

Analytics-based modeling of organizational resistance and resilience in Saudi healthcare supply chains

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ABSTRACT

This study develops an integrated analytical framework that combines partial least squares structural equation modeling (PLS-SEM) and agent-based simulation to examine and address resistance to blockchain-based digital transformation in healthcare supply chains. Data were collected from 619 healthcare supply chain professionals working in public and private organizations in Saudi Arabia. The study investigates technological, organizational, and environmental factors, with competitive intensity as a moderating variable and AI-enabled Physical Internet (AI-PI) readiness as a mitigating strategy. The structural model explains 66.5% of the variance in organizational resistance, with key drivers including technological complexity, system immaturity, high implementation costs, and limited knowledge. Simulation results indicate that AI-PI coordination can achieve up to 25% reduction in operational costs, 20% decrease in emissions, and improved disruption recovery performance. These findings provide empirical support for decision-making in the digital transformation of Saudi healthcare supply chains within the Vision 2030 framework.

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1. Introduction

Healthcare supply chains are complex socio-technical systems operating in a highly regulated environment, with demand uncertainty and critical service continuity obligations. Their actual contribution to patient safety, operational availability, and public health results is immediately apparent. Recent global shocks such as pandemics, climate-related events, and geopolitical instability have revealed structural weaknesses in healthcare supply chains and underscore the importance of advanced analytics to underpin decisions aimed at making the system resilient (Ivanov and Dolgui, 2021; Ivanov, 2021). As health care providers continue to implement digital technologies, the primary challenge is not necessarily finding technological solutions; it is understanding how naturally occurring organizational systems respond to digital transformation efforts and how those reactions can affect operational resilience.

Novel technologies, including blockchain and artificial intelligence (AI), have been frequently suggested to enhance traceability, coordination, and information transparency in healthcare supply chains. Blockchain can facilitate safe, tamper-proof data sharing, which improves transparency and trust in complex, multi-player healthcare logistics networks. Similarly, decision support tools powered by AI can perform advanced forecasting activities, such as optimizing routing and resource allocation. Although there are such technological opportunities, studies suggest that adoption results vary from organization to organization. Existing research mainly focuses on diagnosing barriers to the adoption of digital technology but generally characterizes such adoption as a binary decision and fails to analyze how organizational resistance emerges and affects system-level resilience (Saber et al., 2019; Kouhizadeh et al., 2021).

The organization's resistance to IT transformation is a multidimensional phenomenon influenced by the complexity of technology, limited capabilities, implementation costs, and institutional factors. Conventional analytical methods often oversimplify resistance as a behavioral or attitudinal outcome rather than a continuously distributed latent construct determined by an array of interacting structural factors. Structural Equation Modeling (SEM) and Partial Least Squares Structural Equation Modeling (PLS-SEM) offer a powerful

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methodological toolbox for exploring intricate relationships among latent organizational constructs and predicting transformation outcomes under data-scarce conditions (Hair et al., 2019; 2021). Although SEM has been extensively used in the technology adoption literature, little research has applied this methodology to healthcare supply chain analytics and, more specifically, organizational resistance as an outcome of reliance at the system level.

A further shortcoming found in the literature is the gap between explanatory and prescriptive analysis. Many works identify factors affecting digital transformation; however, most fail to demonstrate how intervention strategies influence system performance under disruptive scenarios. By developing simulation-based analysis tools, such as agent-based models, we can better model decentralized decision-making and network dynamics in adaptive systems. The power of these tools has been proven by the ability to model disruption propagation and resilient strategies in SC systems. A recent study also highlights the importance of combining predictive modeling and simulation to enhance supply chain resilience and digital transformation performance (Ivanov and Dolgui, 2021). However, the incorporation of SEM-based explanatory modeling and simulation-based prescriptive analytics has been under-researched in the healthcare supply chain domain.

In response to these research gaps, the present study offers an integrated analytical framework using the PLS-SEM model and agent-based simulation to investigate organizational resistance and resilience in healthcare supply chains. The framework is based on the Technological–Organizational–Environmental (TOE) framework, which organizes technological, organizational, and environmental factors that impact digital transformation outcomes (Tornatzky et al., 1990; Oliveira and Martins, 2011). Under this framework, organizational resistance is conceptualized as a latent outcome factor that enables the systematic measurement of resistance factors and the targeting of intervention efforts.

Nonetheless, the integration of SEM-based explanatory modeling with simulation-based prescriptive analytics has mainly been overlooked in healthcare supply chain studies. In addition, empirical analytics-driven research on blockchain technology-enabled change in health logistics is limited in Middle Eastern healthcare systems, especially in Saudi Arabia.

The research also presents AI-enabled Physical Internet (AI-PI) readiness as an analytic mitigation solution. The concept of the Physical Internet (PI) is an interoperable logistics network built on shared infrastructure, standardized, modular transport devices, and optimized resource utilization. AI-based PI systems generalize this, embedding predictive analytics, intelligent routing, and distributed decision intelligence. AI-PI readiness reflects an organization's ability to meet the necessary conditions for enabling interoperable data sharing,

adaptive decision support, and collaborative logistics coordination (Treiblmaier, 2019). Factoring AI-PI readiness into the resistance modeling framework enables assessments of resistance reduction and improved supply chain resilience through digital AIC, which can be used to mitigate resistance.

Empirically, the study uses survey data from 619 healthcare supply chain professionals who hold various functional and organizational positions. For the PLS-SEM part, we estimate a resistance-prediction model and test for organizational heterogeneity through moderation. Then, an agent-based simulation model is proposed to estimate the performance of AI-enabled coordination strategies in disruption scenarios, accounting for operational efficiency, sustainability, and recovery dynamics. By incorporating explanatory and prescriptive analytics into an integrated analytical workflow, this research contributes to the evidence-based decision-making process for complex health care supply chain scenarios.

The presented work makes three methodological contributions to the literature on healthcare supply chain analytics. First, employing PLS-SEM provides a novel predictive resistance modeling paradigm for measuring organizational change inhibitors. Second, it uses moderation analysis to incorporate organizational heterogeneity into a segmented intervention design. Third, it expands explanatory analytics into prescriptive decision support by adding agent-based simulation capabilities to assess resilience-oriented intervention strategies. Taken together, the research illustrates how cutting-edge analytical tools can inform digitalization and resilience planning in vital healthcare supply chain systems.

2. Literature review

2.1. Healthcare supply chain resilience as an analytics-driven system

Healthcare supply chains operate in ultra-high-reliability environments, a complex regulatory environment, and higher uncertainty in demand and supply conditions. Unlike commercial supply chains, disruptions in healthcare logistics can directly affect patient safety and public health. As a result, resilience has become a key aspect of healthcare supply chain performance. By contrast, resilience as a quantifiable system property is increasingly featured in recent literature. It is amenable to analysis via modeling and simulation, rather than being merely descriptive or decision-support in nature.

