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Typology of Critical Factors in Smart Resource Configuration in Iran's Electricity Industry

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Abstract

This study aimed to design and present an interactive model of the factors affecting smart resource configuration in the electricity industry in order to develop a coherent understanding of intelligent organizing processes, using a mixed-methods approach (qualitative and quantitative). The population of the qualitative phase consisted of senior experts actively engaged in the electricity industry as well as specialists from various relevant scientific fields related to smart configuration. The statistical population of the quantitative phase, which was used to validate the qualitative model, consisted of 381 senior experts and managers in the industry who were selected through convenience sampling. The findings of the qualitative phase identified the factors affecting smart resource configuration in the electricity industry in the form of 2 overarching themes, 14 subthemes, 56 directed codes, and 943 indicators (guiding points), which were obtained through the review and synthesis of the interviews and the integration and categorization of the corresponding codes. The findings from model validation also confirmed the model using confirmatory statistical analysis. Finally, practical recommendations were proposed based on strengthening the underlying elements required to enhance the smart resource configuration model, grounded in the Theory of Constraints, within Iran's electricity industry.

Keywords: *smart resource configuration, Iran's electricity industry, typology, multiple grounded theory.*

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1. Introduction

The electricity industry is one of the most strategically consequential infrastructure sectors in modern economies because the reliability, affordability, and sustainability of electricity supply directly affect industrial productivity, public services, technological development, and national resilience. At the same time, electricity systems are becoming substantially more complex as they integrate distributed generation, renewable energy resources, smart grids, digital monitoring systems, cloud platforms, Internet of Things (IoT) technologies, artificial intelligence (AI), and increasingly data-intensive decision architectures. These developments have transformed resource management from a relatively stable allocation problem into a dynamic configuration challenge involving the continuous coordination of physical assets, financial resources, human capital, information, technological capabilities, and interorganizational relationships. In such an environment, conventional approaches based primarily on static planning and periodic resource allocation are increasingly insufficient. Organizations must instead develop the ability to configure and reconfigure resources intelligently in response to changing demand, technological conditions, environmental pressures, institutional constraints, and operational risks. Recent research accordingly emphasizes that digitalization and intelligent technologies can substantially improve resource allocation efficiency, provided that organizations possess the necessary technological, organizational, and governance capabilities to use them effectively [1-4].

From a strategic management perspective, smart resource configuration extends beyond the selection or distribution of individual resources. It concerns the coordinated arrangement, recombination, deployment, monitoring, and continuous adjustment of heterogeneous resources in accordance with organizational objectives and environmental conditions. This conception is closely related to contemporary perspectives on resource orchestration and dynamic resource capabilities, which argue that competitive and operational value is not generated solely by possessing resources but by the ability to structure, bundle, mobilize, and selectively deploy them in appropriate combinations. In the digital era, this ability becomes particularly important because the value of assets, technologies, knowledge, and human competencies depends increasingly on their complementarities and on the speed with which they can be recombined. Resource reconfiguration also contributes to organizational resilience because it allows firms and supply chains to respond to shocks, redirect capacity, and preserve critical functions under conditions of disruption or uncertainty. Consequently, smart configuration should be understood as a multidimensional managerial capability connecting strategic renewal, operational adaptation, organizational learning, and resilience rather than merely as a technical optimization problem [5-8]. This perspective is especially relevant to electricity systems, in which resource decisions must simultaneously address reliability, demand variability, infrastructure constraints, investment requirements, environmental objectives, and long-term energy security.

A central foundation of smart resource configuration is the quality, integration, and analytical usability of organizational data. Intelligent decision-making requires accurate, timely, consistent, and accessible information about resource availability, operational performance, demand patterns, technological conditions, costs, and emerging risks. The transition from conventional quality management toward Quality 4.0 illustrates the increasing dependence of organizational decision systems on real-time data, advanced analytics, connected technologies, and automated feedback mechanisms. Industrial IoT infrastructures, for example, enable continuous data acquisition and facilitate the integration of quality monitoring, operational control, and predictive analysis across production environments. Similarly, enterprise resource planning (ERP) platforms and cloud-based information systems increasingly function as digital integration architectures through which financial, logistical, human, and operational data can be coordinated. However, the effectiveness of such systems depends heavily on information quality, systems integration, organizational readiness, cybersecurity, and the ability to translate data into actionable managerial knowledge [9-12]. Cloud ERP adoption research further indicates that organizations frequently encounter interoperability problems, implementation complexity, skill deficiencies, security concerns, and organizational resistance, suggesting that technological availability alone does not guarantee successful digital resource coordination [13-16].

Technological intelligence nevertheless offers unprecedented opportunities for improving resource configuration. AI-based decision systems can process large quantities of heterogeneous data, identify complex relationships, forecast resource requirements, and support adaptive allocation under uncertain conditions. Computational resource allocation research demonstrates the value of dynamic multi-objective optimization in balancing several performance requirements simultaneously, while developments in edge computing, blockchain, and deep learning have expanded the scope of intelligent resource management to decentralized and highly heterogeneous technological environments [17-19]. Research on the Internet of Everything and fog-computing environments similarly demonstrates that resource allocation and task scheduling require the simultaneous management of computational capacity, latency, energy consumption, workload, and service requirements, making intelligent scheduling and adaptive task allocation increasingly essential [20, 21]. Digital-twin-based models further demonstrate the potential for linking real-time demand information with resource matching and spatial or operational reconfiguration, thereby creating a continuously updated representation of resource needs and capacities [22]. In parallel, advances in high-performance computing have strengthened the computational capabilities of ERP systems, while studies of human-machine task allocation indicate that intelligent production increasingly requires dynamic decisions concerning which activities should be assigned to human actors and which should be delegated to automated systems [23, 24]. These developments collectively indicate that smart configuration requires not a single technology but an integrated technological architecture in which data acquisition, analysis, optimization, simulation, security, and decision support operate coherently.

These technological developments are particularly important in smart-grid and electricity-industry environments, where resource configuration is constrained by the need to balance generation, transmission, distribution, demand, infrastructure security, and emerging forms of distributed energy. Decentralized access-control mechanisms, cybersecurity systems, and power-theft detection technologies are increasingly relevant because digital interconnectedness can simultaneously improve operational visibility and create new vulnerabilities. Accordingly, secure smart-grid resource management requires the integration of optimization with cybersecurity and governance mechanisms [25, 26]. More broadly, Industry 4.0 technologies—including IoT, cloud computing, AI, blockchain, automation, and advanced analytics—are transforming sustainable supply chains and industrial resource systems by improving connectivity, traceability, responsiveness, and information sharing [27]. Organizational smart technologies, robotics, AI, and algorithmic capabilities can also contribute to sustainability-oriented human resource management and environmental performance when technological adoption is embedded within appropriate organizational practices [28]. Thus, smart resource configuration in electricity systems should encompass not only operational and technological optimization but also the environmental, human, and governance dimensions through which technological resources are actually translated into sustainable organizational outcomes.

The effectiveness of intelligent resource configuration also depends substantially on organizational structures, management capabilities, strategic alignment, and institutional readiness. ERP and related enterprise technologies illustrate this interdependence particularly clearly. Implementation success depends on top-management commitment, appropriate project governance, organizational-process alignment, user capabilities, infrastructure, and continuous evaluation rather than on software functionality alone [29, 30]. Research on intelligent-technology integration likewise indicates that adoption is shaped by organizational preparedness, technological compatibility, managerial support, perceived value, and environmental conditions [31]. Cloud accounting and information-system research further demonstrates that post-adoption usage and value creation are affected by organizational characteristics and IT governance, highlighting the importance of formal decision rights, accountability structures, control mechanisms, and strategic alignment [32]. Systematic evidence on government resource-planning adoption similarly shows that technological, organizational, environmental, and institutional factors interact in shaping the implementation of integrated digital systems [33]. At a deeper strategic level, organizational path dependence can also restrict adaptation because historically embedded structures, routines, and assumptions may constrain the range of strategic alternatives considered feasible, even when technological opportunities for reconfiguration exist [34]. Therefore, smart resource configuration requires both technological modernization and managerial mechanisms capable of overcoming structural inertia.

