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Dynamic Configuration Mechanisms and Scenario Responses of Enterprise Digital Resources for Operational and ESG Dual-Objective Performance: A Case Study of a Chinese Property Services Enterprise

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Abstract

The coordination and dynamic reconfiguration of heterogeneous digital resources are important mechanisms through which enterprises transform digital investment into Operational Performance and ESG Performance. However, existing studies mainly focus on the overall level of digitalization and its performance effects, while the structural positions, transmission paths, and temporal differences in different digital resources remain insufficiently explained. This study uses a large listed property services enterprise in China as a case and develops an integrated framework that combines a BSC–ESG evaluation system, combination weighting, Grey-DEMATEL–ISM–MICMAC structural analysis, and system dynamics. The framework is used to identify the structural roles of heterogeneous digital resources and their performance transmission relationships and to simulate dynamic responses during the baseline period and under different external scenarios. The structural analysis based on expert assessments indicates that Governance Mechanisms and digital resources occupy prominent upstream positions in the influence network. Digital Human Resources and Digital Organizational Resources have high net-relation scores, Governance Mechanisms have the highest centrality, and Innovation Capability occupies a bridging position between resource inputs and modeled performance outcomes. The case-conditioned simulation also yields different response timings for Operational Performance and ESG Performance. ESG Performance improves earlier during resource accumulation, whereas Operational Performance is realized mainly after capabilities are formed. As external constraints change, the roles of resources and capabilities also shift across stages. This study reveals the structural paths and stage-dependent mechanisms through which heterogeneous digital resources are transformed into the dual objectives of Operational Performance and ESG Performance. It also provides an analytical basis for adjusting enterprise digital resource priorities under different conditions.

Keywords: digital resources; resource orchestration; Operational Performance; ESG Performance; system dynamics

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1. Introduction

Enterprise digital investment is shifting from the purchase of individual technologies to the coordinated configuration of multiple digital resources [1]. Digital Infrastructure Resources, Digital Technology Resources, Digital Human Resources, and Digital Organizational Resources differ in functional attributes, accumulation patterns, and value realization

cycles. Their roles also change with enterprise development stages and capability maturity. Therefore, enterprise performance improvement depends not only on the scale of resource inputs but also on whether different resources are coordinated and reconfigured at appropriate stages [2–4]. Enterprises simultaneously configure technology, talent, infrastructure, and organizational support. Managers must decide which resources to prioritize at each stage and when to adjust existing configurations as conditions change.

Resource inputs for enterprise digitalization are often distributed across departments, business units, and projects. Their allocation pace can be constrained by existing budgets, organizational boundaries, and project cycles. These constraints may cause asynchronous investment, resource mismatch, and local optimization. The relationship between digital investment and enterprise performance is not simply linear. Excessive investment or an inappropriate resource structure may increase operational and managerial burdens [5]. This issue becomes more complex when enterprises pursue Operational Performance and ESG Performance simultaneously because the two types of performance may differ in their dependence on digital resources and in their response speed [6–9]. Existing studies have extensively examined the relationships among overall digitalization, digital capabilities, resource configurations, and enterprise performance [10]. However, the differentiated roles of heterogeneous digital resources and how these roles change with enterprise development conditions and external environments remain insufficiently explained.

Based on these issues, this study examines how heterogeneous digital resources generate Operational Performance and ESG Performance through organizational capabilities and Operational Processes. It also examines how resource priorities change with enterprise conditions and external constraints. A large listed property services enterprise in China is used for case calibration. An analytical framework is developed to connect performance evaluation, structural identification, and dynamic simulation. The framework identifies the structural roles, performance transmission relationships, and stage-dependent changes in different digital resources. The main contribution is to extend digital resource orchestration from static resource configuration to stage-dependent dynamic adjustment. The framework further links resource structure, capability transformation, and the temporal evolution of the dual objectives of Operational Performance and ESG Performance. It therefore provides an analytical basis for identifying which digital resources should receive attention at different stages and why their priorities should be adjusted.

2. Literature Review

2.1. Enterprise Digital Resources and Resource Orchestration

Digital resources have become an important research focus for explaining enterprise digital capabilities and value creation, but no unified classification framework has been established [11]. Grego et al. reviewed 360 studies in management and business and showed that the conceptual boundaries of digital-related resources and capabilities remain inconsistent. The elements covered by this literature have expanded from digital technologies to human resources, processes, and organizational capabilities [12]. Franco et al. classified resources required for digitalization into technical resources, such as software, hardware, networks, and data science, and organizational resources, such as managerial capabilities [13]. Bansal et al. further showed that digital infrastructure and digital architecture need to interact with individual capabilities, professional skills, and creativity [14]. Despite differences in classification, existing studies generally indicate that digital value creation depends on technological foundations, application capabilities, human capabilities, and organizational support. From a resource orchestration perspective, and considering configurability and observability at the enterprise level, this study classifies digital resources into Digital Infrastructure Resources, Digital Technology Resources, Digital Human

Resources, and Digital Organizational Resources. These categories represent underlying digital assets, technology application capabilities, digital talent and skills, and strategic, governance, cultural, and organizational coordination capabilities, respectively.

The value of digital resources largely depends on how different resources are organized, combined, and utilized. Resource orchestration research emphasizes restructuring existing resources into capabilities that support organizational objectives through resource structuring, capability bundling, and the application of developed capabilities [15]. Related studies further show that resource integration also needs to be combined with strategic information exchange and innovation activities to transform resources into organizational capabilities and performance outcomes [16,17].

Resource structuring concerns the development and renewal of the digital-resource base. Digital Infrastructure Resources (B18) provide data connectivity and computing foundations, Digital Technology Resources (B19) supply application and analytical tools, Digital Human Resources (B20) contribute the skills needed to use these tools, and Digital Organizational Resources (B21) support strategic coordination. Capability bundling integrates these complementary resources through organizational routines and Innovation Capability (B8), enabling digital investments to form service and management capabilities. The capabilities formed are subsequently applied to Operational Process (B7), service responsiveness, equipment management, and ESG-related activities, while Governance Mechanisms (B17) support coordination among these activities. These connected processes link digital-resource accumulation and capability development to Operational Performance and ESG Performance [15,18].

Digital Organizational Resources (B21) and Governance Mechanisms (B17) are distinguished by their indicator content. B21 refers to digital strategy, digital culture, and the completeness of the digital organizational structure (C48–C50). B17 captures risk and emergency management, customer privacy protection, and information transparency (C32–C34). The former describes organizational arrangements for digital coordination; the latter captures governance practices evaluated within the ESG dimension. Their modeled feedback relationship does not make them interchangeable constructs.

2.2. Formation and Evaluation Framework of Operational Performance and ESG Performance

Digital resources do not automatically generate business outcomes. Their value is usually realized through further transformation via organizational capabilities and Operational Processes. Sunder and Prashar found that organizational learning systems strongly influence the relationship between digitalization and Operational Performance. Coordination among technology, processes, and people is an important basis for operational improvement [19]. Malik et al. noted that value realization from digital technologies depends on resource integration, process adjustment, and organizational capability formation. A higher level of digitalization alone does not guarantee improved Operational Performance [20]. Therefore, the relationship between digital resources and Operational Performance is better understood as a process in which resource inputs gradually affect business outcomes through capability formation and process transformation.

Benedek et al. found different time horizons for digitalization benefits: asset-use efficiency improved in the short term, whereas the effect on return on equity became significant only after two years [21]. This suggests that operational improvements and financial returns need not emerge simultaneously.

For ESG Performance, digital investment generally affects enterprise outcomes through innovation, governance, and organizational capabilities. Chen et al. found that digital transformation can improve ESG Performance through technological innovation, social responsibility, reduced information asymmetry, and risk management [22]. Organizational resilience can also mediate the relationship between digital transformation and

ESG Performance [23]. Different combinations of digital strategy, digital technology, internal control, and the external environment may produce different ESG outcomes [24]. The review by Yu et al. further summarized the mediating mechanisms and contextual dependence of the effects of digitalization on ESG Performance [25]. Overall, digital resources affect ESG Performance mainly through organizational capabilities, innovation, and governance processes. Integrating Operational Performance and ESG Performance into one framework allows the transmission relationships of heterogeneous digital resources to the two performance dimensions to be compared.

Recent ESG studies have mainly examined innovation, governance, and environmental-responsibility pathways [22–26]. They provide less evidence on how the timing of ESG improvements compares with operational outcomes. This study examines their transmission paths and stage-dependent responses under a common set of digital-resource inputs.

BSC research has expanded from traditional financial and strategic performance evaluation to sustainability, integrated reporting, and systems thinking [27]. The Sustainability Balanced Scorecard (SBSC) further incorporates social and environmental objectives into strategic performance management and increasingly connects them with ESG and corporate governance requirements [28,29]. Accordingly, this study uses the financial, customer, operational management, and learning and development dimensions to represent Operational Performance, and the environmental, social, and governance dimensions to represent ESG Performance.

Conceptually, the Balanced Scorecard and ESG measures are not treated as two independent lists. The BSC perspectives specify the internal value-creation sequence from learning and organizational capabilities through operating processes and customer outcomes to financial performance. The environmental, social, and governance perspectives assess sustainability and stakeholder consequences of the same activities, while the four digital-resource categories represent the common enabling inputs rather than a further performance outcome. Cross-perspective pathways connect these roles, without implying that indicators observed in different dimensions are interchangeable [30–33].

2.3. Dynamic Resource Orchestration and Research Gaps

Existing studies have identified multiple pathways through which digital resources affect enterprise performance through capability formation and organizational processes. However, less attention has been paid to how these relationships change with enterprise development stages and external environments. Based on longitudinal research, Browder et al. found that enterprises continuously integrate and reorganize existing and newly developed digital capabilities to adapt to changing organizational needs [34]. Yan et al. further showed that the roles of different resources and capabilities are not fixed during transformation and need to be reorganized according to stage-specific tasks [35]. External factors such as market conditions, technological opportunities, and operating pressure may also change the suitability of existing resource configurations and the relative importance of different digital resources [36]. These findings indicate that digital resource configuration is not a one-time arrangement. It is a continuous adjustment process associated with internal capability formation, development stages, and external conditions.

A limited number of studies have begun to explain digital value creation from a dynamic systems perspective. Qiao et al. incorporated data, technology, talent, the environment, and enterprise value into a feedback system and revealed value creation through continuous interactions among these elements [37]. Three specific research gaps remain. First, the relationship between heterogeneous digital-resource categories and the three resource-orchestration practices has not been sufficiently clarified. Second, the transmission paths and response timing of Operational Performance and ESG Performance have rarely been examined within the same resource system. Third, how resource-management priori-

ties change with capability development and external constraints remains insufficiently explained. Accordingly, this study integrates resource structure, performance transmission, and temporal evolution into a unified analytical framework. It identifies the structural roles of heterogeneous digital resources and examines changes in resource-management priorities across development stages and external constraints.

The framework addresses three research questions: RQ1: What structural positions do the four digital-resource categories occupy in the expert-informed influence system? RQ2: How are these resources linked to Innovation Capability, operational processes, and the two modeled performance dimensions? RQ3: How do the relative resource priorities implied by the model vary across descriptive stages and assumed external conditions? These questions concern structural interpretation and scenario-dependent mechanisms rather than identification of population-level causal effects.

3. Materials and Methods

3.1. Research Design

A multi-stage integrated research design is adopted, linking indicator construction and combination weighting, structural relationship identification, and system dynamics simulation. First, an indicator system is constructed through literature screening and expert review. SWARA–CRITIC–game-theoretic combination weighting is then used to determine the relative importance of the indicators, with calculations performed using Python (version 3.13.5; Python Software Foundation, Beaverton, OR, USA). Second, Grey-DEMATEL–ISM–MICMAC is used to identify directional influence relationships, hierarchical structures, and driving characteristics among the second-level factors. These structural analyses are also performed using Python. Finally, the structural results are combined with case-enterprise data to construct a system dynamics model using Vensim PLE (version 10.2.0; Ventana Systems, Inc., Harvard, MA, USA). Model validation, baseline simulation, and scenario simulation are then used to analyze the dynamic responses of digital resource configuration.The overall research process is shown in Figure 1.

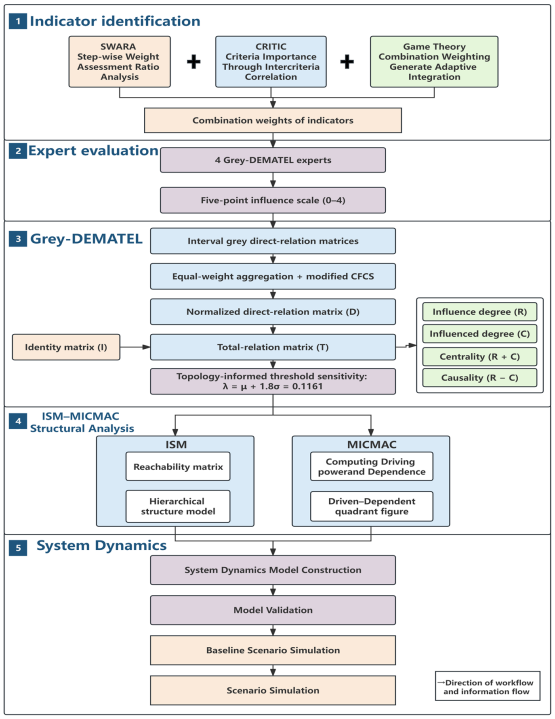


Figure 1. Conceptual framework and analytical process for digital resource configuration and performance simulation.