Digital supply chain twin models have been introduced as sophisticated analytical tools for evaluating resilience, with the potential to simulate the propagation of disruptions and the implementation of adaptive recovery strategies under various conditions (Ivanov and Dolgui, 2021). Thereafter, further development extended this view and proposed models of supply chain viability by

including resilience, adaptability, and sustainability as jointly integrated analyses (Ivanov, 2021). These models highlight that resilience does not rely solely on redundancy or robustness but also on system flexibility and the coordination of nodes in a supply chain.

In healthcare logistics, the agent-based methodology has recently been adopted to study the dynamics of disruption transmission and recovery. These models replicate the interactions among suppliers, healthcare providers, logistics intermediaries, and regulators in heterogeneous supply chains. Empirical studies show that it is not centralized control structures but decentralized interactions and coordination mechanisms that are necessary to achieve resilience. In addition, simulation-based health care logistics literature featuring epidemiological and demand-surge modeling has also highlighted the importance of combining operational logistics analytics with planning for healthcare system preparedness (Ivanov, 2021). Taking them together, these works cast resilience as a goal of prescriptive analytics, targeting decision policies that enhance system performance in the face of uncertainty.

2.2. Organizational resistance to digital transformation as a latent analytical construct

While the promise of blockchain, AI, and digital integration holds firm in driving an industry that relies on access to information, adoption across healthcare organizations' supply chains is far from consistent. Previous studies primarily discuss adoption barriers from a descriptive or behavioral perspective and are centered on intention-based models that emerge from technology acceptance theories. However, these methods often overlook structural barriers and capacity shortfalls that hinder the application of technology.

The Technological–Organizational–Environmental (TOE) framework offers a broad-based perspective for studying the barriers to technology adoption across multiple organizational dimensions (Tornatzky et al., 1990). In the context of TOE, technological factors comprise system complexity, compatibility, and scalability; organizational factors include financial resources, knowledge availability, and technical skills; and environmental factors include the regulatory environment and institutional support (Oliveira and Martins, 2011). Even though TOE-based research has, by and large, succeeded in mapping adoption drivers, a relatively small number of studies model resistance as a latent outcome variable embedded within interacting structural constraints.

The findings of blockchain absorptive capacity research illustrate many drivers of resistance in supply chain contexts. These include system integration complexity, interoperability issues, implementation costs, diffusion, and skill shortage, which raise the perceived severity of organizational risk and tend to decrease readiness for

implementation (Saberi et al., 2019; Kouhizadeh et al., 2021). Nevertheless, the majority of blockchain adoption literature aims to identify static barriers, without comparing them or assessing their effects on system resilience. Resistance, from an analytical perspective, is an emerging property of a system determined by the coincidence between technical demands and organizational potential. By conceptualizing resistance as a latent construct, transformation barriers can be more precisely measured, thereby yielding greater predictive power in digital transformation research.

2.3. Structural equation modeling in explanatory and predictive supply chain analytics

Structural Equation Modeling (SEM) is increasingly employed to test complex relationships between observable indicators and latent organizational constructs. Partial Least Squares Structural Equation Modeling (PLS-SEM) is well-suited for exploratory predictive modeling, complex causal systems, and data sets with non-normal distributions or lacking theoretical development (Hair et al., 2019). Recent methodological advancements in PLS-SEM focus on the rigorous validation of measures, including convergent validity, internal reliability consistency, and discriminant validity based on Heterotrait-Monotrait (HTMT) criteria (Hair et al., 2021; Henseler et al., 2015). In the supply chain literature, PLS-SEM has been used to study sustainability performance, technology adoption, and organizational capability development. However, there are a few dedicated applications for robust modeling in the health supply chain.

PLS-SEM can perform both predictive and explanatory analyses, as it outputs path coefficients, effect size measures, size measurements, and predictive indicators (R^2). These analytical results provide an opportunity to identify critical transformation barriers and to prioritize data-driven interventions. However, SEM-based studies have traditionally focused on explanatory modeling, with few associations made to prescriptive analytical tools that would enable the assessment of intervention performance under dynamic operational conditions.

2.4. Modeling organizational heterogeneity through moderation analysis

There is also a wide range of healthcare supply chains, each with distinct needs, such as size, resources, technology sophistication, and business proficiency. These differences affect the success of digital technology transformations and lead to diverse values regarding adoption. The moderation analysis in the SEM allows us to examine analytically how the structural features of an organization shape the relationship between barriers to transformation and resistance outcomes. In the literature, a firm's size is often used as a proxy for absorptive capacity,

which comprises financial power, technological experience, employees' skill sets, and managerial adaptability. As a rule, larger healthcare providers have more technological infrastructure and financial resources to shoulder the costs of adoption, including those associated with system complexity, than smaller ones (Oliveira and Martins, 2011). However, some evidence indicates that scale alone is not a guarantee of digital transformation success. Instead, the diffusion of knowledge, organizational learning capacity, and data literacy affect the success of transformation. From an analytical viewpoint, moderation analysis provides decision support for segmentation by revealing context-specific drivers of resistance across organizational sectors.

2.5. Simulation and digital twin technologies for prescriptive supply chain analytics

Although SEMs generate explanatory and predictive value, they do not assess the practical effect of transformation strategies. This is supplemented by enhanced prescriptive analytics that incorporate model-based simulation and optimization to analyze decision-making in an uncertain, dynamic operating environment. Simulation modeling is especially appealing in supply chain systems because it can capture network topology, stochastic demand, and dynamic decision-making policies. Digital supply chain twins expand on simulation by combining real-time data with computational models to predict system responses to disturbances. These analysis toolkits provide the opportunity to experiment with policy changes, such as adjusting inventory allocation, changing routing, and introducing supplier diversity strategies, before rolling them out (Ivanov and Dolgui, 2021). Agent-based simulation adds value to digital twin modelling by modelling decentralized decision-making and heterogeneous agent behavior, thereby enabling the assessment of emergent system dynamics and the propagation of unplanned disruptions. In the context of healthcare logistics, simulation-based analytical frameworks have been used to assess the readiness of systems during pandemics and in response to emergencies. The models show that joint coordination efficiency, information transparency, and adaptive resource allocation increase system resilience as disruption levels increase (Ivanov and Dolgui, 2020). Despite these progresses, there has been a limited linkage between prediction-oriented SEM-based resistance models and simulation-based prescriptive evaluation, which exposes a research shortfall.

