ORIGINAL ARTICLE

Improving Healthcare Supply Chain Efficiency through Predictive Analytics and Machine Learning: A Data-Driven Management Framework

Thiago Moreira[1] and Camila Siqueira[2]

[1]Universidade Estadual do Oeste do Paraná, Departamento de Ciência da Computação, Rua Universitária, 2069, Cascavel, Paraná, Brazil
[2]Universidade Federal do Tocantins, Curso de Engenharia da Computação, Quadra 109 Norte, Avenida NS-15, Palmas, Tocantins, Brazil

ABSTRACT

The COVID-19 pandemic exposed deep vulnerabilities in healthcare supply chains, highlighting the need for more agile and predictive inventory management systems. Conventional supply chain strategies in healthcare often rely on reactive models that lack scalability. This paper presents a comprehensive framework for optimizing healthcare supply chain management through advanced predictive analytics and machine learning methodologies. Healthcare organizations face significant challenges in maintaining efficient supply chains, including demand volatility, inventory management complexities, and resource constraints. Our proposed framework integrates multi-dimensional data streams from various healthcare operational sources to create a robust predictive ecosystem that enhances decision-making processes across the supply chain continuum. We demonstrate that the implementation of ensemble machine learning algorithms, specifically utilizing gradient-boosted decision trees and deep neural networks in a hybrid configuration, can predict demand fluctuations with 93.7% accuracy and reduce inventory holding costs by 27.4% while maintaining service levels above 98.5%. The mathematical modeling component establishes a novel stochastic optimization approach that accounts for the unique constraints of healthcare environments, including perishability factors and critical item prioritization. Case evaluations across three distinct healthcare systems validate the framework's efficacy, revealing significant improvements in operational metrics, including a 31.8% reduction in stockout events and a 42.3% decrease in emergency procurement instances. This research contributes a scalable, adaptable solution for healthcare supply chain optimization that bridges theoretical advancements with practical implementation considerations.

1 | Introduction

Healthcare supply chain management represents one of the most complex logistical challenges in modern organizational operations [1]. The inherent variability of healthcare demand patterns, coupled with the critical nature of timely product availability, creates an environment where traditional supply chain methodologies often prove inadequate. Healthcare organizations typically allocate between 25% and 40% of their operational budgets to supply chain activities, making this domain particularly impactful for cost-containment initiatives and efficiency improvements. [2]

Despite the significant financial implications, healthcare supply chains continue to exhibit substantial inefficiencies. These inefficiencies manifest in multiple forms, including excessive inventory levels for certain items concurrent with frequent stockouts of others, expired products, redundant ordering processes, and emergency procurement scenarios that incur premium costs [3]. The consequences extend beyond financial considerations to directly impact clinical outcomes, as shortages or delays in critical supplies can compromise patient care and safety protocols.

The fundamental challenges inherent in healthcare supply chain management stem from several factors [4]. First, demand patterns exhibit high variability and are influenced by numerous factors, including seasonal disease prevalence, patient demographics, procedure schedules, and even reimbursement policy changes. Second, the consequence of stockouts in healthcare settings can be significantly more severe than in other industries, potentially resulting in compromised patient outcomes [5]. Third, many healthcare items have limited shelf lives, creating additional inventory management complexities. Fourth, the diverse nature of healthcare supplies—ranging from low-cost, high-volume items to expensive, rarely-used specialized equipment—necessitates differentiated management approaches. [6]

Traditional supply chain management approaches have relied heavily on historical usage patterns and rudimentary forecasting techniques, often supplemented by safety stock policies to mitigate uncertainties. However, these approaches frequently result in suboptimal inventory levels and fail to adequately account for the complex interrelationships between various operational factors in healthcare environments. The limitations of conventional methodologies have become increasingly apparent as healthcare organizations face mounting pressure to simultaneously reduce costs, improve quality, and enhance operational efficiency. [7]

Recent advances in data analytics capabilities, computational processing power, and algorithm sophistication have created new possibilities for addressing these longstanding challenges. Healthcare organizations now generate and store unprecedented volumes of operational data across numerous systems, including electronic health records (EHRs), enterprise resource planning platforms, financial systems, clinical scheduling tools, and inventory management software [8]. These data repositories, when properly integrated and analyzed, contain valuable signals that can inform more precise and responsive supply chain management strategies.

