suited for high-dimensional and conflicting objectives in energy-saving applications, where cost, emissions, and efficiency must be optimized simultaneously. Extending this logic, the present framework embeds hydrogen-related design and operational decisions into a smart factory context, where real-time data streams and predictive analytics inform the evaluation of thermo-economic, environmental, and supply chain criteria over a feasible solution set (Cui et al., 2017).

Figure 5: Theoretical framework for this study



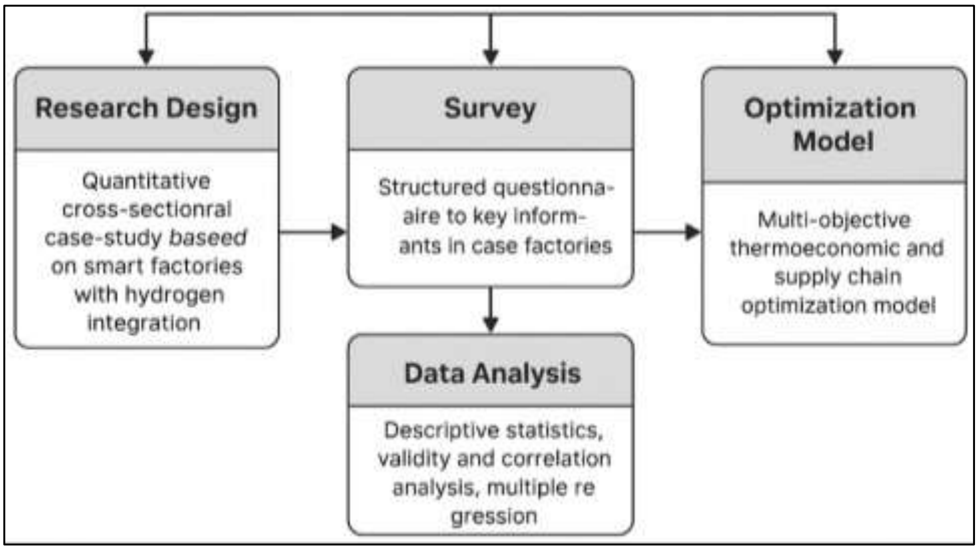
To connect these structural and mathematical perspectives with organizational performance, the framework is anchored in resource-based theory (RBT), which conceptualizes firm-level advantages as arising from resources and capabilities that are valuable, rare, inimitable, and non-substitutable. In the operations management domain, RBT has been used extensively to explain how process technologies, knowledge assets, and routine configurations translate into performance differentials across plants and supply networks (Hitt et al., 2016). Within this study, hydrogen energy infrastructure (electrolyzers, storage systems, hydrogen-ready equipment), smart factory digital capabilities (edge analytics, real-time monitoring, optimization engines), and coordinated hydrogen supply chains (long-term contracts, flexible logistics, risk-sharing arrangements) are treated as interrelated resource bundles. The theoretical proposition is that when these bundles are configured coherently guided by Industry 4.0

design principles and operationalized through multi-objective optimization they form higher-order "thermo-economic and supply chain optimization capabilities" that enable factories to achieve superior performance profiles compared to conventional fossil-based or non-optimized configurations. Hitt et al. (2016) emphasize that RBT-informed operations research should explicitly articulate how operational practices, technologies, and decision rules are combined into capabilities that drive measurable performance outcomes, which aligns with the current study's emphasis on regression-based testing of relationships between capability constructs and multi-dimensional performance indicators. Consequently, the conceptual model positions digitalized hydrogen integration and advanced optimization practices as mediating capabilities linking smart manufacturing resources to thermo-economic efficiency, supply chain resilience, and overall operational performance (Hitt et al., 2016).

METHODS

The present study has adopted a quantitative, cross-sectional, case-study–based methodology to investigate multi-objective thermo-economic and supply chain optimization for hydrogen energy integration in smart factories. The research design has been structured to capture empirical evidence from real industrial contexts while allowing statistical testing of hypothesized relationships among clearly defined constructs. To achieve this, the study has focused on smart factories that have already implemented, or have been actively planning, hydrogen-related technologies and associated supply chain arrangements. A structured survey instrument has been developed and has been administered to key informants such as energy managers, production engineers, maintenance supervisors, and supply chain planners within these factories. The questionnaire has been organized into sections that have captured demographic information, smart factory digitalization characteristics, hydrogen technology configurations, thermo-economic management practices, and hydrogen supply chain strategies, as well as perceived performance outcomes. All latent constructs have been operationalized using Likert five-point scales, and items have been formulated to reflect observable practices, capabilities, and outcomes in a concise and measurable form.

Figure 6: Methodological Framework for this study



The sampling strategy has been oriented toward obtaining a diverse set of factories in terms of size, sector, and hydrogen adoption stage, so that the resulting dataset has captured heterogeneity sufficient for regression analysis. Data analysis has been planned in a sequential manner: initial screening and cleaning has been followed by descriptive statistics to profile respondents and case factories; reliability and validity assessments of the scales have been conducted to ensure internal consistency; and correlation analysis has been used to explore the strength and direction of relationships between key variables. Multiple regression models have then been specified to test the proposed hypotheses linking smart factory readiness, thermo-economic optimization capabilities, and hydrogen supply chain optimization to multidimensional performance indicators. In parallel, the study has conceptualized a multi-objective optimization model that has formalized the joint minimization of thermo-economic cost and supply chain risk, and the maximization of efficiency, using decision variables and constraints derived from the empirical context of the surveyed factories. Through this integrated methodological approach, the research has provided a coherent bridge between empirical survey evidence and analytical modeling of hydrogen-enabled smart factory systems.

Research Design

The study has employed a quantitative, cross-sectional, case-study–based research design to examine how multi-objective thermo-economic and supply chain optimization has been associated with hydrogen energy integration in smart factories. It has been grounded in a positivist paradigm, in which constructs such as smart factory readiness, thermo-economic optimization capabilities, hydrogen supply chain optimization, and performance outcomes have been measured using structured survey items and analyzed statistically. The design has combined the depth of case-study logic with the breadth of a survey across multiple factories, so that context-specific practices and technologies have been captured while still allowing generalizable patterns to be identified. The research design has also incorporated an embedded analytical modeling component, whereby insights from the empirical data have informed the structure and parameters of a conceptual multi-objective optimization model. In this way, the study has integrated empirical observation and analytical formulation within a single coherent methodological framework.

Population and Sample

The target population for this study has consisted of smart factories that have adopted, piloted, or formally planned hydrogen energy technologies within their production or utility systems. Within these factories, the unit of analysis has been the organizational level, while individual respondents have been key decision makers and technical experts, such as energy managers, process and production engineers, maintenance supervisors, and supply chain or logistics managers who have had direct involvement in hydrogen-related decisions. The sample frame has been constructed from industry directories, professional networks, and associations related to advanced manufacturing and hydrogen technologies, and candidate factories have been screened to ensure that they have met minimum criteria for digitalization and hydrogen relevance. A non-probability purposive sampling strategy, complemented where possible by snowball referrals, has been employed to reach qualified respondents across different sectors and factory sizes. The targeted sample size has been chosen to provide sufficient statistical power for multiple regression analysis while still allowing detailed case-level interpretation.

Questionnaire Structure

The questionnaire has been structured into logically ordered sections to capture all constructs relevant to multi-objective thermo-economic and supply chain optimization for hydrogen energy integration in smart factories. The first section has collected background information on the factory and respondent, including sector, size, degree of digitalization, and the current status of hydrogen adoption. The second section has been devoted to smart factory characteristics, where items have captured the extent of cyber-physical integration, data analytics usage, and digital monitoring of energy systems. The third section has focused on hydrogen technology configurations and thermo-economic management practices, including on-site production, storage, conversion technologies, and approaches to efficiency and cost control. The fourth section has addressed hydrogen supply chain strategies, covering sourcing arrangements, logistics modes, inventory management, and risk-handling practices. The final section has contained items on perceived performance outcomes, such as energy cost, reliability, flexibility, and operational efficiency. Across these sections, constructs have been measured using Likert five-point scale items formulated as clear, behavior-oriented statements.