2.6. Physical internet and artificial intelligence as coordinated logistics architecture

The notion of the Physical Internet (PI) embodies a logistics revolution based on the principles and processes that today underpin digital data networks. PI seeks to increase logistics efficiency by sharing infrastructure, using standardized modular

transport containers, and sharing logistics platforms (Montreuil, 2011). PI architecture improves supply chain coordination through resource sharing and network consolidation.

New studies demonstrate the potential of AI technologies within PI systems to enhance predictive logistics coordination and adaptive routing decisions. AI-linked PI frameworks use machine learning algorithms, distributed decision intelligence, and real-time data integration features to improve logistics performance and sustainability outcomes (Treiblmaier, 2019). The realization of AI-PI architecture is constrained by data interoperability and by the technology's maturity and readiness before an organization can operate them. Theoretically, AI-PI readiness can lower the resistance of blockchain adoption in terms of the following: a) Interoperability limitations; b) Reducing coordination uncertainty; and c) Improving decision transparency. Blockchain introduces a secure data infrastructure, and AI-PI systems introduce operational coordination and decision intelligence. The union of those technologies provides a complementary digital transformation architecture that improves visibility throughout the supply chain and reduces system sprawl. However, there is limited empirical examination of AI-PI readiness as a resistance-mitigation solution in healthcare supply chain research.

2.7. Integrating explanatory and prescriptive analytics: Identifying the research gap

While these previous studies contribute significantly to our understanding of the barriers to digitalization and resilient strategies, they share two important analytical gaps. First, while several studies present resistance drivers using descriptive or behavioral models, they often do not employ predictive analytical approaches to quantify the relative importance of these leverage points (Hair et al., 2019). Second, school-based simulation resilience studies generally assess intervention effectiveness but exclude organizational readiness or resistance to change from their analysis frameworks. Filling these gaps in the Saudi healthcare supply chain is particularly critical, as it necessitates a large-scale digital transformation that demands evidence-based assessment and evaluation mechanisms.

This distinction between explanatory and prescriptive analytics restricts the usefulness of digital transformation research. A more cohesive analytical approach that not only measures the drivers of resistance but also assesses how healthy interventions are performing, if we are going to support data-driven advocacy for transforming healthcare supply chains.

2.8. Positioning of the present study

To fill the identified research gaps, we propose an integrative analytical framework that combines PLS-

SEM resistance theory and agent-based simulation. The PLS-SEM model operationalizes resistance drivers and organizational heterogeneity, and the simulation model assesses the practical effect of AI-enabled coordination strategies in disrupted situations. By combining explanatory and prescriptive analytics, this study extends the frontier of healthcare supply chain research by connecting organizational readiness analysis with system-level resilience assessment. This holistic decision-intelligence model is a step towards supporting digital transformation planning for complex logistics arrangements in healthcare.

2.9. Conceptual research framework

This research proposes a holistic analytical framework that links enablers of resistance to digital transformation with resilience-based evaluation interventions. Fig. 1 shows the conceptual model for TOE-driven resistance, mechanisms that moderate and mediate, and simulation-based resilience assessment. The framework is based on the Technological–Organizational–Environmental (TOE) model, which categorizes barriers to transformation into technological, organizational, and environmental factors.

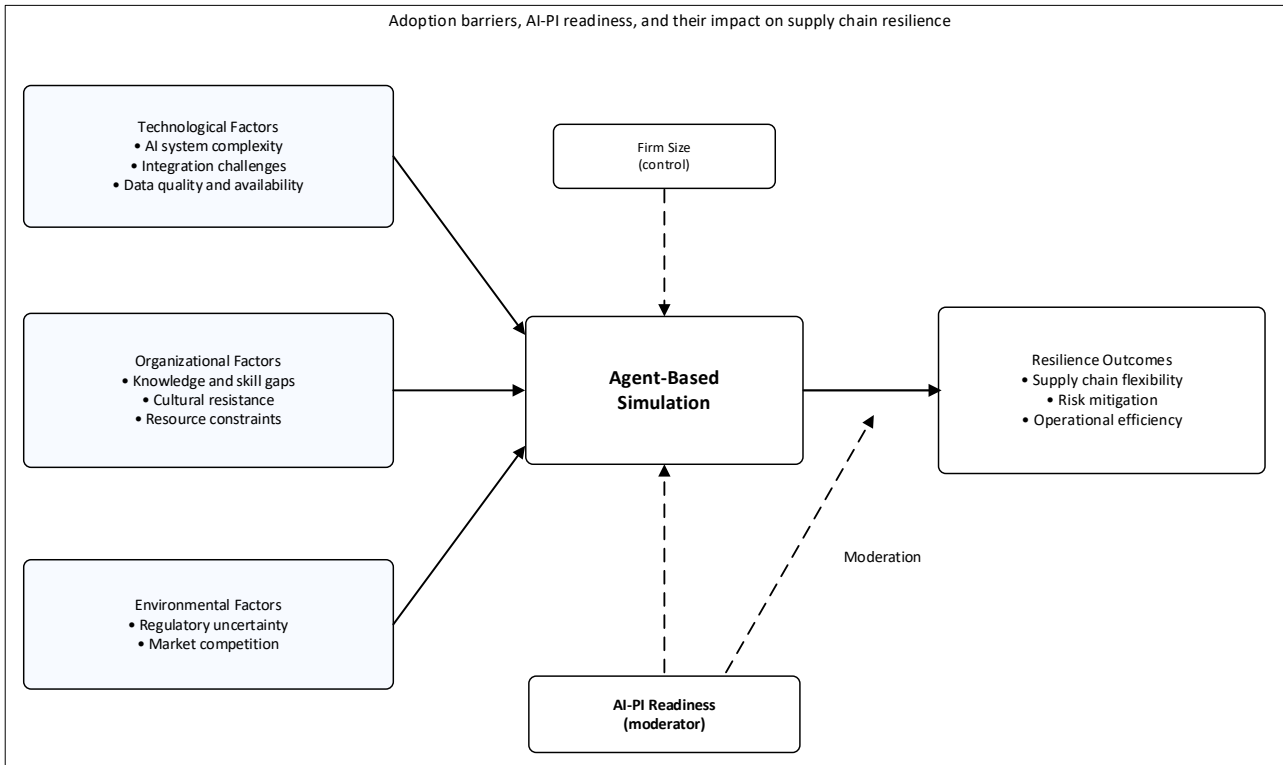


Fig. 1: Conceptual research model

Organizational resistance is conceptualized as a latent system-level response to these interacting determinants. The size of the firm is introduced as a moderating variable to reflect variation in an organization's absorptive capacity, and AI-enabled Physical Internet (AI-PI) readiness is theorized as an attenuating factor that demonstrates digital coordination capability. The framework also links explanatory resistance modeling to prescriptive agent-based simulation for analyzing resilience consequences, such as operational efficiency, sustainability performance, and disruption recovery.