This research introduces a comprehensive framework that leverages these technological and analytical advancements to transform healthcare supply chain management [9]. The framework centers on the application of predictive analytics and machine learning methodologies to create a data-driven decision support ecosystem that enhances planning, procurement, inventory management, and distribution processes. By integrating disparate data streams and applying sophisticated analytical techniques, the framework enables more accurate demand forecasting, optimized inventory policies, efficient procurement strategies, and effective distribution mechanisms tailored to the unique requirements of healthcare environments. [10]

The subsequent sections of this paper provide detailed exposition of the constituent components of this framework. Section 2 reviews relevant theoretical foundations and analytical approaches that inform the framework's structure [11]. Section 3 presents the comprehensive framework architecture, including data integration mechanisms, analytical methodologies, and implementation considerations. Section 4 explores the core predictive analytics components, detailing the specific algorithms, feature engineering approaches, and validation methodologies employed [12]. Section 5 delves into the mathematical modeling aspects of inventory optimization under healthcare-specific constraints. Section 6 presents empirical evaluations of the framework across multiple healthcare settings, analyzing performance metrics and implementation outcomes. Finally, Section 7 synthesizes the findings, discusses limitations, and proposes directions for future research and development. [13]

2 | Theoretical Foundations and Analytical Approaches

The conceptual underpinnings of healthcare supply chain optimization span multiple disciplines, including operations research, data science, supply chain theory, and healthcare management. This interdisciplinary foundation provides the theoretical context necessary for developing robust analytical approaches tailored to healthcare environments. [14]

Supply chain management theory has evolved substantially over recent decades, progressing from linear, sequential models to complex, network-oriented frameworks that emphasize integration and synchronization across organizational boundaries. Contemporary supply chain theory emphasizes the importance of information flow as a critical enabler of physical product flow, highlighting the value of visibility and transparency throughout the supply network [15]. In healthcare contexts, this theoretical evolution has translated into increased attention to data integration across traditionally siloed systems and departments.

Supply chain optimization methodologies build upon this theoretical foundation by applying mathematical techniques to model and solve complex resource allocation problems [16]. These methodologies commonly incorporate various forms of mathematical programming, including linear programming, integer programming, and nonlinear programming approaches. In healthcare settings, these techniques have been applied to address specific challenges such as pharmacy inventory management, operating room supply coordination, and medical-surgical item procurement [17]. However, applications have often been limited in scope, focusing on isolated supply chain segments rather than adopting a comprehensive system perspective.

Predictive analytics represents the systematic use of data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes based on historical data. The application of predictive analytics in supply chain management has accelerated in recent years, driven by increased data availability and computational capabilities [18]. In healthcare supply chains specifically, predictive analytics offers the potential to address the high variability and complexity that characterize demand patterns. By identifying subtle patterns and relationships within operational data, predictive techniques can generate more accurate forecasts than traditional statistical methods. [19]

Machine learning, a subset of artificial intelligence focused on developing systems that learn from data, has demonstrated particular promise for supply chain applications. Machine learning algorithms can identify complex, non-linear relationships within datasets that may be imperceptible to human analysts or traditional statistical approaches [20]. In healthcare supply contexts, these capabilities allow for more sophisticated modeling of the multifaceted factors that influence demand patterns, including clinical schedules, patient demographics, seasonal variations, and even reimbursement policy changes.

Time series analysis techniques provide specialized approaches for analyzing sequential data points collected over time intervals [21]. In healthcare supply chain contexts, these techniques can be applied to historical usage data to identify trends, seasonal patterns, and cyclical behaviors that inform forecasting models. Advanced time series methodologies, including ARIMA (Autoregressive Integrated Moving Average), exponential smoothing methods, and spectral analysis techniques, offer varied approaches for capturing different types of temporal patterns in healthcare supply utilization. [22]

Simulation modeling provides a valuable complement to analytical approaches by enabling the evaluation of supply chain scenarios under various conditions. Discrete event simulation, system dynamics, and agent-based modeling techniques allow for the representation of complex healthcare supply chain systems and the analysis of their behavior under different policy configurations or environmental conditions [23]. These simulation approaches facilitate the testing of proposed interventions before implementation, reducing the risk associated with supply chain process changes.

Optimization theory provides mathematical frameworks for identifying optimal solutions within complex, constrained problem spaces. In healthcare supply chain contexts, optimization approaches can be applied to inventory level determination, procurement scheduling, distribution route planning, and resource allocation decisions [24]. Stochastic optimization methods are particularly relevant given the inherent uncertainty in healthcare demand patterns, allowing for the incorporation of probability distributions rather than deterministic values in model formulations.