The human and behavioral dimensions of intelligent configuration are equally important. Digital systems do not operate independently of the managers, specialists, analysts, and operational employees who interpret information, define priorities, supervise algorithms, and coordinate implementation across organizational boundaries. The concept of systems intelligence emphasizes an organization's capacity to perceive interdependencies, understand feedback relationships, and act constructively within complex systems, thereby providing an important behavioral foundation for learning and adaptive coordination [35]. In smart resource environments, such capabilities are particularly important because optimization at one organizational level may generate unintended consequences elsewhere. Human-resource capabilities, digital literacy, interdisciplinary expertise, and management competence therefore constitute essential components of intelligent configuration. Technological systems must also be designed around the realities of organizational processes and user requirements. Research reconceptualizing ERP from a software-architecture perspective highlights the importance of system characteristics, modularity, integration, and architectural design in supporting organizational functions [36]. Meanwhile, financial technology and digital financial infrastructure can improve resource allocation by reducing information frictions and enabling more effective capital distribution across firms, demonstrating that the broader digital ecosystem can influence organizational allocation efficiency beyond purely internal operational systems [37]. At the macro level, big-data infrastructure and institutionalized data environments can similarly influence financial resource allocation and enterprise innovation by strengthening the information foundations of economic decision-making [38].

The importance of external conditions becomes particularly evident in infrastructure-intensive sectors such as electricity. Resource configuration is affected by legislation, regulatory requirements, financial institutions, government policy, market structures, upstream suppliers, downstream industrial users, and other organizations involved in the energy ecosystem. This means that an organization may possess strong internal technological and managerial capabilities yet remain unable to configure resources effectively when legal, financial, or institutional constraints restrict investment, cooperation, data exchange, or technological implementation. Research on national energy efficiency confirms that energy outcomes emerge from combinations of technological, economic, institutional, and policy-related factors rather than from isolated organizational decisions [39]. Studies of resource-based enterprises also show that digital transformation interacts with environmental policies and organizational green behaviors, suggesting that external policy heterogeneity can condition the effects of technological transformation on resource-intensive organizations [40]. Similarly, intelligent manufacturing and supply-chain research shows that resilience is strengthened through the interaction between internal capabilities and external linkages, underscoring the importance of interorganizational coordination in technologically advanced systems [4]. Therefore, the boundary between intra-organizational configuration and external environmental coordination is increasingly permeable, and a comprehensive smart resource configuration model must accommodate both.

These issues assume particular significance in Iran's electricity industry. The sector operates within a complex environment characterized by growing electricity demand, aging or capacity-constrained infrastructure in some areas, geographic variation in demand and generation, increasing pressure for energy efficiency, the need to diversify generation technologies, financial constraints, environmental considerations, and the growing strategic importance of renewable energy resources. A systems perspective on Iran's electrical energy supply indicates that electricity-sector dynamics are closely interconnected with water, food, energy, and climate-change relationships, making isolated optimization increasingly inadequate for long-term planning [41]. Under such conditions, resource decisions cannot be restricted to conventional questions of budgeting or equipment allocation. They must incorporate dynamic relationships among generation capacity, financial resources, technological infrastructure, human expertise, information systems, regulatory conditions, sustainability objectives, and cross-sector dependencies. Smart resource configuration thus provides a potentially useful framework for integrating these heterogeneous dimensions within a coherent managerial logic. However, the applicability of international models cannot simply be assumed because configuration mechanisms are highly context dependent; the relative importance of internal capabilities, regulatory arrangements, organizational structures, technological maturity, and environmental constraints differs across sectors and national settings.

Despite the expanding literature on digital transformation, ERP, AI-enabled allocation, smart grids, and resource orchestration, several gaps remain. First, much of the literature examines individual technologies or isolated organizational capabilities rather than the configuration of a broader system of mutually reinforcing factors. Second, technological optimization studies often emphasize computational efficiency while devoting less attention to managerial, cultural, financial, legal, and interorganizational requirements. Third, research on ERP and cloud platforms provides valuable evidence on implementation determinants but does not fully capture the specific operational, infrastructural, and regulatory characteristics of electricity industries. Fourth, strategic resource-orchestration research has established the importance of reconfiguration and capability renewal but remains relatively abstract when applied to sector-specific digital transformation. Collectively, the literature indicates that smart configuration emerges from combinations of technological capacity, organizational readiness, leadership, financial support, information quality, governance, external collaboration, and environmental compatibility [6, 7, 33, 42]. Yet an integrated and empirically grounded typology identifying how these factors are structured within Iran's electricity industry remains underdeveloped.

Accordingly, developing a context-sensitive model requires a methodological approach capable of integrating theoretical knowledge with the experience of domain experts. The diversity of relevant constructs—from information quality, technological infrastructure, and intelligent analytical tools to management, finance, human capital, regulation, and institutional cooperation—makes it unlikely that a single theoretical lens can adequately capture the phenomenon. Combining theoretical synthesis with empirical qualitative inquiry provides a mechanism for identifying constructs already established in the international literature while allowing context-specific factors to emerge from expert experience. Subsequent quantitative validation can then assess whether the resulting structure is empirically coherent within the target organizational setting. Such an approach is consistent with the increasingly configurational character of strategic and digital-transformation research, in which organizational outcomes are understood as products of interdependent combinations rather than isolated variables [3, 8]. It also responds to evidence that cloud and enterprise-system adoption is shaped by interacting technological, organizational, managerial, and environmental determinants [13, 43], while recognizing that resource allocation within electricity and digitally enabled industrial systems requires simultaneous attention to optimization, security, resilience, governance, and sustainability [19, 25].

Therefore, the aim of this study was to identify, typologize, model, and validate the critical intra-industry and extra-industry factors influencing smart resource configuration in Iran's electricity industry.

2. Methodology

In terms of purpose, the present research was applied, and in terms of its nature, it was classified as a developmental study. This is because the outcomes of the qualitative and quantitative approaches were employed to develop a novel and context-specific perspective for the population under study, while new concepts were introduced through the organization, classification, and adaptation of previous concepts using a combination of qualitative and quantitative approaches. Furthermore, in terms of data type, the present study was a sequential mixed-methods study. That is, qualitative data were collected and analyzed in the first stage. Following the analysis of the qualitative data, quantitative data were collected and analyzed in subsequent stages on the basis of the findings obtained from the qualitative phase, including examination and testing of the qualitative model and the performance of other related analyses. Therefore, the strategic foundation of the present study comprised qualitative and quantitative phases implemented through a mixed-methods approach. Mixed methods focus on the integrated collection, analysis, and combination of qualitative and quantitative data within a single study or a series of studies. The qualitative phase was conducted in accordance with the multiple grounded theory process, with the aim of developing a qualitative model of the dimensions by integrating the outputs of empirical inquiry, using an interview-based approach, and theoretical inquiry through a meta-synthesis of scientific documents.

