Building Supply-Chain Resilience in Healthcare Via AI-Driven Scenario Planning and Multi-Tier Inventory Optimization

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Abstract

Healthcare supply chains face unprecedented volatility arising from fluctuating patient demand, regulatory shifts, and global disruptions. This paper presents an integrated framework coupling deep generative scenario planning with a multi-tier distributionally robust inventory optimization model to enhance resilience across hospital networks. The scenario planning module employs a conditional variational autoencoder augmented by normalizing flow layers to learn complex demand distributions from heterogeneous time-series and exogenous event streams. Generated latent trajectories are clustered via Wasserstein barycenter methods to form a balanced scenario tree capturing tail risks and regime shifts.The inventory optimization component formulates a two-stage distributionally robust mixed-integer program that enforces service-level chance constraints under ambiguity sets defined by ϕ-divergences, and integrates conditional value-at-risk measures to bound loss in extreme states. Decision variables span manufacturers, central warehouses, regional hubs, and hospitals, incorporating perishability, capacity, and lead-time correlations. A custom branch-and-price algorithm with Benders-driven cut generation and dual stabilization solves large-scale instances within operational horizons. Experiments on a synthetic network with 150 products and 200 hospitals demonstrate a 42% reduction in stockouts, a 15% decrease in holding costs, and maintenance of 99% service levels under simulated pandemic scenarios. Sensitivity analysis over ambiguity radii and risk-aversion parameters traces a convex trade-off surface. The framework's modular architecture supports seamless integration with ERP platforms and streaming analytics, offering a powerful decision support system for proactive resource allocation in volatile healthcare environments.

1 Introduction

The modern healthcare ecosystem relies on complex supply chains that encompass pharmaceutical manufacturers, central distribution centers, regional hubs, and hospital pharmacies [1]. Unlike retail or manufacturing contexts, healthcare demands are mission-critical and highly perishable, where stockouts can directly impact patient outcomes [2]. Traditional inventory management approaches grounded in deterministic forecasts and static safety-stock rules inevitably fail to capture the heavy tails and temporal correlations inherent in demand signals influenced by seasonal epidemics, regulatory changes, and global crises such as pandemics or supply-side collapses. These shortcomings manifest as cascading shortages or waste from expired stock, imposing both economic burdens and clinical risks. [3]

Recent advances in artificial intelligence offer new avenues to model demand uncertainty more faithfully [4]. Generative models, including variational autoencoders (VAEs), normalizing flows, and diffusion processes, can learn complex joint distributions over multivariate time series and exogenous indicators. By sampling from such models, decision makers obtain plausible future demand trajectories that reflect both frequent fluctuations and rare extreme events [5]. However, integrating generated scenarios into tractable inventory optimization poses challenges: naive scenario sampling can lead to combinatorial explosion, and classical stochastic programs struggle under distributional ambiguity.

In response, this paper develops a unified framework that harnesses AI-driven scenario planning to produce a balanced scenario tree whose branching factors adapt to local volatility [6]. The tree's leaf nodes represent extreme demand realizations tied to stress factors such as supply disruptions or demand spikes [7]. A multi-tier distributionally robust optimization (DRO) model then determines base ordering quantities and dynamic safety buffers to minimize worst-case expected cost subject to service-level constraints. The DRO formulation incorporates ϕ-divergence ambiguity sets calibrated from historical residuals and embeds conditional value-at-risk (CVaR) to limit tail losses [8]. By capturing ambiguity in scenario probabilities, the model guards against mis-specification risk. [9]

Key contributions include: (1) a neural-augmented pipeline combining CVAE and flow models for demand scenario generation; (2) a clustering-based tree construction algorithm using Wasserstein barycenters for scenario reduction; (3) a two-stage distributionally robust mixed-integer program with multistage recourse and chance-constrained service guarantees; (4) a tailored branch-and-price algorithm integrating stabilized Benders cuts for computational tractability; and (5) an extensive computational study demonstrating significant resilience gains in large-scale healthcare networks. The remainder of this paper is organized as follows [10]. Section 3 formalizes the problem setting and system architecture. Section 4 details the AI-driven scenario planning framework [11]. Section 5 develops the distributionally robust inventory optimization model [12]. Section 6 describes the solution methodology. Section 7 reports computational experiments [13]. Section 8 discusses managerial implications and future extensions [14]. Section 9 concludes.

2 Problem Setting and System Architecture

Consider a supply chain with product set $\mathcal{P}$, manufacturers $\mathcal{M}$, central warehouses $\mathcal{W}$, regional hubs $\mathcal{R}$, and hospitals $\mathcal{H}$. Time is discretized into periods $t = 1, \ldots, T$ [15]. Each product p has shelf life L_p, and shipments between nodes incur lead time ℓ_{ij}^p and capacity C_{ij}^p. Demand at hospital h for product p in period t is a random variable D_{hpt} influenced by latent factors such as seasonality, epidemiological indicators, and exogenous shocks. Real-time telemetry provides on-hand inventories $I_{j,p,t-1}$ and historical consumption series.

The decision process unfolds in rolling horizons: at each decision epoch t_0, the AI module constructs a scenario tree $\mathcal{T}$ over periods $t_0, \ldots, T$ whose nodes represent joint demand realizations across (h, p, t). Transition probabilities are ambiguous within ϕ-divergence balls around empirical scenario frequencies. The optimization engine solves a two-stage DRO with first-stage decisions determined prior to demand realization (order quantities x_{ij,p,t_0} and safety buffers y_{j,p,t_0}) and second-stage recourse decisions (expedited orders $z_{ij,p,t,n}$, transshipments $u_{ij,p,t,n}$, and unmet demand penalties $s_{h,p,t,n}$) contingent on tree node n outcomes.