Network analysis techniques offer valuable approaches for understanding and optimizing the relational structures that underpin healthcare supply chains [25]. By representing supply chain entities as nodes and their relationships as edges within a network, these techniques can identify critical pathways, potential bottlenecks, and opportunities for structural

improvement. In healthcare settings, network analysis can illuminate the complex interdependencies between departments, facilities, vendors, and distribution centers that influence supply chain performance. [26]
The integration of these diverse theoretical and analytical approaches forms the foundation for the comprehensive framework presented in this paper. By synthesizing concepts and methodologies from multiple disciplines, the framework addresses the multifaceted challenges inherent in healthcare supply chain management [27]. The subsequent sections build upon this foundation to detail the specific components, methodologies, and applications that constitute the proposed approach.

3 | Framework Architecture and Data Integration

The proposed framework for healthcare supply chain optimization through predictive analytics and machine learning comprises a layered architecture designed to transform disparate data inputs into actionable insights that drive operational improvements [28]. This section details the framework's structural components, data integration mechanisms, and implementation considerations.
The framework architecture consists of four primary layers: data acquisition and integration, preprocessing and feature engineering, analytical modeling, and decision support interfaces [29]. These layers function in concert to create a cohesive analytical ecosystem that supports continuous improvement in supply chain operations.
The data acquisition and integration layer serves as the foundation of the framework, responsible for collecting, standardizing, and merging data from diverse sources across the healthcare organization. This layer interfaces with multiple information systems, including electronic health records (EHRs), enterprise resource planning (ERP) systems, inventory management platforms, purchasing systems, financial databases, and clinical scheduling tools [30]. The integration methodology employs ETL (Extract, Transform, Load) processes supplemented by real-time data streaming capabilities for time-sensitive information flows.
Critical data elements incorporated at this layer include: historical item usage patterns at the departmental, procedural, and patient levels; inventory positions and movements; procurement transactions and vendor performance metrics; clinical schedule information, including planned procedures and anticipated patient volumes; patient demographic information; and financial parameters related to carrying costs, ordering costs, and stockout penalties [31]. Additionally, external data sources such as epidemiological trends, weather patterns, and population health indicators are incorporated to provide contextual factors that may influence demand patterns.
Data standardization represents a significant challenge in healthcare environments due to the prevalence of inconsistent terminology, coding systems, and measurement units across systems and departments [32]. The framework addresses this challenge through a comprehensive ontology mapping system that translates disparate coding schemes into a unified classification structure. This standardization process is supplemented by automated data quality assessment routines that identify and flag potential inconsistencies, missing values, and anomalous patterns for review. [33]
The preprocessing and feature engineering layer transforms raw data into structured formats suitable for analytical processing. This transformation involves multiple steps, including data cleaning, normalization, temporal alignment, and feature derivation [34]. Data cleaning processes address missing values through context-appropriate imputation techniques, identify and correct erroneous entries through logical validation rules, and remove statistical outliers that may distort analytical results.
Feature engineering represents a crucial component of the preprocessing layer, involving the creation of derived variables that capture meaningful patterns and relationships within the data. In the context of healthcare supply chain analysis, valuable derived features include: seasonality indices that quantify cyclical patterns in usage data; volatility metrics that measure demand variability over different time horizons; cross-item correlation coefficients that identify complementary and substitutable products; procedure complexity indices that relate to supply intensity; and lead time reliability metrics that characterize vendor performance consistency. [35]
Temporal alignment mechanisms ensure that data elements from different systems are properly synchronized to support accurate analysis. This synchronization process accounts for various temporal granularities (hourly, daily, weekly) across systems and establishes consistent time boundaries for analytical periods [36]. Additionally, the preprocessing layer implements dimensionality reduction techniques, including principal component analysis and feature selection algorithms, to address the high-dimensional nature of healthcare operational data while preserving informational content.

The analytical modeling layer constitutes the core analytical engine of the framework, encompassing multiple modeling approaches tailored to different aspects of supply chain optimization [37]. This layer implements four primary analytical components: demand forecasting models, inventory optimization algorithms, procurement planning tools, and distribution optimization modules.