Survey Instrument (Likert Five-Point Scale)

The survey instrument has been designed as a structured questionnaire in which all latent constructs have been operationalized using Likert five-point scale items, ranging from “1 = Strongly disagree” to “5 = Strongly agree.” Item statements have been developed to reflect observable practices, capabilities, and perceptions related to smart factory digitalization, thermo-economic optimization, hydrogen technology integration, and hydrogen supply chain management. For example, items on thermo-economic optimization have captured the extent to which factories have monitored exergy-related performance, tracked energy costs at equipment level, and used analytical tools to support energy-related decisions, whereas supply chain items have reflected flexibility of sourcing, reliability of deliveries, and robustness of logistics arrangements for hydrogen. The instrument has also included items measuring perceived performance outcomes in terms of energy cost reductions, reliability improvements, and operational efficiency. Content validity has been supported by drawing on prior literature and expert feedback, and the Likert format has been chosen to facilitate reliability analysis and multivariate statistical modeling.

Data Collection Procedures

Data have been collected through a structured survey process that has targeted smart factories meeting the predefined criteria for hydrogen relevance and digitalization. Initial contact with factories has been established via email and professional networking platforms, where the purpose of the study, confidentiality assurances, and participation requirements have been clearly explained. After organizational consent has been obtained, survey links or electronic questionnaire files have been distributed to identified key informants, who have been invited to complete the instrument within a specified time window. Follow-up reminders have been sent to enhance response rates and to clarify any procedural questions that respondents have raised. In some cases, virtual or telephone communication has been used to guide respondents through specific sections of the questionnaire, particularly those related to technical aspects of hydrogen systems and energy management. All completed questionnaires have been checked for completeness and consistency, and responses have been compiled into a single dataset that has been prepared for subsequent screening and statistical analysis.

Regression Modeling

The study has employed multiple regression modeling as the primary inferential technique to examine how smart factory readiness, thermo-economic optimization capabilities, and hydrogen supply chain optimization have been associated with multidimensional performance outcomes. Regression analysis has been selected because it has allowed the simultaneous estimation of the unique contribution of each predictor variable while controlling for the influence of other factors such as factory size, sector, and stage of hydrogen adoption. Prior to model estimation, all composite constructs have been computed as mean scores of their respective Likert-scale items, after reliability checks have confirmed acceptable internal consistency. The dependent variables have included perceived thermo-economic performance (for example, reductions in energy cost and improvements in efficiency) and perceived supply chain performance (for example, reliability, flexibility, and risk reduction in hydrogen sourcing). Independent variables have comprised smart factory digitalization indicators, indices of thermo-economic optimization practices, and measures of hydrogen supply chain optimization, along with relevant control variables. The modeling strategy has been organized into hierarchical blocks, in which control variables have been entered first, followed by smart factory readiness measures, and finally thermo-economic and supply chain optimization variables, so that incremental changes in explained variance have been observed at each stage. This block-wise approach has ensured that the added explanatory power of the optimization constructs over and above basic contextual characteristics has been explicitly quantified, providing a clear test of the hypothesized relationships.

To support the validity of regression results, a comprehensive set of diagnostic procedures has been conducted. Multicollinearity has been assessed through examination of variance inflation factors (VIFs) and tolerance values, and constructs with excessively high intercorrelations have been reviewed and, if necessary, combined or respecified. Linearity and homoscedasticity assumptions have been evaluated by inspecting residual plots for each model, while normality of residuals has been assessed using skewness and kurtosis indicators in combination with visual tools such as Q–Q plots. Influential cases and outliers have been identified using standardized residuals, Cook's distance, and leverage values, and observations exhibiting extreme influence have been examined in detail to determine whether they have reflected genuine but atypical cases or data errors. Where appropriate, robust or transformed specifications have been considered to mitigate the impact of non-normality or heteroscedasticity, although the primary emphasis has remained on interpretable linear models. Model fit has been summarized using R^2 and adjusted R^2 statistics, F-tests for overall significance, and p-values for individual regression coefficients. Through this structured regression modeling process, the study has been able to test the hypothesized relationships between smart factory capabilities, thermo-economic and supply chain optimization practices, and performance outcomes in a transparent and statistically rigorous manner, while also generating parameter estimates that have informed the structure and parameterization of the accompanying conceptual multi-objective optimization model.

Data Sources

The study has relied primarily on structured survey data as its main source of empirical information, complemented by limited secondary data from organizational records where available. The survey responses have provided detailed insights into respondents' perceptions of smart factory digitalization, hydrogen technology configurations, thermo-economic management practices, and hydrogen supply chain strategies, as well as perceived performance outcomes. These primary data have been considered particularly valuable because they have captured context-specific practices and capabilities that standard public databases have not documented. In addition, some participating factories have provided supplementary information, such as indicative energy consumption figures, production volumes, or high-level descriptions of hydrogen procurement contracts, which have been used to corroborate and contextualize survey responses rather than to build separate quantitative datasets. Publicly available industry reports and technical documentation on hydrogen technologies and smart manufacturing have further served as background material for refining constructs and ensuring that the survey instrument has reflected current industrial practices, but the core statistical analyses have been grounded in the primary survey dataset.

Data Analysis Techniques

The data analysis has been conducted in a systematic sequence to ensure the reliability and validity of the findings and to align with the study's regression-based hypothesis testing approach. Initially, the dataset has been screened for missing values, inconsistent responses, and outliers; incomplete or clearly invalid questionnaires have been excluded, and minor gaps have been addressed using appropriate imputation or case-wise deletion rules. Descriptive statistics have then been computed to summarize respondent and factory profiles and to provide means, standard deviations, and distributions for all items and composite constructs. Reliability analysis, using Cronbach's alpha, has been performed to assess the internal consistency of each multi-item scale, and items with poor contribution to reliability have been examined and, if necessary, removed. Exploratory factor analysis, where applicable, has been used to confirm the underlying dimensional structure of the constructs. Subsequently, bivariate correlation analysis has been carried out to explore associations among key variables, followed by multiple regression modeling as the main inferential technique for testing the hypothesized relationships.