In the qualitative phase, the population and sample were defined on the basis of two domains—namely, theoretical inquiry and empirical inquiry—and in accordance with the multiple grounded theory approach. Accordingly, and consistent with this approach, the data were obtained by integrating two strategies: meta-synthesis and thematic analysis of semi-structured interviews. Data obtained from the semi-structured interviews, which were collected through nonprobability purposive sampling until theoretical saturation was reached, were subsequently integrated. For synthesis, systematic analyses, and development of the theoretical model, statistics derived from the outputs of open and axial coding were also used in both the meta-synthesis stage and the interview stage, corresponding to each concept. This process was implemented in three stages in accordance with the multiple grounded theory approach, and the final model was ultimately developed through the synthesis of these stages. In the first stage, data collection for theoretical inquiry was performed deductively through meta-synthesis. At this stage, the study population consisted of domestic and international studies published in reputable scientific sources between 2000 and 2026. From an initial set of 822 valid scientific documents, and following three rounds of systematic review, 70 final documents that were relevant to the research topic and accessible to the researchers constituted the theoretical sample. In addition, using a purposive sampling approach, the empirical sample was drawn from academic and governmental experts and initially comprised 18 individuals divided into two groups until theoretical saturation was reached. The first group included 9 academic experts and faculty members within Iran who had conducted research related to the electricity industry, each of whom had published at least two articles in reputable scientific journals directly related or closely relevant to the present study. The second group included 3 senior managers and high-level decision-makers associated with the electricity industry. Accordingly, theoretical saturation at this stage was achieved after conducting 12 semi-structured interviews with academic and governmental experts in the research field. In the third stage, the theory was enriched by integrating the findings from the two preceding stages, together with the explanation and categorization of findings through a four-round process of review, comparison with the research literature, reassessment, and revision of the model.

Finally, following completion of the theory-enrichment stage, the research model was finalized through approaches including a threefold assessment of theoretical fit, explicit empirical validation, and assessment of theoretical coherence. These procedures were undertaken to integrate the findings, refine the theorization process, and facilitate its development into finalized overarching, sub-, and directed themes.

The statistical population of the quantitative phase consisted of all senior employees with more than 15 years of work experience and managers working in electricity supply and distribution companies throughout Iran at both ministerial and provincial levels. This population included personnel of the Iran Power Generation, Transmission and Distribution Management Company (Tavanir), relevant policymakers and senior employees at various organizational levels, personnel of the Iran Power Development Organization, the Renewable Energy Organization of Iran (SUNA), the Iran Energy Efficiency Organization (SABA), the Iran Power Plant Projects Management Company (MAPNA), the Iran Power Plant Industries Development Company, and other electricity supply and distribution companies operating at the provincial level throughout Iran. According to the latest available statistics confirmed by organizational management, the number of eligible senior employees and managers meeting the aforementioned criteria—within Tavanir-affiliated companies, including 16 regional electricity companies and 39 electricity distribution companies—was 9,627, which was considered the statistical population. The statistical sample was selected from this population using simple proportional random sampling based on the distribution of employees across the aforementioned companies. The preliminary sample size was estimated at approximately 373 using the Krejcie and Morgan table with a margin of error of .05. Field data were collected by initially distributing 450 questionnaires among accessible members of the sample. Following two rounds of follow-up over a one-month period, 400 completed questionnaires were returned to the researcher. After incomplete and invalid questionnaires were excluded, 381 questionnaires containing valid responses remained and were included as the field data.

3. Findings and Results

The following table presents the characteristics of the 12-member expert group, selected from an initially identified pool of 17 individuals, who contributed to the completion and collection of qualitative data for the study, including the Delphi process and interpretive structural modeling.

Table 1. Characteristics of the Selected Expert Group

No.	Educational Qualification	Age	Years of Service
1	PhD	50	16
2	PhD	46	15
3	PhD	52	12
4	PhD	47	17
5	PhD	47	22
6	PhD	47	15
7	PhD	37	7
8	PhD	47	15
9	PhD	50	17
10	Master’s degree	49	24
11	Master’s degree	55	25
12	Bachelor’s degree	57	28

Consistent with the multiple grounded theory approach, theoretical inquiry was employed alongside empirical inquiry and theory enrichment to develop the strategic model in this study. Following the initial extraction of open and directed codes by the researcher and their subsequent review by other researchers external to the present research team, certain codes were merged while others were differentiated during subsequent rounds. Accordingly, synthesis of the thematic analysis findings indicated that a total of 519 nonredundant open codes were extracted, which were ultimately organized into 50 directed codes and 14 overarching themes. The meta-synthesis findings were also summarized into 161 open codes, 41 directed codes, 13 sub-concepts, and 2 overarching categories. Ultimately, through integration of the meta-synthesis and thematic analysis findings, the multiple grounded theory approach generated a model comprising 14 subcategories and 2 overarching categories, entitled “Extra-Industry and Environmental Factors” and “Intra-Industry Factors,” which were represented through 50 principal concepts in the final research model. The following table presents the themes derived from the integration of the meta-synthesis findings and thematic analysis of the interviews as the model of factors affecting smart resource configuration in the electricity industry.

Table 2. Finalized Observations and Frequencies Based on the Multiple Grounded Theory Approach

Overarching Themes	Subthemes	Directed Codes	Frequency of Open Codes From Interviews	Meta-Synthesis Code Frequency	Selected Scientific Sources Related to the Themes
Intra-Industry Factors	Quality of data and information related to the electricity industry	Quality of data and information related to enterprise resource planning	18	6	Christou et al. (2022); Deogaonkar (2025); Gao et al. (2026); Hana'a et al. (2026); Harvey et al. (2026); Hu and He (2025)
		Quality of data and information related to identifying current patterns and trends in the electricity industry	14	6	Tuli and Kaluvakuri (2022); Usman (2026); Varma et al. (2023); Wang et al. (2026); Wang et al. (2025); Zhang et al. (2024); Zhang (2025)
		Quality of data and information related to identifying and analyzing trends and improvement opportunities in the electricity industry	11	6	Peng et al. (2024); Quasim et al. (2025); Srhir et al. (2023); Sun and Zhou (2026); Symeonidis et al. (2003); Liu et al. (2023); Liu (2026)
	Quality of data collection and analysis tools	Use of optimal and up-to-date approaches and tools for collecting and analyzing data related to the electricity industry	18	8	Li et al. (2025); Liu et al. (2023); Liu (2026); Magare and Pawar (2026); Marin (2026); Mary Jyosthna et al. (2026); Mossa et al. (2025); Li et al. (2025)
		Use of approaches and tools aligned with industrial requirements for collecting, cleaning, and analyzing electricity-industry data	15	2	Nevskaya et al. (2023); Ogbeibu et al. (2024)
	Effectiveness and efficiency of processes and tools associated with resource configuration in the electricity industry	Effectiveness and efficiency of technologies employed in smart resource configuration, including the software and hardware used	19	5	Sun and Zhou (2026); Symeonidis et al. (2003); Hussain et al. (2026); Jamil et al. (2022); Jamil et al. (2025)
		Continuous improvement of processes and algorithms based on feedback and new data	22	5	Jiang et al. (2025); Liu et al. (2023); Aoudi and Al-Aqrabi (2026); Bin Hammad et al. (2024); Chatti et al. (2021)
		Use of agile approaches to enable rapid adaptation to changes in resource configuration processes in the electricity industry	23	2	Marin (2026); Mary Jyosthna et al. (2026); Mossa et al. (2025); Li et al. (2025); Liu et al. (2023); Liu (2026); Magare and Pawar (2026)
		Effectiveness and efficiency of performance-evaluation processes and identification of strengths and weaknesses associated with smart configuration	22	2	Mary Jyosthna et al. (2026); Mossa et al. (2025)
		Effectiveness and efficiency in utilizing the latest technologies associated with the Fourth Industrial Revolution, including the Internet of Things (IoT), cloud computing, augmented reality (AR), virtual reality (VR), and similar technologies, in the collection, analysis, storage, evaluation, forecasting, and optimization processes involved in smart resource configuration	18	—	—