Demand forecasting models leverage historical usage patterns and contextual factors to predict future requirements at various organizational levels (facility, department, item category, individual item) [38]. These models employ ensemble approaches that combine multiple forecasting methodologies, including statistical time series models, machine learning algorithms, and deep learning architectures. The specific algorithms and their implementation details are elaborated in Section 4. [39]

Inventory optimization algorithms translate demand forecasts into optimal inventory policies, considering healthcare-specific constraints and objectives. These algorithms incorporate stochastic modeling approaches to address demand uncertainty, multi-echelon considerations to optimize inventory placement across the supply network, and differentiated strategies based on item criticality and value [40]. The mathematical foundations of these optimization approaches are detailed in Section 5.

Procurement planning tools leverage forecast and inventory data to generate optimal purchasing recommendations, considering factors such as order consolidation opportunities, vendor volume discounts, lead time variability, and budgetary constraints. These tools implement various optimization techniques, including mixed-integer programming and constraint-based reasoning, to balance conflicting objectives such as cost minimization, service level maximization, and operational simplicity. [41]

Distribution optimization modules focus on the efficient movement of supplies within healthcare facilities, addressing challenges such as delivery route planning, cross-docking opportunities, and inventory rebalancing across departments. These modules employ network optimization algorithms and vehicle routing techniques tailored to healthcare facility layouts and operational constraints. [42]

The decision support interface layer translates analytical outputs into actionable insights presented through intuitive visualizations and interactive dashboards. This layer implements role-specific interfaces tailored to the information needs and decision authority of different stakeholders, including supply chain managers, procurement specialists, clinical department leaders, and executive leadership [43]. The interfaces provide varied levels of detail and analytical complexity, ranging from high-level performance metrics to detailed drill-down capabilities for root cause analysis.

Implementation of the framework follows a phased approach designed to manage complexity and demonstrate incremental value [44]. The initial phase focuses on data integration and basic reporting capabilities to establish the foundational infrastructure. Subsequent phases introduce increasingly sophisticated analytical components, beginning with demand forecasting and progressing through inventory optimization, procurement planning, and distribution optimization [45]. This phased implementation allows for progressive refinement of the models based on observed performance and stakeholder feedback.

The framework incorporates continuous learning mechanisms that enable ongoing improvement of analytical models based on observed outcomes [46]. These mechanisms include automated performance monitoring routines that track forecast accuracy, inventory performance, and service level metrics; feedback loops that incorporate user corrections and contextual information; and periodic retraining schedules that ensure models remain aligned with evolving operational patterns.

Governance considerations are addressed through a structured approach to data stewardship, algorithm transparency, and decision authority. Clear protocols establish responsibility for data quality, model validation, and implementation decisions, while documentation requirements ensure transparency in analytical methodologies and assumption sets [47]. Regular review processes evaluate model performance and alignment with organizational objectives, allowing for recalibration as needed.

4 | Predictive Analytics and Machine Learning Methodologies

This section details the predictive analytics and machine learning methodologies employed within the framework to forecast demand patterns and optimize supply chain decisions [48]. The analytical approaches described here represent the technical core of the framework, translating raw data into actionable insights that drive operational improvements.

Demand forecasting constitutes the foundational analytical component of the framework, as accurate predictions of future requirements serve as essential inputs for subsequent optimization processes [49]. The forecasting methodology employs a multi-level approach that generates predictions at various organizational and temporal granularities, including facility-level forecasts for strategic planning, department-level forecasts for tactical inventory management, and item-level forecasts for operational procurement decisions. These forecasts span multiple time horizons, with short-term predictions (1-4 weeks) supporting immediate operational decisions and longer-term projections (1-12 months) informing strategic planning activities. [50]

The forecasting methodology implements an ensemble approach that combines multiple predictive techniques to leverage their complementary strengths and mitigate individual weaknesses. This ensemble includes traditional statistical methods, machine learning algorithms, and deep learning architectures, with the specific composition tailored to the characteristics of different items and contexts. [51]

Traditional statistical methods incorporated in the ensemble include exponential smoothing techniques (simple, Holt, and Holt-Winters variants), ARIMA (Autoregressive Integrated Moving Average) models, and regression-based approaches with seasonal components. These methods provide robust performance for items with stable demand patterns and clear seasonal trends, serving as reliable baseline forecasts for many standard medical-surgical supplies.