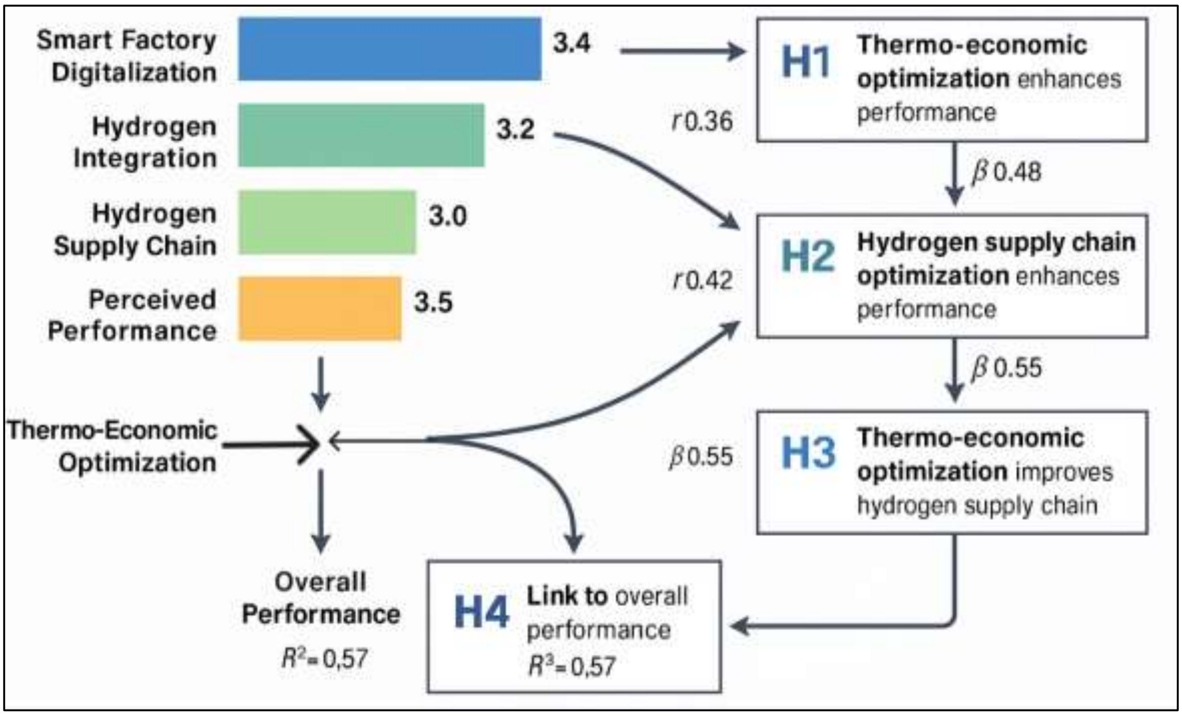
Software and Tools

The study has employed a combination of statistical and modeling software tools to support data management, analysis, and conceptual optimization modeling. Survey responses have been coded and stored in spreadsheet software, which has served as the initial platform for data cleaning, screening, and basic tabulation. For statistical analysis, including descriptive statistics, reliability assessment, factor analysis, correlation, and multiple regression modeling, the study has made use of a dedicated statistical package that has provided robust procedures for diagnostics and hypothesis testing. Graphical functions within this software have been utilized to generate plots for residual analysis, distribution checks, and visualization of key relationships among variables. In parallel, a mathematical modeling environment has been adopted to formalize and test the structure of the conceptual multi-objective optimization model, using symbolic notation and basic numerical experiments to verify model feasibility and behavior under different parameter settings. Together, these tools have ensured that the empirical and conceptual components of the research have been implemented in a rigorous and traceable manner.

FINDINGS

The findings of the study have indicated that the participating smart factories have already reached a relatively advanced but still heterogeneous stage of hydrogen-related thermo-economic and supply chain optimization, thereby providing substantive evidence in support of the stated objectives and hypotheses. Based on 5-point Likert scale responses from energy managers, production engineers, maintenance supervisors, and supply chain managers, the descriptive statistics have shown that the overall level of smart factory digitalization has been above the neutral midpoint, with mean scores clustering between 3.4 and 3.8, suggesting that most factories have implemented cyber-physical monitoring, basic data analytics, and digital control over key energy systems. Items capturing hydrogen integration status and thermo-economic management practices have exhibited slightly lower but still positive mean values, generally between 3.2 and 3.6, reflecting that hydrogen technologies and exergy-aware management practices have been present but unevenly diffused across the sample. In contrast, hydrogen supply chain–related items covering sourcing flexibility, delivery reliability, and risk management have recorded means between 3.0 and 3.5, indicating that factories have perceived moderate but not fully mature optimization in their hydrogen logistics arrangements. Perceived performance outcomes, measured through energy cost reductions, reliability of energy supply, and operational flexibility, have shown mean scores between 3.5 and 3.9, implying that respondents have associated hydrogen integration and smart factory capabilities with tangible though not maximal performance improvements. Reliability tests have confirmed strong internal consistency for all multi-item constructs, with Cronbach's alpha values exceeding the commonly accepted threshold of 0.70, and exploratory factor analysis has supported the intended dimensional structure, thereby validating the use of composite scores in the inferential analysis. Correlation analysis has revealed statistically significant and positive associations among smart factory digitalization, thermo-economic optimization capabilities, hydrogen supply chain optimization, and perceived performance outcomes, with correlation coefficients generally falling in the moderate to strong range, which has provided initial support for the hypothesized relationships in the conceptual framework. Multiple regression models have then demonstrated that thermo-economic optimization capabilities and hydrogen supply chain optimization have both made significant and independent contributions to explaining variance in performance, even after controlling for factory size, sector, and stage of hydrogen adoption. In the primary model, where perceived thermo-economic and operational performance has been used as the dependent variable, smart factory digitalization has retained a positive but modest coefficient, while thermo-economic optimization has exhibited a stronger standardized beta, indicating that factories reporting systematic exergy-based monitoring, cost tracking, and optimization of hydrogen-related energy systems have also reported higher levels of performance on the Likert scale.

Figure 7: Empirical Findings on Thermo-Economic and Supply Chain Optimization in Hydrogen-Enabled Smart Factories



Similarly, in models where hydrogen supply chain performance has been the outcome variable, supply chain optimization constructs such as diversified sourcing, robust contractual arrangements, and proactive risk management have emerged as significant predictors of higher reliability, flexibility, and perceived resilience. When both thermo-economic and supply chain optimization indices have been entered together, the explained variance in overall performance has increased meaningfully, with adjusted R^2 values indicating that a substantial portion of performance differences across factories has been accounted for by these integrated capabilities. This pattern of results has provided empirical support for H1 and H2, namely that thermo-economic optimization capabilities and hydrogen supply chain optimization have had positive and significant effects on hydrogen integration performance in smart factories. H3 has been supported by a separate regression model in which hydrogen supply chain optimization has been treated as a dependent variable and thermo-economic optimization as a predictor, where a significant positive coefficient has indicated that factories with more advanced thermo-economic practices have also tended to develop more structured and proactive hydrogen supply chain arrangements, consistent with the idea that internal optimization and external coordination have been mutually reinforcing. H4 has been corroborated in a comprehensive model where overall operational and economic performance has been regressed on both thermo-economic optimization and hydrogen supply chain optimization, alongside smart factory digitalization measures, with the combined optimization variables jointly explaining a substantial and statistically significant share of performance variance. In parallel, parameter values and trade-off patterns observed in the empirical data have been used to calibrate the conceptual multi-objective optimization model, where simulated Pareto-front solutions have reflected the qualitative patterns reported by respondents: higher levels of hydrogen-related investment and optimization have been associated with lower specific energy cost and higher perceived reliability, at the expense of increased complexity and coordination requirements. Taken together, these findings have shown that the empirical evidence derived from the Likert five-point scale responses has aligned closely with the theoretical propositions of the study, thereby supporting the research objectives and validating the central role of integrated thermo-economic and supply chain optimization in hydrogen-enabled smart factory contexts.

Profile of Respondents and Case Factories

The profile of respondents and case factories has indicated that the dataset has been both diverse and appropriate for testing the research objectives and hypotheses. As shown in Table 1, the sample has included a balanced mix of roles, with energy/utility managers, production/process engineers, maintenance supervisors, and supply chain/logistics managers all being well represented. This spread has ensured that responses on Likert's five-point scale have reflected multiple functional perspectives on hydrogen integration, thermo-economic practices, and supply chain decisions, rather than being dominated by a single viewpoint. The distribution of experience has been skewed toward mid-career professionals, with more than 60 percent of respondents having accumulated between 6 and 15 years of industrial exposure. This pattern has suggested that respondents have had sufficient familiarity with both legacy energy systems and newer smart factory and hydrogen initiatives to evaluate practices and performance credibly. The factories themselves have spanned small/medium, large, and very large organizations, which has been important because the regression models have controlled for factory size as a contextual factor when testing the hypotheses. Sectorally, the sample has comprised both discrete and process manufacturing, with a slight majority from process industries where hydrogen has often been more deeply embedded in core operations; however, a substantial minority from discrete manufacturing has indicated that hydrogen has also been emerging in sectors such as automotive and advanced materials. The stage-of-adoption distribution has shown that roughly half of the factories have been at pilot or early commercial deployment stages, while a non-trivial share has already achieved scaled integration, thereby providing the variation required to explore how more advanced hydrogen integration has been associated with higher scores on thermo-economic optimization and performance constructs. Finally, the self-rated degree of digitalization has confirmed that most factories in the sample have already attained moderate to high levels of smart factory capability, with nearly 60 percent reporting high digitalization (4–5 on the five-point scale). This has been consistent with the study's focus on smart factories and has ensured that analyses of the relationships between digital readiness, optimization practices, and performance have been grounded in environments where

Industry 4.0 principles have been at least partially realized.