The architecture comprises: (i) a data ingestion layer aggregating ERP, EHR (electronic health record) consumption, and external data feeds; (ii) a deep generative modeling component producing latent samples and decoding to demand trajectories; (iii) a scenario reduction and tree-building module using k-means in Wasserstein space; (iv) a DRO formulation builder generating a mixed-integer program; (v) a solver interface implementing branch-and-price with Benders decomposition; (vi) a monitoring dashboard to visualize key metrics and re-optimization triggers; and (vii) an ERP connector to push order recommendations and receive execution feedback. [16]

3 AI-Driven Scenario Planning Framework

We formalize the scenario planning as the generation of a scenario tree $\mathcal{T} = (\mathcal{N}, \mathcal{E})$ rooted at current state n_0. For each node $n \in \mathcal{N}$ at period $t(n)$, we estimate a conditional demand distribution P_n via a normalizing flow f_ψ composed with a CVAE encoder-decoder pair parameterized by ϕ. The encoder maps historical demand history $H_{t-1} = \{D_{h,p,\tau}\}_{\tau<t}$ to latent variable $Z_n \sim \mathcal{N}(\mu_n, \Sigma_n)$, and the decoder yields demand sample $D_{h,p,t:t+\Delta} = g_\phi(Z_n, H_{t-1})$. A trained normalizing flow refines decoder outputs to match higher-order moments. [17]

To construct a finite tree, at each node we sample N_z latent draws and decode to N_d demand trajectories, yielding $N_z \times N_d$ candidate branches. We compute pairwise Wasserstein distances $W(\cdot, \cdot)$ between trajectories using efficient Sinkhorn algorithms [18]. We then solve a clustering problem to select B_t branch representatives per node: [19]

$$\min_{\{c_j\}_{j=1}^{B_t}} \sum_{i=1}^{N_z N_d} \min_{j=1,\ldots,B_t} W\big(\tilde{D}^i, c_j\big),$$

with cluster centroids c_j forming child nodes. Transition probabilities $p_{n \to j}$ are set proportional to cluster sizes adjusted by reconstruction log-likelihood scores. This produces a balanced tree with controlled branching factors $B_{t_0}, B_{t_1}, \ldots$.

The framework supports online updates: as real-time data arrives, the tree is pruned and re-grown in affected subtrees using incremental clustering to avoid full recomputation [20]. Alternative generative modules, such as diffusion models with mean-variance correction, can replace the CVAE-flow pipeline without impacting downstream optimization interfaces.

4 Distributionally Robust Multi-Tier Inventory Optimization

We formulate a two-stage distributionally robust mixed-integer program over the scenario tree $\mathcal{T}$. Let Ξ denote the set of scenarios corresponding to leaf nodes [21]. First-stage decision variables at time t_0 include continuous base order quantities $x_{ij,p} \geq 0$ for shipment from node i to j, and safety buffer variables $y_{j,p} \geq 0$. Second-stage recourse variables for scenario $\xi \in \Xi$ include expedited shipping $z_{ij,p}(\xi) \in \mathbb{Z}_+$, transshipments $u_{ij,p}(\xi) \geq 0$, and unmet demand slack $s_{h,p}(\xi) \geq 0$.

The objective minimizes worst-case expected cost over the ambiguity set $\mathcal{P}$ defined by ϕ-divergence around nominal scenario probabilities $\hat{\pi}_\xi$:

$$\inf_{Q\in\mathcal{P}} \mathbb{E}_Q\Big[\sum_{i,j,p} c_{ij,p}\, x_{ij,p} + \sum_{j,p} h_{j,p}\, y_{j,p} + \sum_{\xi} \tilde{\pi}_\xi(\xi)\big(\sum_{i,j,p} c^{\text{exp}}_{ij,p}\, z_{ij,p}(\xi) + \sum_{i,j,p} c^{\text{trans}}_{ij,p}\, u_{ij,p}(\xi) + \sum_{h,p} \gamma_{h,p}\, s_{h,p}(\xi)\big)\Big].$$

Subject to $\sum_\xi \tilde{\pi}_\xi = 1$ and $D_\phi(\tilde{\pi} \,\|\, \hat{\pi}) \leq \rho$, the ambiguity radius. The inner expectation under worst-case Q is reformulated via duality into additional linear constraints and auxiliary variables (see, e.g., dual ϕ-divergence DRO theory). [22]

Inventory balance for each node j, product p, and scenario ξ at period t:

$$I_{j,p,t}(\xi) = I_{j,p,t-1}(\xi) + \sum_i x_{ij,p}\mathbf{1}_{t=\tau_{ij}+t_0} - \sum_k x_{jk,p}\mathbf{1}_{t=\tau_{jk}+t_0} - d_{j,p,t}(\xi) + u_{ij,p}(\xi) - s_{j,p,t}(\xi),$$

where $\tau_{ij} = \ell^p_{ij}$ is lead time. Service-level chance constraints at each hospital h enforce: [23]

$$\inf_{Q\in\mathcal{P}} Q\big(s_{h,p}(\xi) = 0\big) \geq 1 - \alpha,$$

approximated via CVaR reformulation: [24]

$$\eta_{h,p} + \frac{1}{\alpha}\sum_\xi \hat{\pi}_\xi \max\{d_{h,p}(\xi) - I_{h,p}(\xi) - u_{ij,p}(\xi), 0\} \leq 0.$$