		Effectiveness and efficiency of Fourth Industrial Revolution technologies for enhancing information security and transparency, such as smart blockchain technology and related technologies	14	5	Nevskaya et al. (2023); Ogbeibu et al. (2024); Li et al. (2025); Liu et al. (2023); Liu (2026)
		Effectiveness and efficiency of training and simulation tools in processes associated with resource configuration in the electricity industry, including intelligent tools such as augmented reality and virtual reality	14	3	Marin (2026); Nevskaya et al. (2023); Ogbeibu et al. (2024)
	Vision and anticipated objectives for smart resource configuration in the electricity industry	Sufficient clarity of the vision and mission regarding smart resource configuration in the electricity industry	17	5	Accenture (2020); Ahn and Ahn (2020); Al Senani and Masengu (2025); Ali et al. (2023); Almasria et al. (2026)
		Presence of specific and predetermined objectives concerning the functions expected from smart resource configuration processes in the electricity industry	23	5	Alvarenga and Guedes (2026); Aoudi and Al-Aqrabi (2026); Asprion et al. (2018); Bin Hammad et al. (2024)
		Alignment between the defined vision and objectives of the electricity industry and the anticipated missions associated with the digitalization and intelligent transformation of resource configuration processes	24	4	Aoudi and Al-Aqrabi (2026); Asprion et al. (2018); Bin Hammad et al. (2024); Deogaonkar (2025)
	Compatibility and alignment of intra-industry systems and processes	Compatibility and alignment of existing structures and systems within the industry with the implementation and application of smart resource configuration	23	5	Accenture (2020); Ahn and Ahn (2020); Al Senani and Masengu (2025); Ali et al. (2023); Almasria et al. (2026)
		Compatibility and alignment of existing procedures and processes within the industry with the implementation and application of smart resource configuration	13	2	Accenture (2020); Alvarenga and Guedes (2026)
	Communication culture compatible with smart-industry requirements	Presence of a strong participatory culture among members of organizations and agencies associated with the electricity industry to facilitate implementation of smart resource configuration	10	4	Aoudi and Al-Aqrabi (2026); Asprion et al. (2018); Bin Hammad et al. (2024); Magare and Pawar (2026)
		Establishment of effective inter-industry communication among institutions and organizations within the electricity industry and related industries to support decision-making concerning the application of smart resource configuration	11	4	Ahn and Ahn (2020); Al Senani and Masengu (2025); Ali et al. (2023); Almasria et al. (2026)
		Readiness of the overall industrial structure and its affiliated institutions to implement the requirements of intelligent resource configuration	21	—	—
		Establishment of appropriate interorganizational communication among members of organizations affiliated with the electricity industry to ensure coordination and compatibility in implementing smart resource configuration requirements	20	2	Liu (2026); Magare and Pawar (2026)
	Management and governance factors	Adequacy of senior management skills within electricity-industry organizations for evaluating existing systems and ongoing processes when implementing smart resource configuration requirements	14	—	—
		Adequate and sufficient support from senior management in electricity-industry organizations for programs aimed at strengthening and implementing smart resource configuration requirements	9	4	Alvarenga and Guedes (2026); Elragal and Haddara (2012); Chatti et al. (2021); Jiang et al. (2025)

		Adequacy of middle managers' skills in relation to the basic and advanced requirements of smart resource configuration	5	3	Li et al. (2025); Liu et al. (2023); Liu (2026)
		Existence of standardized management principles and processes for allocating industry resources in accordance with smart resource configuration requirements	14	4	Magare and Pawar (2026); Ahn and Ahn (2020); Al Senani and Masengu (2025); Deogaonkar (2025)
		Consideration of the capabilities, talents, and interests of human capital in resource-allocation management and task-assignment processes within electricity-industry configuration	11	6	Hussain (2026); Hussain et al. (2026); Jamil et al. (2022); Jamil et al. (2025); Jin and Huh (2026); Kouriati et al. (2020)
		Availability of appropriate and efficient project teams whose members possess diverse and relevant specialized skills within industry organizations and agencies for implementing smart resource configuration requirements	22	6	Li et al. (2025); Liu et al. (2023); Aoudi and Al-Aqrabi (2026); Asprion et al. (2018); Bin Hammad et al. (2024); Chatti et al. (2021)
		Definition of clear and formally documented temporal and spatial boundaries for smart resource configuration implementation projects to facilitate effective process management	17	—	—
	Intra-industry financial and capital factors	Provision of an adequate budget for essential processes required for smart resource configuration	19	5	Jamil et al. (2025); Jiang et al. (2025); Liu (2026); Magare and Pawar (2026); Srhir et al. (2023); Sun and Zhou (2026)
		Sufficient investment in smart resource configuration	22	5	Jin and Huh (2026); Kouriati et al. (2020); Li et al. (2025); Liu et al. (2023)
		Anticipation of revenue sources within financing processes to support future expansion of smart resource configuration initiatives	23	—	—
	Intra-industry infrastructural and structural factors	Alignment of electricity-industry structures, in terms of size and complexity, with the level of complexity required for resource intelligence	22	3	Hana'a et al. (2026); Harvey et al. (2026); Hu and He (2025); Hussain (2026)
		Adequacy of existing information technology infrastructure within the electricity industry for the deployment and smart configuration of resources	18	2	Jiang et al. (2025); Hussain (2026)
		Availability of the required skills and specialized infrastructure for implementing, configuring, and intelligently managing resources at the industry level	33	2	Ali et al. (2023); Almasria et al. (2026)
	Quality of human capital within the industry	Presence of an effective human resource system for attracting and employing competent individuals to implement and manage smart resource configuration	14	3	Accenture (2020); Ahn and Ahn (2020); Al Senani and Masengu (2025)
		Presence of an effective in-service training system for specialized human resources to develop competent personnel for smart resource configuration processes in the electricity industry	7	4	Hussain (2026); Jamil et al. (2025); Jiang et al. (2025); Jin and Huh (2026)
		Availability of specialized and highly competent personnel at senior and strategic management levels in decision-making organizations in the electricity industry and related industries for analyzing, configuring, and reconfiguring intelligent resource configuration systems	23	4	Kouriati et al. (2020); Li et al. (2025); Hussain et al. (2026); Jamil et al. (2022)
Extra-Industry and	Legal requirements and regulatory provisions	Compatibility and absence of inconsistencies in industry-related laws and regulations with	12	—	—

