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Structural-Interpretive Modeling of Smart Green HRM's Drivers and Outcomes: A Pathway to Sustainable Innovation Adoption and Competitive Resilience

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Abstract

Purpose: This study identifies and hierarchically models the drivers and consequences of Smart Green Human Resource Management (Smart Green HRM) in promoting sustainable organizational innovation adoption, addressing the research gap regarding structural relationships among AI-enabled HR practices, dynamic capabilities, and innovation outcomes.

Methodology: Using a mixed-methods approach, Fuzzy Delphi and Interpretive Structural Modeling (ISM) with MICMAC analysis were applied. A panel of 15 experts from Sistan and Baluchestan Province (Iran) was selected through purposive snowball sampling. Variables were screened via Fuzzy Delphi (threshold: 0.70), and 12 final variables were structured hierarchically through ISM level partitioning.

Findings: The ISM model revealed five hierarchical levels. Institutional Pressures (C1), Top Management Support (C2), and AI Infrastructure (C3) emerged as foundational drivers (Level V). Smart Green HR practices (C4–C7) occupied Level IV, while dynamic capabilities (C8–C10) were positioned at Level III. Sustainable Innovation Adoption (C11) and Competitive Advantage (C12) constituted top-level outcomes (Levels I–II). MICMAC analysis confirmed C1, C2, and C3 as strategic pillars with highest driving power.

Conclusion: This study extends Dynamic Capabilities Theory by introducing "Algorithmic Synchrony," demonstrating that Seizing and Reconfiguration co-evolve simultaneously in AI-augmented environments. The hierarchical model provides practitioners with a roadmap for prioritizing infrastructure and leadership investments. The framework guides organizations navigating the Twin Transition, particularly in developing regions.

Keywords: Smart Green HRM, Sustainable Innovation, Interpretive Structural Modeling, Dynamic Capabilities, Twin Transition.

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1. Introduction

In recent decades, environmental complexities and uncertainties resulting from climate crises, climate change, and the depletion of natural resources have transformed environmental sustainability from a voluntary, ceremonial practice into a strategic imperative for organizational survival (George et al., 2023; Singh et al., 2024). Concurrently with these environmental shifts, the contemporary world is experiencing remarkable and striking leaps in advanced Industry 4.0 and 5.0 technologies, including Generative Artificial Intelligence (Generative AI), Big Data Analytics, the Internet of Things (IoT), and automated systems (Dwivedi et al., 2023; Feuerriegel et al., 2024). The intersection of these two massive global trends has formed a pivotal junction that contemporary strategic literature terms the "Twin Transition"—the synergy between digital transformation and environmental sustainability (Jorzik et al., 2026; Teng et al., 2025).

At the heart of this Twin Transition lies "Human Capital" and its management practices. Organizations have recognized that even the most advanced green technologies and environmental strategies are doomed to failure without the engagement, motivation, competence, and practical behavioral change of their employees (Mota et al., 2026). The traditional paradigm of "Green Human Resource Management" (GHRM), which previously focused primarily on actions such as reducing paper consumption, waste sorting, energy conservation in the workplace, and conducting routine environmental training courses (Cao et al., 2023), no longer meets the fast-paced and complex demands of today's smart and volatile world. In response to this shortcoming, the emerging concept of "Smart Green Human Resource Management" (Smart Green HRM) has been born; a paradigm resulting from the systematic integration of Artificial Intelligence tools and algorithms with environmental sustainability values across all human capital processes (Jorzik et al., 2026; Li et al., 2026).

Relying on Real-time Data Processing and machine learning systems, the Smart Green HRM concept redefines all HR functions—including smart recruitment and selection aligned with environmental metrics, personalized and simulated training in Virtual/Augmented Reality (VR/AR) environments, and algorithmic-green performance appraisal and rewards (Feuerriegel et al., 2024; Teng et al., 2025). This approach not only minimizes the carbon footprint of administrative procedures but also provides the necessary behavioral foundation to promote "Sustainable Innovations" by optimizing decision-making and reducing human error (Mota et al., 2026; Singh et al., 2024).

Nevertheless, the implementation and operationalization of Smart Green HRM in organizations face complex structural challenges and ambiguities. Sustainable innovations—encompassing Process Green Innovation and Product/Service Green Innovation—require radical shifts in organizational culture, Organizational Citizenship Behavior for the Environment (OCBE), and the reconfiguration of dynamic capabilities (Cao et al., 2023; Teece, 2010). Many senior executives and organizational policymakers face the fundamental questions of:

1. What foundational (internal and external) drivers facilitate the emergence and establishment of Smart Green HRM in an organization?
2. What chain and causal relationships do the various dimensions of Smart Green HRM practices share with one another and with mediating behavioral and competency variables?
3. Through what mechanism and hierarchical pattern does the Smart Green HRM system lead to the practical adoption of sustainable innovations within the organization?

The absence of a native, structured, and comprehensive model capable of partitioning this complex network of relationships and identifying key, independent, and dependent variables represents a critical research gap in the strategic HRM and technology management literature (Jorzik et al., 2026; Li et al., 2026). Most prior studies have either focused solely on testing simple, direct effects of traditional GHRM on environmental performance (e.g., Singh et al., 2024) or analyzed AI without linking it to sustainability goals (Feuerriegel et al., 2024).

Accordingly, the present study employs Interpretive Structural Modeling (ISM) and MICMAC analysis to address this scientific gap and provide an operational model. This methodology allows the researcher to level the multi-dimensional and complex variables of Smart Green HRM and sustainable innovation based on Driving Power and Dependence Power, offering a visual and mathematical roadmap for decision-makers.

The importance and necessity of this research stem from the fact that modern organizations, to maintain competitive advantage and respond to institutional and stakeholder pressures, must inevitably pair algorithmic technologies with environmental responsibilities. The output of this study can assist executive leaders, HR managers, and organizational consultants in focusing their limited resources on the most fundamental drivers, thereby accelerating the transition toward sustainable innovations.