3.2. Research Context and Data Sources

A large listed property services enterprise in China is selected for case calibration to examine the applicability of the research method in an enterprise operating context. The enterprise operates across residential, commercial, office, industrial-park, and urban-service settings. Its operations are labor-intensive, geographically dispersed, maintenance-intensive, and supported by numerous data touchpoints. Property services involve equipment operation, energy management, customer service, employee management, and public-space governance. This setting therefore allows the joint effects of digital resources on Operational Performance and ESG Performance to be observed. The case data are used mainly for model parameterization and behavioral calibration. Results from the single enterprise are not directly generalized as industry-wide patterns.

The case was chosen because property services combine geographically dispersed facilities, continuous equipment maintenance, energy management, and frequent interactions with customers and employees. Digital infrastructure, technologies, skills, and organizational coordination therefore influence both daily service operations and ESG-related activities [38,39]. The enterprise's multiple service settings and quarterly records allow these two performance dimensions to be examined within one resource system.

The historical enterprise inputs cover 16 quarters from 2022Q1 to 2025Q4. Financial, market, environmental, and selected governance indicators are drawn mainly from public disclosures, whereas service operations, equipment management, employee development, and digital-resource inputs are drawn mainly from authorized management records. The observations are aligned to a common quarterly time index, direction-unified so higher normalized values indicate more favorable states, and converted into 0–1 lookup series for the baseline simulation. Questionnaire importance ratings are used for indicator weighting rather than as quarterly enterprise observations.

The model uses three main types of data. The first type includes enterprise operational and ESG data from public operational and sustainability disclosures and authorized internal management records. Public disclosures are mainly used for financial, market, environmental, social responsibility, and selected governance indicators. Internal records are mainly used for Operational Processes, Equipment Management, Service Responsiveness, Employee Development, and digital resource inputs. Together, these data are used for baseline parameterization and behavioral calibration. The second type consists of CRITIC objective-weighting data from two anonymous questionnaire datasets at different hierarchical levels. The datasets contain 147 ratings for the B1–B21 second-level factors and 178 ratings for the C1–C50 third-level indicators, with respondents from multiple industries. These data are used only to calculate indicator dispersion and information conflict and to derive objective weights. They are not used to calibrate the quarterly operating trajectory of the case enterprise. The third type consists of expert judgment data. SWARA uses 11 anonymous rating records to determine subjective relative importance. DEMATEL uses 21×21 direct-influence judgment matrices completed by four senior enterprise experts to identify directional influence structures. The experts represent property operations, digital/information management, ESG and corporate governance, and asset and equipment management.

The datasets are integrated according to distinct analytical functions rather than treated as interchangeable population samples. The BSC–ESG framework includes cross-sector organizational functions, including governance, finance, human resources, operations, and digital capabilities [12,27–29]. Accordingly, cross-industry CRITIC ratings are used to characterize dispersion and inter-indicator conflict within this shared indicator framework, while case-specific operational observations and enterprise experts provide the property-

services context. Sector composition is evaluated by re-estimating the weights separately for service- and non-service-sector respondents.

The second-level dataset includes 48 service-sector and 99 non-service-sector respondents; the third-level dataset includes 75 and 103 respondents, respectively. Differences in sector-specific importance perceptions can alter local CRITIC weights and, when propagated through combination weighting, affect aggregated model inputs. DEMATEL–ISM–MICMAC relationships, by design, are derived separately from the enterprise expert influence matrices rather than from CRITIC respondent scores.

For DEMATEL, four purposively selected senior experts covered property operations, digital and information management, ESG and corporate governance, and asset/equipment management. The panel eligibility criteria specified at least eight years of relevant experience, managerial or cross-functional decision responsibilities, and familiarity with enterprise digitalization. The anonymous profiles report 17, 11, 9, and 14 years of relevant experience, respectively. The complementary domains support assessment of the 21-factor directed influence matrix.

The CRITIC respondents came from service and non-service industries and included senior, middle, and frontline managers, professional staff, operational personnel, and ESG-related practitioners. Their reported work experience ranged from 0 to 3 years to more than 10 years. All 147 second-level and 178 third-level questionnaire records contained complete 1–5 importance ratings for their respective indicators. The 11 SWARA experts separately rated indicator importance on a 1–9 scale. The four purposively selected DEMATEL experts completed individual 21 × 21 direct-influence matrices using a 0–4 scale. Their anonymized judgments were aggregated with equal expert weights to identify structural relationships; the CRITIC, SWARA, and DEMATEL data served different analytical purposes.

3.3. Indicator System Construction and Expert Judgment

3.3.1. Indicator Construction

The boundaries of the indicator system are defined based on digital resource and resource orchestration theories, the Balanced Scorecard (BSC), and the ESG framework. Candidate indicators are identified from the relevant peer-reviewed literature. They are screened according to theoretical relevance, representativeness, measurability, data availability, non-redundancy, and contextual applicability. The cross-functional expert group described in Section 3.2 then reviews indicator definitions, hierarchical assignment, construct coverage, measurability, data availability, overlap, and contextual applicability. The final system contains 8 first-level dimensions, 21 second-level factors, and 50 third-level indicators, as shown in Table 1.

The indicator system combines a BSC value-creation pathway with ESG consequence assessment. Financial (A1), customer (A2), operational management (A3), and learning and development (A4) represent operational performance, while environmental (A5), social (A6), and governance (A7) assess corresponding sustainability outcomes. Digital resources (A8) supply the common resource base that links these objectives through capability formation and operating activities. Market Share (B16) is retained in A6 as a context-specific measure of service reach and stakeholder-facing market presence in property services.

Indicator selection is documented in Supplementary Section S1, including the six screening criteria, expert-review rules, and treatment of conceptual overlap (Tables S1–S3). Table S1A evaluates 18 additional indicator concepts alongside the 50 retained measures: eleven overlap the coverage of existing indicators, and seven lack comparable case-level measurements for separate operationalization. Supplementary Data File S1 links each of the 50 final indicators to its literature sources and operational definition. Table S1B explains

the conceptual integration of digital-resource inputs, BSC performance pathways, and ESG outcomes [30–33].

Table 1. Overview of the hierarchical indicator system.

First-Level Dimension	Second-Level Factor	Third-Level Indicators
A1 Financial	B1 Profitability; B2 Growth Capability	C1–C3
A2 Customer	B3 Service Process; B4 Service Responsiveness	C4–C5
A3 Operational Management	B5 Organizational System; B6 Equipment Management; B7 Operational Process	C6–C13
A4 Learning and Development	B8 Innovation Capability; B9 Employee Development	C14–C18
A5 Environmental	B10 Resource Consumption; B11 Pollution Prevention and Control; B12 Climate Change	C19–C23
A6 Social	B13 Protection of Employee Rights and Interests; B14 Protection of Customer Rights and Interests; B15 Protection of Community Rights and Interests; B16 Market Share	C24–C31
A7 Governance	B17 Governance Mechanisms	C32–C34
A8 Digital Resources	B18 Digital Infrastructure Resources; B19 Digital Technology Resources; B20 Digital Human Resources; B21 Digital Organizational Resources	C35–C50

3.3.2. Data Preprocessing and Expert Judgment

CRITIC rating data are processed separately at the B1–B21 and C1–C50 levels. Both questionnaires use a 1–5 importance scale. Each indicator is first normalized to the range of 0–1 using the sample minimum and maximum. The standard deviation and Pearson correlation coefficients within the same parent group are then calculated. The information content in CRITIC is jointly determined by indicator dispersion and inter-indicator conflict [40–42]. Equation (1) presents the normalization, and Equation (2) presents the information content and local weights.

To examine industry-composition effects, the complete CRITIC calculation is repeated separately for service- and non-service-sector responses, preserving the same parent-factor groups, normalization conventions, and correlation-based information measure [42].

$$r_{ij} = \frac{x_{ij} - \min\limits_{i} x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}}. \quad (1)$$

$$C_j = \sigma_j \sum_{k=1}^{m} (1 - \rho_{jk}), \quad w_j^C = \frac{C_j}{\sum_{h=1}^{m} C_h}. \quad (2)$$

In Equation (1), the normalized score is calculated. In Equation (2), the standard deviation represents contrast intensity, and the Pearson correlation coefficient represents

inter-indicator conflict. C_j denotes the information content, and w_j^C denotes the local CRITIC weight.

SWARA is used to determine subjective local weights for indicators under the same parent factor. Experts independently assign importance scores from 1 to 9. Indicators are first ranked by the group mean score. The comparison coefficient is then derived from the relative decline between the mean scores of adjacent indicators, and the weights are calculated using the SWARA recursive procedure [43–45], as shown in Equation (3).

$$s_j = \frac{G_{j-1} - G_j}{G_{j-1}}, \quad k_j = 1 + s_j, \quad q_1 = 1, \quad q_j = \frac{q_{j-1}}{k_j}, \quad w_j^S = \frac{q_j}{\sum_h q_h}. \tag{3}$$

This study adopts an adapted group-SWARA approach. As the 11 experts had independently provided importance ratings on a common 1–9 scale, the existing judgments are used to establish a consistent group ranking without a second elicitation round. Indicators are ranked by the mean expert scores, and the relative decline between adjacent mean scores is used to construct successive comparison coefficients. These coefficients are then entered into the SWARA recursive weighting procedure [44]. This approach derives the ranking and pairwise comparison coefficients from the same set of ratings and makes the group-level calculation transparent and reproducible. Unlike conventional SWARA, which directly elicits the relative importance of adjacent criteria, the adapted procedure treats score differences as an operational approximation of relative-importance differences. It retains the stepwise recursion but does not presume numerical equivalence to conventional SWARA weights. DEMATEL is conducted separately using 0–4 direct-influence ratings encoded as interval grey numbers.

3.4. Combination Weighting and Structural Identification

3.4.1. Game-Theoretic Combination Weighting

A game-theoretic combination method is used to integrate the SWARA subjective local weights and CRITIC objective local weights. The two weight vectors are treated as basic strategies. Combination coefficients are determined by minimizing the total deviation between the combined weights and the basic weights [46–48]. The final combined weights are calculated using Equation (4).

$$w = \alpha_1 w^S + \alpha_2 w^C, \quad \alpha_1 \geq 0, \quad \alpha_2 \geq 0, \quad \alpha_1 + \alpha_2 = 1. \tag{4}$$

In Equation (4), the two vectors represent the SWARA and CRITIC local weights, and the two α values are the combination coefficients. If the unconstrained solution falls outside the nonnegative unit simplex, it is projected onto the feasible region in which both coefficients are nonnegative and sum to 1. With two weight vectors, a negative coefficient corresponds to a boundary solution of (0, 1) or (1, 0) [49]. The combined weights represent only the relative importance of indicators under the same parent factor and are not interpreted as structural causal strength.

3.4.2. Grey-DEMATEL–ISM–MICMAC Structural Identification

Grey-DEMATEL–ISM–MICMAC is used to analyze the structural relationships among B1–B21. Grey-DEMATEL represents uncertainty in expert judgments using interval grey numbers and obtains a direct-relation matrix through crispification [50,51]. The integrated use of these methods has been applied to structural analysis of complex systems [52,53].

The four 0–4 direct-influence matrices are encoded as interval grey numbers, aggregated with equal expert weights, and crispified using modified CFCS. For the adopted 0–1 interval-grey scale, the global lower and upper bounds are fixed at 0 and 1. The resulting

crisp direct-relation matrix is then normalized for DEMATEL to calculate the normalized direct-relation matrix D and total-relation matrix T [50,51,54].

Expert-judgment agreement for each pair of experts was assessed using Equation (5), averaging the agreement scores over all 420 directed off-diagonal judgments (i ≠ j). The mean across the six expert pairs was 0.9006, with individual pairwise values ranging from 0.8768 to 0.9232. The anonymized judgment matrices and complete interval-grey scale mapping are retained in Supplementary Data File S1.

$$A_{ab} = \frac{1}{420}\sum_{i=1}^{21}\sum_{\substack{j=1 \\ j\neq i}}^{21}\left(1 - \frac{\left|x_{ij}^{(a)} - x_{ij}^{(b)}\right|}{4}\right). \quad (5)$$

The ISM threshold is selected through topological sensitivity analysis of the 420 off-diagonal entries of T [53,55], as shown in Equation (6). The leave-one-expert-out analysis repeats interval-grey aggregation, modified CFCS, DEMATEL normalization, and ISM identification under the same threshold-selection rule for each three-expert subset.

$$\lambda_c = \mu + c\sigma, \quad \lambda = \mu + 1.8\sigma = 0.1161. \quad (6)$$

The adjacency matrix and reachability matrix are constructed using the selected threshold. ISM levels are then derived through Boolean transitive closure. In MICMAC, driving power and dependence are calculated from the row sums and column sums of the final reachability matrix M, respectively.