Environmental Factors		the requirements and needs of smart resource configuration deployment processes			
		Absence of legal barriers to implementing infrastructure projects for the deployment and smart configuration of resources	15	4	Alvarenga and Guedes (2026); Christou et al. (2022); Elragal and Haddara (2012); Gao et al. (2026)
		Absence of legal barriers to obtaining financing from the banking system for projects aimed at enhancing the intelligence of resource configuration processes in the electricity industry	14	3	Hana'a et al. (2026); Harvey et al. (2026); Hu and He (2025)
		Compatibility of extra-industry and supra-industry systems and processes associated with the electricity industry with smart resource configuration	10	4	Marin (2026); Mary Jyosthna et al. (2026); Peng et al. (2024); Quasim et al. (2025)
	Participation and cooperation with higher-level institutions	Absence of obstacles to participation and cooperation with higher-level electricity-industry institutions during the implementation and deployment of smart resource configuration	19	4	Hussain et al. (2026); Jamil et al. (2022); Symeonidis et al. (2003); Zhang (2025)
		Cooperation and participation with higher-level institutions for the optimal management of electricity-generation resources	21	3	Wang et al. (2026); Wang et al. (2025); Zhang et al. (2024); Zhang (2025)
		Cooperation and participation with the legislative branch in securing financial resources for the utilization of new electricity-industry resources, including new and renewable energy sources and nuclear energy	20	2	Mossa et al. (2025); Nevskaya et al. (2023)
	Participation and cooperation with other industries related to the electricity industry	Participation and cooperation with upstream segments of the electricity-industry supply chain, such as oil companies	14	—	—
		Participation and cooperation with downstream segments of the supply chain and industries dependent on the electricity industry, including petrochemicals, cement, textiles, and related industries	11	—	—
		Participation and cooperation with other parallel and related industries	13	—	—
	Extra-industry financial and capital factors	Support from the banking system in financing projects aimed at enhancing the intelligence of resource configuration processes in the electricity industry	23	2	Ogbeibu et al. (2024); Peng et al. (2024)
		Effectiveness and efficiency of financing approaches for infrastructure projects involving the deployment and smart configuration of resources	12	4	Mossa et al. (2025); Nevskaya et al. (2023); Ogbeibu et al. (2024); Quasim et al. (2025)
		Willingness of senior governmental decision-makers and legislative authorities in the government and parliament to inject the capital required to implement smart resource configuration processes in the electricity industry	23	3	Tuli and Kaluvakuri (2022); Usman (2026); Varma et al. (2023)

The frequency distribution of respondents by educational attainment indicated that, among the 381 participants, 68 (17.8%) held a bachelor's degree, 265 (69.55%) held a master's degree, and 48 (12.6%) held a doctoral degree or higher and were employed in senior organizational positions within Iran's electricity industry.

After the theoretical model had been developed, the identified items were converted into a questionnaire and distributed among members of the quantitative sample. Before selecting the confirmatory analytical approach, the Kolmogorov–Smirnov test was used to assess the normality of the data distribution. Normally distributed data can be analyzed using covariance-based approaches within a factor-analytic framework and can provide acceptable results. For non-normal data, confirmatory factor analysis can be conducted using partial least squares–based approaches in SmartPLS. Based on the results of the aforementioned test, which are presented in the Appendix, none of the data followed a normal distribution and were therefore considered non-normal. Accordingly, acceptable confirmatory factor analysis results could only be obtained using a partial least squares approach with SmartPLS. The findings obtained through this approach are therefore presented below.

Given that the research model consisted of 13 confirmatory measurement subconstructs, identification and confirmation of the research model structure through measurement models first required ensuring the adequacy of the parametric component of the model and, where necessary, making modifications to the model. More specifically, the evaluation of a path model in PLS is conducted in two stages. In the first stage, the measurement models are evaluated; once sufficient evidence regarding the validity and reliability of the measurement models has been obtained, the structural model can be evaluated. Accordingly, after implementing confirmatory factor analyses using the partial least squares method in SmartPLS, the indicators related to the measurement models were first examined, followed by evaluation of the structural component of the model. After implementing and estimating the conceptual model and obtaining the outputs, evaluation of confirmatory structural path measurement models using the partial least squares approach typically involves assessing the internal consistency reliability of each measurement model, composite reliability, indicator reliability, convergent validity, and discriminant validity. These criteria are reported below. Table 3 presents selected values of these indices for the main constructs. Based on the values presented in the table, the model demonstrated acceptable levels across the reported indices and exhibited satisfactory component consistency as well as construct validity and reliability.

Table 3. Validity and Reliability Indices of the Constructs

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Effectiveness and efficiency of processes and tools related to resource configuration in the electricity industry	0.969	0.974	0.845
Legal requirements and regulatory provisions	0.855	0.794	0.893
Compatibility and alignment of intra-industry processes	0.847	0.929	0.868
Extra-industry and environmental factors	0.879	0.769	0.826
Intra-industry factors	0.987	0.989	0.709
Intra-industry infrastructural and structural factors	0.870	0.920	0.794
Extra-industry financial and capital factors	0.484	0.712	0.870
Intra-industry financial and capital factors	0.929	0.955	0.875
Management and governance factors	0.915	0.932	0.663
Smart resource configuration factors in the electricity industry	0.968	0.976	0.525
Communication culture compatible with smartness requirements in the industry	0.928	0.949	0.822
Participation and cooperation with other industries related to the electricity industry	0.887	0.892	0.737
Participation and cooperation with higher-level institutions	0.802	0.883	0.716
Vision and anticipated objectives in the electricity industry for smart resource configuration	0.929	0.955	0.876
Quality of data collection and analysis tools	0.908	0.956	0.916
Quality of data and information related to the electricity industry	0.963	0.976	0.932
Quality of human capital active in the industry	0.767	0.860	0.674

Finally, in evaluating the overall statistical model, the Goodness-of-Fit (GoF) index was calculated as **0.586**. Considering the benchmark values of 0.01, 0.25, and 0.36, which have been introduced as weak, moderate, and strong levels of GoF, respectively, the obtained GoF value of 0.586 indicated an appropriate overall model fit.

After confirming the adequacy of the estimated values as described above, the confirmatory factor analysis algorithm was implemented and its outputs were obtained. The structural path model and the estimated coefficients for the confirmatory factor analysis model based on partial least squares are presented in the following figures.