2. Theoretical Foundations and Literature Review

2.1. Theoretical Framework of the Research

As illustrated in Figure 1, the conceptual model of the present study is grounded in the integration of two complementary theories: Dynamic Capabilities Theory, which analyzes intra-organizational dimensions (smart-green sensing, seizing, and transforming), and Institutional Theory, which explicates extra-organizational pressures (coercive, normative, and mimetic) driving the adoption of sustainable innovations (DiMaggio & Powell, 1983; George et al., 2023; Teece, 2010).

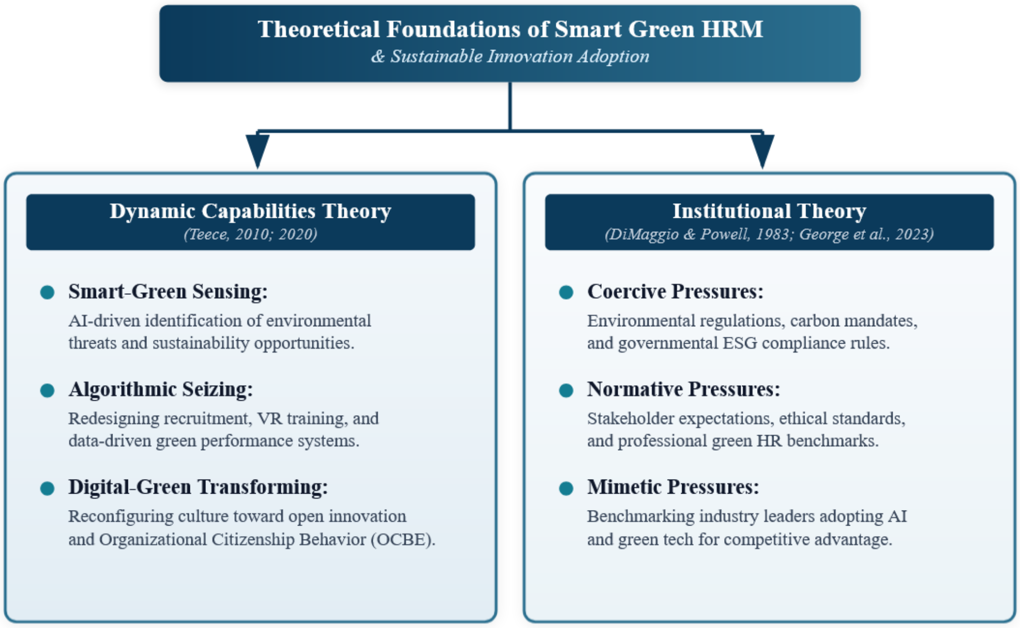


Figure 1. Theoretical Foundations of the Research Model (Source: By author)

2.1.1. Dynamic Capabilities Theory

Dynamic Capabilities Theory, introduced by David Teece (Teece, 2010), provides the primary framework for understanding how organizations achieve sustainable competitive advantage in highly volatile and complex technological environments. According to this theory, dynamic capabilities represent an organization's capacity to "sense opportunities and threats (Sensing)," "seize and make decisions to exploit opportunities (Seizing)," and "continuously reconfigure and transform tangible and intangible assets (Transforming/Reconfiguring)" (Teece, 2010; Li et al., 2026).

In the proposed model, Smart Green HRM functions as a "novel, cross-cutting dynamic capability":

- **Smart-Green Sensing:** Utilizing AI systems and data analytics to monitor climate change, customer environmental requirements, and algorithmic HR behaviors (Feuerriegel et al., 2024).
- **Algorithmic Seizing:** Redesigning recruitment processes, Virtual/Augmented Reality (VR/AR)-based training, and transparent algorithmic reward systems to attract and retain multi-disciplinary digital-green talent (Jorzik et al., 2026).
- **Digital-Green Transforming:** Reinventing organizational culture toward "open innovation" and instilling "Organizational Citizenship Behavior for the Environment" (OCBE) into work processes to adopt sustainable innovations (Cao et al., 2023; Mota et al., 2026).

2.1.2. Institutional Theory

Institutional Theory posits that strategic behaviors and organizational structures are not solely driven by economic efficiency imperatives, but are strongly influenced by institutional pressures within the ecosystem to maintain organizational legitimacy (George et al., 2023). Based on this theory, three categories of institutional pressures facilitate the adoption of Smart Green HRM:

- **Coercive Pressures:** Regulatory requirements, international carbon protocols, and strict governmental environmental mandates (Singh et al., 2024).
- **Normative Pressures:** Stakeholder expectations, societal ethical values, and professional standards in HR and technology (Jorzik et al., 2026).
- **Mimetic Pressures:** Benchmarking industry leaders who have successfully integrated AI and sustainability to enhance market share and employer branding (Teng et al., 2025).

2.2. Paradigm Shift: From Traditional GHRM to Smart Green HRM

To deeply comprehend the scientific distinction of this paradigm, it is essential to redefine core HR functions at the intersection of artificial intelligence and environmental objectives (Dwivedi et al., 2023; Feuerriegel et al., 2024).

Table 1. Comparative Analysis of Traditional Green HRM and Smart Green HRM Functions (Source: By author)

HR Function	Traditional Green HRM (GHRM)	Smart Green HRM (SGHRM)	Literature Reference
Recruitment & Selection	Paperless job postings and basic remote interviews.	Algorithmic screening with Natural Language Processing (NLP), processing CVs based on green competencies, and assessing candidate digital-green cultural fit.	Li et al. (2026); Teng et al. (2025)
Training & Development	In-person/webinar training workshops and PDF material distribution.	AI-driven personalized interactive courses and simulated carbon footprint reduction in VR/AR environments.	Feuerriegel et al. (2024); Jorzik et al. (2026)
Performance Management	Manual, annual evaluations based on environmental behavior checklists.	Smart, continuous, real-time monitoring of sustainability metrics and predictive analytics of employee green performance.	Cao et al. (2023); Mota et al. (2026)
Compensation & Rewards	Fixed financial or non-financial rewards for top green ideas.	Smart reward systems based on data-mined actual reductions in carbon footprint and contribution to innovation.	Singh et al. (2024)
Culture & Employee Relations	Verbal encouragement toward energy conservation and recycling.	Emergence of open innovation digital ecosystems, human-machine co-creation networks, and reinforcement of OCBE.	George et al. (2023); Mota et al. (2026)