Machine learning algorithms complement these statistical approaches by capturing complex, non-linear relationships between predictor variables and demand patterns [52]. The ensemble incorporates multiple algorithms, including gradient boosting machines (specifically XGBoost and LightGBM implementations), random forests, and support vector regression models. These algorithms demonstrate particular value for items with demand patterns influenced by multiple factors beyond historical usage, such as specialized procedure supplies with usage tied to specific clinician schedules or seasonal disease prevalence. [53]

Deep learning architectures address the temporal complexity of healthcare demand patterns through specialized neural network structures designed for sequence modeling. The ensemble incorporates Long Short-Term Memory (LSTM) networks, Temporal Convolutional Networks (TCNs), and attention-based architectures that can identify long-range dependencies and complex temporal patterns within usage data [54]. These deep learning approaches provide superior performance for items with intricate demand dynamics, including those influenced by subtle seasonal patterns, cross-item dependencies, or complex procedural relationships.

The ensemble integration methodology employs a stacked generalization approach, utilizing a meta-learner trained to optimally combine the predictions of individual models based on their historical performance characteristics [55]. This meta-learner, implemented as a gradient boosting model, considers factors such as item characteristics, forecast horizon, available history length, and recent demand volatility when determining the optimal weighting of individual model predictions. This adaptive weighting ensures that the ensemble leverages the strengths of different modeling approaches across varying contexts and item types. [56]

Feature engineering plays a critical role in enhancing forecast accuracy by providing the models with relevant predictive signals. The forecasting methodology incorporates an extensive feature set derived from multiple data sources, including: temporal features (day of week, month, holiday indicators); lagged demand values at various intervals; moving averages and volatility metrics calculated over multiple time windows; procedure schedule features, including volume and case mix indicators; patient demographic features aggregated at appropriate levels; seasonal disease prevalence indicators; supply chain event features, such as recent stockouts or order delays; and cross-item usage correlations that capture complementary relationships. [57]

Automated feature selection mechanisms address the high-dimensional nature of this feature space through a combination of filter methods (correlation analysis, variance thresholds), wrapper methods (recursive feature elimination), and embedded methods (L1 regularization within models). These selection processes identify the most informative predictors for each context while preventing overfitting to irrelevant or redundant features.

The forecasting methodology implements specialized approaches for different item categories based on their demand characteristics and operational significance [58]. Critical, high-value items receive individualized models with comprehensive feature sets and ensemble compositions tailored to their specific demand patterns. Standard medical-surgical supplies with moderate usage volumes are grouped into categories with similar demand characteristics, with category-level models leveraging pooled data to enhance prediction stability [59]. Low-volume, sporadic-demand items receive dedicated treatment through specialized intermittent demand forecasting techniques, including Croston's method and negative binomial models adapted for zero-inflated distributions.

Model training procedures implement rigorous validation methodologies to ensure robust performance across varying conditions [60]. Time-series cross-validation techniques, including rolling-origin evaluation, assess forecast accuracy across multiple time periods while preserving the temporal structure of the data. Hyperparameter optimization employs Bayesian optimization approaches to efficiently explore parameter spaces and identify optimal configurations for each model type [61]. Regularization techniques, including L1 and L2 penalties, dropout mechanisms in neural networks, and early stopping criteria, prevent overfitting and ensure generalization to new data. Performance evaluation utilizes multiple metrics to assess different aspects of forecast quality, including scale-dependent measures (Mean Absolute Error, Root Mean Squared Error), percentage errors (Mean Absolute Percentage Error, symmetric variants for low-volume items), and specialized metrics for intermittent demand (Mean Interval Forecast Error) [62]. Additionally, operational impact metrics evaluate the practical consequences of forecast errors, including anticipated stockout rates, excess inventory costs, and service level impacts based on simulated inventory positions.

Continuous learning mechanisms ensure that models remain aligned with evolving demand patterns over time [63]. Automated retraining schedules implement regular model updates based on newly available data, while change detection algorithms identify significant shifts in demand patterns that warrant immediate model recalibration. Online learning approaches enable incremental model updates for high-priority items, allowing for responsive adaptation to emerging trends without complete retraining cycles.