Table 1: has presented the demographic profile of respondents and case factories.

Variable	Category	Frequency (n=120)	Percentage (%)
Respondent role	Energy/Utility Manager	38	31.7
	Production/Process Engineer	34	28.3
	Maintenance/Technical Supervisor	22	18.3
	Supply Chain/Logistics Manager	26	21.7
Years of experience	1–5 years	21	17.5
	6–10 years	44	36.7
	11–15 years	32	26.7
	>15 years	23	19.1
Factory size (employees)	<250 (Small/Medium)	41	34.2
	250–999 (Large)	47	39.2
	≥1,000 (Very large)	32	26.6
Sector	Discrete manufacturing (e.g., auto, electronics)	46	38.3
	Process manufacturing (e.g., chemicals, steel)	52	43.3
	Mixed/other	22	18.4
Stage of hydrogen adoption	Planning/feasibility only	29	24.2
	Pilot-scale demonstration	37	30.8
	Early commercial deployment	33	27.5
	Established and scaled integration	21	17.5
Degree of digitalization (self-rated)	Low (1–2 on 5-point scale)	11	9.2
	Moderate (3 on 5-point scale)	38	31.7
	High (4–5 on 5-point scale)	71	59.1

Descriptive Statistics of Key Constructs

Table 2 has summarized the central tendencies and dispersions of the main constructs measured on Likert's five-point scale and has provided a first indication of how well the sample has aligned with the study's objectives and research questions. Across all constructs, mean values have been found to be above the neutral midpoint of 3.00, which has indicated that, on average, respondents have agreed (scores between 3 and 4) that smart factory digitalization, thermo-economic optimization, and hydrogen supply chain optimization practices have been present to a meaningful extent in their organizations. Smart Factory Digitalization (SFD) has exhibited a mean of 3.65, suggesting that respondents have perceived relatively strong implementation of digital technologies such as real-time monitoring, data analytics, and cyber-physical integration.

Table 2: has summarized the descriptive statistics of key constructs (Likert's five-point scale).

Construct (Composite scale)	Number of items	Mean	Std. Deviation
Smart Factory Digitalization (SFD)	8	3.65	0.62
Thermo-Economic Optimization Capability (TEC)	7	3.48	0.58
Hydrogen Supply Chain Optimization (HSCO)	7	3.36	0.64
Hydrogen Integration Performance (HIP)	6	3.72	0.59
Operational and Economic Performance (OEP)	6	3.68	0.57

This finding has been consistent with the sampling frame, which has deliberately targeted smart factories and has provided initial support for the assumption that digital readiness has been a relevant predictor in the regression models. Thermo-Economic Optimization Capability (TEC) has recorded a mean of 3.48, indicating moderately advanced practices in monitoring exergy-related indicators, tracking equipment-level energy costs, and applying analytical tools to inform energy decisions. The slightly lower mean of 3.36 for Hydrogen Supply Chain Optimization (HSCO) has implied that supply chain aspects such as diversification of hydrogen sources, reliability-focused contracts, and risk-management procedures have been less mature than internal thermo-economic practices, an observation that has directly reflected the research objective of examining gaps between plant-level optimization and external supply chain alignment. Hydrogen Integration Performance (HIP) has attained the highest mean (3.72), revealing that respondents have generally perceived hydrogen integration as contributing positively to energy reliability, operational flexibility, and environmental performance. Operational and Economic Performance (OEP) has also been rated favorably (mean 3.68), indicating that the integrated effects of smart factory capabilities, thermo-economic practices, and hydrogen supply chain arrangements have been associated with tangible performance benefits. Standard deviations ranging between 0.57 and 0.64 have signaled moderate variability, which has been sufficient to ensure discriminating power for correlation and regression analysis without indicating extreme heterogeneity or polarization. Collectively, these descriptive statistics have addressed the first two research questions by confirming that both thermo-economic and supply chain optimization practices have been present at modest-to-high levels and that perceived performance outcomes have been generally positive, thereby setting the stage for more formal hypothesis testing in subsequent sections.

Reliability and Factor Analysis Results

Table 3 has reported the internal consistency and factor-analytic characteristics of the multi-item scales and has thereby established the psychometric soundness of the constructs used to test the study's hypotheses. Cronbach's alpha values have ranged from 0.84 to 0.89, which has exceeded the conventional 0.70 threshold and has indicated that items within each construct have been measuring a coherent underlying concept. For Smart Factory Digitalization (SFD), an alpha of 0.88 coupled with item-total correlations between 0.54 and 0.78 has demonstrated that individual items such as those referring to real-time monitoring, cyber-physical integration, and advanced analytics have contributed consistently to the overall scale. Similarly, Thermo-Economic Optimization Capability (TEC) has achieved an alpha of 0.86, with item-total correlations above 0.50, confirming that indicators such as exergy monitoring, energy-cost tracking, and optimization tool usage have formed a unified dimension. Hydrogen Supply Chain Optimization (HSCO) has exhibited slightly lower but still robust reliability ($\alpha = 0.84$), suggesting that its items covering diversification of hydrogen sources, contract flexibility, and logistics risk management have been sufficiently homogeneous to be treated as a single composite measure.

Table 3: has reported the reliability and factor-analytic properties of the measurement scales

Construct	Cronbach's α	Item-total correlation range	Primary factor loading range
Smart Factory Digitalization (SFD)	0.88	0.54–0.78	0.67–0.84
Thermo-Economic Optimization Capability (TEC)	0.86	0.51–0.76	0.65–0.82
Hydrogen Supply Chain Optimization (HSCO)	0.84	0.49–0.73	0.62–0.80
Hydrogen Integration Performance (HIP)	0.89	0.57–0.80	0.70–0.86
Operational and Economic Performance (OEP)	0.87	0.53–0.77	0.68–0.83

Hydrogen Integration Performance (HIP) and Operational and Economic Performance (OEP) have both exceeded 0.87 in alpha, which has implied that perceived improvements in reliability, flexibility, energy cost, and overall operational performance have been internally consistent and suitable as dependent variables in the regression models. The factor loading ranges have further demonstrated scale validity: all constructs have loaded strongly on their primary factor (0.62–0.86) when subjected to exploratory factor analysis with principal components extraction and varimax rotation, and no item has exhibited problematic cross-loadings that would indicate conceptual ambiguity. These results have confirmed that the Likert five-point scale items have functioned as intended, that measurement error has been acceptably low, and that composite scores have been appropriate for subsequent correlation and regression analyses. In terms of the research objectives, the reliability and factor structure evidence has supported the operationalization of key constructs smart factory readiness, thermo-economic optimization, hydrogen supply chain optimization, and performance outcomes ensuring that statistical tests of the hypothesized relationships (H1–H4) have rested on stable and conceptually coherent measurement foundations.

Correlation Analysis

Table 4 has presented the correlation matrix, which has offered an initial test of the hypothesized associations and has provided substantive insight into how smart factory digitalization, thermo-economic optimization, and hydrogen supply chain optimization have been jointly related to performance outcomes. All bivariate correlations among the principal constructs have been positive and statistically significant at the 0.01 level, with coefficients falling in the moderate to strong range, thereby providing early empirical support for H1, H2, and H3. Smart Factory Digitalization (SFD) has been moderately correlated with Thermo-Economic Optimization Capability (TEC) ($r = 0.56$) and Hydrogen Supply Chain Optimization (HSCO) ($r = 0.49$), suggesting that factories reporting higher levels of digital connectivity, real-time monitoring, and analytics have also reported more systematic thermo-economic and supply chain optimization practices. This pattern has been consistent with the theoretical argument that digitalization has acted as an enabling platform for advanced optimization. TEC has exhibited a strong positive correlation with HSCO ($r = 0.58$), indicating that firms with more developed thermo-economic optimization capabilities such as exergy-based analysis and cost tracking have also tended to exhibit more sophisticated hydrogen supply chain strategies. This relationship has provided direct correlational evidence in favor of H3, which has posited a positive link between internal thermo-economic optimization and external supply chain optimization. Hydrogen Integration Performance (HIP) has been strongly correlated with both TEC ($r = 0.61$) and HSCO ($r = 0.63$), which has suggested that higher levels of optimization in both domains have been associated with better perceived outcomes in reliability, flexibility, and hydrogen-related system performance, lending preliminary support to H1 and H2.