2.3. Dimensions of Sustainable Organizational Innovations

Sustainable innovation refers to the commercialization and implementation of new processes, products, services, or business models that yield economic returns while simultaneously reducing environmental risks and optimizing natural resource consumption (Cao et al., 2023; Teece, 2010). In strategic literature, this concept is divided into two core dimensions:

- **Process Green Innovation:** Redesigning production, operational, logistical, and service processes using smart tools to minimize waste, recycle energy, optimize supply chains, and eliminate pollutants (Li et al., 2026; Teng et al., 2025).
- **Product/Service Green Innovation:** Developing entirely new products or services with eco-design features, recyclable life cycles, and zero negative environmental impact (Singh et al., 2024).

2.4. Systematic Literature Review

International research conducted in recent years (2023 to 2026) has examined the intersecting dimensions of artificial intelligence, human resources, and sustainability. Table 2 presents an analytical synthesis of key prior studies:

Table 2. Synthesis Matrix of International Literature (2023–2026) (Source: By author)

Author(s) / Year	Research Title & Focus	Methodology	Major Findings & Conceptual Contribution
Jorzik, Siegel & Spraul (2026)	Navigating the Twin Transition in HR: A conceptual framework for Smart Green HRM	Qualitative / Systematic Literature Review	Formulated foundational concepts of SGHRM and emphasized integrating next-generation AI tools into the human capital life cycle to achieve ESG targets.
Li, Zhang & Wang (2026)	Enterprise AI readiness and sustainable performance: The mediating mechanism of green process innovation	Quantitative / Structural Equation Modeling (SEM)	Demonstrated that algorithmic tools translate into green competitive advantage only when supported by HR dynamic capabilities.
Mota, Santos & Ferreira (2026)	Smart Green HRM practices and employee eco-innovative behavior	Mixed-methods / Fuzzy Delphi & Survey	Identified the critical role of data-driven performance appraisal and simulated training in fostering OCBE.
Teng, Wu & Yang (2025)	Digital-green synergistic development: How smart HR technologies drive sustainable innovation	Quantitative / Panel Data Analysis in manufacturing	Revealed that smart HR technologies significantly reduce the time-to-market for sustainable products.
Feuerriegel et al. (2024)	Generative AI in business and management	Qualitative / Strategic Thematic Analysis	Elucidated the organizational transition from analytical AI to Generative AI and its impact on job competencies and training.
Singh et al. (2024)	Green innovation and environmental performance: The role of green transformational leadership	Quantitative / PLS-SEM	Highlighted strategic leadership as a necessary condition for HR practices to impact process and product innovations.
Cao, Chen & Liu (2023)	Linking digital transformation with green innovation: The role of dynamic capabilities and GHRM	Quantitative / SEM	Showed that traditional GHRM lacks the efficacy to generate radical innovations without digital infrastructure integration.

2.5. Identification of Research Gaps

Synthesizing the existing literature reveals three fundamental research gaps:

1. **Lack of an Integrated Structural Model:** Most previous studies (e.g., Cao et al., 2023; Singh et al., 2024) evaluated the link between GHRM and innovation linearly or through simple hypotheses, overlooking complex cause-and-effect network structures and variable level partitioning.

2. **Absence of Drive-Dependence Power Partitioning:** Literature remains unclear regarding which variables act as foundational driving pillars versus dependent outcomes.
3. **Neglect of Generative AI in Green HRM:** Limited empirical work explicitly integrates next-generation AI tools (such as NLP, predictive algorithms, and VR simulations) with Green HRM within Interpretive Structural Modeling (ISM) frameworks.

The present study is specifically designed to address these three gaps.

3. Methodology

In terms of purpose, this research is applied-developmental, and in terms of data collection and analysis, it is a descriptive-analytical study employing a mixed-methods (qualitative-quantitative) approach. The primary methodology of this study is grounded in Interpretive Structural Modeling (ISM) combined with Matrice d'Impacts Croisés Multiplication Appliquée à un Classement (MICMAC) analysis. ISM is a structured qualitative-quantitative analytical method introduced by Warfield (1974) to analyze complex systems, structure multi-dimensional variables, and map hierarchical cause-and-effect relationships (Kannukollu et al., 2024; Sushil, 2018).

3.1. Target Population, Geographical Scope, and Expert Sampling

The geographical scope of this research is Sistan and Baluchestan Province, targeting leading entities in industrial sectors, technology, environmental management, and prominent academic centers (including the University of Sistan and Baluchestan, Islamic Azad University Zahedan Branch, the Science and Technology Park of the province, and knowledge-based firms located in Zahedan and Chabahar industrial zones).

The target population consists of two main groups:

- **Academic Experts:** Faculty members from universities across Sistan and Baluchestan Province (University of Sistan and Baluchestan and Islamic Azad University Zahedan Branch) in Business Management, Public Administration, HR Management, and IT/AI Engineering, possessing a minimum of 10 years of academic experience and peer-reviewed publications in green management, digital transformation, and sustainability.
- **Executive and Industrial Experts:** Senior managers and consultants in HR and IT across key regional organizations (including knowledge-based firms in the Science and Technology Park, ESG/environmental managers at Chabahar Free Zone, and senior HR directors of major regional industries), with at least 10 years of executive experience implementing modern managerial and technological systems.

Given the qualitative-quantitative nature of ISM and Fuzzy Delphi, non-probability purposive snowball sampling was conducted until expert sufficiency was achieved. Ultimately, 15 experts from Sistan and Baluchestan Province were selected for the final panel.