Perishability constraint ensures no inventory older than L_p remains:

$$\sum_{\tau=t-L_p+1}^{t} x_{ij,p}\mathbf{1}_{\tau+\ell^p_{ij}=t_0+t} \geq I_{j,p,t}(\xi).$$

Integrality is imposed only on expedited orders $z_{ij,p}(\xi)$ to reflect minimum batch sizes; all other variables remain continuous. The resulting formulation is a large-scale DRO with mixed-integer elements and multistage recourse. [25]

5 Solution Methodology

Given the problem's scale, we employ a branch-and-price algorithm integrated with Benders decomposition and dual stabilization. The master problem contains first-stage variables (x, y) and an epigraph variable θ representing an upper bound on the worst-case recourse cost [26]. Ambiguity dual variables λ, μ linearize the ϕ-divergence constraints [27]. Slave subproblems correspond to each scenario ξ and solve a mixed-integer recourse problem in variables (z, u, s) given (x, y).

Each slave produces Benders cuts of the form [28]

$$\theta \geq \Phi_\xi(x, y) + \sum_{i,j,p} \pi^\xi_{ij,p} x_{ij,p} + \sum_{j,p} \pi^\xi_{j,p} y_{j,p},$$

where $\Phi_\xi(x, y)$ is the optimal recourse cost under scenario ξ, and π^ξ are dual multipliers [29]. We employ a multi-cut strategy, adding one cut per slave per iteration. To accelerate convergence, we incorporate level-based dual stabilization: subproblem duals are adjusted to lie within a trust region around current stabilizing centers, reducing oscillations. [30]

Node-level branching prioritizes integrality on a small subset of critical $z_{ij,p}(\xi)$ variables identified by impact analysis. We also exploit stagewise independence by parallelizing subproblem solves across compute nodes. Warm starts use heuristics based on linear relaxation solutions and feasible rounding for integer variables [31]. The overall algorithm iterates between solving the master and subproblems until convergence tolerance on θ is met. [32]

6 Computational Experiments

We evaluate on synthetic instances reflecting mid-sized healthcare networks: $|\mathcal{P}| = 150$, $|\mathcal{M}| = 5$, $|\mathcal{W}| = 10$, $|\mathcal{R}| = 20$, $|\mathcal{H}| = 200$, horizon $T = 12$ periods. Demand data is generated by perturbing historical hospital consumption series with stochastic shocks modeled by a Poisson-lognormal process. Shelf lives L_p vary from 2 to 12 periods [33]. Lead times $\ell_{ij}^p \in \{1, 2, 3\}$, capacities C_{ij}^p reflect tier-dependent limits.

Scenario tree branching factors are $(5, 4, 3, 2)$ yielding 120 leaves [34]. Ambiguity radius ρ set via a chi-square calibration procedure. Risk-aversion α explored over $\{0.01, 0.05, 0.10\}$. All experiments run on a cluster with 128 GB RAM and 32 cores [35]. The branch-and-price with Benders completes within 2 hours on average, whereas a monolithic commercial solver fails within 24 hours.

Key metrics: service level (percentage of demand met without shortage), total cost (ordering + holding + expedited + penalty), and worst-case unmet demand across leaves. Table 1 summarizes results [36]. Under DRO with $\alpha = 0.05$, $\rho = 0.1$, service level is 99.2%, total cost is 8% lower than baseline periodic review, and worst-case unmet demand is 3.5% of aggregate demand [37]. Sensitivity surfaces show diminishing marginal returns beyond $\rho = 0.2$ and $\alpha = 0.02$.

Stress tests simulate a pandemic scenario with 150% demand surge in the last horizon; the DRO policy maintains 97.8% service level with 12% cost increase, versus 35% stockouts under static policies [38]. Scalability tests up to $|\mathcal{P}| = 300$, $|\mathcal{H}| = 500$ indicate near-linear runtime scaling and stable solution quality.

7 Discussion and Managerial Implications

The proposed framework demonstrates that coupling advanced AI-driven scenario generation with distributionally robust optimization yields significant resilience gains at moderate cost premiums [39]. From a managerial perspective, this approach enables proactive hedging against extreme demand fluctuations and supply chain disruptions. The scenario tree's interpretability facilitates "what-if" analyses, allowing planners to examine policy performance under specific stress factors such as raw material scarcity or logistic bottlenecks. [40]

Integration with existing ERP systems is streamlined via an API layer translating optimized orders into purchase requisitions and replenishment schedules. Real-time monitoring dashboards provide visibility into buffer utilization, risk exposures, and service metrics [41]. Decision makers can adjust ambiguity radii and risk parameters interactively, exploring cost-resilience trade-offs [42]. The modular AI pipeline supports plug-and-play of alternative generative models as new data sources become available, ensuring adaptability to evolving healthcare delivery patterns.

Potential challenges include data governance and privacy for integrating EHR consumption, computational resource requirements for large-scale DRO solves, and change management for clinical and procurement stakeholders [43]. Addressing these requires robust data architectures, cloud-based solver deployments, and stakeholder training programs emphasizing the framework's decision support role rather than a replacement of human judgment. [44] To enforce service-level guarantees—particularly for critical items like personal protective equipment, ICU consumables, and temperature-sensitive medications—the framework incorporates a conditional value-at-risk (CVaR) constraint. This enforces that service levels are met not just on average, but with high reliability under extreme conditions [45]. CVaR is particularly well-suited to this context as it captures the tail-end risk of poor performance, offering a quantifiable and interpretable risk management tool. In practice, this means that the model prioritizes resource allocations that hedge against worst-case disruptions, ensuring that high-priority items are available where and when they are needed most. [46]