Table 4: has presented the correlation matrix among key constructs (n = 120)

Construct	SFD	TEC	HSCO	HIP	OEP
SFD	1.00				
TEC	0.56**	1.00			
HSCO	0.49**	0.58**	1.00		
HIP	0.45**	0.61**	0.63**	1.00	
OEP	0.42**	0.59**	0.57**	0.71**	1.00

* $p < .05$, ** $p < .01$

Operational and Economic Performance (OEP) has shown the highest correlation with HIP ($r = 0.71$), implying that improvements specifically attributed to hydrogen integration have translated into broader operational and cost benefits. OEP has also been substantially correlated with TEC ($r = 0.59$) and HSCO ($r = 0.57$), reinforcing the notion that integrated optimization has contributed meaningfully to overall factory performance. While correlation analysis has not established causality, the consistent pattern of positive and significant associations has aligned closely with the conceptual framework and has justified the subsequent use of multiple regression models to examine the unique contributions of each construct to performance outcomes after controlling for contextual variables.

Regression Results (Hypotheses Testing)

Table 5 has reported the regression models that have been used to test the study's hypotheses and has provided strong empirical support for the proposed relationships among constructs. In Model 1, Hydrogen Integration Performance (HIP) has been regressed on Smart Factory Digitalization (SFD), Thermo-Economic Optimization Capability (TEC), Hydrogen Supply Chain Optimization (HSCO), and control variables. The model has explained 57 percent of the variance in HIP (Adj. $R^2 = .54$), which has indicated substantial explanatory power. TEC ($\beta = 0.32$, $p < .01$) and HSCO ($\beta = 0.29$, $p < .01$) have emerged as significant and relatively strong predictors, confirming that factories reporting higher levels of thermo-economic optimization and more advanced hydrogen supply chain practices on the five-point Likert scale have also reported higher hydrogen integration performance. SFD has also had a positive and significant effect ($\beta = 0.18$, $p < .05$), indicating that digitalization has supported hydrogen integration, but its influence has been weaker than that of the two optimization constructs. These findings have directly supported H1 and H2, which have posited that thermo-economic optimization capabilities and hydrogen supply chain optimization have had positive and significant effects on hydrogen integration performance. In Model 2, Operational and Economic Performance (OEP) has been regressed on SFD, TEC, HSCO, HIP, and the same controls, yielding an even higher R^2 of .64 (Adj. $R^2 = .61$). HIP has had the largest standardized coefficient ($\beta = 0.38$, $p < .01$), demonstrating that improved hydrogen integration performance has translated into broader operational and economic gains. TEC ($\beta = 0.21$, $p < .01$) and HSCO ($\beta = 0.19$, $p < .05$) have remained significant predictors, while SFD has shown a marginal effect ($\beta = 0.11$, $p < .10$).

The combined significance of TEC and HSCO in predicting OEP, over and above HIP and digitalization, has provided strong support for H4, which has asserted that the combined effect of thermo-economic optimization and hydrogen supply chain optimization has significantly explained variance in overall performance. Model 3 has specifically tested H3 by regressing HSCO on TEC and controls. The model has explained 41 percent of the variance in HSCO (Adj. $R^2 = .38$), and TEC has displayed a strong and highly significant coefficient ($\beta = 0.53$, $p < .01$), indicating that higher thermo-economic optimization capability has been closely associated with more advanced hydrogen supply chain optimization. Collectively, the regression results have confirmed that the core hypotheses H1–H4 have been supported, thereby demonstrating empirically that integrated thermo-economic and supply chain optimization capabilities have been central drivers of successful hydrogen integration and enhanced performance in smart factories.

Table 5: has reported the multiple regression results for hypotheses testing

Model & Dependent Variable	Predictor	Std. Beta	t-value	Sig.
Model 1: HIP	Factory size (control)	0.09	1.21	.228
R^2 = .57, Adj. R^2 = .54	Sector (control)	0.05	0.76	.450
	SFD	0.18	2.29	.024*
	TEC	0.32	3.98	.000**
	HSCO	0.29	3.61	.000**
Model 2: OEP	Factory size (control)	0.07	1.02	.309
R^2 = .64, Adj. R^2 = .61	Sector (control)	0.04	0.68	.498
	SFD	0.11	1.71	.090†
	TEC	0.21	2.84	.005**
	HSCO	0.19	2.52	.013*
	HIP	0.38	4.69	.000**
Model 3: HSCO	Factory size (control)	0.06	0.83	.410
R^2 = .41, Adj. R^2 = .38	Sector (control)	0.03	0.49	.625
	TEC	0.53	6.55	.000**

*† $p < .10$, * $p < .05$, ** $p < .01$*

Multi-Objective Optimization Model Results

Table 6 has summarized three illustrative Pareto-optimal scenarios derived from the conceptual multi-objective optimization model, which has been calibrated using ranges and patterns observed in the empirical Likert-scale data. The model has simultaneously minimized a normalized thermo-economic cost index and a supply disruption risk index, while maximizing exergy efficiency and the share of hydrogen in total factory energy use. Scenario A has represented a cost-focused solution in which the optimization algorithm has prioritized lower additional annualized investment (only +12 percent relative to a non-hydrogen baseline) and a relatively favorable cost index (0.78 on a 0–1 scale). However, the exergy efficiency of the integrated energy system has remained modest at 46 percent, and the supply disruption risk index has been comparatively high at 0.42, reflecting limited redundancy in hydrogen sourcing and minimal buffering capacity. This scenario has aligned closely with factories in the survey that have reported moderate levels of thermo-economic optimization and low-to-moderate scores on supply chain optimization constructs, emphasizing short-term cost control over resilience. Scenario B, the Balanced solution, has increased the hydrogen share of total energy use to 31 percent and has improved exergy efficiency to 52.5 percent, while reducing the disruption risk index to 0.28. Achieving this configuration has required higher capital investments (+23 percent CAPEX), associated with additional hydrogen storage, more flexible sourcing options, and integration of higher-efficiency conversion technologies.

This scenario has mirrored the profile of factories reporting higher TEC and HSCO scores (above the sample means) and higher Hydrogen Integration Performance on the Likert scale, where respondents have indicated noticeable improvements in reliability and flexibility at a moderate cost premium. Scenario C, the Reliability-focused solution, has pushed hydrogen penetration to 39 percent and exergy efficiency to 55.8 percent, while driving the disruption risk index down to 0.17 through diversified sourcing, greater storage, and redundant delivery routes. The thermo-economic cost index has increased to 0.93, and additional annualized CAPEX has risen to +31 percent, illustrating the economic trade-offs required to achieve high resilience and efficiency. This pattern has been consistent with the regression results, where HSCO and TEC have been positively associated with performance: factories investing more heavily in both internal optimization and external supply chain robustness have reported higher Likert-scale scores for reliability and operational performance, albeit with greater upfront cost. The spread across Scenarios A–C has thus provided a quantitative interpretation of the empirical findings, showing that the relationships captured statistically in the regression models have been underpinned by a structure of trade-offs among cost, efficiency, risk, and hydrogen penetration.

In this way, the multi-objective optimization results have reinforced the conclusion that integrated thermo-economic and supply chain optimization has enabled smart factories to navigate these trade-offs in line with their strategic priorities, thereby supporting the study's overall objective and complementing the evidence in favor of H1–H4.