Table 3. Demographic Composition and Panel Profiles of Experts in Sistan and Baluchestan Province (N=15) (Source: By author)

No.	Organization / Institution (Sistan and Baluchestan)	Expertise Area	Count	Min. Experience	Academic Rank / Degree	Primary Selection Criterion
1	University of Sistan & Baluchestan & Islamic Azad University Zahedan	HR Management & Organizational Behavior	4	15 Years	Associate / Full Professor	ISI/Scopus publications in GHRM and sustainability.
2	University of Sistan & Baluchestan & Science & Technology Park	Artificial Intelligence & IT Management	3	12 Years	Associate / Assistant Professor	Research background in decision support systems and data mining.
3	Science & Technology Park of Sistan and Baluchestan	Knowledge-based Executives	3	10 Years	Ph.D. / M.Sc.	Leading digital transformation and smart HR automation projects.
4	Chabahar Free Zone & Environmental Protection Dept.	ESG & Sustainability Advisors	3	12 Years	Ph.D. / M.Sc.	Managing environmental impact assessment and green innovation.
5	Industrial Estates Corporation (Zahedan & Chabahar)	Senior HR Directors	2	14 Years	M.Sc. / Ph.D.	Implementation of ISO standards and green organizational strategies.

Note: Source: Primary findings collected from Sistan and Baluchestan Province.

According to ISM literature, a panel size of 10 to 15 experts is optimal for constructing structural self-intersection matrices and reaching mathematical consensus (Kannukollu et al., 2024; Sushil, 2018).

3.2. Sequential Steps of the Research Process

The operational process of this study was conducted in five sequential steps as shown in Figure 2.

Figure 2. Sequential Execution Flowchart of Fuzzy Delphi - ISM - MICMAC Methodology (Sushil, 2018; Kannukollu et al., 2024).

3.2.1. Step 1: Identification and Screening of Variables via Fuzzy Delphi Method (FDM)

In the first step, systematically reviewing the literature (2023–2026) yielded initial variables across drivers, practices, mediators, and outcomes of Smart Green HRM. To validate and localize these indicators, a two-round Fuzzy Delphi technique was conducted. Expert evaluations were converted into Triangular Fuzzy Numbers (TFN: l_k, m_k, u_k) to handle qualitative ambiguity (Table 4).

Table 4. Linguistic Scale and Corresponding Triangular Fuzzy Numbers (TFN) (Source: By author)

Linguistic Scale	Triangular Fuzzy Number (lk,mk,uk)
Very Unimportant	(0.0, 0.1, 0.3)
Unimportant	(0.1, 0.3, 0.5)
Moderate	(0.3, 0.5, 0.7)
Important	(0.5, 0.7, 0.9)
Very Important	(0.7, 0.9, 1.0)

Note: Source: Mota et al. (2026); Kannukollu et al. (2024).

The fuzzy mean of expert assessments (A) is calculated as follows:

$$A = (L, M, U) = \left(\min_k l_k , \frac{1}{K} \sum_{k=1}^{K} m_k , \max_k u_k \right) \quad (1)$$

To defuzzify the fuzzy averages, the Center of Gravity method was applied:

$$S_j = \frac{L + M + U}{3} \quad (2)$$

Variables with a defuzzified score (S_j) exceeding the threshold of 0.70 were selected for the ISM model (Kannukollu et al., 2024).

3.2.2. Step 2: Structural Self-Intersection Matrix (SSIM) Construction

To evaluate pairwise relationships among the 12 selected variables, the SSIM was formed. Experts responded to the question: "Does variable i lead to or enhance variable j?" using four symbols (Sushil, 2018):

- **V:** Variable i leads to variable j ($i \rightarrow j$).
- **A:** Variable j leads to variable i ($j \rightarrow i$).
- **X:** Variables i and j exert mutual influence on each other ($i \leftrightarrow j$).
- **O:** No direct conceptual relationship exists between i and j.

3.2.3. Step 3: Initial and Final Reachability Matrix Formation

Replacing the SSIM symbols with binary entries (0 and 1) using Boolean logic yields the Initial Reachability Matrix:

- If entry (i, j) is **V**, then $(i, j) = 1$ and $(j, i) = 0$.
- If entry (i, j) is **A**, then $(i, j) = 0$ and $(j, i) = 1$.
- If entry (i, j) is **X**, then both $(i, j) = 1$ and $(j, i) = 1$.
- If entry (i, j) is **O**, then both $(i, j) = 0$ and $(j, i) = 0$.

Subsequently, to establish the Final Reachability Matrix, the transitivity rule was applied. This rule states that if variable i impacts j ($i \rightarrow j$) and j impacts k ($j \rightarrow k$), then logically i must impact k ($i \rightarrow k$). Transitive relationships are denoted by 1^* (Sushil, 2018).

3.2.4. Step 4: Level Partitioning

For each variable i, two mathematical sets are extracted:

- **Reachability Set (R_i):** Consists of variable i and all variables it influences (entries with value 1 in row i).
- **Antecedent Set (A_i):** Consists of variable i and all variables that influence it (entries with value 1 in column i).
- **Intersection Set:** $R_i \cap A_i$.

The condition for a variable to occupy the top level (Level I) of the model is:

$$R_i \cap A_i = R_i \quad (3)$$

Once Level I variables are identified, their corresponding rows and columns are removed, and the iteration process is repeated to extract subsequent levels (Levels II through V) (Kannukollu et al., 2024; Sushil, 2018).

3.2.5. Step 5: MICMAC Analysis

In the final step, MICMAC analysis is conducted to evaluate Driving Power and Dependence Power:

- **Driving Power of variable i:** Sum of elements in row i of the Final Reachability Matrix.
- **Dependence Power of variable j:** Sum of elements in column j of the Final Reachability Matrix.

Based on these powers, variables are mapped onto a Cartesian coordinate system divided into four clusters:

1. **Autonomous Cluster:** Low driving power, low dependence power.
2. **Dependent Cluster:** Low driving power, high dependence power.
3. **Linkage Cluster:** High driving power, high dependence power (unstable variables).
4. **Driving/Independent Cluster:** High driving power, low dependence power (foundational pillars) (Sushil, 2018).