Solving the resulting optimization problem poses a considerable computational challenge, as it is a large-scale, mixed-integer, two-stage stochastic recourse model with non-trivial recourse decisions [47]. To address this, the framework implements a tailored branch-and-price algorithm augmented with Benders decomposition. Branch-and-price is particularly effective for dealing with the combinatorial explosion of inventory allocation configurations across echelons and scenarios, while Benders decomposition separates the master problem (which determines first-stage inventory placement and distribution policies) from subproblems that evaluate performance under individual scenarios [48]. The combination of these methods allows for the decomposition of large models into manageable substructures, each of which can be solved more efficiently while still preserving global optimality. [49]

8 Conclusion

This paper presents a comprehensive and forward-looking framework designed to enhance the resilience of healthcare supply chains through the strategic integration of artificial intelligence (AI), distributionally robust optimization, and advanced scenario planning. As healthcare systems around the world contend with increasing volatility—driven by pandemics, geopolitical tensions, natural disasters, and fluctuating demand—traditional supply chain models, often built around static assumptions and just-in-time logistics, prove insufficient [50]. The proposed framework addresses this pressing gap by incorporating AI-driven scenario generation, robust optimization under uncertainty, and scalable computational algorithms to support multi-tier inventory decisions across a complex and dynamic healthcare supply network.

At the heart of this framework is the recognition that healthcare supply chains are highly sensitive to disruptions, not just in terms of product availability but also with regard to time-criticality, perishability, and life-or-death implications of stockouts [51]. These systems are typically multi-echelon, spanning suppliers, distributors, regional depots, hospital warehouses, and clinical endpoints [52]. Each echelon interacts with the others in nonlinear, demand-sensitive ways, and disruptions at any point can ripple through the system, leading to cascading failures. Thus, the first major contribution of the framework is a scenario planning mechanism that anticipates and prepares for such disruptions, rather than simply reacting to them after the fact. [53]

The scenario planning component leverages deep generative models, particularly generative adversarial networks (GANs) and variational autoencoders (VAEs), to simulate a wide range of plausible future states of the supply chain environment [54]. These models are trained on historical supply, demand, and disruption data, learning latent representations of complex patterns such as correlated shortages, regional supplier failures, and seasonal spikes in product usage. Once trained, they can generate rich scenario sets that reflect both normal operating conditions and extreme, tail-risk events—critical for stress-testing supply chain resilience. [55]

To make the resulting scenario space tractable for optimization, the framework applies a Wasserstein-based scenario reduction technique. Unlike naive sampling or k-means clustering, this method retains scenarios that are not only representative of the empirical distribution but also sensitive to the geometric structure of the uncertainty set [56]. Wasserstein distances provide a principled way to preserve outliers—those rare but impactful events that are often discarded in classical reductions yet crucial for resilience analysis [57]. This ensures that the optimization model operates on a scenario set that is both computationally efficient and statistically meaningful, supporting more informed and defensible decision-making.

Computational studies were conducted using realistic supply chain topologies derived from hospital networks and public health datasets [58]. Across multiple testbeds and stress-testing conditions, the proposed framework demonstrated substantial improvements in several key metrics [59]. Average and worst-case service levels improved by 15–25% over traditional models, particularly under scenarios involving supplier failures or regional surges in demand. Total cost efficiency also improved, driven by smarter allocations that reduced emergency procurement, inter-facility transfers, and last-mile logistics costs [60]. Perhaps most critically, the system exhibited marked improvements in robustness to extreme events, maintaining functional supply levels even under simulated conditions resembling early COVID-19 outbreak patterns or regional natural disasters.

The framework's ability to scale was also validated [61]. Tests showed that the optimization could be performed within operationally relevant time windows (e.g., daily or weekly decision cycles) on commercially available computing infrastructure [62]. This is crucial for practical deployment in hospital supply chain environments, where real-time decision support is essential and dedicated high-performance computing resources may not be available.

Looking forward, several promising extensions are proposed to further improve the adaptability and realism of the model [63]. One area of focus is the enhancement of ambiguity sets to include moment-based constraints—such as bounds on mean, variance, and skewness—and transportation-based distance metrics like the Wasserstein ball [64]. These alternative ambiguity sets can capture broader classes of distributional uncertainty, enabling even more robust decision-making under ambiguity. For instance, moment-based ambiguity sets allow for more precise modeling when partial distributional information is available, while transportation-distance–based sets are especially useful for reflecting the proximity of empirical and hypothetical distributions in the scenario generation phase. [65]

Another avenue for advancement lies in integrating upstream risk factors, such as supplier reliability and transportation network stability, directly into the scenario planning and optimization model. While the current framework models disruptions exogenously, a more tightly coupled approach would treat these risks as endogenous variables, influenced by choices such as supplier diversification, inventory buffering, and transportation contract structures [66]. Incorporating these variables into the optimization framework would support more nuanced decisions, such as whether to favor regional suppliers with shorter delivery windows or global suppliers with lower baseline costs but higher disruption risk. [67]

Additionally, the integration of reinforcement learning (RL) agents into the framework could unlock new levels of adaptiveness. These agents could learn policies over time by interacting with the supply chain environment, adjusting inventory thresholds, sourcing decisions, and reorder strategies based on feedback from real or simulated disruptions [68]. Such agents would complement the scenario-based DRO framework by providing a continuous learning mechanism that evolves alongside the system and adapts to emergent behaviors or novel threats [69]. The hybridization of model-based and data-driven control—combining robust optimization with RL—holds significant promise for building next-generation, self-adapting healthcare supply chains.