3. Research methodology

3.1. Study design and analytics workflow

This research employs a quantitative cross-sectional approach, combined with explanatory, predictive, and prescriptive analytical methods, to investigate organizational resistance and resilience in the health sector supply chain. The

methodological approach integrates PLS-SEM and agent-based simulation as tools for resistance modeling and evaluation, as well as for the simultaneous evaluation of intervention performance.

The analytical process is divided into four consecutive steps. First, the drivers of resistance are conceptualized using the Technological–Organizational–Environmental (TOE) framework to categorize barriers to digital transformation. Second, data from surveys with health supply chain experts are gathered and analyzed using PLS-SEM to estimate latent resistance constructs (LRCs) and structural paths. Third, a moderation analysis assesses the extent of organizational diversity in AI-enabled Physical Internet (AI-PI) readiness across firm sizes. 4th, the PLS-SEM outcomes are operationalized as parameter inputs for agent-based intervention to assess possible interventions in perturbation scenarios. This hybrid model-building aligns with recommendations for combining predictive and simulation analytics in a complex

supply chain resilience study (Hair et al., 2019; Ivanov and Dolgui, 2021).

3.2. Data source and sampling procedure

3.2.1. Target population and sampling design

The research targets healthcare supply chain managers of procurement, logistics coordination and warehousing, planning, and operations management among public and private healthcare institutions. A purposive sampling design using snowballing was used to ensure that the research sampled only those with practical and technological knowledge (as advocated in domain-specific sampling guidelines (Etikan et al., 2016).

3.2.2. Data collection and respondent profile

The online, self-administered, structured questionnaire was administered between March and October 2025. The instrument was available for completion in Arabic and English to reduce language bias and increase response diversity. A pilot test among 280 participants was conducted to assess the clarity, reliability, and construct validity of the questionnaire.

After discounting questionnaires with missing data, 619 responses were included, a response rate of 68.8%. The demographic structure of the respondents is presented in Table 1, including gender, job position, education, work experience, and company size distribution. The mix of small and medium enterprises (SMEs) and large companies allows for modeling heterogeneity and moderation effects within the structural model.

The presence of both SMEs and large enterprises supports heterogeneity modeling through moderation, which is valuable for segmented decision support.

3.3. Construct operationalization and measurement structure

3.3.1. Organizational resistance (dependent construct)

Resistance from organizations to blockchain-facilitated digital transformation is conceptualized as the key dependent variable. Resistance is operationalized as a formative second-order latent construct with seven measures based on perceived implementation uncertainty, technological turbulence, and organizational capacity constraints. Latent-variable modeling is appropriate because resistance is a multidimensional construct that cannot be directly observed (Hair et al., 2021).

3.3.2. Predictor constructs (feature groups)

The predictor variables are grouped into three categories, with a TOE foundation, according to the

measurement framework described in Table 2. The Technological Predictors: Maturity (system); Compatibility; Scalability; Complexity; Security and privacy. The Organizational Predictors: Implementation cost, knowledge and awareness, technical capacity, Vendor lock-in risk, and Collaboration effort. The Environment Predictors: Government support, Regulatory/law environment, and Infrastructure preparedness. All predictor constructs are modeled as reflective and measured with multi-item 5-point Likert scales. The standard deviation, skewness, and kurtosis of these constructs are shown in Table 2, along with moderate to high perceived transformation barriers among respondents.

Table 1: Demographic profile of respondents (n = 619)

Variable	Category	Frequency	Percentage
Gender	Male	381	61.5%
	Female	238	38.5%
Position	CEO	15	2.4%
	EVP	11	1.8%
	CIO	16	2.6%
	IT Director	45	7.3%
	Supply chain manager	142	22.9%
	Supply chain specialist	292	47.2%
	Supply chain professional	53	8.6%
Education	Other	45	7.3%
	Diploma	84	13.6%
	Bachelor's	433	70.0%
	Master's	56	9.0%
	PhD	46	7.4%
Experience	< 1 year	71	11.5%
	1-5 years	200	32.3%
	6-10 years	97	15.7%
	11-15 years	120	19.4%
Firm size	> 15 years	131	21.2%
	SMEs	252	40.7%
	Large enterprises	367	59.3%

CEO: Chief executive officer; CIO: Chief information officer; EVP: Executive vice president

3.3.3. Moderation and mitigation constructs

Two structural enhancements are introduced to enhance segmented analysis interpretation as follows.

For the Firm Size Moderation: The size of the organization (SME/large enterprise) is a factor that allows differentiation in the capacity to detect absorptive differences, which influence resistance to change (Oliveira and Martins, 2011).

For the AI-Enabled Physical Internet Readiness, AI disruption readiness (AI-PI) is conceptualized as a formative second-order composite variable composed of digital coordination capability, data interoperability, and decision intelligence integration. This profile is based on the formative specification of digital logistics maturity and represents the multidimensional capability profile that characterizes DLM.

3.4. Descriptive statistics and data diagnostics

The descriptive statistics shown in Table 2 suggest that most constructions have means above the scale midpoint, indicating moderate to high

perceived resistance barriers in technological and organizational contexts. The observed coefficients of skewness and kurtosis are also acceptable, thus supporting the suitability of the sample for variance-

based structural modeling. The PLS-SEM is chosen for its applicability to non-normal data distributions and for its predictive nature in analytics research (Hair et al., 2019).

Table 2: Descriptive statistics and measurement structure of predictor constructs

Construct group	Construct	Model specification	Scale	Mean	SD	Skewness	Kurtosis
Technological factors	System maturity	Reflective	5-point Likert	3.42	0.88	-0.41	-0.32
	Compatibility			3.36	0.91	-0.29	-0.44
	Scalability			3.58	0.86	-0.47	-0.21
	Complexity			3.81	0.79	-0.62	0.18
	Security and privacy			3.49	0.90	-0.35	-0.27
Organizational factors	Implementation cost			3.92	0.76	-0.71	0.36
	Knowledge and awareness			3.74	0.82	-0.58	0.11
	Technical capacity			3.51	0.87	-0.33	-0.30
	Vendor lock-in risk			3.29	0.94	-0.18	-0.49
	Collaboration effort			3.46	0.89	-0.26	-0.34
Environmental factors	Government support			3.21	0.96	-0.14	-0.58
	Regulatory and legal environment			3.18	0.98	-0.09	-0.61
	Infrastructure preparedness			3.33	0.92	-0.22	-0.46

SD: Standard deviation

3.5. Hypothesis development and model specification

This structural model will examine the drivers of predictive resistance, organizational heterogeneity, and constraining mechanisms. Three sections formulate the hypothesis framework described in Table 3.