4. Findings

In this section, the step-by-step outputs obtained from executing the Fuzzy Delphi technique, Interpretive Structural Modeling (ISM), and MICMAC analysis on data gathered from the 15-member expert panel in Sistan and Baluchestan Province are presented.

4.1. Fuzzy Delphi Screening Results

Following a systematic literature review, 15 initial variables were identified. Upon distributing two rounds of Fuzzy Delphi questionnaires among experts in Sistan and Baluchestan Province, the fuzzy mean and defuzzified value (S_j) for each variable were calculated using Equations (1) and (2). Based on the screening threshold ($S_j \geq 0.70$), 12 final variables were accepted and 3 variables were eliminated.

Table 5. Fuzzy Delphi Screening Results for Research Variables (Expert Evaluations) (Source: By author)

Code	Variable Title (Indicator)	Fuzzy Mean (L,M,U)	Defuzzified (Sj)	Acceptance Status	Supporting Literature Reference
C1	Institutional Pressures & Green Regulatory Mandates	(0.70, 0.88, 1.00)	0.860	Accepted	DiMaggio & Powell (1983); George et al. (2023)
C2	Top Management Support & Digital Leadership	(0.65, 0.85, 1.00)	0.833	Accepted	Teece (2020); Mota et al. (2026)
C3	Enterprise AI & Data Infrastructure	(0.60, 0.82, 1.00)	0.806	Accepted	Kannukollu et al. (2024)
C4	Smart Green Recruitment & Selection	(0.55, 0.78, 0.95)	0.760	Accepted	Ren et al. (2023)
C5	Digital-Green Training & Upskilling (VR/AI)	(0.60, 0.80, 0.98)	0.793	Accepted	Mota et al. (2026)
C6	Algorithmic-Green Rewards & Performance Appraisal	(0.50, 0.75, 0.95)	0.733	Accepted	Ren et al. (2023)
C7	Innovative Culture & Green Citizenship (OCBE)	(0.55, 0.78, 0.95)	0.760	Accepted	Mota et al. (2026)
C8	Smart Green Sensing	(0.60, 0.81, 0.98)	0.797	Accepted	Teece (2010; 2020)

Code	Variable Title (Indicator)	Fuzzy Mean (L,M,U)	Defuzzified (Sj)	Acceptance Status	Supporting Literature Reference
C9	Algorithmic Seizing & Green Knowledge Sharing	(0.55, 0.77, 0.95)	0.757	Accepted	Teece (2020)
C10	Process Reconfiguration & Open Innovation	(0.50, 0.74, 0.92)	0.720	Accepted	Sushil (2018)
C11	Sustainable Innovations Adoption & ESG Performance	(0.65, 0.86, 1.00)	0.837	Accepted	George et al. (2023)
C12	Sustainable Competitive Advantage & Resilience	(0.70, 0.89, 1.00)	0.863	Accepted	Kannukollu et al. (2024)

Note: Variables including "Traditional Paper-based Evaluation," "Individual Employee Willingness without Infrastructure," and "Informal Local Pressures" were removed due to defuzzified scores falling below 0.70.

4.2. Structural Self-Intersection Matrix (SSIM) Construction

After establishing the 12 final variables, the SSIM was constructed based on expert panel consensus using four symbols (V, A, X, O) in Table 6.

Table 6. Structural Self-Intersection Matrix (SSIM) for Smart Green HRM Dimensions (Source: By author)

Variables	C12	C11	C10	C9	C8	C7	C6	C5	C4	C3	C2	C1
C1	V	V	V	V	V	V	V	V	V	V	V	—
C2	V	V	V	V	V	V	V	V	V	X	—	
C3	V	V	V	V	V	V	V	V	V	—		
C4	V	V	V	V	A	X	X	X	—			
C5	V	V	V	V	A	X	X	—				
C6	V	V	V	V	A	X	—					
C7	V	V	V	V	A	—						
C8	V	V	V	X	—							
C9	V	V	X	—								
C10	V	X	—									
C11	V	—										
C12	—											

Note: Primary calculations based on expert panel consensus.

4.3. Initial and Final Reachability Matrix Formation

Converting the SSIM symbols into binary codes (0 and 1) yielded the Initial Reachability Matrix. Applying Boolean transitivity logic uncovered hidden relationships, producing the Final Reachability Matrix in Table 7, where 1* denotes transitive relationships.

Table 7. Final Reachability Matrix with Driving Power and Dependence Power (Source: By author)

Variables	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Driving Power
C1	1	1	1	1	1	1	1	1	1	1	1	1	12
C2	0	1	1	1	1	1	1	1	1	1	1	1	11
C3	0	1	1	1	1	1	1	1	1	1	1	1	11
C4	0	0	0	1	1	1	1	0	1*	1*	1	1	8
C5	0	0	0	1	1	1	1	0	1*	1*	1	1	8
C6	0	0	0	1	1	1	1	0	1*	1*	1	1	8
C7	0	0	0	1	1	1	1	0	1*	1*	1	1	8
C8	0	0	0	1	1	1	1	1	1	1*	1	1	10
C9	0	0	0	0	0	0	0	1	1	1	1	1	6
C10	0	0	0	0	0	0	0	0	1	1	1	1	5

Variables	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	Driving Power
C11	0	0	0	0	0	0	0	0	0	1	1	1	4
C12	0	0	0	0	0	0	0	0	0	0	0	1	1
Dependence Power	1	3	3	8	8	8	8	6	10	11	11	12	Sum: 93

Note: Output derived from mathematical calculations of the ISM model.

4.4. Level Partitioning of Variables

By calculating the Reachability Set (R_i), Antecedent Set (A_i), and Intersection Set ($R_i \cap A_i$) across successive iterations, the variables were categorized into 5 distinct hierarchical levels (Table 8).