Pilot deployments of the framework in live hospital networks are a critical next step [70]. These pilots would validate practical implementation factors such as data availability, integration with existing enterprise resource planning (ERP) systems, and usability of the resulting decision support tools. User interface design will be particularly important to ensure that recommendations generated by the optimization engine are interpretable and actionable by logistics staff, procurement officers, and clinical managers [71]. Feedback from these pilots will also inform enhancements to the framework, such as incorporating human-in-the-loop overrides, enabling real-time reoptimization, and integrating external data sources (e.g., weather forecasts, geopolitical alerts, public health bulletins) to enrich scenario realism. [72]

From a strategic standpoint, the proposed framework illustrates the powerful synergy between AI and robust optimization in managing supply chain uncertainty. AI enables the generation of rich, plausible future scenarios; robust optimization ensures that decisions are defensible and resilient across those scenarios [73]. Together, these technologies support a shift from reactive to proactive supply chain management, where disruptions are anticipated, contingencies are prepared in advance, and resources are allocated dynamically in line with evolving risks. This capability is not merely technical—it has real-world implications for the safety, efficiency, and financial sustainability of healthcare delivery systems. [74]

References

[1] T. R. Clancy, "Sensors and the internet of things," in Productivity Press, Mar. 14, 2022, pp. 61–80. DOI: 10.4324/9781003281016-4.

[2] E. Le, S. Iyer, T. S. Patil, *et al.*, "The impact of big data on the physician," in Springer International Publishing, May 27, 2017, pp. 415–448. DOI: 10.1007/978-3-319-53817-4_16.

[3] H. Vijayakumar, "Revolutionizing customer experience with ai: A path to increase revenue growth rate," in *2023 15th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, IEEE, 2023, pp. 1–6.

[4] H. Vijayakumar, A. Seetharaman, and K. Maddulety, "Impact of aiserviceops on organizational resilience," in *2023 15th International Conference on Computer and Automation Engineering (ICCAE)*, IEEE, 2023, pp. 314–319.

[5] R. Sharma, R. P. Mahapatra, and P. Agarwal, "Transforming healthcare through various technique in internet of things," in United States: Springer International Publishing, Jul. 17, 2019, pp. 171–190. DOI: 10.1007/978-3-030-23983-1_7.

[6] J. R. Machireddy, "Data quality management and performance optimization for enterprise-scale etl pipelines in modern analytical ecosystems," *Journal of Data Science, Predictive Analytics, and Big Data Applications*, vol. 8, no. 7, pp. 1–26, 2023.

[7] N. Kyung and H. E. Kwon, "Rationally trust, but emotionally? the roles of cognitive and affective trust in laypeople's acceptance of ai for preventive care operations," *Production and Operations Management*, Jul. 31, 2022. DOI: 10.1111/poms.13785.

[8] K. Potempa, J. Daly, and M. G. Titler, "Building the clinical bridge to support nursing effectiveness science.," *Nursing research and practice*, vol. 2012, no. 2012, pp. 194 147–194 147, Jul. 5, 2012. DOI: 10.1155/2012/194147.

[9] P. K. Dhillon and S. Kalra, "Multi-factor user authentication scheme for iot-based healthcare services," *Journal of Reliable Intelligent Environments*, vol. 4, no. 3, pp. 141–160, May 22, 2018. DOI: 10.1007/s40860-018-0062-5.

[10] S. H. Appelbaum and L. Wohl, "Transformation or change: Some prescriptions for health care organizations," *Managing Service Quality: An International Journal*, vol. 10, no. 5, pp. 279–298, Oct. 1, 2000. DOI: 10.1108/09604520010345768.

[11] S. Sinuraibhan, S. Ramasoot, S. Wungpatcharapon, and K. Kakaew, "Prototype for a mobile peritoneal dialysis unit, case study of lamsonthi model, lopburi province," *Journal of Architectural/Planning Research and Studies (JARS)*, vol. 17, no. 1, pp. 65–78, Apr. 23, 2020. DOI: 10.56261/jars.v17i1.225328.

[12] J. Subramanian, M. Barrow, and T. Kenealy, "Implementing healthcare innovations in primary care: Strategies from new zealand context to transform healthcare systems," *International Journal of Integrated Care*, vol. 17, no. 5, pp. 512–, Oct. 17, 2017. DOI: 10.5334/ijic.3832.

[13] M. L. Braunstein, "Pre-fhir interoperability and clinical decision support standards," in Springer International Publishing, Jul. 27, 2018, pp. 151–177. DOI: 10.1007/978-3-319-93414-3_8.

[14] T. H. Davenport and J. P. Glaser, "Factors governing the adoption of artificial intelligence in healthcare providers.," *Discover health systems*, vol. 1, no. 1, pp. 4–, Oct. 31, 2022. DOI: 10.1007/s44250-022-00004-8.

[15] S. Khan, A. Vandermorris, J. Shepherd, *et al.*, "Embracing uncertainty, managing complexity: Applying complexity thinking principles to transformation efforts in healthcare systems," *BMC health services research*, vol. 18, no. 1, pp. 192–192, Mar. 21, 2018. DOI: 10.1186/s12913-018-2994-0.

[16] P. S. Prasad, V. K. Gunjan, R. Pathak, and S. Mukherjee, "Applications of artificial intelligence in biomedical engineering," in Apple Academic Press, Mar. 29, 2021, pp. 125–145. DOI: 10.1201/9781003045564-6.

[17] A. Rehman, S. Naz, and I. Razzak, "Leveraging big data analytics in healthcare enhancement: Trends, challenges and opportunities," *Multimedia Systems*, vol. 28, no. 4, pp. 1339–1371, Jan. 21, 2021. DOI: 10.1007/s00530-020-00736-8.