For the Main Predictive Effects, 14 hypotheses (H1-H13) have been developed to test the direct effects of technological, organizational, and environmental predictors on organizational resistance. These theories of resistance assess the

major drivers of transformation and enable predictive resistance modeling.

For the Moderation Effects, H14–H17 integrate corporate size as a moderator that guides segmented decision analytics by cost, knowledge, expertise, and infrastructure constraints.

For the Mitigation Effect, Hypothesis H18 assesses AI-PI readiness as an intervention vehicle for blunting resistance driver influences and enhancing transformation readiness.

Such an organized hypothesis architecture can eliminate model overcomplications and correlate intervention efficacy.

Table 3: Hypotheses summary (analytics-oriented)

Group	Hypotheses	Relationship type	Purpose
Technological predictors	H1-H5	Main effects on resistance	Predict key technical drivers
Organizational predictors	H6-H10	Main effects on resistance	Predict readiness/capability drivers
Environmental predictors	H11-H13	Main effects on resistance	Assess institutional constraints
Firm-size heterogeneity	H14-H17	Moderation	Segmented decision analytics
AI-PI mitigation	H18	Moderation/mitigation	Intervention lever for resistance reduction

3.6. Model estimation, simulation development, and validation

3.6.1. PLS-SEM estimation and model validation

The analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, following the established protocol for variance-based structural modeling (Hair et al., 2021). Estimation was conducted, and the measurement and structural models were assessed to determine construct reliability, validity, and predictive power.

Validation of the measurement model primarily focuses on assessing internal consistency, reliability, convergent validity, and discriminant validity. Internal consistency reliability was established using Cronbach's Alpha and Composite Reliability, both of which exceeded 0.70. Convergent validity was determined using Average Variance Extracted (AVE), with values above 0.50 considered good. Standardized loadings of 0.70 or more establish indicator reliability. Discriminant validity was tested using the HTMT ratio, by adopting its recommended

threshold of 0.85 to ensure a unique construct (Henseler et al., 2015).

Structural model testing was based on predictive and explanatory adequacy. The path coefficient (β) predictive power was tested with the coefficient of determination (R^2), and effect size (f^2) was employed as a measure of how the predictor constructs contributed relatively. A bootstrapping method with 5,000 resamples was used to test the significance of path coefficients. Interaction path analysis was used to test the moderating effects of firm size and AI-enabled Physical Internet (AI-PI) readiness on resistance relationships.

Procedural and statistical checks were run to document potential response biases. Standard method bias and non-response bias were tested by comparing responses from early and late mail survey returns and through complete collinearity tests.

3.6.2. Agent-based simulation model development

The Agent-Based Model has been developed to continue predictive modeling into prescriptive

decision analytics to assess HSC resilience under disruption scenarios. A simulation model was developed in AnyLogic 8.8 that integrates ABM and DEM, enabling the simultaneous modeling of complex, multi-level supply chain systems.

The simulation is a healthcare logistics network that includes medical providers, distribution centers, healthcare facilities, and logistics intermediaries. Each node in the supply chain is represented as an independent agent following a pre-defined strategy for inventory management, route choice, and coordination. This decentralized model architecture enables the representation of dynamic interactions and emergent system dynamics under disruptive conditions. The simulation parameters were validated through empirical surveys and reliable resilience modelling benchmarks in previous works on SC risk management (Ivanov and Dolgui, 2021). Calibration parameters included the severity of demand surge, the probability distribution of transportation delay, the frequency of supplier failures, and inventory policy settings. Two types of coordination were developed to test the intervention's effectiveness. The baseline model represents traditional decentralized coordination without advanced digital decision support. The intervention considers AI-PI facilitated coordination through predictive demand forecasting, adaptive routing optimization, and shared logistics resource pooling. The performance of the simulations was assessed using three types of outcome measures. Order fulfillment cycle time and logistics throughput were used as operational efficiency measures. The carbon-emission proxy indicators were used to assess corporate sustainability performance. System robustness was measured by the average recovery time of disruption events.

Sensitivity analysis and testing against extreme-case scenarios were used to test the validity of the simulation model. 100 simulations were conducted for each scenario to ensure the statistical robustness and reliability of the simulation results.

3.6.3. Ethical compliance

This investigation adhered to the institution's research ethics guidelines. Responses were voluntary, informed consent was obtained from all participants, and privacy and confidentiality were ensured throughout data collection and analysis. The study received ethical approval from the Effat University Research Ethics Committee.

4. Results

This section presents the empirical results of the structural and simulation models used to examine resistance and resilience in the Saudi healthcare supply chain. The study discusses the model fit, the relevance of constraints in inducing resistance, the impacts of varying conditions, and potential solutions derived from simulations in line with current best practices in data research.

4.1. Measurement model assessment

The validity and reliability of the measurement model were established before performing structural modelling to ensure the operationalization of latent constructs was robust. Internal consistency reliability was established, as all constructs exceeded the recommended cutoffs for Cronbach's alpha and CR ($CR \geq 0.70$). The average variance extracted (AVE) for each construct was greater than 0.50, indicating convergent validity, i.e., the indicators adequately represent the latent constructs.

Examination of indicator reliability showed that standardized factor loadings were above the cutoff of 0.70, supporting strong indicator contribution to construct measurement. The HTMT ratio was used to test discriminant validity. HTMT values were all below the cutoff of 0.85, suggesting that construct distinctiveness has been achieved and that the measurement model is adequate (Hair et al., 2021; Henseler et al., 2015). These findings indicate that the measurement model is reliable and valid, and that we can proceed with the estimation of the structural model.

4.2. Structural model performance and predictive capability

The structural model was assessed using R^2 and effect size measures. The model has good predictive ability, accounting for 66.5% of the variance in organizational resistance ($R^2 = 0.665$) and an adjusted R^2 of 0.652. Such a level of prediction is considered strong in organizational and behavioral modeling environments, suggesting that technological, organizational, and environmental factors together account for variation in resistance to the healthcare supply chain.

Analytically, these findings confirm the key hypothesis that resistance is a quantifiable, latent outcome rather than just a behavior pattern or attitude. The findings also support the utility of PLS-SEM for estimating complex socio-technical relationships in the healthcare logistics setting. Positive coefficients indicate that as people see more barriers, they resist more. Negative coefficients indicate that when people feel less capable (lower in maturity, scale, and knowledge), they resist more. The cost of change, among all factors, exerts the most significant and positive impact ($\beta = 0.166$). Information and awareness gaps, and scaling constraints follow this. This is a reminder, however, that resistance is not about abstract technological risks but whether changes are affordable, scalable, and whether the organization can learn. No matter the security and privacy concerns, vendor lock-in risk, cooperation effort, and all other factors (such as government support, regulations, or IT infrastructure), they were all important. This is a statement that, in an enabling and well-resourced environment, resistance stems primarily from internal readiness and capacity issues rather than external governance barriers.