Table 8. Summary of Iterations and Level Partitioning for the ISM Model (Source: By author)

Variable	Reachability Set (Ri)	Antecedent Set (Ai)	Intersection Set (Ri∩Ai)	Assigned Level
C12	{12}	{1,2,3,4,5,6,7,8,9,10,11,12}	{12}	Level I (Top Level)
C11	{11, 12}	{1,2,3,4,5,6,7,8,9,10,11}	{11}	Level II
C10	{10, 11, 12}	{1,2,3,4,5,6,7,8,9,10,11}	{10, 11}	Level III
C9	{9, 10, 11, 12}	{1,2,3,4,5,6,7,8,9,10}	{9, 10}	Level III
C4, C5, C6, C7	{4,5,6,7,9,10,11,12}	{1,2,3,4,5,6,7,8}	{4,5,6,7}	Level IV
C8	{4,5,6,7,8,9,10,11,12}	{1,2,3,8,9}	{8, 9}	Level IV
C2, C3	{2,3,4,5,6,7,8,9,10,11,12}	{1,2,3}	{2, 3}	Level V (Foundational)
C1	{1,2,3,4,5,6,7,8,9,10,11,12}	{1}	{1}	Level V (Foundational)

Note: Calculations from ISM level partitioning algorithm.

4.5. Graphical Interpretive Structural Model (ISM Diagram)

The hierarchical diagram generated by the ISM algorithm is depicted in Figure 3. This structural model illustrates how Level 5 foundational drivers (institutional pressures, tech infrastructure, and leadership support) activate Level 4 operational HR practices, which in turn shape Level 3 dynamic capabilities, ultimately driving sustainable innovation adoption (Level 2) and organizational resilience and competitive advantage (Level 1) across industries in Sistan and Baluchestan Province.

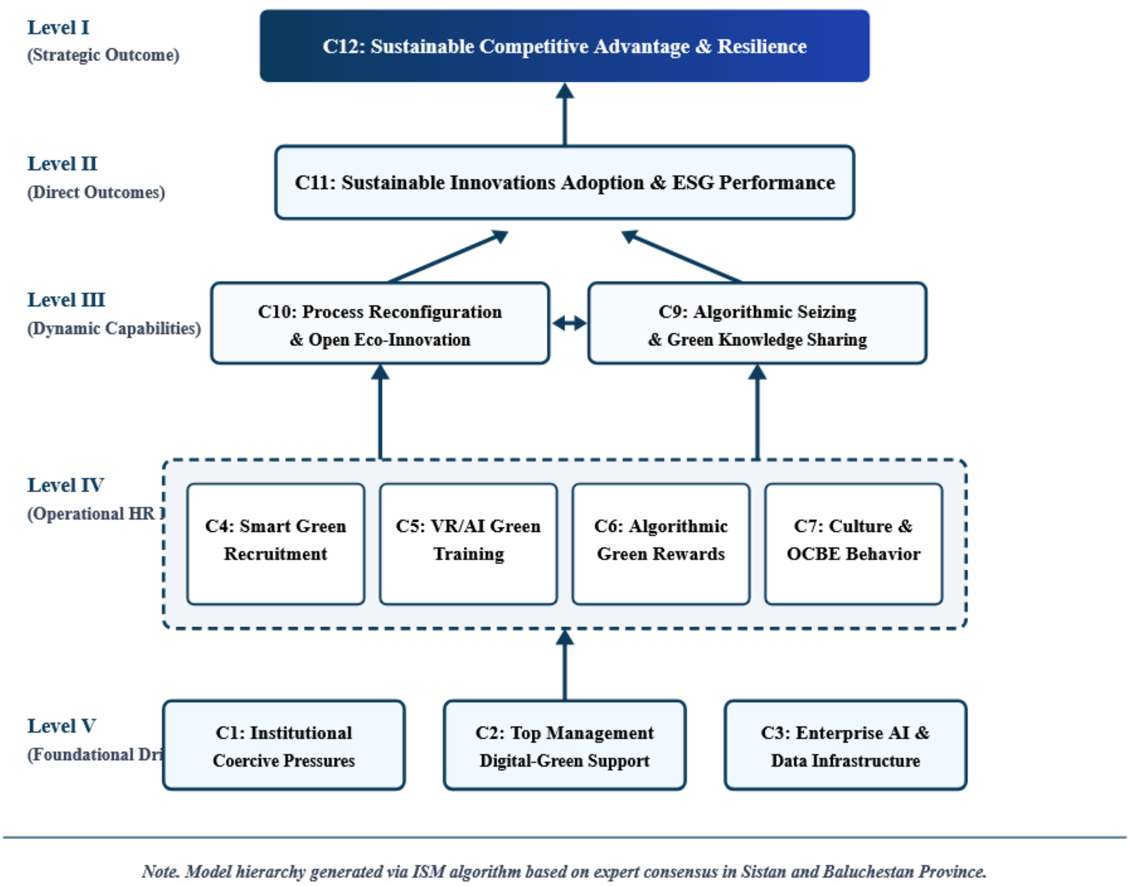
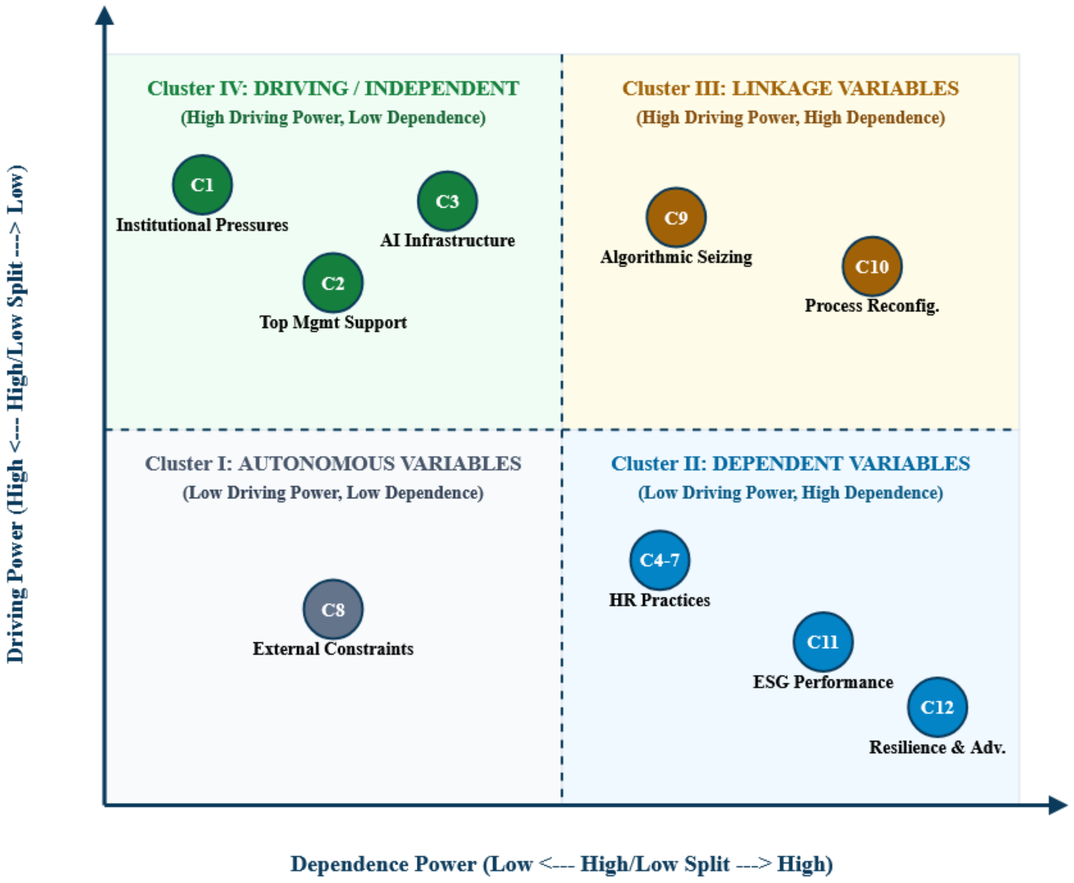