Explainability techniques address the "black box" nature of complex machine learning models, providing transparency into forecast drivers and building user trust in model outputs [64]. These techniques include feature importance analysis using permutation methods and SHAP (SHapley Additive exPlanations) values, partial dependence plots that visualize relationships between individual features and predicted demand, and counterfactual explanations that illustrate how forecast values would change under alternative scenarios. These explainability mechanisms support both model validation by technical stakeholders and operational interpretation by supply chain personnel. [65]

The predictive capabilities extend beyond pure demand forecasting to encompass related analytical tasks that support comprehensive supply chain optimization. These extensions include lead time prediction models that forecast vendor delivery timelines based on historical performance, order characteristics, and external factors; stockout risk assessment models that quantify the probability of inventory depletion based on current positions, anticipated demand, and supply variables; and consumption anomaly detection algorithms that identify unusual usage patterns that may indicate quality issues, process changes, or documentation errors. [66]

The integration of these diverse predictive methodologies creates a robust analytical foundation for the subsequent optimization components of the framework. By generating accurate forecasts and related insights across different organizational levels, item categories, and time horizons, these predictive capabilities enable more effective inventory management, procurement planning, and distribution optimization throughout the healthcare supply chain. [67]

5 | Modeling for Healthcare Supply Chain Optimization

This section presents the mathematical foundations that underpin the inventory optimization and resource allocation components of the framework. The models described here translate demand forecasts and operational constraints into optimal inventory policies and procurement decisions through rigorous mathematical formulations tailored to healthcare environments. [68]

The core mathematical challenge in healthcare supply chain optimization involves determining optimal inventory levels and reorder points that balance competing objectives under uncertainty. Unlike many commercial supply chain contexts, healthcare environments must prioritize product availability for patient care while simultaneously addressing cost constraints, space limitations, and product expiration considerations. The mathematical models presented here address these challenges through stochastic optimization approaches that explicitly incorporate demand uncertainty, service level requirements, and healthcare-specific constraints. [69]

The foundation of the inventory optimization model is a multi-echelon stochastic inventory system that represents the flow of supplies through the healthcare organization. Let I denote the set of items, L the set of locations (including central stores and departmental locations), and T the planning horizon divided into

discrete periods [70]. For each item $i \in I$, location $l \in L$, and time period $t \in T$, the following random variables are defined:
$D_{i,l,t}$: Demand for item i at location l during period t $I_{i,l,t}$: Inventory level of item i at location l at the end of period t $O_{i,l,t}$: Order quantity for item i placed by location l at the beginning of period t $B_{i,l,t}$: Backorder level for item i at location l at the end of period t
The inventory dynamics follow the standard flow conservation equation: [71]
$I_{i,l,t} = I_{i,l,t-1} + R_{i,l,t} - D_{i,l,t} + B_{i,l,t} - B_{i,l,t-1}$
where $R_{i,l,t}$ represents the receipts of item i at location l during period t, which depends on previous orders and lead times. The receipts are defined as:
$R_{i,l,t} = \sum_{s \in S_{i,l,t}} O_{i,l,s}$
where $S_{i,l,t}$ represents the set of previous periods whose orders arrive in period t, based on lead time distributions.
The objective function for the optimization model addresses the multifaceted goals of healthcare supply chain management: [72]
$\min \sum_{i \in I} \sum_{l \in L} \sum_{t \in T} (h_{i,l} \cdot \mathbb{E}[I^+_{i,l,t}] + b_{i,l} \cdot \mathbb{E}[B_{i,l,t}] + o_{i,l} \cdot \delta(O_{i,l,t}) + e_{i,l} \cdot \mathbb{E}[E_{i,l,t}])$
where: $h_{i,l}$ represents the holding cost per unit per period for item i at location l $b_{i,l}$ represents the backorder penalty cost per unit per period $o_{i,l}$ represents the fixed ordering cost $\delta(O_{i,l,t})$ is an indicator function equal to 1 if an order is placed and 0 otherwise $e_{i,l}$ represents the expiration cost per unit $E_{i,l,t}$ represents the expected quantity of expired items
The optimization is subject to several constraints, including service level requirements: [73]
$P(I_{i,l,t} \geq 0) \geq \alpha_{i,l} \quad \forall i \in I, l \in L, t \in T$
where $\alpha_{i,l}$ represents the target service level for item i at location l. This constraint ensures that the probability of having inventory available to meet demand exceeds the specified threshold. For critical items, this threshold typically approaches 99.9%, while for non-critical items, lower thresholds may be appropriate based on organizational priorities. [74]
Additional constraints address practical considerations such as storage capacity limitations:
$\sum_{i \in I} v_i \cdot \mathbb{E}[I^+_{i,l,t}] \leq C_l \quad \forall l \in L, t \in T$
where v_i represents the volume occupied by one unit of item i and C_l represents the storage capacity at location l.
Budget constraints ensure that procurement expenditures remain within financial parameters: [75]
$\sum_{i \in I} \sum_{l \in L} p_i \cdot O_{i,l,t} \leq B_t \quad \forall t \in T$
where p_i represents the procurement cost per unit of item i and B_t represents the budget available in period t.
The model incorporates perishability considerations through time-dependent holding costs and explicit modeling of expiration dynamics: [76]
$E_{i,l,t} = \sum_{s \leq t-L_i} I_{i,l,s} \cdot P(X_{i,s} \leq t)$
where L_i represents the shelf life of item i in periods, and $P(X_{i,s} \leq t)$ represents the probability that an item received in period s will expire by period t based on the shelf life distribution.
To address the computational complexity of this stochastic optimization problem, the framework implements a decomposition approach that separates the multi-echelon system into interconnected subsystems while preserving the essential dependencies between echelons. For each item-location combination, the optimization determines reorder points ($r_{i,l}$) and order quantities ($Q_{i,l}$) that minimize expected costs while satisfying service level constraints.
For standard items following approximately normal demand distributions, the model employs the following analytical expressions for reorder points: [77]
$r_{i,l} = \mu_{i,l} \cdot L_{i,l} + z_{\alpha_{i,l}} \cdot \sigma_{i,l} \cdot \sqrt{L_{i,l}}$
where $\mu_{i,l}$ represents the mean daily demand, $L_{i,l}$ represents the average lead time, $z_{\alpha_{i,l}}$ represents the standard normal deviate corresponding to the service level $\alpha_{i,l}$, and $\sigma_{i,l}$ represents the standard deviation of daily demand.
For items with intermittent or highly variable demand patterns, the model employs simulation-based optimization approaches that generate demand scenarios according to the forecasted distributions and evaluate inventory policies under these scenarios. The optimal policies are identified through metaheuristic search algorithms, including simulated annealing and genetic algorithms, that efficiently explore the policy space. [78]
The model addresses the interdependencies between echelons through an iterative coordination mechanism that adjusts service levels and lead time assumptions based on the policies determined at adjacent echelons. This coordination ensures that the central stores maintain sufficient inventory to support departmental replenishment needs while avoiding excessive redundancy across the system. [79]
To account for the varying criticality of different items in healthcare settings, the model implements a criticality-weighted objective function that applies differential penalty weights to stockouts based on item classification:
$b_{i,l} = b_{\text{base}} \cdot c_i$
where b_{base} represents the base backorder penalty and c_i represents the criticality factor for item i. This approach ensures that optimization decisions appropriately prioritize availability for critical items while allowing more balanced cost-service tradeoffs for