4.3. Direct effects of resistance drivers

Results of hypothesis tests show that organizing resistance is dominated by technical and organizational skill constraints, and that environmental constraints on resistance behavior in organizations have a weak influence. Based on Table 4, the direct effect finding indicates that all five predictor constructs have significant contributions to organizational resistance.

4.4. Moderation effects and organizational heterogeneity

The moderation analysis examined the impact of organizational scale on resistance relationships. The findings reported in Table 5 indicate that the interactions between firm size and specific salient resistance drivers are statistically significant. The impact of firm size on the relationship between implementation costs and resistance is highly significant, indicating that larger firms exhibit comparatively weaker cost-induced resistance effects. Likewise, firm size also moderates knowledge gap effects, the absence of technical expertise, and infrastructure limitations. The above results indicate that larger organizations have stronger absorptive capacity and can reduce resource-based conversion costs more effectively.

However, the small number of significant moderation interactions suggests that organizational size itself does not remove resistance to change. This aligns with previous research, which suggests that

digital transformation success depends not only on structural size but also on organizational learning capability and analytical maturity (Oliveira and Martins, 2011). It is found that AI-PI-based coordination enables a 25% increase in operational efficiency and reduces emissions by around 20%, while recovering faster than traditional recovery processes after disruptions. Such results justify the prescriptive use of analytics-informed intervention design and illustrate how AI-supported coordination not only helps overcome perceived resistance but also provides tangible system-level resilience.

4.5. Mitigation effect of AI-enabled physical internet readiness

AI-PI readiness was conceptualized as a proximal mitigating factor rather than an independent driver of resistance. The structural findings show a significant adverse moderation effect of AI-PI preparedness on the influence of dominant resistance drivers. This finding is theoretically important because it shows that resistance balances as a static attribute of the organization rather than as a dynamic outcome of its digital coordination capability. AI-PI readiness promotes interconnectivity, enhances decision visibility, and reduces coordination uncertainty, thereby mitigating transformation barriers.

The moderating role also contributes to the theoretical integration of blockchain adoption barriers with AI-based logistics coordination architectures, a key gap in prior literature.

Table 4: Direct effects on organizational resistance

Hypothesis	Path	β	p-value	Outcome
H1	Complexity to resistance	0.079	0.001	Supported
H2	Maturity to resistance	-0.110	0.008	Supported
H4	Scalability to resistance	-0.125	0.002	Supported
H6	Implementation costs to resistance	0.166	< 0.001	Supported
H7	Knowledge and awareness of resistance	-0.147	0.009	Supported
H3, H5, H8-H13	-	-	> 0.05	Not supported

Table 5: Significant firm size moderation effects

Interaction term	β	p-value
Firm size \times implementation costs	-0.091	0.021
Firm size \times knowledge and awareness	-0.088	0.030
Firm size \times technical expertise	-0.082	0.041
Firm size \times infrastructure	-0.079	0.047

4.6. Simulation-based prescriptive analytics results

The agent-based simulation results operationalize the explanatory findings of the PLS-SEM model by evaluating how analytically informed coordination interventions influence healthcare supply chain resilience under disruption scenarios. Specifically, AI-enabled Physical Internet (AI-PI) coordination strategies were assessed against baseline decentralized coordination to examine operational efficiency, environmental sustainability, and recovery performance. To bridge the gap between explanatory and prescriptive decision support, agent-based simulation experiments were conducted to assess the supply chain's resilience

under different types of disruptions. The simulation compares the baseline decentralized coordination with AI-PI-assisted strategies. The findings presented in Table 6 indicate a significant difference in the performance of coordination methods.

Simulation outcomes indicate that AI-PI-enabled coordination achieves up to a 25% reduction in total logistics operating costs, approximately 20% reduction in emissions-related indicators, and significantly shorter disruption recovery times compared to traditional coordination structures. These prescriptive analytics results demonstrate how resistance-mitigating digital coordination capabilities translate into tangible gains in system-level resilience. Detailed scenario-specific results and sensitivity analyses are reported in Table 6.

AI-PI increased operational efficiency by 25% compared to baseline comparisons. The intervention also lowered proxy metrics for carbon emissions by one-fifth, supporting performance improvements in sustainability initiatives. Further, AI-enabled

coordination led to a drastic reduction in recovery time after disruptions while enhancing supply chain resilience. From a systems analysis perspective, these findings demonstrate that digital coordination power reduces organizational resistance and ultimately provides a measurable improvement in

system-level performance. The combination of predictive resistance modeling with simulation-based assessment provides a concrete basis for deploying AI-enabled logistics architecture as a practical resilience intervention measure.

Table 6: Simulation outcomes under disruption scenarios

Scenario	Operational efficiency change	Emissions change	Recovery speed
Baseline coordination	-	-	Slow
AI-PI-enabled coordination	+25%	-20%	Fast

4.7. Integrated analytical interpretation

The integrated PLS-SEM and simulation findings provide a coherent storyline based on our theoretical model, moving from resistance drivers to the operational resilience outcome. The determined transformation barriers also indicate that the dominant mechanism can be used to generate performance advantages, as confirmed by simulation experiments. This is to overcome the traditional separation between explanatory and prescriptive analytics in the digital transformation literature. By integrating organizational readiness modelling with intervention performance assessment, the present research offers an integrative analytical framework for evidence-based planning of healthcare supply chain transformation.

5. Discussion

The purpose of this research was to develop and test a new approach to conceptualizing and enhancing the handling of problems in the healthcare supply chain. The scientists employed two techniques: one to describe why problems arise and another to solve them. They accomplished this using data analysis and experiments. The report considers the findings, considering contemporary ideas about data analysis, and speculates what they might mean for the field.

5.1. Explanatory analytics: Modeling organizational resistance as a predictive system outcome

The explanatory part of the present research reveals that resistance to an organization's adoption of blockchain-based digital transformation can be perceived as a measurable latent construct affected by the interplay between technological and organizational readiness barriers. The structural model had good predictive capacity, accounting for 66.5% of the variability in resistance. This result validates the analytical thesis that resistance is not just a behavioral and/or attitudinal phenomenon; it is indeed an organizational effect influenced by the system's complexity, the level of capability development, and resource allocation dynamics.

These findings contribute to a theory of resistance and a descriptive analytics approach by reframing the analytical orientation from intentions

to adopt to modelling resistance in the predictive system-level variable. Most existing conventional technology acceptance frameworks emphasize motivational factors, including perceived usefulness and behavioral intention. The results establish that implementation feasibility constraints, in particular technological complexity and organizational capability deficiencies, are more critical determinants of transformation outcomes. This meaning is consistent with the new research on supply chain analytics, which stresses that the adoption of technology by itself does not determine success but rather operational readiness for transformation (Hair et al., 2019).