DEMATEL identifies directional influence relationships and their relative strengths. ISM identifies the hierarchical positions of variables, and MICMAC distinguishes driving and dependent roles. These structural results jointly support the subsequent system dynamics model [56]. They are not used to derive resource configuration proportions.

Across the four leave-one-out runs, all 21 factors retained their DEMATEL cause/effect signs, with Spearman correlations of net-relation ranks between 0.9688 and 0.9948 relative to the four-expert reference. B17–B21 remained among the prominent net driving factors; the re-estimated ISM solutions contained 26–35 direct links and four to eight hierarchical levels. These tests distinguish the stability of upstream drivers from variations in finer-grained thresholded relations.

3.5. System Dynamics Model Construction

3.5.1. System Boundary and Variable Setting

System dynamics is used to describe the temporal evolution of resource accumulation, capability formation, performance realization, and feedback adjustment. It is suitable for analyzing feedback, delays, and nonlinear relationships in digital value creation. Previous research has used system dynamics to explain value creation and dynamic feedback mechanisms in digital transformation [37]. The model boundary includes internal resources, capabilities, and performance factors that can be directly allocated or influenced through managerial actions. Macroeconomic conditions, regulatory changes, industry-level technological developments, and extreme events are not modeled through internal feedback loops but are introduced as exogenous scenario variables.

Four core stock variables are specified: Digital Infrastructure Resources, Digital Technology Resources, Digital Human Resources, and Digital Organizational Resources. Each resource has an inflow and an outflow to represent resource investment, capability accumulation, and depreciation or loss. Governance Mechanisms, Innovation Capability, Equipment Management, Operational Process, Service Responsiveness, Profitability, Market Share, and Resource Consumption are treated as auxiliary variables that connect resource

stocks with Operational Performance and ESG Performance. The basic change in each resource stock is expressed in Equation (7).

A construct-to-equation check is necessary for Governance Mechanisms (B17). The model defines Governance Performance as Governance Mechanisms and includes it directly in ESG Performance with a coefficient of 0.33. B17 also enters some feedback relations involving digital resources and operations. Thus, a reported B17–ESG association partly reflects index construction and cannot be interpreted as an independent mediated effect.

$$\frac{dR_i(t)}{dt} = \text{Inflow}_i(t) - \text{Outflow}_i(t). \quad (7)$$

Equation (7) states that the rate of change in the stock of digital resource i equals its inflow minus its outflow. Vensim performs discrete integration with a TIME STEP of 0.25 years. Resource inflows are driven by third-level input indicators, configuration intensity, and feedback terms, while a saturation term limits unconstrained growth. Resource outflows represent depreciation or loss.

3.5.2. System Dynamics Model Construction and Parameter Setting

The system dynamics model is parameterized according to the sources and determination methods of its inputs and coefficients. Directly observed indicators cover financial and market performance, customer services, equipment operations, energy and environmental management, employee management, and digital-resource inputs. These indicators are obtained from the case enterprise's operational and ESG records and converted into direction-unified, normalized quarterly input series for baseline specification and historical behavior reproduction. Within-parent aggregation weights are calculated through the adapted group-SWARA–CRITIC–game-theoretic combination method. The directions and hierarchical positions of major transmission relationships are informed by Grey-DEMATEL–ISM structural identification, rather than directly converting expert influence ratings into numerical feedback coefficients. Behavioral parameters without directly observed counterparts, including resource depreciation and loss, feedback coupling, response delays, and saturation constraints, are specified as case-informed assumptions based on enterprise operating characteristics, identified structural relationships, and managerial judgment [57]. Extreme-condition and sensitivity analyses are applied to assess the model's dynamic responses under these specifications. Overall Performance aggregates Operational Performance and ESG Performance with equal weights. Within the BSC–ESG framework, Operational Performance and ESG Performance represent two parallel evaluation objectives [27–29]. Because both indices are normalized to the same 0–1 scale and no prior basis is specified for assigning greater importance to either objective, equal weighting provides a symmetric aggregation at the top level, consistent with composite-index weighting methodology in the absence of a justified differential priority [58,59].

Figure 2 presents the core feedback structure. Performance improvement affects digital resource orchestration in the next stage. Higher Profitability supports investment in Digital Infrastructure Resources and Digital Technology Resources. Improved Governance Mechanisms support the development of Digital Organizational Resources. Protection of employee rights supports the attraction, development, and retention of digital talent. These relationships form a dynamic process in which digital resource inputs, capability improvement, and performance improvement interact.

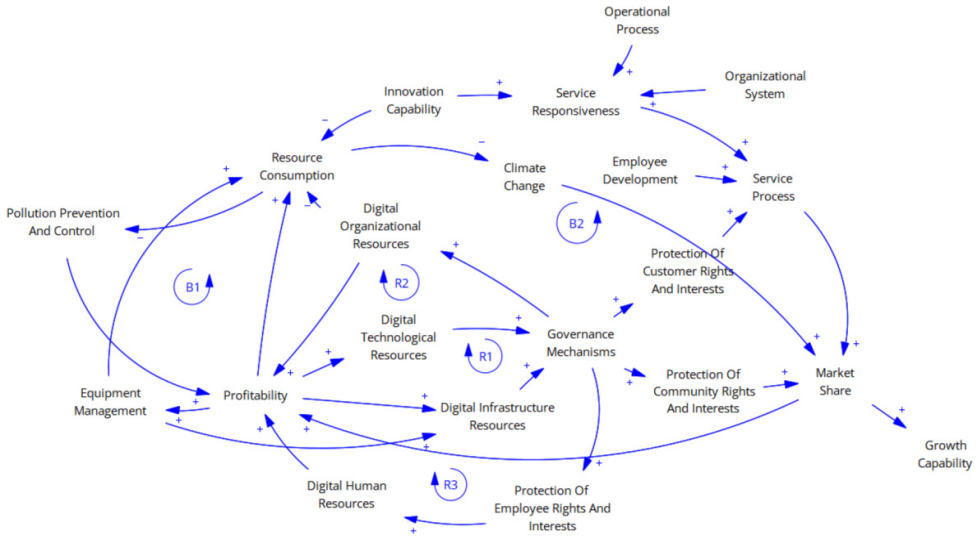


Figure 2. Feedback structure.

3.5.3. Simulation Settings and Scenario Design

The model is implemented in Vensim. The baseline model covers 2022–2026 with a TIME STEP of 0.25 years. The analysis window corresponds to quarterly observations from 2022Q1 to 2025Q4 and is used to examine the historical evolution and stage differences in Operational Performance, ESG Performance, and Overall Performance under the existing resource structure. The adaptive model covers 2026–2029 and corresponds to quarterly scenario analysis for 2026–2028.

The adaptive model includes three types of exogenous inputs: receivables disposal and business contraction shocks, AI platform development and market expansion incentives, and extreme-weather and aging-asset pressure. These inputs represent operating and cash-flow pressure, expansion of digital capabilities and market opportunities, and pressure from physical assets and the operating environment, respectively. All three inputs are expressed as normalized intensity indices from 0 to 1. They are used to compare system responses under different constraints and are not interpreted as probabilities of future events or forecasts of quarterly operating results [60].

The three exogenous trajectories were specified by a mechanism-based scenario design rather than extrapolating a single historical trend. The contraction profile represents the rapid effect of receivables and cash-flow pressure on investment and operations, followed by gradual relief. The AI/market profile rises more gradually to reflect the time needed for platform adoption, capability formation, and market expansion before its incremental impulse tapers. The weather/aging-asset profile is delayed to represent the later accumulation of equipment-maintenance and environmental pressures. The respective high-intensity peaks (0.78, 0.95, and 0.82) were chosen as bounded comparative stress-test levels that distinguish strong downside pressure, near-upper-bound opportunity, and substantial facility stress; they are not values statistically inferred from future enterprise outcomes. Their onset, turning and recovery points were assigned to express these different response horizons within 2026–2028, and quarterly lookup interpolation connects the stated knots. This scenario-based construction follows the use of coherent alternative development pathways to examine dynamic mechanisms [60,61].

3.6. Model Validation and Robustness Tests

Following system dynamics model testing principles [62], the model is evaluated in terms of structural validity, extreme conditions, and local sensitivity. First, the model boundary and main influence directions are checked for consistency with indicator definitions,

the DEMATEL–ISM structure, and enterprise management logic. Vensim model-checking functions are also used to verify equation completeness and unit consistency. Second, each of the four digital resources is fixed at 0.95 and 0.05 while other conditions remain unchanged. This extreme-condition test examines whether performance outputs remain bounded and directionally reasonable. Third, Governance Mechanisms and Operational Process are selected based on the structural results and are perturbed by ±20% to examine local responses in Operational Performance, ESG Performance, and Overall Performance.

These tests address equation consistency, response bounds, and sensitivity to selected inputs. They do not provide independent predictive validation because the 2022–2025 enterprise-derived series enter the same baseline model used to produce the reported historical trajectories. No independently observed quarterly composite-performance outcome series or genuinely withheld validation period is supplied. The baseline patterns are therefore assessed as conditional simulation behavior, not out-of-sample confirmation; independent organizational records or a prespecified holdout would be required for the stronger claim [62,63].

Sensitivity to the assumed shock magnitude and timing was examined separately. Each exogenous trajectory was rescaled by ±20% within the 0–1 bounds or advanced/delayed by one quarter, while the other input trajectories, initial conditions, and model equations were held fixed. The comparison considers both deviations in Overall Performance and whether the broad sequence of contraction, capability recovery, and later facility-pressure adjustment persists. This is a structure-oriented behavioral sensitivity check of nearby alternative scenario specifications [62,63]. Historical behavior reproduction was checked at all 16 quarterly points during 2022Q1–2025Q4 using the original input lookups and 0.25-year integration step.

Historical Behavior Consistency Test

The historical-behavior consistency test compares the 2022–2025 simulated trajectories with the anonymized case enterprise's audited financial disclosures and annual ESG reports. Quarterly simulated performance scores were aggregated into annual arithmetic means. To preserve the actual year-to-year financial changes without disclosing identifiable monetary amounts, revenue and profit attributable to owners were transformed into fixed-base indices (2022 = 100), calculated using Equation (8) [64]. Here, X_t is the reported financial value in year t, and X_{2022} is its corresponding value in 2022. The resulting financial indices were compared with the model-generated Operational Performance composite, which comprises financial, customer, operational management, and learning and development dimensions. The comparison examines directional changes and turning points rather than numerical equality between differently defined measures, consistent with historical behavior-pattern testing [63,65].

$$I_{X,t} = \frac{X_t}{X_{2022}} \times 100 \tag{8}$$

Modeled Operational Performance averaged 0.6970, 0.7466, 0.8699, and 0.8560 in 2022, 2023, 2024, and 2025, respectively. The enterprise's disclosed fixed-base revenue indices for these years were 100.0, 103.0, 106.3, and 116.9, while the corresponding indices of profit attributable to owners were 100.0, 15.0, 93.1, and 31.0. In 2023, the revenue increase was directionally consistent with the modeled improvement in Operational Performance, although accounting profit declined in the same year. In 2024, the recovery in actual profit coincided with a pronounced improvement in simulated Operational Performance; in 2025, both actual profit and the simulated composite declined from their 2024 levels.

These comparisons reveal meaningful agreement in selected historical movements while capturing distinct aspects of business expansion and profitability.

Modeled ESG Performance, defined as a normalized composite of Environmental, Social, and Governance Performance, had annual means of 0.7903, 0.9076, 0.9383, and 0.9490 during 2022–2025. The simulated improvement was most pronounced in 2022–2023 and became more gradual thereafter. The dated evidence below is used to compare this temporal pattern with observable developments in digital-service coordination, environmental management, customer outcomes, and equipment-related capabilities.

In 2022, the enterprise expanded low-carbon community charging facilities to more than 30,000 charging points by year-end and applied algorithm-supported work-order allocation. Its disclosed work-order management practices included approximately 98% automated dispatch and a closure rate of approximately 99% for quality-task work orders. These documented service outcomes reflect the application of Digital Infrastructure Resources (B18) and Digital Technology Resources (B19) through Operational Process (B7), alongside low-carbon community services related to the environmental-management domain (B10–B12). In 2023, integration of feedback from multiple customer-service channels through the digital customer-experience platform and community co-governance activities reflected the continued use of Digital Technology Resources (B19) and Digital Organizational Resources (B21) in customer and community engagement (B14–B15). The earlier stage of documented digital coordination is consistent with the period in which the model exhibits its largest increase in ESG Performance.