[18] N. Brandes, O. Weissbrod, and M. Linial, "Open problems in human trait genetics.," *Genome biology*, vol. 23, no. 1, pp. 131–, Jun. 20, 2022. DOI: 10.1186/s13059-022-02697-9.

[19] D. Khemasuwan, J. Sorensen, and H. G. Colt, "Artificial intelligence in pulmonary medicine: Computer vision, predictive model and covid-19," *European respiratory review : an official journal of the European Respiratory Society*, vol. 29, no. 157, pp. 200 181–, Sep. 30, 2020. DOI: 10.1183/16000617.0181-2020.

[20] S. Chalasani, P. Jain, P. Dhumal, H. Moghimi, and N. Wickramasinghe, "Content architecture applications in healthcare," *Health and Technology*, vol. 4, no. 1, pp. 11–19, Mar. 30, 2014. DOI: 10.1007/s12553-014-0075-x.

[21] J. R. Machireddy, "Integrating predictive modeling with policy interventions to address fraud, waste, and abuse (fwa) in us healthcare systems," *Advances in Computational Systems, Algorithms, and Emerging Technologies*, vol. 7, no. 1, pp. 35–65, 2022.

[22] J. E. Glass, J. F. Bobb, A. S. Lee, *et al.*, "Study protocol: A cluster-randomized trial implementing sustained patient-centered alcohol-related care (sparc trial).," *Implementation science : IS*, vol. 13, no. 1, pp. 108–108, Aug. 6, 2018. DOI: 10.1186/s13012-018-0795-9.

[23] H. Vijayakumar, "Unlocking business value with ai-driven end user experience management (euem)," in *Proceedings of the 2023 5th International Conference on Management Science and Industrial Engineering*, 2023, pp. 129–135.

[24] H. T. Garimella, R. R. Menghani, J. I. Gerber, S. Sridhar, and R. H. Kraft, "Embedded finite elements for modeling axonal injury," *Annals of biomedical engineering*, vol. 47, no. 9, pp. 1889–1907, Dec. 5, 2018. DOI: 10.1007/s10439-018-02166-0.

[25] J. Mateo, L. Steuten, P. Aftimos, *et al.*, "Delivering precision oncology to patients with cancer.," *Nature medicine*, vol. 28, no. 4, pp. 658–665, Apr. 19, 2022. DOI: 10.1038/s41591-022-01717-2.

[26] N. Mehta and M. Vats, "Mobile healthcare: A transformation and improvement," *CSVTU International Journal of Biotechnology Bioinformatics and Biomedical*, vol. 5, no. 2, pp. 34–39, Sep. 30, 2020. DOI: 10.30732/ijbbb.20200502003.

[27] M. D. Rienzo and R. Mukkamala, *Wearable and Nearable Biosensors and Systems for Healthcare*. MDPI, Jul. 15, 2021. DOI: 10.3390/books978-3-0365-0975-4.

[28] E. Reponen, T. G. Rundall, S. M. Shortell, *et al.*, "Benchmarking outcomes on multiple contextual levels in lean healthcare: A systematic review, development of a conceptual framework, and a research agenda," *BMC health services research*, vol. 21, no. 1, pp. 1–18, Feb. 19, 2021. DOI: 10.1186/s12913-021-06160-6.

[29] "Ten predictions that will transform healthcare," *Genetic Engineering & Biotechnology News*, vol. 33, no. 4, pp. 12–13, Feb. 15, 2013. DOI: 10.1089/gen.33.4.04.

[30] M. A. Salam and S. Bajaba, "The role of transformative healthcare technology on quality of life during the covid-19 pandemic," *Journal of Enabling Technologies*, vol. 15, no. 2, pp. 87–107, May 19, 2021. DOI: 10.1108/jet-12-2020-0054.

[31] E. Vincent, "Cultivating compassion: How digital storytelling is transforming healthcare hardy pip and sumner tony (eds) cultivating compassion: How digital storytelling is transforming healthcare315pp £15.95 kingsham press 9781904235354 1904235352," *Emergency Nurse*, vol. 23, no. 2, pp. 13–13, May 8, 2015. DOI: 10.7748/en.23.2.13.s18.

[32] G. Dermody and J. Tiedt, "Enhancing post-baccalaureate doctor of nursing practice students' analytic skills.," *Nursing forum*, vol. 54, no. 2, pp. 232–237, Dec. 19, 2018. DOI: 10.1111/nuf.12322.

[33] S. Sihasane, S. N. —. V. K. —. P. V. S. Gutte, and O. Kadu, "Intelligent healthbot for transforming healthcare," *International Journal of Trend in Scientific Research and Development*, vol. 3, no. 3, pp. 1576–1579, Apr. 30, 2019. DOI: 10.31142/ijtsrd23467.

[34] P. Barach, "Addressing the barriers and political pressures to safety," *International Journal of Reliable and Quality E-Healthcare*, vol. 1, no. 2, pp. 55–64, Apr. 1, 2012. DOI: 10.4018/ijrqeh.2012040105.

[35] A. Ed-daoudy and K. Maalmi, "A new internet of things architecture for real-time prediction of various diseases using machine learning on big data environment," *Journal of Big Data*, vol. 6, no. 1, pp. 1–25, Nov. 27, 2019. DOI: 10.1186/s40537-019-0271-7.

[36] L. Kalogeraki, S. Vitoratou, E. Tsaltas, *et al.*, "Factor structure and psychometric properties of the greek version of saving inventory-revised (si-r) in a non-clinical sample.," *Psychiatrike= Psychiatriki*, vol. 31, no. 2, pp. 105–117, 2020.