The dominance of technological maturity and scalability is an evident indication of the importance of digital infrastructure readiness as a prerequisite for transformation in healthcare supply chains. The mobility of healthcare logistics systems also requires a high level of system reliability and service continuity, which heightens organizations' sensitivity to technical performance uncertainty. Resistance, it reported, can thus be viewed as a sensible organizational reaction to the perceived risk posed by an innovation, rather than a barrier deliberately chosen and implemented against an organization's best interests.

5.2. Reinterpreting environmental non-significance through an analytics perspective

A significant explanatory finding of this analysis is the lack of statistical significance for environmental determinants, including regulatory features, government incentives, and infrastructure availability. Though these elements are often emphasized in the literature on digital transformation, their limited explanatory power suggests that institutional readiness serves as a boundary condition rather than a primary driver of change.

Analytically, this result emphasizes the difference between enabling and predictive factors. Institutional support and regulatory conditions may be important antecedents to digital transformation, but they do not necessarily account for differences in transformation outcomes when minimum institutional requirements are met. This view aligns with previous supply chain transformation literature, which claims that organizational capabilities maturity and knowledge absorption

mechanisms are better predictors of successful transformation than macro-environmental conditions (Oliveira and Martins, 2010). Furthermore, the lack of significance for security and privacy concerns could indicate healthcare entities favor operational practicality and deployment scalability over theoretical technology risks. This result challenges traditional assumptions in the blockchain adoption literature, which commonly assume that security issues are the primary barriers to change. Instead, the findings suggest that practical effort burden and organizational learning needs are the main drivers behind resistance in the healthcare logistics context.

5.3. Organizational capability and cost constraints as dominant predictive drivers

Among all predictors of resistance, implementation cost and the lack of organizational knowledge emerged as the most powerful explanatory variables. These results contribute, first and foremost, to understanding the economic vs. cognitive drivers of resistance to digital transformations. The cost of implementation affects resistance to change by increasing the risk of investment and complicating the cost-benefit calculus. Without a solid analytical forecasting mechanism to estimate return on negative investment, perceived implementation risk increases because the upfront investment is significant. From an explanatory analytics perspective, cost-related resistance can be seen as an effect of decision uncertainty and not simply financial constraints.

Likewise, knowledge gaps and awareness deficits play a critical role in the effectiveness of transformation outcomes by limiting the organization's ability to interpret digital system outputs and incorporate analytical decision support into its operational processes. These results are consistent with the nascent idea of analytic opacity, in which pushback arises from a lack of interpretability regarding how system performance and functionality translate into organizational functions. This interpretation is especially relevant to the healthcare settings where decision responsibility and service reliability place limitations on how these services can operate.

5.4. Moderation effects and organizational heterogeneity in transformation analytics

Moderation analysis sheds light on this issue by revealing that resistance to organizational change differs across the structural and capability dimensions. Firm size strongly moderates several of the resistance pathways, with large healthcare organizations demonstrating greater absorptive capacity to cope with implementation costs, technical expertise demands, and infrastructure limitations.

Nevertheless, the small number of significant moderate effects suggests that large organizations

are not necessarily well prepared for transformation on their own. These results support the theoretical separation between structural scale and capability maturity. Absorptive capacity is composed of organizational learning, data literacy, and decision-making discretion, which are not necessarily indivisibly related to company size. From an analytical model perspective, segmentation variables, including firm size, should thus be viewed as conditional have puts rather than primary explanatory overdependencies.

5.5. Transition from explanatory to prescriptive analytics

Whereas explanatory analytics uncovers the structural causes of a system's resistance to change, prescriptive analytics assesses interventions conducive to enhancing performance under operational uncertainty. One of the significant contributions of this research is the incorporation of the SEM-based resistance model into agent-based simulation for intervention assessment.

Considering AI-PI readiness as a mitigation tool introduces a shift from descriptive transformation analysis to intervention-oriented analytics. By conceptualizing resistance not as a static feature of the organization but as something that can be dismantled step-by-step through increased digital coordination capabilities, the theoretical model also shows how resistance is overcome.

This holistic analytical perspective aligns with the call for hybrid modeling frameworks that connect organizational readiness diagnosis to operational performance assessment (Ivanov and Dolgui, 2021).

5.6. Prescriptive insights from simulation-based coordination strategies

Simulation results provide empirical evidence in favor of the prescriptive nature of AI-based logistics coordination mechanisms. AI-PI coordination led to substantial improvements in operational requirements, sustainability performance, and disruption recovery time compared to baseline coordination cases.

From a prescriptive analytics perspective, our findings support the idea that AI-augmented coordination mechanisms act as decision accelerators, enabling healthcare supply chains to adapt to disruption scenarios proactively. Predictive demand, dynamic routing, and shared resource coordination work in synergy to enhance system transparency and reduce information asymmetry between supply chain nodes.

Crucially, these simulation results suggest that digital coordination technologies improve decision quality rather than removing decision-making authority from humans. Human collaboration with AI in this hybrid coordination structure is essential in healthcare supply chains, where operational decisions entail complex trade-offs among cost, service, and patient safety.

5.7. Theoretical integration of blockchain infrastructure and AI-enabled physical internet coordination

Conceptually, one significant contribution is the applied empirical link between blockchain adoption barriers and an AI-enabled Physical Internet coordination architecture. Blockchain applications primarily focus on data integrity, traceability, and trust-building among stakeholders in supply chain networks. However, the blockchain does nothing to alleviate this tactical coordination complexity or decision-making latency.

By doing so, AI-PI systems support blockchain infrastructure through predictive logistics coordination, distributed decision intelligence, and real-time operational optimization. The results of this research reveal that AI-PI readiness mitigates constraints on the predominant resistance drivers to blockchain adoption by enhancing interoperability, reducing coordination uncertainty, and increasing operational scalability. This synergy underscores the importance of unified digital transformation architectures over individual technology adoption approaches.

5.8. Implications for analytics science and supply chain engineering

From the perspective of analytics science, this research has enabled the development of hybrid analysis frameworks combining latent-variable modeling and simulation-based experimentation. Results show that behavioral phenomena in an organization, such as resistance, can be measured and operationalized within a predictive modelling framework, thereby providing insight into the type of analysis conducted in research on supply chain transformation. This means that, from a supply chain engineering perspective, it also underscores the need to develop digitization strategies based on technological capabilities, with organizational readiness in mind. Modular solutions: interoperability and transparent system design will reduce resistance and increase the sustainability of long-term adoption.