In 2024, the enterprise reported retrofitting more than 36,000 energy-saving light fixtures and 864 water pumps, with annual electricity savings exceeding 17.4 million kWh. Customer satisfaction reached 94.7%, while the total number of owner complaints decreased by 13% year on year. Cleaning robots were also routinely deployed in seven communities. These observable environmental and service outcomes correspond to Equipment Management (B6), Resource Consumption (B10), climate-related management (B12), customer-related factors (B4 and B14), and Digital Technology Resources (B19). By October 2025, more than 130 self-developed cleaning robots were in use across 17 projects, showing a broader deployment of digital technology in routine service delivery (B19 and B7), for which digital skills and organizational coordination (B20–B21) form complementary capabilities. These successive initiatives provide a documented context for the model's more gradual later-period ESG improvement and its resource-to-performance transmission pathways.

Overall, the historical behavior consistency test shows qualitative correspondence between the enterprise's development activities and the modeled pathways from digital resources to operational activities. Digital service-system development and organizational coordination characterize the earlier period, while equipment upgrading, process integration, and broader digital-service deployment accompany the later realization of operating capabilities. Changes in financial performance during 2024–2025 also correspond to the operational adjustment displayed in the baseline simulation.

4. Results

4.1. Factor Relationships and Structural Characteristics

The DEMATEL results show that different factors perform distinct structural functions in the influence network. Governance Mechanisms have high centrality $(R + C)$, indicating extensive connections with other factors and an important bridging role among resource inputs, organizational capabilities, and performance outcomes. Digital Human Resources and Digital Organizational Resources have high influence degrees (R) and net relation values $(R - C)$. They therefore actively influence multiple factors while being relatively less constrained by other factors and act as strong endogenous drivers. Digital Infrastructure

Resources and Digital Technology Resources also show positive net relations and mainly provide a foundation for subsequent capability formation and operational improvement. In contrast, Market Share and Operational Process have high influence-degree values (C), indicating greater sensitivity to upstream changes. Representative results are reported in Table 2.

Table 2. Representative results of DEMATEL structural identification.

Factor	R (Influence Degree)	C (Influenced Degree)	$R + C$ (Centrality)	$R - C$ (Net Relation)
B21 Digital Organizational Resources	1.760	0.591	2.351	1.169
B20 Digital Human Resources	1.920	0.791	2.711	1.129
B17 Governance Mechanisms	1.813	1.052	2.865	0.760
B18 Digital Infrastructure Resources	1.553	0.805	2.358	0.749
B19 Digital Technology Resources	1.549	0.999	2.548	0.550
B16 Market Share	1.094	1.545	2.639	−0.451
B7 Operational Process	1.021	1.534	2.555	−0.513

These DEMATEL values summarize the four experts' assessed influence structure. In particular, an upstream position or a positive net-relation score identifies a structural property of that judgment-based network, not an econometrically identified treatment effect or a verified causal mechanism.

The ISM threshold is determined using a mean–standard deviation candidate-threshold topological sensitivity method based on the total-relation matrix T. The selection criterion is the elimination of nontrivial strongly connected components while preserving the maximum strict hierarchical depth. The final threshold is $\lambda = \mu + 1.8\sigma = 0.1161$, which retains 33 off-diagonal direct relationships. Boolean transitive closure produces 52 off-diagonal reachable relationships, and the 21 factors are divided into five hierarchical levels (Figure 3). L5 and L4 are located at the bottom of the system and mainly provide governance, infrastructure, technology, and human-resource conditions. L3 occupies the middle of the structure and connects underlying resource inputs with upper-level performance outcomes. L2 mainly transmits capabilities to organizational operations, Equipment Management, and market performance. L1 is located at the top of the structure and mainly reflects financial, operational, environmental, employee, customer, and social responsibility outcomes.

The MICMAC results are shown in Figure 4. Governance Mechanisms and the four types of digital resources are mainly located in the driving quadrant and act as upstream sources in the current system. Innovation Capability is located in the linkage quadrant and has both relatively high driving power and dependence. It therefore serves as an important transmission node linking resources to operations and performance outcomes. Financial, operational, environmental, and market factors are mainly located in the dependent quadrant and primarily receive effects from upstream resources and capabilities. Taken together, the DEMATEL, ISM, and MICMAC results show that Governance Mechanisms and digital resources form the upstream drivers, Innovation Capability connects resources with performance, and operational and market factors mainly receive upstream effects. This hierarchy from resource drivers through capability transmission to performance outcomes provides the structural basis for the main influence chains and feedback relationships in the subsequent system dynamics model.

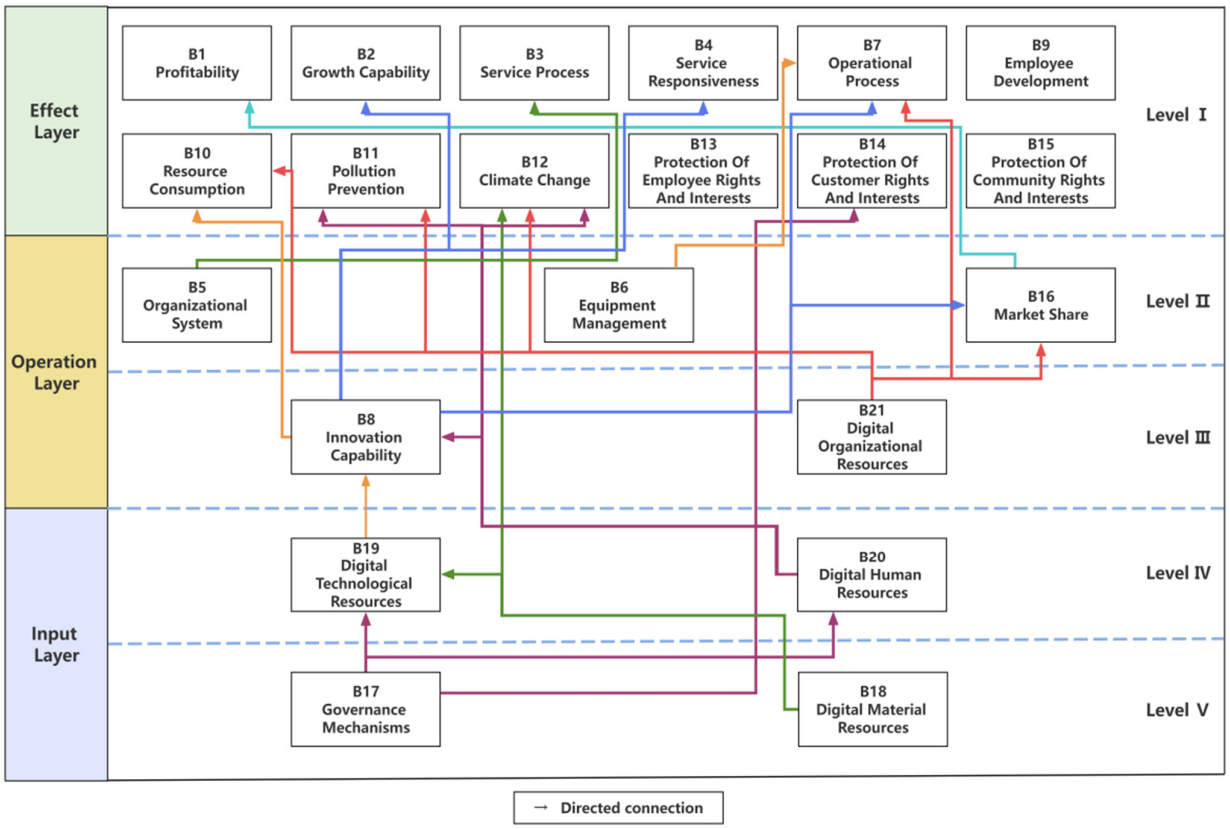


Figure 3. ISM hierarchical structure.

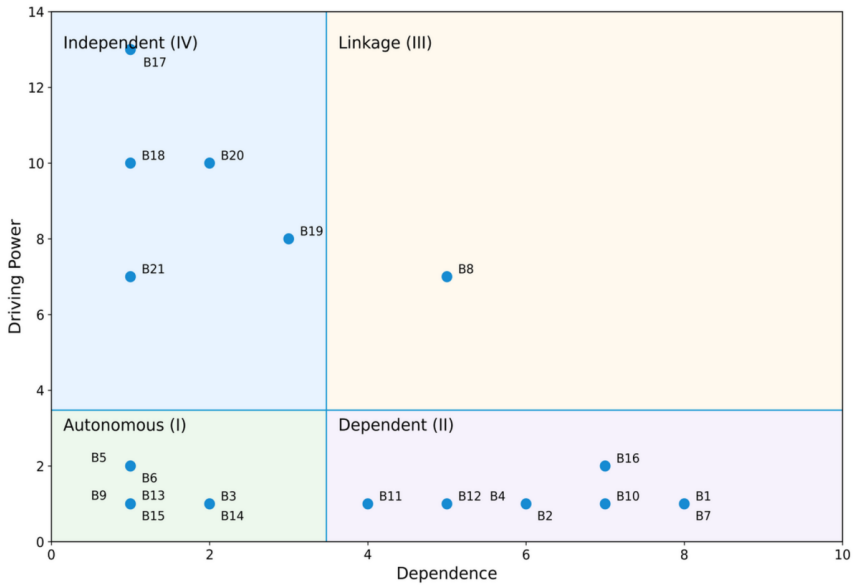


Figure 4. MICMAC classification results.

4.2. Model Validation and Local Sensitivity Results

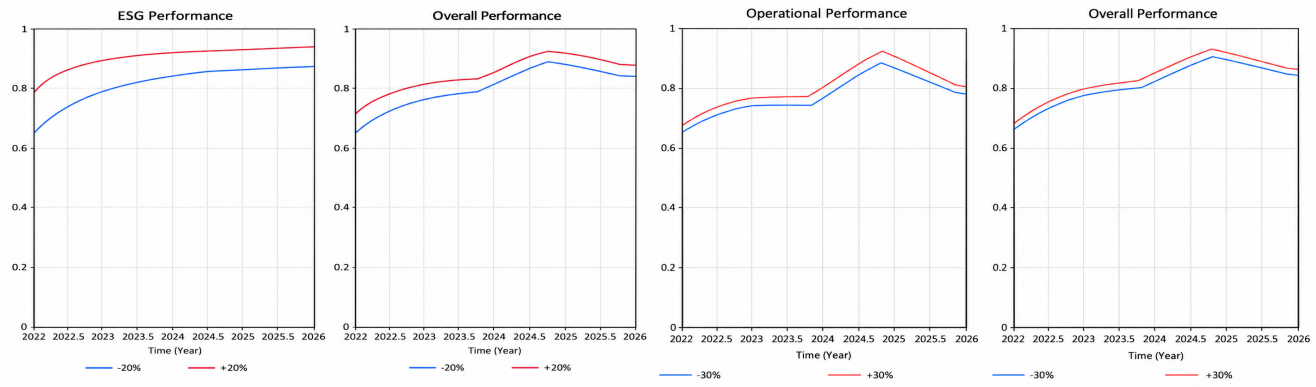
The baseline experiment represents a case-conditioned historical reconstruction over the 16 quarters from 2022Q1 through 2025Q4. Observed enterprise-derived indicator inputs are supplied through quarterly lookups, whereas Operational Performance, ESG Performance, and Overall Performance are calculated as modeled composite outputs using the reported equations and normalization rules. Reproduction of the supplied model gives Overall Performance values of 0.6811 in 2022Q1, 0.9397 in 2024Q4, and 0.8732 in 2025Q4,

consistent with the reported accumulation, capability-realization, and adjustment phases. This assessment checks historical behavior and accounting consistency within the calibrated case, rather than testing an independent predictive sample.

In the sector-composition check, the mean and maximum absolute differences between full-sample and service-sector CRITIC local weights were 0.0641 and 0.1234 for B1–B21, and 0.0113 and 0.0443 for C1–C50. For B1 (Profitability), the local weight increased from 0.4802 to 0.6035 under the service-sector subset, illustrating that relative weights depend on respondent composition. The independently elicited DEMATEL influence matrices are unchanged by this CRITIC re-estimation.

When each of the four digital resources is fixed at 0.95, all three performance measures remain bounded and within relatively high ranges. When each resource is fixed at 0.05, performance declines to different degrees without abnormal jumps or boundary violations. The low-value scenarios differ across resources. Insufficient Digital Technology Resources have a relatively strong effect on ESG Performance and Overall Performance. Insufficient Digital Organizational Resources reduce Operational Performance and ESG Performance simultaneously. Insufficient Digital Infrastructure Resources mainly constrain basic services and environmental performance. Insufficient Digital Human Resources mainly affect operational execution and service processes.