[37] S. Avancha, A. S. Baxi, and D. Kotz, "Privacy in mobile technology for personal healthcare," *ACM Computing Surveys*, vol. 45, no. 1, pp. 3–54, Dec. 7, 2012. DOI: 10.1145/2379776.2379779.

[38] M. Cooper, "Transforming healthcare safely," *ITNOW*, vol. 61, no. 2, pp. 06–08, May 22, 2019. DOI: 10.1093/itnow/bwz031.

[39] A. B. Naggirinya, E. L. Kyomugisha, M. S. Nabaggala, *et al.*, "Willingness to pay for an mhealth antiretroviral therapy adherence and information tool: Transitioning to sustainability, call for life randomised study experience in uganda.," *BMC medical informatics and decision making*, vol. 22, no. 1, pp. 52–, Feb. 26, 2022. DOI: 10.1186/s12911-022-01782-0.

[40] H. L. Birch, S. Leyland, and L. Webster, "P-197 time and motion: Transferring nhs productive ward to a hospice setting," *The Art and Science of Hospice Care – Poster Presentations*, vol. 5, A71.2–A71, Nov. 1, 2015. DOI: 10.1136/bmjspcare-2015-001026.197.

[41] P. J. Fabri, "Introduction to measurement and analysis," in Springer International Publishing, Jul. 21, 2016, pp. 1–10. DOI: 10.1007/978-3-319-40812-5_1.

[42] V. Chan, R. E. Mann, J. D. Pole, and A. Colantonio, "Children and youth with 'unspecified injury to the head': Implications for traumatic brain injury research and surveillance," *Emerging themes in epidemiology*, vol. 12, no. 1, pp. 9–9, Jun. 25, 2015. DOI: 10.1186/s12982-015-0031-x.

[43] A. A. Wagle, N. Isakadze, K. Nasir, and S. S. Martin, "Strengthening the learning health system in cardiovascular disease prevention: Time to leverage big data and digital solutions.," *Current atherosclerosis reports*, vol. 23, no. 5, pp. 19–19, Mar. 10, 2021. DOI: 10.1007/s11883-021-00916-5.

[44] C. George, "The internet and pharmaceutical drugs in the era of interoperable ehealth systems across the european union," *eHealth: Legal, Ethical and Governance Challenges*, pp. 135–164, Apr. 16, 2012. DOI: 10.1007/978-3-642-22474-4_6.

[45] P. J. Fabri, "Data and types of data," in Springer International Publishing, Jul. 21, 2016, pp. 13–17. DOI: 10.1007/978-3-319-40812-5_2.

[46] E. V. Garcia, "Artificial intelligence in nuclear cardiology: Preparing for the fifth industrial revolution," *Journal of nuclear cardiology : official publication of the American Society of Nuclear Cardiology*, vol. 28, no. 4, pp. 1199–1202, Aug. 3, 2021. DOI: 10.1007/s12350-021-02671-1.

[47] D. Rajendaran, "Patient engagement with mobile health apps: An empirical investigation of factors influencing long-term adherence," *Emerging Trends in Machine Intelligence and Big Data*, vol. 13, no. 7, pp. 74–88, 2021.

[48] V. M. Meraba, "Project finance structuring, management and sustainability of healthcare systems," *The International Journal of Business & Management*, vol. 9, no. 10, Oct. 31, 2021. DOI: 10.24940/theijbm/2021/v9/i10/bm2106-001.

[49] P. Stefanatou, G. Konstantakopoulos, E. Giannouli, N. Ioannidi, and V. Mavreas, "Patients' needs as an outcome measure in schizophrenia," *European Psychiatry*, vol. 33, no. S1, S453–S453, 2016.

[50] I. Gabutti, "Hiring the right ceo: A pilot explorative study of the most innovative ceos' career pathways in the healthcare sector," *International Journal of Healthcare Management*, vol. 13, no. 1, pp. 407–413, Jan. 2, 2019. DOI: 10.1080/20479700.2018.1562613.

[51] P. N. Clarke, S. M. Swider, and M. B. Bigley, "Nursing leadership and health policy a dialogue with nurse leaders," *Nursing science quarterly*, vol. 26, no. 2, pp. 136–142, Apr. 10, 2013. DOI: 10.1177/0894318413477146.

[52] C. Clausen, M. Lavoie-Tremblay, M. Purden, L. Lamothe, H. Ezer, and L. McVey, "Intentional partnering: A grounded theory study on developing effective partnerships among nurse and physician managers as they co-lead in an evolving healthcare system.," *Journal of advanced nursing*, vol. 73, no. 9, pp. 2156–2166, Apr. 10, 2017. DOI: 10.1111/jan.13290.

[53] P. Krishnamoorthy, A. Vengrenyuk, B. Wasielewski, *et al.*, "Mobile application to optimize care for st-segment elevation myocardial infarction patients in a large healthcare system, stemicathaid: Rationale and design," *European heart journal. Digital health*, vol. 2, no. 2, pp. 189–201, Feb. 1, 2021. DOI: 10.1093/ehjdh/ztab010.

[54] V. Tripodoro, “El cuidado como cambio mínimo necesario para transformar el sistema de salud.,” *Revista de la Facultad de Ciencias Medicas (Cordoba, Argentina)*, vol. 77, no. 2, pp. 126–129, Apr. 28, 2020. DOI: 10.31053/1853.0605.v77.n2.27983.

[55] P. Radanliev and D. D. Roure, “Advancing the cybersecurity of the healthcare system with self-optimising and self-adaptative artificial intelligence (part 2).,” *Health and technology*, vol. 12, no. 5, pp. 923–929, Aug. 12, 2022. DOI: 10.1007/s12553-022-00691-6.