5.9. Synthesis: Analytics as a mechanism for understanding and shaping transformation behavior

The integrated explanatory and prescriptive analytic approach in this work supports a central tenet of analytics theory: that analytics not only predicts system behavior but can also shape behavior through intervention design. Through measuring resistance drivers and assessing mitigation strategies, analytics can turn resistance from an institutional obstacle into a surmountable system parameter.

This unifying analytical point of view augments healthcare supply chain transformation research by

blending organizational behavior modeling with operations performance optimization, thereby delivering a decision-intelligence framework that can facilitate digital transformation planning in complex healthcare logistics systems.

6. Conclusions

This research developed and validated an integrated analytical framework to examine organizational resistance and resilience in Saudi Arabian healthcare supply chains undergoing blockchain-enabled digital transformation. By combining Partial Least Squares Structural Equation Modeling (PLS-SEM) with agent-based simulation, the research provides a hybrid analytical approach that simultaneously identifies transformation barriers and evaluates intervention effectiveness under disruption conditions within the Saudi healthcare logistics ecosystem. The results demonstrate that organizational resistance in Saudi healthcare supply chains is a measurable and predictable outcome, influenced primarily by technological complexity, limitations in system maturity, implementation costs, and organizational knowledge gaps. The structural model explained a substantial proportion of resistance variance, confirming the suitability of predictive analytics for modeling transformation readiness in Saudi healthcare logistics environments.

From an applied engineering perspective, the findings demonstrate that resistance to digital transformation in Saudi Arabia's healthcare sector is strongly associated with operational feasibility and organizational capability maturity rather than external institutional constraints. The limited influence of regulatory and environmental predictors reflects the Kingdom's strong institutional support for healthcare digitalization through national initiatives such as Vision 2030 and the National Transformation Program, as well as centralized procurement strategies led by entities such as the National Unified Procurement Company (NUPCO). These findings provide practical guidance for Saudi healthcare supply chain managers by emphasizing the importance of capability development strategies focusing on knowledge diffusion, technical workforce training, and scalable system architecture design.

The integration of AI-enabled Physical Internet (AI-PI) readiness as a mitigation mechanism represents a significant applied contribution of this research within the Saudi transformation context. The results indicate that AI-enabled logistics coordination significantly reduces resistance intensity by improving interoperability, transparency in coordination, and integration of decision intelligence across Saudi healthcare logistics networks. Simulation-based evaluation further demonstrates that AI-PI coordination strategies improve operational efficiency, reduce sustainability-related emissions, and accelerate disruption recovery performance under high-

demand conditions characteristic of the Saudi healthcare environment, including seasonal demand surges during events such as Hajj and pandemic-related emergency responses.

From an operational implementation perspective, the research provides decision-support insights for Saudi healthcare organizations planning digital transformation initiatives. The results suggest that transformation strategies within Saudi Arabia should prioritize incremental capability development rather than large-scale technology deployment. Modular implementation approaches that integrate blockchain infrastructure with AI-enabled coordination systems are more likely to reduce transformation risk and improve the long-term sustainability of adoption in Saudi healthcare supply chains. Additionally, simulation-based evaluation provides Saudi policymakers and healthcare organizations with a practical decision-support tool that enables testing of digital transformation policies under disruption scenarios before full-scale national implementation.

From a scientific contribution perspective, this research advances supply chain analytics research by demonstrating the value of integrating explanatory and prescriptive analytical methodologies within a Middle Eastern healthcare transformation context. The proposed framework illustrates how latent-variable modeling can be combined with simulation-based experimentation to support evidence-based decision making in complex socio-technical systems. Within the Saudi Arabian context, this hybrid analytical approach contributes to the development of decision-intelligence frameworks supporting national healthcare logistics modernization and digital transformation initiatives aligned with Vision 2030. Despite its contributions, the research has several limitations. First, the research relies on cross-sectional survey data collected from Saudi healthcare supply chain professionals, which limits the ability to evaluate longitudinal transformation dynamics as digital transformation initiatives continue to evolve under Vision 2030. Second, the simulation model represents a generalized Saudi healthcare supply chain structure rather than a fully operational real-time digital twin. Third, while the empirical data capture major healthcare hubs such as Riyadh and Jeddah, regional variations in infrastructure readiness across Saudi Arabia may influence transformation outcomes.

Future research should extend this framework by incorporating longitudinal datasets to evaluate the evolution of transformation maturity across Saudi healthcare sectors over time. The integration of real-time operational data from national healthcare logistics platforms such as NUPCO or emerging innovative healthcare initiatives would improve intervention precision and enhance the reliability of practical implementation. Comparative studies across Gulf Cooperation Council (GCC) healthcare systems may also provide deeper insight into how institutional readiness and digital infrastructure

maturity influence transformation resistance across regional healthcare supply chains.

In conclusion, this research demonstrates that organizational resistance in Saudi Arabian healthcare supply chains can be systematically analyzed and mitigated using advanced analytics and simulation-based intervention design. The findings highlight the importance of integrating technological capability development with organizational readiness strategies to support sustainable digital transformation of the healthcare supply chain in Saudi Arabia. By providing a structured analytical framework linking resistance modeling with resilience intervention evaluation, the research offers practical and scientific insights that support the development of robust, adaptive, and digitally coordinated healthcare logistics systems aligned with Saudi Arabia's Vision 2030 ambitions.

List of abbreviations

ABM	Agent-based modeling
AI	Artificial intelligence
AI-PI	AI-enabled Physical Internet
AVE	Average variance extracted
CEO	Chief executive officer
CIO	Chief information officer
CR	Composite reliability
DEM	Discrete event modeling
EVP	Executive vice president
GCC	Gulf Cooperation Council
HSC	Healthcare supply chain
HTMT	Heterotrait-monotrait ratio
IT	Information technology
LRC	Latent resistance construct
LRCs	Latent resistance constructs
NUPCO	National Unified Procurement Company
PI	Physical Internet
PLS-SEM	Partial least squares structural equation modeling
RCI_REC	Research ethics committee reference code
R ²	Coefficient of determination
SC	Supply chain
SD	Standard deviation
SEM	Structural equation modeling
SME	Small and medium-sized enterprise
TOE	Technological-organizational-environmental

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Compliance with ethical standards

Ethical considerations

This study adhered to internationally recognized ethical standards, including the principles outlined in the Declaration of Helsinki and its amendments. Ethical approval was granted by the Research Ethics Committee of Effat University (Decision No.

RCI_REC/12.Marh.2025/7-7.1.Exp./1(103); approval date: March 12, 2025). All participation was voluntary, and respondents provided informed consent before participating in the study. Participants were thoroughly briefed on the research aims, methods, potential risks, and their rights to privacy, anonymity, and the right to withdraw at any time without repercussions. The collected data were anonymized and used exclusively for scholarly research purposes.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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