The local sensitivity results are shown in Figure 5. Within a ±20% perturbation range, changes in Governance Mechanisms mainly affect ESG and Overall Performance, whereas changes in Operational Process mainly affect Operational Performance and Overall Performance. Neither perturbation produces abnormal oscillations or boundary violations. The model therefore maintains directionally consistent behavioral responses for the tested variables and perturbation range.



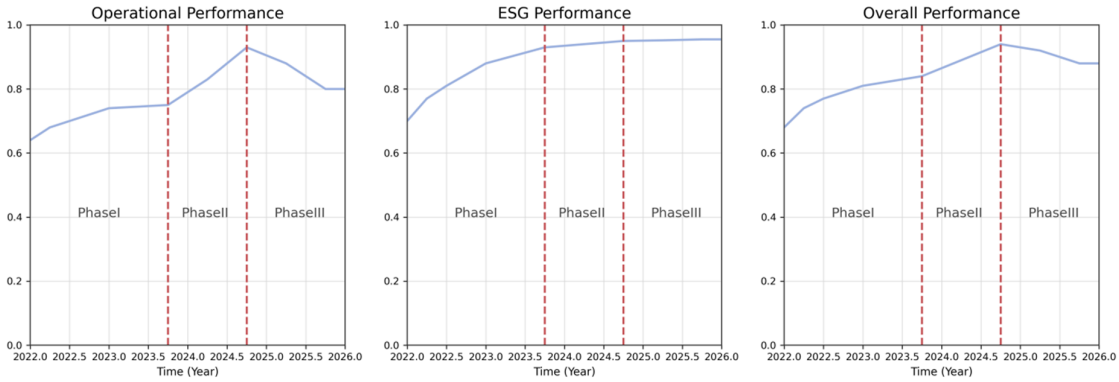
(**a**) Sensitivity analysis of Governance Mechanisms (**b**) Sensitivity analysis of Operational Process

Figure 5. Sensitivity analysis of Governance Mechanisms and Operational Process.

In the alternative-input tests, maximum absolute deviations in Overall Performance ranged from 0.0066 to 0.0109 under individual ±20% intensity changes and from 0.0104 to 0.0346 when an input profile was shifted by one quarter. The tested variants retained the qualitative progression from early contraction through capability-led recovery to later facility-pressure adjustment. Timing changes produced larger deviations than amplitude changes in several cases, particularly for the early contraction shock. Accordingly, the main stage-dependent interpretation is supported at the level of response sequence and transmission mechanisms, while exact turning quarters and peak performance values depend on the scenario specification.

4.3. Baseline Scenario Analysis

Figure 6 shows the dynamic changes in Operational Performance, ESG Performance, and Overall Performance under the baseline scenario from 2022Q1 to 2025Q4. The baseline period is divided into three stages with reference to the enterprise's changes in digital-resource deployment, managerial arrangements, and operating priorities. At the beginning of Stage I, the enterprise concentrated on digital infrastructure and service-platform development, together with the establishment of organizational coordination and governance arrangements. Stage I (2022Q1–2023Q4) is characterized by resource accumulation and earlier improvement in ESG Performance. Operational Performance initially increases and then gradually enters a plateau in Figure 6a. ESG Performance continues to increase in Figure 6b, and Overall Performance improves steadily in Figure 6c. In the model, Governance Mechanisms, Digital Technology Resources, and Digital Organizational Resources can affect ESG variables such as Pollution Prevention and Control, Climate Change, and stakeholder rights and interests relatively directly. In contrast, the effects of digital resources on Operational Performance pass through more intermediate links, including Innovation Capability, Operational Process, Service Responsiveness, and Employee Development. ESG Performance therefore responds earlier during resource accumulation, while Operational Performance shows a more evident transmission delay.



(**a**) Operational Performance under the Baseline Scenario (**b**) ESG Performance under the Baseline Scenario (**c**) Overall Performance under the Baseline Scenario

Figure 6. Baseline trajectories of Operational Performance, ESG Performance, and Overall Performance from 2022 to 2025.

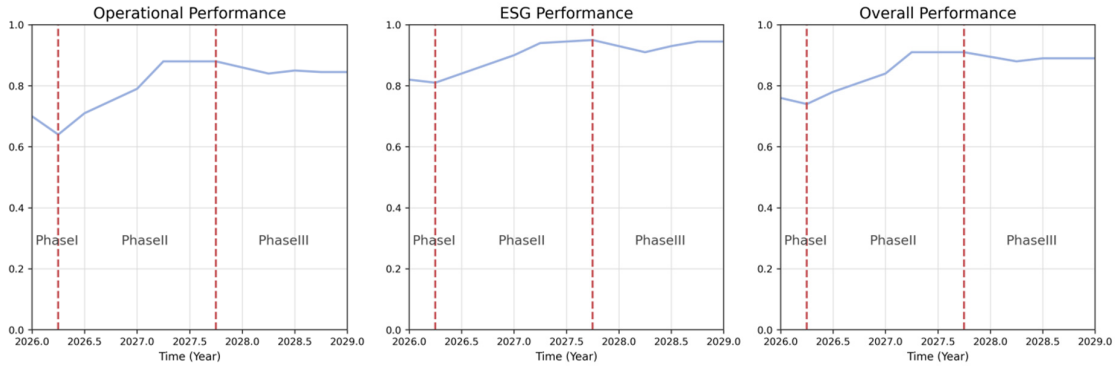
At the transition to Stage II in 2024Q1, adjustments to senior management and ESG-governance responsibilities were accompanied by a stronger emphasis on cost efficiency, integrated operations, and the application of accumulated digital capabilities. Stage II (2024Q1–2024Q4) is characterized by concentrated realization of operational capabilities. Operational Performance in Figure 6a clearly moves above the earlier plateau and continues to increase. ESG Performance in Figure 6b is already at a relatively high level, and its growth gradually slows. Further improvement in Overall Performance in Figure 6c therefore comes mainly from the operational dimension. Digital Technology Resources, Digital Human Resources, and Digital Organizational Resources accumulated in the earlier period continue to strengthen Innovation Capability and then affect Operational Process, Service Responsiveness, and Employee Development. Resource inputs are gradually converted into operational outcomes. At the same time, ESG-related variables approach high levels and are constrained by saturation mechanisms, which reduce their marginal improvement.

At the transition to Stage III in 2025Q1, the enterprise shifted its strategic emphasis toward stabilizing operations, pursuing quality-oriented growth, and extending AI-enabled service applications while adjusting resource deployment. Stage III (2025Q1–2025Q4) is

characterized by high-level adjustment and performance divergence. Operational Performance in Figure 6a declines from a high level, while ESG Performance in Figure 6b remains generally stable. Overall Performance in Figure 6c therefore adjusts with the operational dimension. When some financial, equipment, and operation-related inputs shift from improvement to stabilization or decline, their effects are transmitted relatively quickly to Operational Performance through Profitability, Equipment Management, and Operational Process. In contrast, governance and Digital Organizational Resources formed earlier have stronger stock characteristics, so ESG Performance remains relatively stable. Overall, the baseline scenario shows a stage-dependent pattern in which ESG Performance improves earlier, Operational Performance is realized later, and the operational dimension adjusts in the later period. This pattern mainly results from differences in resource transmission paths and time delays between the two performance dimensions.

4.4. Scenario Simulation Analysis

Figure 7 shows performance responses from 2026 to 2028 under the joint effects of three external scenario inputs and internal system feedback. The stages are identified from major turning points in the operational and Overall Performance curves and from the strengthening, weakening, and alternation of the three exogenous inputs. In the model, operating and cash-flow contraction mainly affects Profitability, Equipment Management, Market Share, and resource accumulation. AI platform development and market expansion mainly affect Innovation Capability and digital technology, human, and organizational resources. Extreme-weather and aging-asset pressure mainly affect Equipment Management, Resource Consumption, Service Responsiveness, and digital infrastructure.



(**a**) Operational Performance under the Scenario Simulation (**b**) ESG Performance under the Scenario Simulation (**c**) Overall Performance under the Scenario Simulation

Figure 7. Adaptive-scenario trajectories of Operational Performance, ESG Performance, and Overall Performance from 2026 to 2028.

The three stages were distinguished using two complementary criteria: transitions in the specified exposure mechanisms (onset, accumulation, peak and decline of the input profiles) and the sustained direction of change in simulated Operational Performance and Overall Performance. The 2026Q1–Q2 interval describes the initial response to rising contraction pressure; 2026Q3–2027Q4 covers the transition from contraction toward capability and market recovery as the AI impulse strengthens; and 2028Q1–Q4 captures subsequent adjustments as equipment and environmental pressure intensifies while the AI impulse weakens. The boundaries reflect these changes at the model's quarterly resolution and serve as interpretive stage markers, rather than independently estimated statistical breakpoints [60,61].

The combined scenario should be read as a sequence of management-relevant what-if conditions: liquidity pressure constrains spending and maintenance; AI/platform op-

portunity supports capability investment and service expansion; and aging assets with weather exposure shift attention toward equipment resilience and resource consumption. The numerical inputs are researcher-defined stress-test trajectories rather than company-approved forecasts. Because all three mechanisms vary across the joint scenario, its final trajectory cannot uniquely attribute performance changes to any one shock; the reported one-at-a-time timing and amplitude perturbations examine local robustness, not isolated causal contributions.

Stage I (2026Q1–2026Q2) is characterized by short-term adjustment under a contraction shock. As operating and cash-flow pressure increases rapidly, Operational Performance in Figure 7a declines first, and Overall Performance in Figure 7c decreases simultaneously, while ESG Performance in Figure 7b changes only modestly. The contraction shock has strong direct negative effects on Profitability and Equipment Management and also suppresses Market Share and digital resource accumulation. Its effects can therefore be transmitted relatively quickly to financial and operational management performance. In contrast, Governance Mechanisms receive weaker direct shocks, while Digital Human Resources and Digital Organizational Resources have some stock persistence. Short-term fluctuations in ESG Performance are therefore smaller.

Stage II (2026Q3–2027Q4) is characterized by recovery and expansion of digital capabilities. As contraction pressure gradually weakens and the effects of AI platforms and market expansion strengthen, Operational Performance in Figure 7a recovers from a low level, ESG Performance in Figure 7b continues to improve, and Overall Performance in Figure 7c increases accordingly. AI and market expansion first strengthen Innovation Capability and the accumulation of Digital Technology Resources, Digital Human Resources, and Digital Organizational Resources. These effects are then transmitted to performance through Service Responsiveness, Operational Process, and Market Share. Innovation Capability receives inputs from multiple digital resources and further affects operational and environmental variables. It therefore becomes an important transmission node that converts external opportunities into performance improvement.

Stage III (2028Q1–2028Q4) is characterized by readjustment under increasing facility pressure. As the positive effect of AI weakens and pressure from extreme weather and aging assets increases, Operational Performance and Overall Performance in Figure 7 decline again, while ESG Performance also fluctuates. This pressure mainly affects Equipment Management, Resource Consumption, Service Responsiveness, and Digital Infrastructure Resources and further influences Profitability and Operational Process. The operational dimension therefore responds more strongly. Governance-related factors and Digital Organizational Resources are less directly affected by physical-asset pressure, which gives ESG Performance greater stability. As facility pressure weakens later, the affected operational variables gradually recover, and all three performance measures improve. The performance responses across the three stages are shown in Figure 7. Overall, the adaptive scenario contains three stages: operating contraction, digital capability recovery, and facility-pressure adjustment. Different external conditions affect performance through differentiated resource and capability transmission paths.

5. Discussion

5.1. Resource Orchestration Mechanisms and Theoretical Implications

First, the study specifies the structural roles of heterogeneous digital resources. The results show that the value of digital resources is not realized directly through individual resource inputs but is gradually transmitted through governance, capability formation, and Operational Processes. Consistent with findings on organizational management channels and innovation mechanisms in studies of enterprise-level IT productivity and sustainable

performance [66,67], this study further distinguishes the structural roles of four types of digital resources. Governance Mechanisms and digital resources act as the main drivers. Innovation Capability performs a key transmission function, while operational and market factors mainly receive effects from upstream resources and capabilities. Resource orchestration therefore concerns not only whether resource combinations are effective but also the different positions of resources within the transmission chain.

Second, it clarifies the different response horizons of the two performance objectives. The dynamic model shows different realization patterns for Operational Performance and ESG Performance. In the baseline scenario, ESG Performance improves earlier during resource accumulation, while Operational Performance shows a more evident increase only after capabilities are formed. This pattern is consistent with previous evidence that digital capabilities gradually create value through adaptation mechanisms, Innovation Capability, and process adjustment [68,69]. This study further shows that the temporal difference between the two performance dimensions is related to their transmission paths and resource-stock characteristics. The resource–capability–performance relationship is therefore extended from a static structure to a temporal evolution process. Compared with studies that examine digitalization-related operational or ESG outcomes separately, the integrated model distinguishes their transmission paths and stage-dependent response timing.