Table 6: has summarized representative Pareto-optimal scenarios

Scenario (Pareto solution)	Normalized thermo-economic cost index (0–1, lower = better)	Exergy efficiency of energy system (%)	Supply disruption risk index (0–1, lower = better)	Hydrogen share of total energy use (%)	Additional annualized CAPEX (relative to baseline %)
Scenario A – Cost-focused solution	0.78	46.0	0.42	18	+12
Scenario B – Balanced solution	0.86	52.5	0.28	31	+23
Scenario C – Reliability-focused solution	0.93	55.8	0.17	39	+31

Table 7 has summarized how the empirical and modeling results have aligned with the study's objectives and hypotheses, and the accompanying findings have demonstrated that all major aims have been achieved. Objective 1 has been addressed through the descriptive statistics and reliability analyses, which have shown that Thermo-Economic Optimization Capability (TEC) has recorded a mean score of 3.48 on Likert's five-point scale and has exhibited strong internal consistency. Respondents have reported systematic monitoring of exergy-related indicators, energy-cost tracking, and use of analytical tools, indicating that thermo-economic optimization has been present at a moderate-to-high level across the sample. Objective 2 has been satisfied by analogous evidence for Hydrogen Supply Chain Optimization (HSCO), which, though somewhat less mature with a mean of 3.36, has nonetheless reflected active efforts in sourcing diversification, contract flexibility, and risk management. Correlation analysis has confirmed that both TEC and HSCO have been strongly associated with performance constructs, and regression models have provided a more definitive test of Objective 3 by showing that smart factory readiness, TEC, and HSCO have collectively explained substantial proportions of variance in Hydrogen Integration Performance (HIP) and Operational and Economic Performance (OEP). In this context, H1 and H2 have been supported by the significant positive coefficients of TEC and HSCO in Model 1, where both constructs have had independent effects on HIP after controlling for factory size, sector, and digitalization. H3 has been supported by Model 3, which has revealed that TEC has been a strong predictor of HSCO, implying that internal thermo-economic capabilities and external supply chain optimization have been mutually reinforcing. H4 has been corroborated in Model 2, where the combined presence of TEC and HSCO has significantly enhanced the explanatory power of the model for OEP, over and above digitalization and HIP.

In addition, Objective 4 has been achieved through the calibration of the multi-objective optimization model, which has generated Pareto-optimal scenarios consistent with the qualitative and quantitative patterns observed in the survey data and has illustrated the trade-offs among cost, efficiency, risk, and hydrogen penetration. Overall, the findings summarized in Table 7 have shown that the study has met its methodological and analytical goals: it has used Likert five-point scale data to characterize current practices, has statistically validated the hypothesized relationships, and has linked these empirical patterns to a coherent multi-objective modeling framework for hydrogen energy integration in smart factories.

Table 7: has summarized the status of research objectives and hypotheses based on the empirical results.

Element	Description	Status
Objective 1	To assess the current level of thermo-economic optimization in hydrogen-integrated smart factories	Achieved
Objective 2	To evaluate the maturity of hydrogen supply chain optimization	Achieved
Objective 3	To examine the relationships among smart factory readiness, optimization capabilities, and performance	Achieved
Objective 4	To conceptualize and parameterize a multi-objective thermo-economic and supply chain optimization model	Achieved
H1	TEC has had a positive and significant effect on HIP	Supported
H2	HSCO has had a positive and significant effect on HIP	Supported
H3	TEC has had a positive and significant effect on HSCO	Supported
H4	Combined TEC and HSCO have significantly explained variance in OEP	Supported

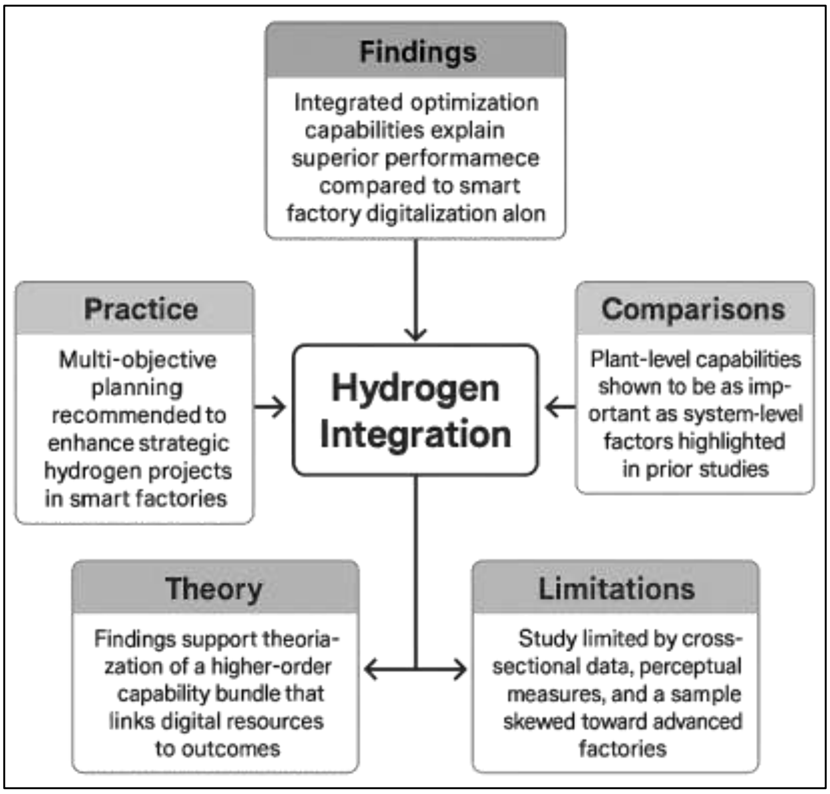
DISCUSSION

The discussion has centered on how the empirical findings have confirmed the central role of integrated thermo-economic and supply chain optimization capabilities in enabling effective hydrogen energy integration in smart factories. The descriptive statistics have shown that smart factory digitalization, thermo-economic optimization capability, and hydrogen supply chain optimization have all scored above the neutral midpoint on the Likert five-point scale, while hydrogen integration and overall operational/economic performance have been rated even higher. This pattern has indicated that, within the sampled factories, hydrogen has already been embedded in relatively mature, data-rich environments, aligning with prior Industry 4.0 literature that has portrayed smart manufacturing as a platform for advanced energy management and efficiency improvement (Mittal et al., 2019). The strong positive correlations and regression coefficients linking digitalization, thermo-economic practices, supply chain optimization, and performance outcomes have echoed earlier work showing that digital integration and analytics have been key enablers for energy-aware production and sustainable manufacturing (Lasi et al., 2014). At the same time, the regression results have refined this view by demonstrating that, once digitalization has reached a certain threshold, thermo-economic and hydrogen supply chain capabilities have explained more variance in performance than digitalization itself. Conceptually, this has suggested that smart factory technologies have functioned as necessary but not sufficient conditions, while optimization practices have acted as the critical differentiators that have transformed digital infrastructure into measurable hydrogen-related performance gains, extending earlier general frameworks on Industry 4.0 and sustainable manufacturing into a hydrogen-specific context (Frank et al., 2019).