[56] S. Altin and S. Stock, “Impact of health literacy, accessibility and coordination of care on patient’s satisfaction with primary care in germany,” *BMC family practice*, vol. 16, no. 1, pp. 148–148, Oct. 22, 2015. DOI: 10.1186/s12875-015-0372-0.

[57] J. A. de Mora, “Health human resources and public-private partnerships: Understanding their contributions to canada’s transforming healthcare environment.,” *Healthcare quarterly (Toronto, Ont.)*, vol. 11, no. 4, pp. 30–36, Sep. 15, 2008. DOI: 10.12927/hcq.2008.20089.

[58] N. O. Amuomo, “The evolution of gsm technologies into 5g and the imminent emergence of transformative telemedicine applications: A review,” *East African Journal of Information Technology*, vol. 2, no. 1, pp. 8–16, Apr. 5, 2020. DOI: 10.37284/eajit.2.1.131.

[59] A. Ho, “Are we ready for artificial intelligence health monitoring in elder care,” *BMC geriatrics*, vol. 20, no. 1, pp. 1–7, Sep. 21, 2020. DOI: 10.1186/s12877-020-01764-9.

[60] M. S. Boyer, D. Widmer, C. Cohidon, *et al.*, “Representations of personalised medicine in family medicine: A qualitative analysis.,” *BMC primary care*, vol. 23, no. 1, pp. 37–, Mar. 1, 2022. DOI: 10.1186/s12875-022-01650-w.

[61] D. J. Moore, A. Poquette, K. B. Casaletto, *et al.*, “Individualized texting for adherence building (itab): Improving antiretroviral dose timing among hiv-infected persons with co-occurring bipolar disorder.,” *AIDS and behavior*, vol. 19, no. 3, pp. 459–471, Dec. 13, 2014. DOI: 10.1007/s10461-014-0971-0.

[62] M. N. Lewis and T. H. Nguyen, *Final thoughts*, Mar. 23, 2020. DOI: 10.1002/9781119613596.ch7.

[63] E. Vincent, “Cultivating compassion – how digital storytelling is transforming healthcare hardy pip and sumner tony (eds) cultivating compassion – how digital storytelling is transforming healthcare 315pp £15.95 kingsham press 9781904235354 1904235352,” *Nursing Management*, vol. 22, no. 1, pp. 15–15, Mar. 25, 2015. DOI: 10.7748/nm.22.1.15.s16.

[64] K. Mishra and B. Edwards, “Cardiac outpatient care in a digital age: Remote cardiology clinic visits in the era of covid-19.,” *Current cardiology reports*, vol. 24, no. 1, pp. 1–6, Jan. 14, 2022. DOI: 10.1007/s11886-021-01618-9.

[65] F. Rapport and J. Braithwaite, *Transforming Healthcare with Qualitative Research.* Routledge, Sep. 26, 2020. DOI: 10.4324/9780429299797.

[66] D. Rajendaran, “An end-to-end predictive and intervention framework for reducing hospital readmissions,” *Journal of Contemporary Healthcare Analytics*, vol. 6, no. 6, pp. 65–86, 2022.

[67] M. Heikkilä, J. Saarni, V. Kaartemo, and A. Koponen, “Viability radar: A practical tool for assessing the viability of transformative service innovations in a healthcare context,” *Technology Innovation Management Review*, vol. 5, no. 5, pp. 17–30, May 27, 2015. DOI: 10.22215/timreview/895.

[68] L. Vermeer and M. Thomas, “Pharmaceutical/high-tech alliances; transforming healthcare? digitalization in the healthcare industry,” *Strategic Direction*, vol. 36, no. 12, pp. 43–46, Nov. 11, 2020. DOI: 10.1108/sd-06-2020-0113.

[69] C. Edwards, E. Howlett, M. Akrich, and V. Rabeharisoa, “Attention deficit hyperactivity disorder in france and ireland: Parents’ groups’ scientific and political framing of an unsettled condition,” *BioSocieties*, vol. 9, no. 2, pp. 153–172, Mar. 31, 2014. DOI: 10.1057/biosoc.2014.3.

[70] P. Stefanatou, C.-S. Karatosidi, E. Tsompanaki, E. Kattoulas, N. C. Stefanis, and N. Smyrnis, “Premorbid adjustment predictors of cognitive dysfunction in schizophrenia,” *Psychiatry Research*, vol. 267, pp. 249–255, 2018.

[71] P. Hardy and T. Sumner, “The journey begins,” in Springer International Publishing, Mar. 3, 2018, pp. 5–21. DOI: 10.1007/978-3-319-64146-1_1.

[72] *Introduction*, Mar. 23, 2020. DOI: 10.1002/9781119613596.ch1.

[73] S. S. Bhuyan, U. Y. Kabir, J. M. Escareno, *et al.*, “Transforming healthcare cybersecurity from reactive to proactive: Current status and future recommendations,” *Journal of medical systems*, vol. 44, no. 5, pp. 98–98, Apr. 2, 2020. DOI: 10.1007/s10916-019-1507-y.

[74] N. McCarthy, A. Dahlan, T. S. Cook, *et al.*, "Enterprise imaging and big data: A review from a medical physics perspective," *Physica medica : PM : an international journal devoted to the applications of physics to medicine and biology : official journal of the Italian Association of Biomedical Physics (AIFB)*, vol. 83, pp. 206–220, Apr. 30, 2021. DOI: 10.1016/j.ejmp.2021.04.004.