Third, it extends resource orchestration to stage-dependent adjustment under changing constraints. The baseline and adaptive scenarios show that continuously expanding a single digital resource is not universally effective. Previous studies have shown that digital value is constrained by multiple conditions, including marginal effects, structural fit, organizational absorption, governance requirements, and long-term innovation [36,70–76]. Building on this evidence, this study emphasizes stage-dependent orchestration. Enterprises need to adjust resource priorities according to capability maturity and external constraints rather than maintain a fixed investment structure over time.

These results extend digital resource orchestration from static resource combinations to a dynamic process characterized by structural differences, feedback, time delays, and scenario dependence.

The distinctive role of Digital Human Resources (B20) and Digital Organizational Resources (B21) lies in how they enable technological resources to become repeatable service capabilities. In a labor-intensive property-services enterprise, digital platforms and infrastructure do not independently complete maintenance tasks, respond to residents, or coordinate widely dispersed sites. B20 supplies frontline digital skills, platform-use competence, and the capacity to translate data into field actions. B21 supplies common operating standards, digital strategy, and cross-project coordination, allowing those actions to be reproduced across business units. Consequently, technology deployment can be converted into Innovation Capability (B8), Operational Process (B7), Equipment Management (B6), and Service Responsiveness (B4) only when human execution and organizational integration develop together. The pronounced upstream influence of B20 and B21 is therefore consistent with their role as complementary capability-building resources, rather than merely as additional categories of digital expenditure [18–20,66–69].

More specifically, the structural results distinguish three functions that are often combined in general accounts of digital transformation: B21 coordinates and recombines digital resources across projects, B20 supports their practical adoption and repeated execution, and Governance Mechanisms (B17) connect resource decisions with risk, information, and stakeholder-related requirements. B21 and B20 have the two highest positive net-relation scores among the four digital-resource categories (1.169 and 1.129, respectively), whereas B17 has the highest centrality (2.865). This differentiation helps explain why the conversion of technology into performance is stage-dependent. Organizational arrangements and

employee capabilities play an enabling role during resource accumulation; as routines become established, their influence is expressed increasingly through innovation, operating processes, and service outputs.

The earlier response of ESG Performance can also be explained through this transmission structure. In the property-services context, information transparency, risk-management routines, digital customer-feedback channels, and coordination of community and environmental services can improve as governance and organizational systems are established. These activities are comparatively close to the upstream resource and governance variables. By contrast, improvements in Operational Performance require digital skills to be embedded in daily work, platform information to be translated into standardized service processes, and equipment and personnel to be coordinated across numerous sites. Labor productivity, response efficiency, and profitability therefore emerge through a longer capability-formation and operational-execution pathway. The resulting time difference is a stage-dependent feature of resource orchestration in this organizational setting, rather than a fixed rule that digitalization must always improve ESG before operations. It is consistent with evidence on the complementary roles of organizational capability and process change, while refining the literature by distinguishing the response horizons of two objectives within the same resource system [19–21,68,69].

The observed timing also reflects how the two performance dimensions are represented. Digital Organizational Resources (B21) are modeled as an accumulating resource that can sustain governance and stakeholder-facing routines. ESG indicators derived from periodic disclosure can register formalized policies, management practices, and environmental or social initiatives earlier than operational indicators register changes in service productivity or financial returns. Differences in normalization, stock persistence, saturation, and response-delay settings can further accentuate the separation between the two trajectories. These measurement and model features complement, rather than replace, the resource-transmission explanation. Compared with studies emphasizing immediate efficiency gains from individual technologies or delayed financial returns from digital investment, the present findings indicate that the temporal pattern of digital value realization is shaped by the intervening organizational mechanisms and the performance dimensions being evaluated [21,66–69]. The specific contribution is therefore to connect heterogeneous-resource coordination to different performance horizons, not to claim that early ESG improvement is an intrinsic or universal effect of digital transformation.

5.2. Managerial Implications

From a managerial perspective, enterprise digital investment should shift from a fixed-proportion approach to stage-dependent resource orchestration. The adaptive scenario further shows that managerial priorities need to change with external conditions. The model does not provide optimal investment shares under a fixed budget. Instead, it identifies the resources and capabilities that should receive greater attention at different stages. During resource accumulation, priority should be given to digital strategy, organizational coordination, governance rules, and employee skills. During capability formation, the alignment among digital platforms, data applications, and digital talent should be strengthened [77]. When the system becomes mature or faces stronger operation and maintenance pressure, greater attention should be given to system compatibility, data governance, process optimization, and equipment maintenance [38,39].

Performance evaluation should also consider the time delay between resource inputs and outcome realization. In the early stage of digitalization, greater attention can be given to leading indicators such as governance transparency, personnel capabilities, service processes, and resource and environmental performance. After capabilities begin to

generate outcomes, more attention can be shifted to operational efficiency, customer value, and financial results. This approach can reduce the risk of rejecting digital investment prematurely because short-term business outcomes show limited change.

The practical implications are most directly relevant to property and facility-service enterprises. Their geographically dispersed sites, labor-intensive service delivery, recurring equipment maintenance, and close contact with residents mean that digital investment must be coordinated with frontline skills, service standards, and asset-management routines. During the initial period, managers should prioritize interoperable information infrastructure, governance arrangements, digital training, and coordination among service projects. As capabilities mature, attention can progressively shift toward the efficiency of service processes, equipment utilization, and the quality and consistency of customer responses.

For property and facility management in particular, this means linking digital work-order platforms to staff training and standardized dispatch procedures, using equipment data to schedule preventive maintenance, and integrating energy-consumption monitoring with building retrofits and daily operations. Digital Organizational Resources help headquarters and on-site teams implement common rules, while Digital Human Resources determine whether those rules can be executed effectively. Managers should therefore assess digital investment not only by the number of platforms installed, but also by service-cycle time, equipment reliability, energy performance, and customer responsiveness. These recommendations follow directly from the resource and service-delivery relationships examined in the case.

Other operations-intensive service organizations may draw on the same mechanism when they manage dispersed facilities, rely on frontline employees, and require consistent service execution. Multi-site logistics, hotel operations, outsourced cleaning, and infrastructure services, for example, may benefit from combining digital tools with employee capability development and cross-unit coordination before expecting broad operational gains. The exact mix of resources should nevertheless reflect each industry's asset intensity, labor structure, customer interface, and governance needs. More general propositions—such as a single investment sequence for all service sectors or the same relative importance of human and organizational resources in every context—remain subjects for further examination rather than ready-made managerial rules.

5.3. Research Limitations and Future Research

This study has four limitations. First, the system dynamics model is calibrated using a single large property services enterprise. It is mainly intended to explain resource transmission and stage-dependent orchestration. Specific investment intensities and time points require further testing with cross-enterprise and cross-industry data. Second, DEMATEL structural identification is based on judgments from four senior experts. The results represent directional influence structures under expert judgment and do not constitute causal identification in an experimental or econometric sense. They also do not have statistical sampling implications. Third, the two CRITIC rating datasets include respondents from multiple industries and are used to construct objective information weights at the enterprise level rather than to estimate population parameters for the property services industry. Industry-specific applicability may therefore be limited. Fourth, some system dynamics feedback coefficients and the 2026–2028 exogenous inputs are case-specific parameters and exploratory scenario assumptions. The current extreme-condition and local sensitivity tests cannot replace global parameter uncertainty analysis. Future studies can use cross-enterprise panel data, project-level longitudinal data, and more systematic uncertainty analysis to further test structural relationships, feedback parameters, and stage boundaries.

Additional interpretation boundaries follow from the model specification. Governance Mechanisms (B17) both interact with upstream factors and contribute directly to the ESG index, while Market Share (B16) is a context-specific social-block indicator with a commercial component. These features should be considered when interpreting differences between the two composite performance trajectories and when extending the framework to other organizational settings.

6. Conclusions

This study develops a dynamic enterprise digital resource orchestration framework for the dual objectives of Operational Performance and ESG Performance. Within the expert-assessed structure, Governance Mechanisms and digital resources occupy the principal upstream positions. Digital Human Resources and Digital Organizational Resources have high net-relation scores, while Innovation Capability plays an important transmission role in transforming resources into performance outcomes. These findings indicate that digital performance depends more on complementarity and coordination among multiple resources across governance, capability, and application stages than on the continuous expansion of a single resource.

The dynamic simulation shows different realization patterns for Operational Performance and ESG Performance. In the case-conditioned simulation, ESG Performance rises earlier during resource accumulation, whereas Operational Performance rises more visibly after modeled capabilities develop. When external constraints change, the managerial priorities of resources and capabilities also change. Enterprise digital resource configuration is therefore better understood as a stage-dependent orchestration process characterized by structural dependence, feedback, time delays, and scenario dependence.

Overall, this study provides an analytical framework for identifying which digital resources should receive priority at different stages and why these priorities should be adjusted. The framework is intended to explain resource structures, transmission relationships, and stage-dependent managerial priorities. It is not intended to provide fixed budget shares, probabilistic forecasts, or globally optimal allocations. Its managerial implications are mainly applicable to stage-based digital resource decisions in property services, facility management, and other operations-intensive enterprises.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su182110747/s1. The supplementary document contains Table S1, S1A,B and S2–S20, and Figures S1–S3. Supplementary Data File S1 provides machine-readable indicator definitions, indicator-development documentation, anonymous SWARA and DEMATEL expert data, respondent-level CRITIC data and processed results, sector-sensitivity analyses, combination weights, interval Grey-DEMATEL, ISM, and MICMAC calculations, system-dynamics equations, parameter provenance, expert leave-one-out analyses, scenario-robustness results, baseline-reproduction results, and scenario inputs. Supplementary Files S2 and S3 provide the executable baseline and adaptive-scenario Vensim models, respectively. References [78–115] are cited in the Supplementary Materials.

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References

1. Piccoli, G.; Grover, V.; Rodriguez, J. Digital Transformation Requires Digital Resource Primacy: Clarification and Future Research Directions. *J. Strateg. Inf. Syst.* **2024**, *33*, 101835. [CrossRef]
2. Fang, K.; Wu, X.; Zhang, W.; Lei, L. Unfolding the Resource Configuration and Interaction in Digital Servitization: An Exploratory Two-Stage Research Design. *Int. J. Oper. Prod. Manag.* **2025**, *45*, 594–627. [CrossRef]
3. Mao, H.; Liu, S.; Gong, Y. Balancing Structural IT Capabilities for Organizational Agility in Digital Transformation: A Resource Orchestration View. *Int. J. Oper. Prod. Manag.* **2024**, *44*, 315–344. [CrossRef]
4. Feroz, A.K.; Zo, H.; Eom, J.; Chiravuri, A. Identifying Organizations' Dynamic Capabilities for Sustainable Digital Transformation: A Mixed Methods Study. *Technol. Soc.* **2023**, *73*, 102257. [CrossRef]
5. Guo, X.; Li, M.; Wang, Y.; Mardani, A. Does Digital Transformation Improve the Firm's Performance? From the Perspective of Digitalization Paradox and Managerial Myopia. *J. Bus. Res.* **2023**, *163*, 113868. [CrossRef]
6. Lu, Y.; Xu, C.; Zhu, B.; Sun, Y. Digitalization Transformation and ESG Performance: Evidence from China. *Bus. Strategy Environ.* **2024**, *33*, 352–368. [CrossRef]
7. Ding, X.; Vuković, D.B.; Sokolov, B.I.; Vukovic, N.; Liu, Y. Enhancing ESG Performance through Digital Transformation: Insights from China's Manufacturing Sector. *Technol. Soc.* **2024**, *79*, 102753. [CrossRef]
8. Xiao, S.; Xu, J.; Li, R. Are Digital Trends Driving Corporate Environmental, Social, and Governance Practices? Evidence from China. *Bus. Strategy Environ.* **2024**, *33*, 5366–5385. [CrossRef]
9. Li, Y.; Zheng, Y.; Li, X.; Mu, Z. The Impact of Digital Transformation on ESG Performance. *Int. Rev. Econ. Financ.* **2024**, *96*, 103686. [CrossRef]
10. Jiang, W.; Li, J. Digital Transformation and Its Effect on Resource Allocation Efficiency and Productivity in Chinese Corporations. *Technol. Soc.* **2024**, *78*, 102638. [CrossRef]
11. Inceoglu, I.; Vanacker, T.; Vismara, S. Digitalization and Resource Mobilization. *Br. J. Manag.* **2024**, *35*, 576–593. [CrossRef]
12. Grego, M.; Bartosiak, M.; Palese, B.; Piccoli, G.; Denicolai, S. Disentangling the 'Digital': A Critical Review of Information Technology Capabilities, Information Technology–Enabled Capabilities and Digital Capabilities in Business Research. *Int. J. Manag. Rev.* **2025**, *27*, 238–260. [CrossRef]
13. Franco, C.W.; Benitez, G.B.; de Sousa, P.R.; Kliemann Neto, F.J.; Frank, A.G. Managing Resources for Digital Transformation in Supply Chain Integration: The Role of Hybrid Governance Structures. *Int. J. Prod. Econ.* **2024**, *278*, 109428. [CrossRef]
14. Bansal, A.; Panchal, T.; Jabeen, F.; Mangla, S.K.; Singh, G. A Study of Human Resource Digital Transformation (HRDT): A Phenomenon of Innovation Capability Led by Digital and Individual Factors. *J. Bus. Res.* **2023**, *157*, 113611. [CrossRef]
15. Andersén, J. Green Resource Orchestration: A Critical Appraisal of the Use of Resource Orchestration in Environmental Management Research, and a Research Agenda for Future Study. *Bus. Strategy Environ.* **2023**, *32*, 5506–5520. [CrossRef]
16. Shen, L.; Shi, Q.; Parida, V.; Jovanovic, M. Ecosystem Orchestration Practices for Industrial Firms: A Qualitative Meta-Analysis, Framework Development and Research Agenda. *J. Bus. Res.* **2024**, *173*, 114463. [CrossRef]
17. Tajeddini, K.; Hussain, M.; Gamage, T.C.; Papastathopoulos, A. Effects of Resource Orchestration, Strategic Information Exchange Capabilities, and Digital Orientation on Innovation and Performance of Hotel Supply Chains. *Int. J. Hosp. Manag.* **2024**, *117*, 103645. [CrossRef]