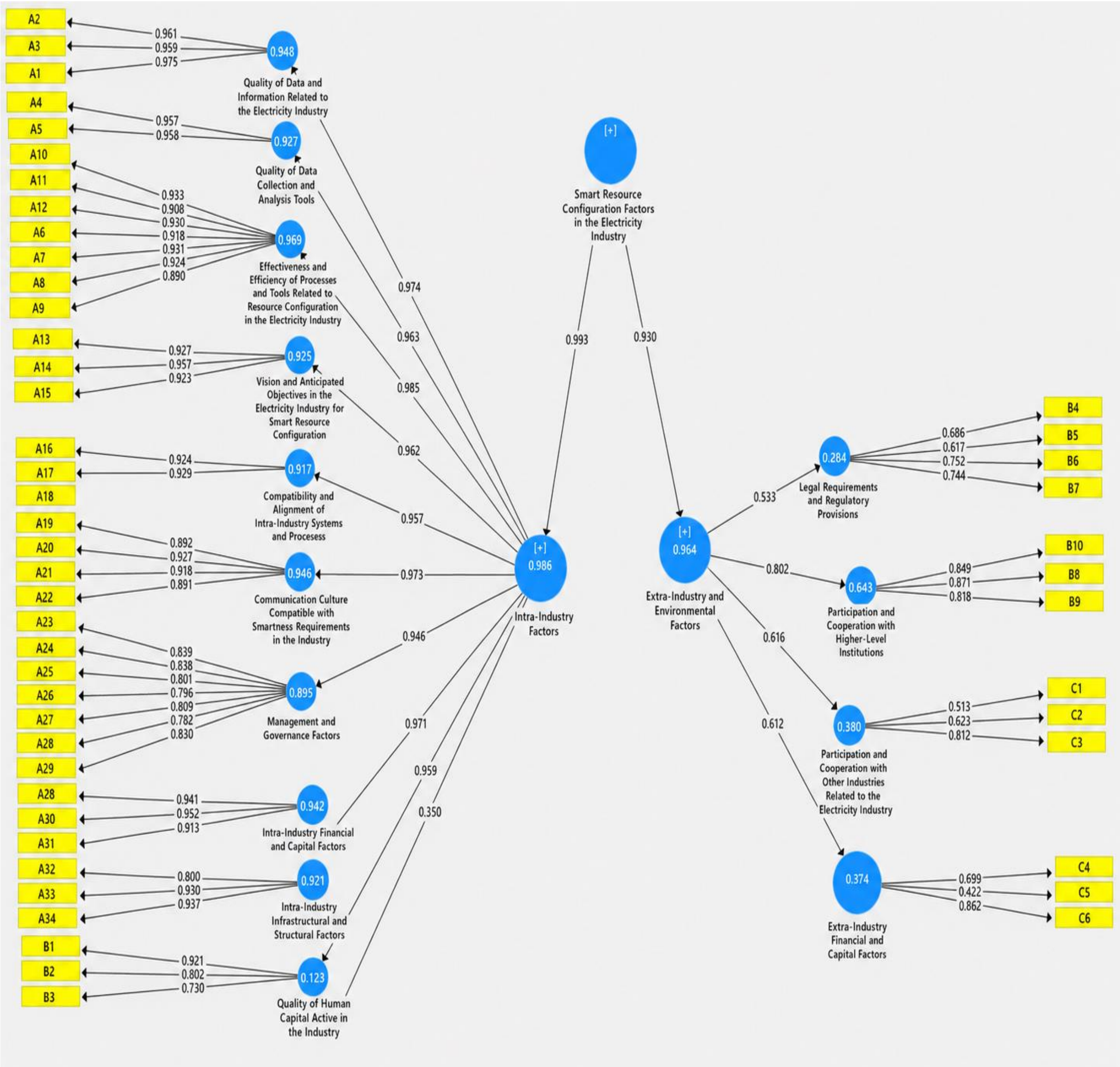

Figure 1. Estimated coefficients of the confirmatory factor analysis model based on partial least squares

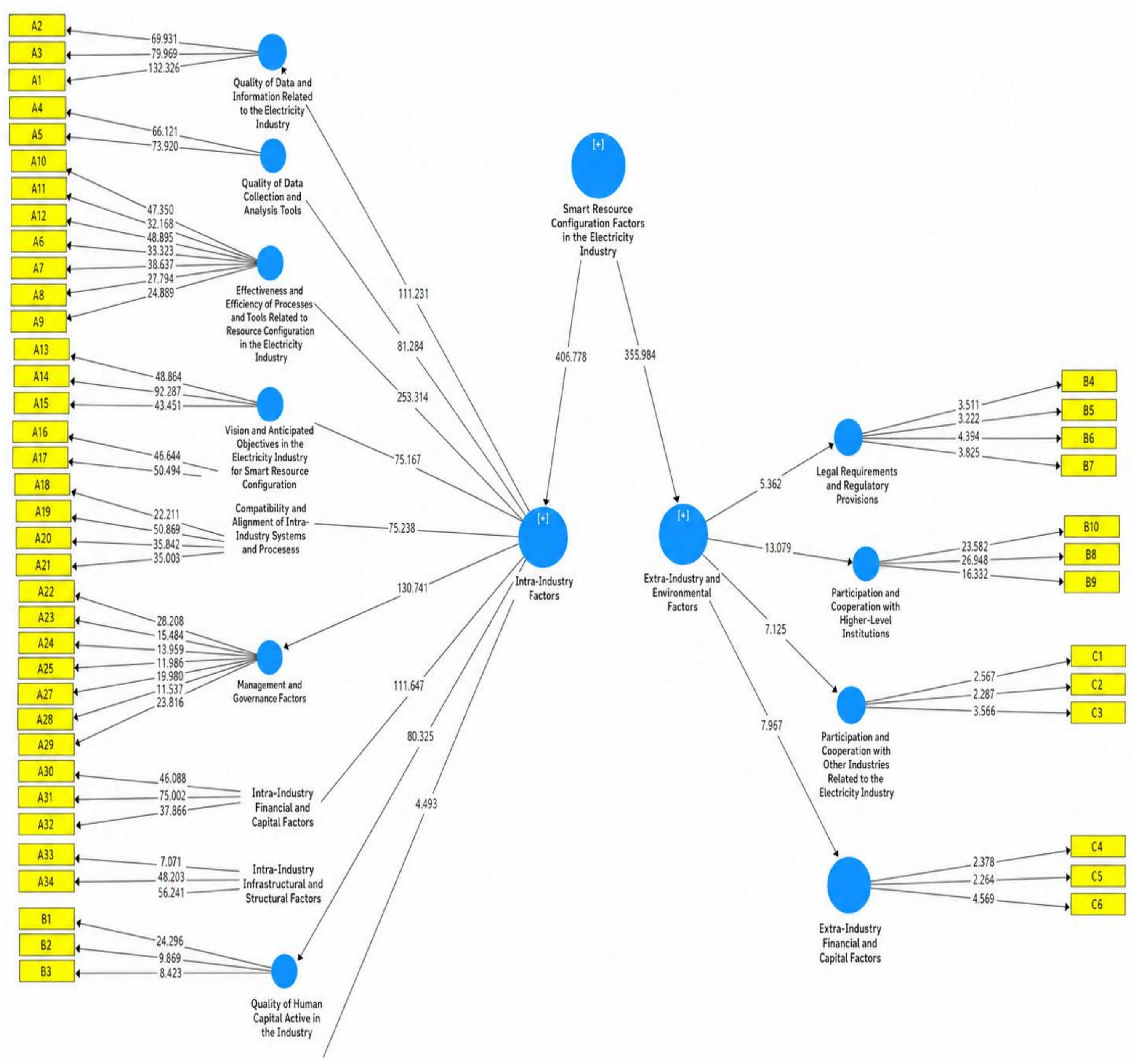

Figure 2. t statistics in the confirmatory factor analysis model based on partial least squares

The following table presents the significance levels and direct-effect coefficients among the main constructs of the study. Based on the table, the relationships among all main constructs were statistically significant and were therefore confirmed.

Table 4. Significance Levels and Direct-Effect Coefficients Among the Main Constructs of the Study

Structural Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	*t* Statistics (|O/STDEV|)	*p* Values
Extra-industry and environmental factors → Legal requirements and regulatory provisions	0.533	0.551	0.099	5.362	0.000
Extra-industry and environmental factors → Extra-industry financial and capital factors	0.612	0.640	0.077	7.967	0.000

Extra-industry and environmental factors → Participation and cooperation with other industries related to the electricity industry	0.616	0.626	0.086	7.125	0.000
Extra-industry and environmental factors → Participation and cooperation with higher-level institutions	0.802	0.797	0.061	13.079	0.000
Intra-industry factors → Perceived effectiveness and efficiency of processes and tools related to resource configuration in the electricity industry	0.985	0.985	0.004	253.314	0.000
Intra-industry factors → Compatibility and alignment of intra-industry systems and processes	0.957	0.958	0.013	75.238	0.000
Intra-industry factors → Intra-industry infrastructural and structural factors	0.959	0.966	0.012	80.325	0.000
Intra-industry factors → Intra-industry financial and capital factors	0.971	0.971	0.009	111.647	0.000
Intra-industry factors → Management and governance factors	0.946	0.949	0.016	57.817	0.000
Intra-industry factors → Communication culture compatible with smartness requirements in the industry	0.973	0.973	0.007	130.741	0.000
Intra-industry factors → Vision and anticipated objectives in the electricity industry for smart resource configuration	0.962	0.961	0.013	75.167	0.000
Intra-industry factors → Quality of data collection and analysis tools	0.963	0.964	0.012	81.284	0.000
Intra-industry factors → Quality of data and information related to the electricity industry	0.974	0.974	0.009	111.231	0.000
Intra-industry factors → Quality of human capital active in the industry	0.350	0.374	0.078	4.493	0.000
Smart resource configuration factors in the electricity industry → Extra-industry and environmental factors	0.130	0.940	0.133	340.984	0.000
Smart resource configuration factors in the electricity industry → Intra-industry factors	0.993	0.992	0.002	406.778	0.000