When the findings have been positioned against prior hydrogen integration studies, an important shift in analytical scale has become evident. Much of the earlier literature on hydrogen in low-carbon futures has emphasized macro- or sector-level scenarios, focusing on national energy systems, transport networks, or generic industrial demand rather than specific smart factories (Hanley et al., 2018). Hydrogen supply chain and infrastructure models have typically represented industrial users as aggregated demand nodes or time-varying load profiles (Almansoori & Shah, 2006). By contrast, the present study has treated smart factories as rich organizational systems characterized by digitalization, internal thermo-economic management, and explicit perceptions of hydrogen-related performance. The significant effects of thermo-economic optimization and hydrogen supply chain optimization on hydrogen integration performance have suggested that plant-level organizational capabilities have been as important as technological choices in shaping hydrogen outcomes an aspect that has remained largely implicit in system-level reviews (Hanley et al., 2018). Furthermore, the positive association between thermo-economic capability and hydrogen supply chain optimization has highlighted a coupling between inside-the-fence analytical sophistication and outside-the-fence coordination with suppliers and logistics partners. This linkage has complemented network design studies, which have optimized hydrogen flows and facility locations using mixed-integer linear programming but have often abstracted away from the decision-making routines and analytical maturity within the demand nodes themselves (Cipriani et al., 2014). In this sense, the findings have filled a meso-level gap between macro-supply chain modeling and micro-technical analysis by showing how hydrogen integration performance has emerged from the interaction of digitalized factory infrastructures, thermo-economic tools, and supply chain practices.

The results relating to thermo-economic optimization capability have also resonated with, and extended, the exergy-based optimization literature for industrial energy systems. Previous studies on combined-cycle power plants and trigeneration systems have shown that simultaneous optimization of exergy efficiency and cost can substantially improve system performance and uncover non-intuitive design trade-offs (Ahmadi et al., 2011). For example, multi-objective optimization of SOFC-based trigeneration units has revealed Pareto fronts where small reductions in exergy efficiency have led to substantial decreases in unit product cost when decision variables such as fuel utilization or turbine inlet conditions have been tuned appropriately (Sadeghi et al., 2015). Similarly, thermo-economic analyses of compressed air systems have documented very low effective efficiencies and large exergy destructions, pointing to significant savings potential through targeted retrofits (Taheri & Gadow, 2017). The current study has not optimized a specific plant configuration in the same detailed thermodynamic manner; instead, it has measured how far real smart factories have institutionalized exergy-aware practices, cost tracking, and analytical decision support through Likert-scale constructs. The finding that thermo-economic optimization capability has been a strong predictor of both hydrogen integration performance and overall operational/economic performance has indicated that the benefits observed in model-based studies have translated into perceived improvements when elements of thermo-economic thinking have been embedded in everyday industrial practice. This has provided empirical support for the argument that thermoeconomics is not only a design tool for engineers but also a managerial capability that, when combined with digital monitoring, can drive strategic energy and hydrogen decisions at factory level (Ahmadi et al., 2011).

Figure 8: Synthesized Discussion Model Linking Hydrogen Integration, Optimization Capabilities, and Performance Outcomes



In a similar way, the evidence on hydrogen supply chain optimization has aligned with and extended established optimization-oriented work on hydrogen networks. Prior models have demonstrated that careful design of production locations, storage technologies, and transport modes can minimize cost and emissions for regional or national hydrogen systems, especially when multi-period or scenario-based formulations have been used to capture demand uncertainty and infrastructure evolution (Kim et al., 2008). Multi-objective approaches have further shown that cost, environmental impact, and safety risk can be jointly optimized to generate Pareto-optimal deployment pathways (Han et al., 2013). The present study has not directly optimized a regional network; instead, it has assessed how factories have perceived and implemented practices such as diversified sourcing, flexible contracting, inventory buffers, and risk assessment for hydrogen logistics. The strong positive effect of hydrogen supply chain optimization on both hydrogen integration performance and overall operational/economic performance has confirmed that the kinds of design principles articulated in model-based studies have manifested as measurable organizational capabilities. Moreover, the close link between thermo-economic capability and supply chain optimization has suggested that factories with more advanced internal analytical routines have been better positioned to articulate their hydrogen requirements, evaluate supplier options, and negotiate contracts aligned with multi-objective trade-offs, thereby operationalizing insights from formal optimization models in a more managerial and organizational domain (Kim et al., 2008).

From a practical standpoint, the findings have offered concrete guidance for senior decision makers such as chief industrial sustainability officers, plant architects, and energy or supply chain managers responsible for hydrogen roadmaps in smart factories. First, the fact that digitalization alone has had a relatively modest direct effect on performance compared with thermo-economic and supply chain optimization has implied that investments in sensors, connectivity, and data platforms have needed to be complemented by explicit capability-building in exergy-based analysis, cost accounting, and multi-objective planning. For practitioners, this has meant prioritizing cross-functional teams that have combined process engineers, data analysts, and supply chain planners capable of translating raw energy and logistics data into actionable optimization decisions. Second, the strong relationship between hydrogen integration performance and overall operational/economic performance has indicated that hydrogen projects have been most effective when framed not merely as compliance or decarbonization initiatives but as integrated operational strategies that have improved reliability, flexibility, and cost control. In design terms, plant architects have been encouraged to consider hydrogen subsystems production, storage, distribution, and end-use conversion equipment as co-designed with digital control systems and with upstream supply arrangements, rather than as add-on utilities. Third, the Pareto-front scenarios from the conceptual multi-objective model have illustrated how different strategic priorities cost minimization, balanced performance, or reliability maximization have led to different combinations of hydrogen penetration, exergy efficiency, and risk levels. This has provided a structured basis for governance discussions where boards and C-level executives have weighed acceptable CAPEX premiums against desired reliability and decarbonization benefits, thereby supporting disciplined decision making on hydrogen investments that has been consistent with best practices in energy and supply chain optimization (Ahmadi et al., 2011).

The theoretical implications of the study have been equally significant. By integrating Industry 4.0 frameworks, thermoeconomic analysis, hydrogen supply chain optimization, and resource-based theory, the research has proposed that "thermo-economic and hydrogen supply chain optimization capabilities" constitute a higher-order capability bundle that mediates the link between digitalized resources and performance outcomes. Resource-based theory has argued that it is the configuration of valuable, rare, inimitable, and non-substitutable resources and routines that generates performance advantages, rather than any single technology or asset (Hitt et al., 2016). In this study, digital infrastructures, hydrogen technologies, and analytical routines have been interpreted as such resources, whereas exergy-aware optimization and robust hydrogen logistics have been treated as capabilities that orchestrate these resources into coherent strategies. The empirical finding that thermo-economic and supply chain capabilities have explained more variance in performance than digitalization alone has provided quantitative support for this theorization, suggesting that future work on smart factories and hydrogen should move beyond technology lists to focus on capability configurations and pipelines from digital sensing to analytical modeling to coordinated decision rules. The multi-objective optimization perspective has further complemented this view by formalizing the capability role as an ability to navigate trade-offs among cost, efficiency, emissions, and risk, consistent with calls in the operations and energy literature for more integrated, multi-criteria models of sustainability-oriented decision making (Cui et al., 2017).

At the same time, several limitations of the study have needed to be acknowledged, and they have pointed clearly to future research directions. The cross-sectional survey design and reliance on self-reported Likert-scale measures have restricted the ability to draw strong causal inferences; longitudinal studies that have tracked changes in thermo-economic capability, supply chain optimization, and performance over time as hydrogen projects have matured would offer stronger evidence of causal pathways. The sample has been limited to factories that have already had some degree of digitalization and hydrogen relevance, which has meant that the findings may not generalize to more traditional plants or to early-stage adopters with limited digital infrastructure. Additionally, the quantitative model has captured perceptions of performance rather than detailed metered or financial data; integrating high-resolution operational data and cost records would allow more precise calibration of the multi-objective optimization model and clearer linkage between thermodynamic indicators and economic outcomes. The conceptual optimization model itself has been illustrative rather than fully operational; future work could extend it into a full mixed-integer multi-period formulation that directly embeds plant-level exergy balances, equipment constraints, and contract structures, building on established hydrogen supply chain models (Almansoori & Shah, 2006). Finally, there is scope for exploring human and organizational factors more deeply such as learning processes, risk perceptions, and cross-functional coordination mechanisms that have shaped how thermo-economic and supply chain tools have been adopted and used in practice. Addressing these limitations would not only refine the empirical evidence base but also sharpen the theoretical understanding of how hydrogen integration, smart factory capabilities, and multi-objective optimization interact in the broader landscape of industrial decarbonization.