18. Hou, E.; Zhang, T.; Yin, X.; Chen, J.; Ding, Y. The Evolution of Digitalization Capabilities during Strategic Renewal: A Case Study Based on the Ecological Restoration Enterprise Practice. *J. Clean. Prod.* **2024**, *459*, 142570. [CrossRef]
19. Sunder, M.V.; Prashar, A. The Interplay of Lean Practices and Digitalization on Organizational Learning Systems and Operational Performance. *Int. J. Prod. Econ.* **2024**, *270*, 109192. [CrossRef]
20. Malik, M.; Andargoli, A.; Ali, I.; Chavez, R. A Socio-Cognitive Theorisation of How Data-Driven Digital Transformation Affects Operational Productivity? *Int. J. Prod. Econ.* **2024**, *277*, 109403. [CrossRef]
21. Benedek, B.; Csiki, O.; Demeter, K.; Losonci, D.; Szász, L. Financial Impact of Digitalization—A Time-Lagged Analysis. *Int. J. Prod. Econ.* **2025**, *288*, 109699. [CrossRef]
22. Chen, W.; Ren, H.; Shu, Y. The Impact of Corporate Digital Transformation on Sustainable Development in China. *Bus. Strategy Environ.* **2025**, *34*, 2721–2747. [CrossRef]
23. Zhang, W.; Yang, K.; Li, X. How Does Digital Transformation Affect Firms' ESG Performance? The Evidence from China. *J. Environ. Manag.* **2025**, *395*, 128021. [CrossRef]
24. Li, J.; Li, Q.; Chen, Y.; An, Q. How Digital Transformation Facilitates ESG Performance to Heavy Polluting Enterprises: A Panel fsQCA Based on National Big Data Comprehensive Pilot Zones. *Technol. Forecast. Soc. Change* **2025**, *221*, 124366, Corrigendum in *Technol. Forecast. Soc. Change* **2026**, *224*, 124503. [CrossRef]
25. Yu, Y.; Chan, H.-L.; Cho, E. Enhancing ESG Performance through Digital Transformation: Recent Development, Cases and Relationships. *J. Bus. Res.* **2026**, *202*, 115763. [CrossRef]
26. Lin, M.; Zhang, Z.; Arif, M. The Intersection of Digital Transformation and Environmental Responsibility in Traditional Manufacturing Enterprises amid New Productive Forces. *J. Clean. Prod.* **2025**, *503*, 145426. [CrossRef]
27. Kumar, S.; Lim, W.M.; Sureka, R.; Jabbour, C.J.C.; Bamel, U. Balanced Scorecard: Trends, Developments, and Future Directions. *Rev. Manag. Sci.* **2024**, *18*, 2397–2439. [CrossRef]
28. Chehimi, M.; Naro, G. Balanced Scorecards and Sustainability Balanced Scorecards for Corporate Social Responsibility Strategic Alignment: A Systematic Literature Review. *J. Environ. Manag.* **2024**, *367*, 122000. [CrossRef]
29. Hristov, I.; Searcy, C. Integrating Sustainability with Corporate Governance: A Framework to Implement the Corporate Sustainability Reporting Directive through a Balanced Scorecard. *Manag. Decis.* **2025**, *63*, 443–467. [CrossRef]
30. Dağıdır, B.D.; Özkan, B. A Comprehensive Evaluation of a Company Performance Using Sustainability Balanced Scorecard Based on Picture Fuzzy AHP. *J. Clean. Prod.* **2024**, *435*, 140519. [CrossRef]
31. Nicoletti Junior, A.; de Oliveira, M.C.; Helleno, A.L. Sustainability Evaluation Model for Manufacturing Systems Based on the Correlation between Triple Bottom Line Dimensions and Balanced Scorecard Perspectives. *J. Clean. Prod.* **2018**, *190*, 84–93. [CrossRef]
32. de Villiers, C.; Rouse, P.; Kerr, J. A New Conceptual Model of Influences Driving Sustainability Based on Case Evidence of the Integration of Corporate Sustainability Management Control and Reporting. *J. Clean. Prod.* **2016**, *136*, 78–85. [CrossRef]
33. Dočekalová, M.P.; Kocmanová, A. Composite Indicator for Measuring Corporate Sustainability. *Ecol. Indic.* **2016**, *61*, 612–623. [CrossRef]
34. Browder, R.E.; Dwyer, S.M.; Koch, H. Upgrading Adaptation: How Digital Transformation Promotes Organizational Resilience. *Strateg. Entrep. J.* **2024**, *18*, 128–164. [CrossRef]
35. Yan, X.; Chen, X.; Lu, C.; Liu, W.; Shi, X.; Gong, Y. Strategy for Sustainable Supply Chain Transformation: A Resource Orchestration Perspective. *Ind. Manag. Data Syst.* **2024**, *124*, 2633–2662. [CrossRef]
36. Ciszewska-Mlinarič, M.; Morgan-Thomas, A.; Wójcik, P. Navigating Turbulence: Resource Orchestration in Developing International Dynamic Marketing Capabilities. *J. Bus. Res.* **2026**, *211*, 116183. [CrossRef]
37. Qiao, W.; Ju, Y.; Dong, P.; Tiong, R.L.K. How to Realize Value Creation of Digital Transformation? A System Dynamics Model. *Expert Syst. Appl.* **2024**, *244*, 122667. [CrossRef]
38. Asare, K.A.B.; Liu, R.; Anumba, C.J.; Issa, R.R.A. Real-World Prototyping and Evaluation of Digital Twins for Predictive Facility Maintenance. *J. Build. Eng.* **2024**, *97*, 110890. [CrossRef]
39. van Roosmale, S.; Hellinckx, P.; Meysman, J.; Verbeke, S.; Audenaert, A. Building Automation and Control Systems for Office Buildings: Technical Insights for Effective Facility Management—A Literature Review. *J. Build. Eng.* **2024**, *97*, 110943. [CrossRef]
40. Zhang, Q.; Fan, J.; Gao, C. CRITID: Enhancing CRITIC with Advanced Independence Testing for Robust Multi-Criteria Decision-Making. *Sci. Rep.* **2024**, *14*, 25094. [CrossRef]
41. Lebepe, P.; Mathaba, T.N.D. Enhancing Energy Resilience in Enterprises: A Multi-Criteria Approach. *Sustain. Energy Res.* **2025**, *12*, 7. [CrossRef]
42. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining Objective Weights in Multiple Criteria Problems: The CRITIC Method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [CrossRef]
43. Tarafdar, A.; Kanika; Shaikh, A.; Majumder, P.; Pamucar, D.; Simic, V.; Bera, U.K. Prediction of Eco Sustainability Component Using Fuzzy Z Numbers Based Ratio Analysis and Interval Type 3 Fuzzy Logic System. *J. Clean. Prod.* **2024**, *481*, 144125. [CrossRef]

44. Keršulienė, V.; Zavadskas, E.K.; Turskis, Z. Selection of Rational Dispute Resolution Method by Applying New Step-Wise Weight Assessment Ratio Analysis (SWARA). *J. Bus. Econ. Manag.* **2010**, *11*, 243–258. [CrossRef]
45. Mizrak, F.; Karakaya, T.; Vatansever Durmaz, B. A Systems Thinking Perspective on Cyber Awareness-to-Action in Organizations: Prioritizing Human-Centric Drivers Using a q-Rung Orthopair Fuzzy Approach. *Systems* **2026**, *14*, 638. [CrossRef]
46. Jin, T.; Zhang, P.; Niu, Y.; Lv, X. Integrating Combination Weighting of Game Theory and Fuzzy Comprehensive Evaluation for Selecting Deep Foundation Pit Support Scheme. *Buildings* **2024**, *14*, 619. [CrossRef]
47. Ma, J.; Li, X. Performance Evaluation of Education Infrastructure Public–Private Partnership Projects in the Operation Stage Based on Limited Cloud Model and Combination Weighting Method. *Buildings* **2025**, *15*, 1833. [CrossRef]
48. Lv, Z.; Xiong, J.; Zhuo, M.; Ke, Y.; Kang, Q. Resilience Assessment of Forest Fires Based on a Game-Theoretic Combination Weighting Method. *Sustainability* **2025**, *17*, 7907. [CrossRef]
49. Condat, L. Fast Projection onto the Simplex and the l_1 Ball. *Math. Program.* **2016**, *158*, 575–585. [CrossRef]
50. Deepu, T.S.; Ravi, V. Exploring Critical Success Factors Influencing Adoption of Digital Twin and Physical Internet in Electronics Industry Using Grey-DEMATEL Approach. *Digit. Bus.* **2021**, *1*, 100009. [CrossRef]
51. Yan, M.; Jia, J.; Chen, Y. Research on Accident Early Warning of Metallurgical Enterprises Based on Grey DEMATEL/ISM and Bayesian Network. *Sci. Rep.* **2024**, *14*, 18312. [CrossRef]
52. Zhang, S.; Liu, J.; Li, Z.; Xiahou, X.; Li, Q. Analyzing Critical Factors Influencing the Quality Management in Smart Construction Site: A DEMATEL–ISM–MICMAC Based Approach. *Buildings* **2024**, *14*, 2400. [CrossRef]
53. Li, T.; You, J.; Sörqvist, E.; Lin, H.; Zhou, L. Stage-Sensitive Risk Structure Analysis in Construction Digital Transformation: An Unsupervised Learning-Enhanced DEMATEL–ISM Framework. *Buildings* **2026**, *16*, 2386. [CrossRef]
54. Liza, S.A.; Chowdhury, N.R.; Munjerin, R.; Morshed, S.M.; Paul, S.K.; Xames, M.D.; Rahman, R. Post-Pandemic Sustainable Supply Chain Recovery Planning: A Case Study from an Automobile Industry. *J. Manag. Anal.* **2025**, *12*, 509–551. [CrossRef]
55. Tan, Z.; Zhang, B.; Zhou, Z.; Li, Q.; Wan, B. Research on Risk Factors Identification and Optimization Strategies for Railway Tunnel Construction in Ecologically Sensitive Areas. *Sci. Rep.* **2025**, *15*, 40697. [CrossRef]
56. Weng, X.; Wu, H.; Zhong, M.; Oteng, D. Driving Mechanisms and Evolutionary Simulation of Cross-Regional Collaborative Management for Construction and Demolition Waste: Evidence from the Guangdong–Hong Kong–Macao Greater Bay Area. *Resour. Conserv. Recycl.* **2026**, *232*, 108964. [CrossRef]
57. Pluchinotta, I.; Zhou, K.; Zimmermann, N. Dealing with Soft Variables and Data Scarcity: Lessons Learnt from Quantification in a Participatory System Dynamics Modelling Process. *Syst. Dyn. Rev.* **2024**, *40*, e1770. [CrossRef]
58. Seth, S.; McGillivray, M. Composite Indices, Alternative Weights, and Comparison Robustness. *Soc. Choice Welf.* **2018**, *51*, 657–679. [CrossRef]
59. Greco, S.; Ishizaka, A.; Tasiou, M.; Torrisi, G. On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness. *Soc. Indic. Res.* **2019**, *141*, 61–94. [CrossRef]
60. Kunc, M. Integrating System Dynamics and Scenarios: A Framework Based on Personal Experience. *Futures Foresight Sci.* **2024**, *6*, e174. [CrossRef]
61. Börjeson, L.; Höjer, M.; Dreborg, K.-H.; Ekvall, T.; Finnveden, G. Scenario Types and Techniques: Towards a User's Guide. *Futures* **2006**, *38*, 723–739. [CrossRef]
62. Richardson, G.P. Building Confidence in Exploratory Models. *Syst. Dyn. Rev.* **2024**, *40*, e1769. [CrossRef]
63. Barlas, Y. Formal Aspects of Model Validity and Validation in System Dynamics. *Syst. Dyn. Rev.* **1996**, *12*, 183–210. [CrossRef]
64. Saavedra-Nieves, A.; Saavedra-Nieves, P. IndexNumber: An R Package for Measuring the Evolution of Magnitudes. *R J.* **2021**, *13*, 253–275. [CrossRef]
65. Alizadeh, M.R.; Peng, X.; Adamowski, J.; Albano, R.; Ozga-Zielinski, B.; Inam, A. Development of a Behaviour Pattern-Based Testing Approach for Coupled Socioeconomic and Environmental Models. *J. Environ. Manag.* **2023**, *347*, 119088. [CrossRef]
66. Khanna, R.; Sharma, C. Beyond Information Technology and Productivity Paradox: Analysing the Channels of Impact at the Firm-Level. *Technol. Forecast. Soc. Change* **2024**, *203*, 123369. [CrossRef]
67. Le, T.T.; Vo Nhu, Q.P.; Bui Ngoc Bao, T.; Nguyen Thao, L.V.; Pereira, V. Digitalisation Driving Sustainable Corporate Performance: The Mediation of Green Innovation and Green Supply Chain Management. *J. Clean. Prod.* **2024**, *446*, 141290. [CrossRef]
68. Yang, G.; Nie, Y.; Li, H.; Wang, H. Digital Transformation and Low-Carbon Technology Innovation in Manufacturing Firms: The Mediating Role of Dynamic Capabilities. *Int. J. Prod. Econ.* **2023**, *263*, 108969. [CrossRef]
69. Chen, W.; Lu, H.; Mora, L.; Chen, T.; Beckers, D.; Hu, M. Linking Manufacturing Digitalization and Technological Innovation: The Mediating Role of Dynamic Capabilities. *Technol. Soc.* **2025**, *83*, 103041. [CrossRef]
70. Suo, X.; Zhang, L.; Guo, R.; Lin, H.; Yu, M.; Du, X. The Inverted U-Shaped Association between Digital Economy and Corporate Total Factor Productivity: A Knowledge-Based Perspective. *Technol. Forecast. Soc. Change* **2024**, *203*, 123364. [CrossRef]
71. Pappas, I.O.; Mikalef, P.; Dwivedi, Y.K.; Jaccheri, L.; Krogstie, J. Responsible Digital Transformation for a Sustainable Society. *Inf. Syst. Front.* **2023**, *25*, 945–953. [CrossRef]