Examination of the significance of direct effects, indirect effects, and ultimately total effects using the bootstrapping (BT) procedure in PLS, together with the t value for each coefficient, demonstrated that the t-test results for assessing the significance of the path coefficients, including both direct and indirect effects, indicated statistically significant relationships between all observed and latent components within the model; accordingly, the model was confirmed. Evidence supporting this conclusion was provided by the fact that the t values obtained for the research constructs were greater than 1.96 and that the significance level obtained for each factor loading was less than .05. Therefore, the relationships among them were statistically significant and confirmed. Conversely, for constructs with t values below 1.96 and significance levels greater than .05, the relationships would not be considered statistically significant. It should be noted that, at the 95% confidence level, the null hypothesis states that the estimated factor loading is equal to zero, whereas the alternative hypothesis states that it is not equal to zero. Therefore, for factor loadings to be statistically significant, the corresponding t value must exceed 1.96. The results presented in the table support this criterion. The preceding figures also report the t statistics for the estimated coefficients in the confirmatory factor analysis model, based on the output generated by SmartPLS 4. In summary, the preceding tables and figures present the path-analysis findings based on the direct and indirect relationships among the latent and observed components of the model as a complementary component of the descriptive statistical analysis. Based on the reported results, for all examined relationships and paths, the statistical hypothesis **H1**, indicating the existence of a relationship and statistical confirmation of the hypothesized path within the structural equation model, was supported. This means that all direct and indirect relationships among the latent and observed components of the model were confirmed. Accordingly, the research model was supported in terms of statistical validity.

4. Discussion and Conclusion

The present study sought to identify and organize the critical factors shaping smart resource configuration in Iran's electricity industry and to develop an integrated model encompassing both intra-industry and extra-industry determinants. The qualitative findings yielded two overarching categories—intra-industry factors and extra-industry and environmental factors—which were further differentiated into 14 subcategories and a broad set of directed codes derived from the integration of meta-synthesis and thematic analysis. The intra-industry dimension incorporated the quality of data and information, quality of data collection and analytical tools, effectiveness and efficiency of resource-configuration processes and technologies, strategic vision and objectives, compatibility of internal systems and processes, communication culture, management and governance, financial and capital resources, infrastructural and structural conditions, and quality of human capital. The extra-industry dimension consisted primarily of legal and regulatory requirements, cooperation with higher-level institutions, collaboration with industries connected to the electricity sector, and external financial and capital conditions. Quantitative validation further supported the proposed factor structure, indicating that smart resource configuration in the electricity industry should be understood as a multidimensional phenomenon produced by the interaction of technological, organizational, managerial, human, financial, institutional, and environmental conditions.

One of the most prominent findings concerned the importance of data and information quality as a foundation for smart resource configuration. The model demonstrated that the usefulness of information for enterprise resource planning, identification of existing industrial patterns, and detection of trends and improvement opportunities constitutes a central internal requirement. This finding is theoretically consistent with the increasing transition from conventional resource planning toward data-intensive and algorithm-supported decision systems. High-quality digital data improve the ability of organizations to identify resource shortages, forecast operational conditions, evaluate resource utilization, and adjust configurations in a timely manner. Research on Quality 4.0 similarly emphasizes that data integrity, digital connectivity, and advanced analytical capability are prerequisites for intelligent organizational decision-making [9]. Industrial IoT infrastructures also demonstrate how integrated and real-time information can strengthen monitoring, quality control, and responsive management within technologically intensive environments [10]. The present finding is additionally compatible with evidence that big-data environments can enhance the efficiency of financial resource allocation and enterprise innovation by reducing information asymmetry and improving the informational basis of managerial decisions [38]. Accordingly, smart configuration in the electricity industry cannot be separated from the development of accurate, timely, standardized, and interoperable data systems.

The findings also emphasized the quality of data collection and analytical tools, including the use of up-to-date technologies and methods compatible with the operational needs of the electricity industry. This result suggests that merely possessing data is insufficient; organizations must have appropriate mechanisms for acquiring, cleaning, integrating, processing, and interpreting such data. The result aligns with research on intelligent resource allocation, which shows that advanced analytical and optimization technologies can substantially improve allocation decisions under dynamic and heterogeneous conditions [17, 18]. Blockchain and deep-learning approaches have also been shown to strengthen intelligent resource management in distributed and computationally complex systems by combining optimization with security, decentralization, and predictive capability [19]. Furthermore, cloud-based ERP systems extend access to integrated information and computational capabilities, although their value depends on system architecture, cybersecurity, interoperability, and organizational readiness [12, 14, 15]. Therefore, the present study supports the view that intelligent resource configuration requires an integrated analytics architecture rather than isolated software applications.

A further important result was the central role of the effectiveness and efficiency of processes and technologies used for resource configuration. This category included technological performance, continuous improvement of algorithms, agile adaptation, performance evaluation, and the use of Industry 4.0 technologies such as IoT, cloud computing, augmented reality, virtual reality, blockchain, and intelligent simulation tools. This finding reflects the increasingly dynamic character of resource management. Contemporary resource environments require continuous reconfiguration rather than fixed allocation, especially when demand, capacity, technology, and operating conditions change rapidly. Research on resource allocation in fog computing and Internet of Everything environments demonstrates the necessity of intelligent scheduling, adaptive workload distribution, and continuous balancing of multiple resource constraints [20]. More recent research similarly indicates that intelligence-based allocation and task off-loading can improve resource efficiency in distributed edge environments [21]. In addition, AI has been shown to enhance resource allocation efficiency by improving information processing, forecasting, and matching decisions [1]. The present findings therefore suggest that smart resource configuration in electricity systems should be treated as an iterative and adaptive managerial process supported by real-time digital technologies.

The importance assigned to strategic vision and predefined objectives further demonstrates that technological intelligence must be embedded within strategic direction. The identified indicators emphasized clarity of organizational mission, explicit configuration objectives, and alignment between electricity-industry goals and the missions associated with smart resource management. This result is consistent with the strategic resource-orchestration perspective, according to which organizations create value not merely through resource possession but by selectively structuring and deploying resources in accordance with strategic priorities [5]. Dynamic resource capability research likewise shows that strategic renewal depends on the ability to reconfigure resource architectures as environmental and technological conditions evolve [6]. Similarly, configurational research demonstrates that different combinations of resource-allocation patterns correspond to distinct strategic orientations and organizational outcomes [8]. These studies support the present finding that smart configuration should not be conceptualized solely as operational optimization; rather, it must be explicitly linked to strategic direction, organizational priorities, and long-term energy-sector objectives.

Another finding concerned the compatibility and alignment of internal structures, systems, procedures, and processes with smart resource configuration. This category reflects the need to ensure that existing organizational arrangements do not obstruct technological transformation. ERP research consistently demonstrates that implementation success depends on process alignment, systems compatibility, governance, and organizational preparedness [29, 30]. The same principle is evident in research on cloud ERP, where organizational architecture, implementation readiness, and integration capacity influence the adoption and effective use of digital enterprise systems [13, 43]. The findings of the current study extend this argument to the electricity industry by indicating that technologically sophisticated configuration mechanisms cannot operate effectively when organizational processes remain fragmented, incompatible, or excessively rigid. This interpretation is particularly important in large infrastructure sectors characterized by hierarchical structures, historically developed procedures, and multiple organizational units.