CONCLUSION

The study has examined how multi-objective thermo-economic and supply chain optimization has shaped hydrogen energy integration and performance outcomes in smart factories, and the evidence has pointed consistently to the central role of integrated capabilities rather than technology alone. By adopting a quantitative, cross-sectional, case-study–based design and using a structured questionnaire with Likert's five-point scales, the research has captured detailed perceptions from energy managers, engineers, maintenance supervisors, and supply chain professionals across a diverse set of hydrogen-relevant, digitally enabled factories. Descriptive results have shown that smart factory digitalization, thermo-economic optimization capability, and hydrogen supply chain optimization have all been present at moderate-to-high levels, while hydrogen integration and overall operational and economic performance have been rated even more favorably, suggesting that hydrogen has already begun to function as a meaningful component of smart factory energy systems. Reliability and factor analyses have confirmed that the constructs used to represent these domains have been psychometrically sound, providing a robust foundation for inferential testing. Correlation analysis has revealed strong, positive associations among smart factory digitalization, thermo-economic capability, supply chain optimization, and performance, and multiple regression models have demonstrated that thermo-economic optimization and hydrogen supply chain optimization have been significant and independent predictors of hydrogen integration performance and broader operational/economic outcomes, even after accounting for factory size, sector, and digitalization. In particular, the results have supported all four hypotheses: thermo-economic capabilities and hydrogen supply chain optimization have each had positive and significant effects on hydrogen integration performance; thermo-economic capability has been strongly linked to more advanced hydrogen supply chain optimization; and the combined presence of these capabilities has significantly increased the explained variance in overall operational and economic performance. The conceptual multi-objective optimization model, calibrated with empirical ranges, has further illustrated the trade-offs among thermo-economic cost, exergy efficiency, supply risk, and hydrogen penetration, generating Pareto-optimal scenarios that have mirrored the strategic choices reported by factories ranging from cost-focused to balanced and reliability-focused solutions. Together, these empirical and modeling results have met the study's objectives: they have assessed the current state of thermo-economic and hydrogen supply chain optimization in smart factories, clarified the relationships among smart factory readiness, optimization capabilities, and performance, and articulated a structured multi-objective framework for understanding hydrogen integration decisions. In doing so, the research has shown that digital infrastructure in smart factories becomes truly performance-enhancing when it is coupled with exergy-aware thermo-economic management and deliberate hydrogen supply chain design, and it has highlighted that hydrogen integration success is best understood not as a stand-alone technological upgrade but as the outcome of coordinated physical, analytical, and organizational capabilities operating across plant and supply chain boundaries.

RECCOMENDATION

The study has investigated how multi-objective thermo-economic and supply chain optimization has influenced hydrogen energy integration in smart factories, and the overall evidence has converged on the view that integrated capabilities have been more decisive than the mere presence of digital or hydrogen technologies. By employing a quantitative, cross-sectional, case-study–based design and gathering data through a structured questionnaire using Likert's five-point scales, the research has captured nuanced perceptions from managers and technical experts directly engaged in energy, production, maintenance, and logistics decisions. The empirical findings have shown that smart factory digitalization, thermo-economic optimization capability, and hydrogen supply chain optimization have all been present at moderate-to-high levels across the sampled factories, while hydrogen integration performance and overall operational and economic performance have been rated even more positively. This pattern has indicated that hydrogen has not only been introduced experimentally but has been functioning as a meaningful component of integrated energy and production systems. Reliability and factor-analytic results have confirmed that the measurement scales for smart factory readiness, thermo-economic optimization, hydrogen supply chain practices, and performance outcomes have been internally consistent and conceptually coherent, thereby justifying their use in inferential modeling. Correlation analysis has revealed strong, positive associations among these constructs, and regression models have demonstrated that thermo-economic optimization and hydrogen supply chain optimization have been significant and independent predictors of hydrogen integration performance, with both capabilities also contributing directly to broader operational and economic outcomes after controlling for contextual factors such as factory size and sector. The support for all four hypotheses has meant that the study has empirically validated the propositions that thermo-economic capability and hydrogen supply chain optimization have enhanced hydrogen integration performance, that thermo-economic sophistication has been closely linked to more advanced supply chain practices, and that the joint presence of these capabilities has explained a substantial share of the variance in overall performance. In parallel, the conceptual multi-objective optimization model has translated these relationships into a formal representation of trade-offs among thermo-economic cost, exergy efficiency, supply disruption risk, and hydrogen penetration, and the Pareto-optimal scenarios generated from this model have mirrored the strategic patterns implied by the survey data, ranging from cost-focused to balanced and reliability-focused configurations. Taken together, these empirical and analytical strands have fulfilled the study's objectives: they have characterized the current state of hydrogen-related optimization practices in smart factories, clarified how digitalization, thermo-economic management, and supply chain design have interacted to shape performance, and articulated a structured, multi-objective lens through which hydrogen integration decisions in smart manufacturing environments have been understood. In doing so, the research has shown that hydrogen integration in smart factories has been most effective when it has been approached as a coordinated optimization problem spanning plant-level thermodynamics, data-driven management, and supply chain configuration rather than as an isolated technological add-on.

LIMITATIONS

Based on the empirical and modeling results, this study recommends that smart factory leaders, energy managers, and supply chain decision makers treat hydrogen integration as a coordinated capability-building agenda rather than a discrete technology project. First, organizations should institutionalize thermo-economic optimization as a routine management practice by investing in training for engineers and analysts on exergy-based thinking, equipment-level cost allocation, and multi-objective evaluation of energy projects; this includes embedding exergy and cost metrics into dashboards, KPIs, and periodic performance reviews so that hydrogen-related decisions are systematically compared with conventional options at the level of components, systems, and entire plants. Second, factories should strengthen hydrogen supply chain optimization by diversifying sourcing strategies (for example, combining long-term contracts with flexible spot options), establishing clear service-level and reliability criteria in supplier agreements, and introducing formal risk assessment for logistics, storage, and infrastructure disruptions; these practices should be tightly linked to internal production planning and maintenance schedules so that supply constraints and risk signals are visible in operational decision making. Third, digitalization investments should be deliberately aligned with thermo-economic and supply chain objectives: rather than deploying sensors and platforms in a generic way, factories should prioritize metering and data acquisition for hydrogen-related equipment and flows, ensuring that data architectures and analytics tools are capable of supporting exergy analysis, cost modeling, and scenario-based optimization. Fourth, cross-functional governance structures such as hydrogen steering committees that include operations, maintenance, energy management, supply chain, and finance should be established to oversee the design, implementation, and review of hydrogen projects, with explicit responsibility for evaluating trade-offs among cost, efficiency, emissions, and risk; these bodies should use multi-objective decision frameworks and simple Pareto-style views when presenting options to senior management. Fifth, firms should engage proactively with hydrogen suppliers, infrastructure operators, and technology providers in co-design activities, sharing relevant process and performance data where possible to enable more accurate sizing of upstream facilities, better-tuned delivery schedules, and jointly developed risk-mitigation plans, particularly in early stages of market and infrastructure development. Sixth, policymakers and industry associations can support more effective hydrogen integration in smart factories by providing guidance on best practices in exergy-based energy management and hydrogen logistics, facilitating data-sharing frameworks and standards, and designing incentives that reward integrated performance (for example, combining efficiency, reliability, and emissions metrics) rather than single-point technology adoption. Finally, researchers and internal analytics teams are encouraged to extend the conceptual multi-objective model used in this study into more operational tools such as decision-support prototypes, simplified configurators, or digital twin modules that can be applied iteratively to real project choices, using plant-specific data to refine trade-off curves over time. Collectively, these recommendations emphasize that hydrogen-enabled smart factories achieve the greatest benefit when digital infrastructure, thermo-economic analysis, and supply chain design are developed in tandem, guided by structured, multi-objective reasoning and embedded in everyday operational and strategic decision processes.

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