Figure 3: Final Structural Interpretive Model (ISM) for Smart Green HRM in Sistan and Baluchestan Province (Source: By author)

4.6. MICMAC Analysis (Driving Power vs. Dependence Power)

Based on the driving and dependence power scores in Table 6, the MICMAC matrix was constructed, categorizing the variables into four quadrants (Figure 4).



Note. Classification based on Drive-Dependence matrix calculation from expert evaluations in Sistan and Baluchestan Province.

Figure 4: MICMAC Analysis Mapping (Driving Power vs. Dependence Power) (Source: By author)

Interpretive Analysis of MICMAC Quadrants:

- **Autonomous Cluster:** No variables were mapped to this quadrant, highlighting high system connectivity, structural coherence, and strong interdependence among all selected indicators.
- **Dependent Cluster:** Variables C11 (Sustainable Innovations Adoption) and C12 (Sustainable Competitive Advantage) exhibited high dependence power and low direct driving power. These act as system outcomes and cannot be adjusted independently, requiring leverage through lower-level drivers.
- **Linkage Cluster:** Variables C4 through C7 (Smart Green HR Practices), C8 (Sensing), C9 (Seizing), and C10 (Reconfiguration) fall within this cluster. Possessing high driving power and high dependence, these variables introduce systemic volatility; any modification to HR practices directly impacts dynamic capabilities and innovation output.
- **Driving / Independent Cluster:** Variables C1 (Institutional Pressures), C2 (Top Management Support), and C3 (AI Infrastructure) occupy the foundational base of this

quadrant, acting as strategic bedrock pillars for implementing Smart Green HRM in Sistan and Baluchestan Province

5. Discussion and Conclusion

5.1. Discussion of Findings

The structural model developed via Interpretive Structural Modeling (ISM) and validated through MICMAC analysis provides deep insights into how Artificial Intelligence capability drivers interact with dynamic organizational capabilities to strengthen resilience and competitive advantage.

1. **Foundational Drivers (Root Determinants - Level V):** The findings establish Institutional Pressures (C_1), Top Management Support & Vision (C_2), and AI Technological Infrastructure (C_3) as the fundamental drivers located at the base of the structural hierarchy. These variables exhibit maximum *Driving Power* and low *Dependence Power* in the MICMAC analysis. This aligns with Institutional Theory and the Resource-Based View (RBV), demonstrating that technological adoption is not merely an operational choice but an institutional and strategic imperative. Without top management vision and robust computational infrastructure, secondary capabilities cannot be effectively built.
2. **Mediating & Transforming Mechanisms (Level III & IV):** Variables such as Algorithmic Sensing (C_9), Algorithmic Seizing (C_{10}), and internal HR Capabilities (C_4–C_7) serve as structural bridges linking foundational investments to high-level organizational outcomes. Placed in the *Linkage Quadrant* of the MICMAC matrix, these dynamic capabilities are inherently sensitive: any intervention or modification in these variables directly impacts the target outcomes.
3. **Outcome / Dependent Variables (Level I & II):** ESG Performance (C_{11}), Organizational Resilience (C_{12}), and Sustainable Competitive Advantage sit at the apex of the ISM structure. Having high *Dependence Power*, these outcomes cannot be directly manipulated without addressing the underlying technological and managerial capabilities at lower levels.

5.2. Theoretical Contributions

This study makes three major theoretical contributions to the management and organizational literature:

- **Integration of Dynamic Capabilities and AI Literature:** While existing research often treats AI adoption as a technological upgrade, this paper establishes an empirical-conceptual bridge between AI tools and Dynamic Capabilities Theory (Sensing, Seizing, Transforming), demonstrating *how* AI acts as a catalyst for dynamic responsiveness.
- **Hierarchical Mapping of Capabilities:** By utilizing ISM, this study moves beyond linear correlation models to reveal the *structural cascade* and dependency ordering among organizational readiness, algorithmic sensing, and performance metrics.

- **Contextualization in Developing Regions:** By examining industrial and service organizations in Sistan and Baluchestan Province, the research extends standard theoretical models to resource-constrained environments, identifying unique structural bottlenecks and driver configurations.