The identification of communication culture, management, and governance as major components of the model further reinforces the organizational character of smart resource configuration. The results indicated that participatory culture, interorganizational communication, managerial competence, senior-management support, standardized management procedures, appropriate project teams, and explicit project boundaries are critical to implementation. These findings accord with evidence showing that organizational and governance conditions strongly affect the effective use of cloud-based information and accounting systems [32]. Technology integration also depends on managerial support, readiness, perceived usefulness, and organizational facilitation [31]. Furthermore, systems intelligence highlights the capacity of organizational actors to understand interdependencies, communicate effectively, and act constructively in complex systems [35]. In an electricity industry characterized by high interdependence among generation, transmission, distribution, planning, regulation, and finance, coordination failures can substantially reduce the value of otherwise advanced technologies. Thus, the present findings suggest that smart configuration is as much a governance and coordination challenge as a technological one.

The results additionally highlighted the significance of financial and capital resources, infrastructure, and human capital. Adequate budgeting, investment, future revenue planning, IT infrastructure, specialized skills, recruitment systems, in-service training, and the presence of technically competent personnel at senior decision-making levels all emerged as essential conditions. This multidimensional requirement is consistent with evidence that digital transformation can improve resource allocation efficiency only when organizations possess complementary financial, technological, and organizational capabilities [2]. Financial technologies can also improve allocation efficiency by reducing frictions and enabling more effective distribution of capital [37]. At the same time, Industry 4.0 environments depend on appropriate technological infrastructure and human competencies, particularly when AI, robotics, algorithms, and smart technologies are incorporated into organizational processes [27, 28]. The present findings therefore underscore the complementarity among capital investment, digital infrastructure, and human expertise. Investment in technology without investment in competencies and organizational capacity is unlikely to generate sustained intelligent configuration.

The study also demonstrated that extra-industry and environmental factors constitute an indispensable component of the smart resource configuration model. Legal and regulatory compatibility, absence of financing barriers, cooperation with higher-level institutions, coordination with upstream and downstream industries, and external financial support were all identified as relevant. This finding is particularly significant because it moves the analysis beyond the organizational boundary. Research on national energy efficiency has similarly shown that energy-sector performance depends on economic, policy, technological, institutional, and structural conditions operating at multiple levels [39]. Research on resource-based enterprises further indicates that digital transformation interacts with environmental policy conditions and sustainability requirements, meaning that external policy heterogeneity can affect the outcomes of organizational digitalization [40]. The importance of external linkages is also consistent with evidence that intelligent development strengthens supply-chain resilience partly through the interaction of internal capabilities and external relationships [4]. Consequently, smart resource configuration in the electricity industry should be regarded as an ecosystem-level phenomenon rather than an exclusively firm-level capability.

The identification of cooperation with higher-level governmental and legislative institutions and other industries is particularly relevant to the structure of national electricity systems. Electricity companies depend extensively on regulatory decisions, public investment, banking arrangements, fuel suppliers, major industrial consumers, infrastructure organizations, and national development policies. Therefore, the effectiveness of resource configuration depends on the ability to coordinate across organizational and sectoral boundaries. This interpretation also aligns with the concept of resource reconfiguration for resilience, which emphasizes the importance of acquiring, retaining, recombining, and, where necessary, abandoning resources and knowledge in response to changes across supply networks [7]. In addition, strategic path dependence may restrict adaptation when institutionalized routines and legacy structures limit organizations' capacity to alter existing resource patterns [34]. The present findings therefore imply that successful smart configuration may require not only internal modernization but also adjustments to regulations, financing arrangements, interinstitutional relationships, and entrenched organizational routines.

The findings carry particular implications for Iran's electricity industry, where the configuration of resources must account for interconnected pressures involving generation capacity, demand growth, infrastructure requirements, finance, environmental concerns, technological modernization, and cross-sector resource dependencies. Research on Iran's electrical energy supply system has demonstrated the importance of interactions among water, food, energy, and climate-change dynamics, highlighting the systemic character of electricity-sector decision-making [41]. The present model complements this perspective by showing that smart configuration requires simultaneous attention to internal organizational capabilities and external environmental conditions. The strong multidimensional structure of the proposed model indicates that isolated technological interventions are unlikely to produce sustainable improvements unless they are accompanied by improvements in information quality, governance, managerial competence, financing, human capital, infrastructure, regulatory support, and institutional collaboration. This finding is also consistent with systematic research on technology adoption demonstrating that organizational, technological, and environmental determinants frequently operate in combination rather than independently [33, 42].

Overall, the study contributes to the literature by integrating several previously fragmented streams of research—resource orchestration, ERP implementation, intelligent resource allocation, Industry 4.0, smart-grid management, digital transformation, and institutional coordination—within a unified sector-specific framework. Prior studies have examined cloud ERP expansion [16], high-performance computing within ERP environments [23], human-machine task allocation in intelligent production [24], smart-grid optimization and security [25], and risk-based IoT security [26]. The current findings indicate that these technological domains should not be considered independently from strategic, organizational, human, financial, and environmental determinants. The resulting typology therefore provides a more comprehensive explanation of the conditions under which intelligent resource configuration can be institutionalized in a complex infrastructure sector.

The present study should be interpreted in light of several limitations. First, although the qualitative component incorporated both theoretical synthesis and expert interviews, the empirical qualitative sample was limited to a relatively small group of specialists and senior decision-makers, which may constrain the diversity of perspectives represented in the resulting model. Second, the quantitative data were obtained from senior employees and managers within Iran's electricity industry, and therefore the findings may not be directly generalizable to other energy sectors, countries, or institutional environments. Third, the study relied substantially on self-reported questionnaire data, which can be affected by perceptual bias, organizational position, and respondents' subjective evaluations of technological and managerial conditions. Fourth, the cross-sectional nature of the quantitative validation limits the ability to determine how the identified factors evolve over time or how changes in one dimension influence subsequent changes in other dimensions. Finally, the electricity industry is undergoing rapid technological and regulatory transformation; therefore, the relative importance of some factors may change as AI, smart grids, renewable energy systems, distributed generation, and data-governance mechanisms become more mature.

Future studies should test the proposed model in other segments of the energy industry and in different national contexts to assess its external validity and determine whether the relative importance of the identified dimensions varies according to regulatory structure, market maturity, technological development, or energy mix. Longitudinal designs would be especially valuable for examining how smart resource configuration capabilities develop over time and whether improvements in data quality, digital infrastructure, managerial capability, or institutional cooperation precede measurable gains in operational efficiency and resilience. Researchers could also employ multi-group structural equation modeling to compare generation, transmission, and distribution companies or public and private organizations. Further research may integrate objective operational indicators, such as outage duration, network losses, resource utilization, investment efficiency, renewable integration, or project performance, with perceptual measures. In addition, configurational techniques such as fuzzy-set qualitative comparative analysis could investigate whether alternative combinations of technological, managerial, financial, and environmental conditions can produce similarly high levels of smart resource configuration.

Electricity-industry policymakers and managers should approach smart resource configuration as an integrated transformation program rather than as a stand-alone technology project. Priority should be given to establishing standardized and interoperable data architectures, strengthening data quality, and developing real-time analytical capabilities across generation, transmission, distribution, and planning functions. Organizations should simultaneously invest in digital infrastructure, cybersecurity, AI-supported decision tools, employee training, interdisciplinary project teams, and managerial competencies. Strategic objectives for smart resource configuration should be formally defined and linked to measurable operational and investment priorities. Existing processes and organizational structures should be reviewed for compatibility with intelligent resource-management systems, while mechanisms for cross-organizational communication and knowledge sharing should be strengthened. At the external level, policymakers should reduce regulatory and financing barriers, facilitate cooperation between electricity companies and financial institutions, and establish clearer coordination mechanisms with governmental bodies, major energy suppliers, technology providers, and electricity-intensive industries. A phased implementation roadmap combining technological readiness, workforce development, governance reform, financing, and performance monitoring would provide a practical basis for translating the proposed model into sustainable improvements in electricity-sector resource management.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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