72. Zareie, M.; Attig, N.; El Ghoul, S.; Fooladi, I. Firm Digital Transformation and Corporate Performance: The Moderating Effect of Organizational Capital. *Financ. Res. Lett.* **2024**, *61*, 105032. [CrossRef]
73. Sang, Y.; Loganathan, K.; Lin, L. Digital Transformation and Firm ESG Performance: The Mediating Role of Corporate Risk-Taking and the Moderating Role of Top Management Team. *Sustainability* **2024**, *16*, 5907. [CrossRef]
74. Li, W.; Zhang, M. Digital Transformation, Absorptive Capacity and Enterprise ESG Performance: A Case Study of Strategic Emerging Industries. *Sustainability* **2024**, *16*, 5018. [CrossRef]
75. Marczewska, M.; Hegerty, S.W.; Panwar, R.; Kostrzewski, M. Digital Transformation, ESG, and Companies' Performance: An Exploratory Study of the European Food Sector. *J. Technol. Transf.* **2026**, *51*, 1798–1819. [CrossRef]
76. Du, J.; Shen, Z.; Song, M.; Zhang, L. Nexus between Digital Transformation and Energy Technology Innovation: An Empirical Test of A-Share Listed Enterprises. *Energy Econ.* **2023**, *120*, 106572. [CrossRef]
77. Peretz-Andersson, E.; Tabares, S.; Mikalef, P.; Parida, V. Artificial Intelligence Implementation in Manufacturing SMEs: A Resource Orchestration Approach. *Int. J. Inf. Manag.* **2024**, *77*, 102781. [CrossRef]
78. Gu, J.; Shi, X.; Wang, J.; Xu, X. Examining the impact of market power discrepancy between supply chain partners on firm financial performance. *Int. J. Prod. Econ.* **2024**, *268*, 109100. [CrossRef]
79. Poretti, C.; Heo, C.Y. COVID-19 and firm value drivers in the tourism industry. *Ann. Tour. Res.* **2022**, *95*, 103433. [CrossRef]
80. Mouzas, S.; Bauer, F. Rethinking business performance in global value chains. *J. Bus. Res.* **2022**, *144*, 679–689. [CrossRef]
81. Goel, K.; Bandara, W.; Gable, G. Conceptualizing Business Process Standardization: A Review and Synthesis. *Schmalenbach J. Bus. Res.* **2023**, *75*, 195–237. [CrossRef]
82. Oberle, L.J. How to build responsive service processes in German banks: The role of process documentation and the myth of automation. *Bus. Process Manag. J.* **2023**, *29*, 578–596. [CrossRef]
83. Ghosh, S.; Hughes, M.; Hodgkinson, I.; Hughes, P. Digital transformation of industrial businesses: A dynamic capability approach. *Technovation* **2022**, *113*, 102414. [CrossRef]
84. Wang, J.; Liu, F. Examining the link between integrated management systems and firm performance: Do the integration strategies matter? *Int. J. Oper. Prod. Manag.* **2023**, *43*, 332–372. [CrossRef]
85. Khan, H.; Ozkan, K.S.L.; Deligonul, S.; Cavusgil, E. Redefining the organizational resilience construct using a frame based methodology: A new perspective from the ecology based approach. *J. Bus. Res.* **2024**, *172*, 114397. [CrossRef]
86. Banerjee, P.; Deb, S.G. Capital investment, working capital management, and firm performance: Role of managerial ability in US logistics industry. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *176*, 103224. [CrossRef]
87. Vanderschueren, T.; Boute, R.; Verdonck, T.; Baesens, B.; Verbeke, W. Optimizing the preventive maintenance frequency with causal machine learning. *Int. J. Prod. Econ.* **2023**, *258*, 108798. [CrossRef]
88. Zhu, M.; Liang, C.; Yeung, A.C.L.; Zhou, H. The impact of intelligent manufacturing on labor productivity: An empirical analysis of Chinese listed manufacturing companies. *Int. J. Prod. Econ.* **2024**, *267*, 109070. [CrossRef]
89. Kim, H.; So, K.K.F. The evolution of service failure and recovery research in hospitality and tourism: An integrative review and future research directions. *Int. J. Hosp. Manag.* **2023**, *111*, 103457. [CrossRef]
90. Akter, S.; Hossain, M.A.; Sajib, S.; Sultana, S.; Rahman, M.; Vrontis, D.; McCarthy, G. A framework for AI-powered service innovation capability: Review and agenda for future research. *Technovation* **2023**, *125*, 102768. [CrossRef]
91. Liu, Y.; Dong, J.; Mei, L.; Shen, R. Digital innovation and performance of manufacturing firms: An affordance perspective. *Technovation* **2023**, *119*, 102458. [CrossRef]
92. Cheng, C.; Wang, L. How companies configure digital innovation attributes for business model innovation? A configurational view. *Technovation* **2022**, *112*, 102398. [CrossRef]
93. Hutchinson, D.; Luria, G.; Pindek, S.; Spector, P. The effects of industry risk level on safety training outcomes: A meta-analysis of intervention studies. *Saf. Sci.* **2022**, *152*, 105594. [CrossRef]
94. Koon, V.-Y.; Yulita. Do employee perception of HR training quality and manager innovation signals employee thrive? *Creat. Innov. Manag.* **2024**, *33*, 766–780. [CrossRef]
95. Comoglio, C.; Castelluccio, S.; Scarrone, A.; Fiore, S. Analysis of environmental sustainability reporting in the waste-to-energy sector: Performance indicators and improvement targets of the EMAS-registered waste incineration plants in Italy. *J. Clean. Prod.* **2022**, *378*, 134546. [CrossRef]
96. Qing, L.; Li, P.; Dagestani, A.A.; Woo, C.; Zhong, K. Does climate change exposure impact on corporate finance and energy performance? Unraveling the moderating role of CEOs' green experience. *J. Clean. Prod.* **2024**, *461*, 142653. [CrossRef]
97. Bendig, D.; Schulz, C.; Erbar, F.; Heubeck, T. Apples to apples: Accurately assessing corporate carbon performance. *J. Clean. Prod.* **2025**, *486*, 144338. [CrossRef]
98. Park, R.; Kim, J. Differential effects of autonomy on employee satisfaction and organizational performance depending on the type of financial incentives: Evidence from a four-wave panel of Korean companies. *Int. J. Hum. Resour. Manag.* **2023**, *34*, 3656–3686. [CrossRef]

99. Rahman, M.; Faroque, A.R.; Sakka, G.; Ahmed, Z.U. The impact of negative customer engagement on market-based assets and financial performance. *J. Bus. Res.* **2022**, *138*, 422–435. [CrossRef]
100. Zhong, M.; Zhao, W.; Shahab, Y. The philanthropic response of substantive and symbolic corporate social responsibility strategies to COVID-19 crisis: Evidence from China. *Corp. Soc. Responsib. Environ. Manag.* **2022**, *29*, 339–355. [CrossRef]
101. Hoque, M.T.; Nath, P.; Ahammad, M.F.; Tzokas, N.; Yip, N. Constituents of dynamic marketing capability: Strategic fit and heterogeneity in export performance. *J. Bus. Res.* **2022**, *144*, 1007–1023. [CrossRef]
102. Kübler, R.V.; Seggie, S.H. The impact of COVID-19 on how core and peripheral service satisfaction impacts customer satisfaction. *J. Bus. Res.* **2024**, *182*, 114784. [CrossRef]
103. Patel, P.C.; Oghazi, P.; Arunachalam, S. Does consumer privacy act influence firm performance in the retail industry? Evidence from a US state-level law change. *J. Bus. Res.* **2023**, *162*, 113881. [CrossRef]
104. Riaz, Z.; Ray, P.; Ray, S. The impact of digitalisation on corporate governance in Australia. *J. Bus. Res.* **2022**, *152*, 410–424. [CrossRef]
105. Chen, X.; Guo, M.; Shangguan, W. Estimating the impact of cloud computing on firm performance: An empirical investigation of listed firms. *Inf. Manag.* **2022**, *59*, 103603. Corrigendum in *Inf. Manag.* **2022**, *59*, 103644. [CrossRef]
106. Oduro, S.; De Nisco, A.; Mainolfi, G. Do digital technologies pay off? A meta-analytic review of the digital technologies/firm performance nexus. *Technovation* **2023**, *128*, 102836. [CrossRef]
107. Aryal, A.; Truex, D.P.; El Amrani, R. Lessons from enterprise systems competency centers in adopting digital transformation initiatives: An assemblage approach. *Inf. Organ.* **2023**, *33*, 100490. [CrossRef]
108. Wang, Y.; Tian, Q.; Li, X.; Xiao, X. Different roles, different strokes: How to leverage two types of digital platform capabilities to fuel service innovation. *J. Bus. Res.* **2022**, *144*, 1121–1128. [CrossRef]
109. Pang, M.-S.; Tanriverdi, H. Strategic roles of IT modernization and cloud migration in reducing cybersecurity risks of organizations: The case of U.S. federal government. *J. Strateg. Inf. Syst.* **2022**, *31*, 101707. [CrossRef]
110. Huang, Q.; Xu, C.; Xue, X.; Zhu, H. Can digital innovation improve firm performance: Evidence from digital patents of Chinese listed firms. *Int. Rev. Financ. Anal.* **2023**, *89*, 102810. [CrossRef]
111. Marchiori, D.M.; Rodrigues, R.G.; Popadiuk, S.; Mainardes, E.W. The relationship between human capital, information technology capability, innovativeness and organizational performance: An integrated approach. *Technol. Forecast. Soc. Change* **2022**, *177*, 121526. [CrossRef]
112. Ostmeier, E.; Strobel, M. Building skills in the context of digital transformation: How industry digital maturity drives proactive skill development. *J. Bus. Res.* **2022**, *139*, 718–730. [CrossRef]
113. Zahedi Nejad, Z.; Sabokro, M.; Oikarinen, E.-L. Challenges in adopting and using online recruitment tools from employers' perspective. *Int. J. Organ. Anal.* **2025**, *33*, 1203–1218. [CrossRef]
114. Morton, J.; Amrollahi, A.; Wilson, A.D. Digital strategizing: An assessing review, definition, and research agenda. *J. Strateg. Inf. Syst.* **2022**, *31*, 101720. [CrossRef]
115. Pattij, M.; van de Wetering, R.; Kusters, R.J. Enhanced digital transformation supporting capabilities through enterprise architecture management: A fsQCA perspective. *Digit. Bus.* **2022**, *2*, 100036. [CrossRef]

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