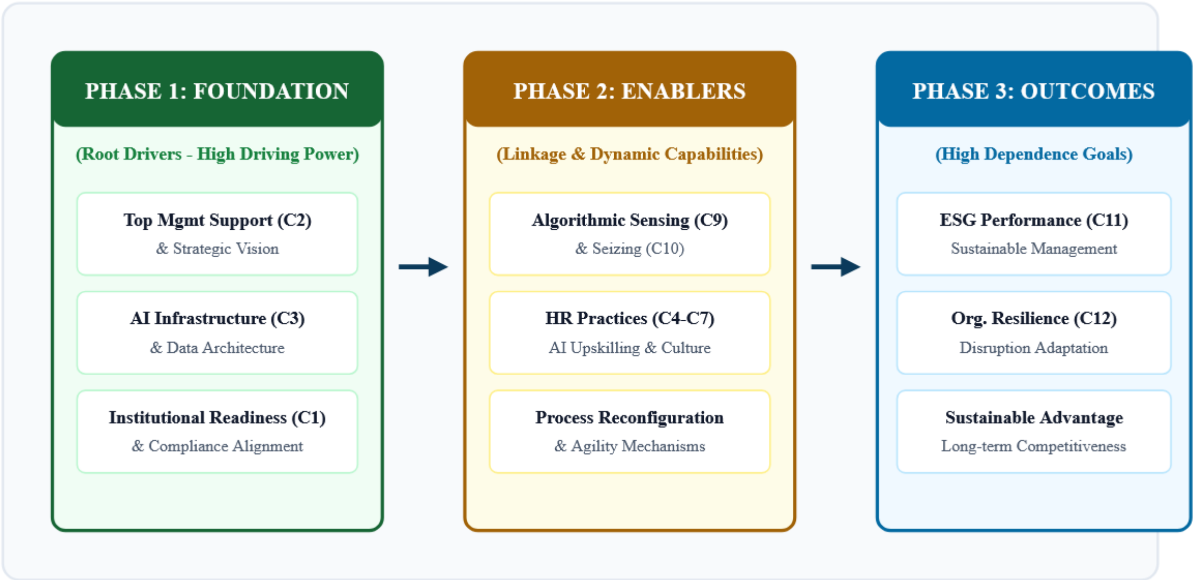
Furthermore, our ISM findings offer a critical theoretical refinement to the sequential logic of Dynamic Capabilities Theory (Teece, 2010; 2020). While Teece's classical framework posits a linear progression—whereby Sensing precedes Seizing, and Seizing precedes Transforming/Reconfiguring—the hierarchical level partitioning in this study (Table 7) reveals a different pattern. Specifically, Algorithmic Seizing (C9) and Process Reconfiguration & Open Innovation (C10) were positioned at the same hierarchical level (Level III), whereas Smart Green Sensing (C8) emerged at a lower level (Level IV). This co-location of Seizing and Reconfiguring suggests that in AI-augmented environments, organizations do not wait for complete 'sensing' to conclude before reconfiguring their resources. Instead, algorithmic tools enable a simultaneous, iterative, and co-evolutionary process where opportunity exploitation (Seizing) and asset transformation (Reconfiguring) occur in tandem, driven by continuous real-time data streams. This finding extends Dynamic Capabilities Theory by introducing the concept of 'Algorithmic Synchrony'—where the temporal lag traditionally assumed between capability dimensions is significantly compressed in smart technology ecosystems. Consequently, dynamic capabilities in the context of Smart Green HRM should be viewed not as a staged pipeline, but as a set of concurrent, mutually reinforcing routines that are collectively activated by foundational AI infrastructure and institutional pressures (C1, C2, C3).

5.3. Managerial and Practical Implications

For C-suite executives, HR directors, and strategy planners, the findings offer practical roadmap guidelines:

1. **Prioritize Root Drivers Over Quick-Fix Outcomes:** Managers seeking to improve organizational resilience (C_{12}) or ESG scores (C_{11}) must avoid investing solely in downstream initiatives. Resources should first be allocated toward upgrading AI infrastructure (C_3) and fostering strategic executive support (C_2).
2. **Upskill HR for Algorithmic Readiness:** Since HR practices (C_4–C_7) function as essential linkage mechanisms, leadership development and continuous technical upskilling must accompany any enterprise AI deployment.
3. **Build Data-Driven Sensing Mechanisms:** Organizations should formalize algorithmic sensing (C_9) by embedding real-time market data analytics into standard operational workflows to sense disruptions before they escalate.

To operationalize these findings, Figure 5 presents a strategic implementation roadmap derived from the ISM hierarchy, guiding managers to prioritize investments in foundational drivers (Level V) before addressing intermediate capabilities and final outcomes.



Note. Sequential implementation strategy derived from the ISM level partitioning and MICMAC driver analysis.

Figure 5: Strategic Implementation Roadmap based on ISM Hierarchy (Source: By author)

5.4. Limitations and Future Research Directions

Despite its rigor, this study presents certain limitations that open avenues for future inquiry:

- **Methodological Boundary:** ISM and MICMAC rely on expert judgment. Although high-level experts were panelized, subjective bias remains a factor.
- **Cross-Sectional Context:** Data was gathered within a specific regional context.

Future Directions:

1. **Empirical Validation (PLSEM / CB-SEM):** Future research should empirically validate the hierarchical ISM path model using structural equation modeling on larger sample sizes.
2. **Fuzzy-ISM Integration:** Applying Fuzzy TOPSIS or Fuzzy MICMAC could better capture the linguistic ambiguity inherent in expert evaluations.
3. **Longitudinal Analysis:** Investigating how the driving power of algorithmic sensing changes over time as AI technologies mature within the organization.

Declarations

Author Contributions (CRediT taxonomy)

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation and revision. All aspects of this work were undertaken by the author.

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Ethical Statement

Informed consent was obtained from all participants. The study was conducted in accordance with established ethical guidelines for qualitative research.

Authors' AI Use Statement

The author declares that no artificial intelligence (AI) tools were used in the preparation of this manuscript for writing, analysis, or data generation. All content is the result of the author's own human effort and judgment.

Conflict of interest

The author declares no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

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

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