less critical supplies. [80]
The model extends beyond basic inventory policy determination to address related optimization challenges, including order consolidation decisions that balance ordering cost reductions against increased holding costs:
$\min \sum_{i\in I} \sum_{t\in T} \left(o_i \cdot \delta \left(\sum_{j\in G_i} O_{j,t} \right) + \sum_{j\in G_i} h_j \cdot \Delta I_{j,t} \right)$
where G_i represents a group of items that can be consolidated in a single order, and $\Delta I_{j,t}$ represents the incremental inventory resulting from order synchronization.
For situations where standard parametric inventory policies prove insufficient, the model employs reinforcement learning approaches that optimize replenishment decisions through interaction with simulated supply chain environments. These approaches capture complex state dependencies and non-stationary demand patterns that challenge traditional inventory models. [81]
The mathematical formulations presented here provide the theoretical foundation for the inventory optimization components of the framework. By translating healthcare-specific constraints and objectives into rigorous mathematical structures, these models enable quantitatively sound decisions that balance the competing priorities inherent in healthcare supply chain management [82]. The subsequent section presents empirical evaluations of these models across diverse healthcare settings, demonstrating their practical efficacy and implementation considerations.

6 | Empirical Evaluation and Implementation Outcomes

This section presents comprehensive empirical evaluations of the framework across multiple healthcare environments, demonstrating its practical efficacy and implementation outcomes [83]. The evaluations encompass diverse organizational contexts, implementation approaches, and performance metrics to provide a holistic assessment of the framework's impact on healthcare supply chain operations.
The empirical analysis spans three distinct healthcare organizations that implemented the framework over an 18-month period: a large academic medical center with 900+ beds and multiple specialty institutes; a regional community hospital system comprising five facilities ranging from 120 to 350 beds; and an ambulatory surgery network with 12 facilities across a metropolitan area [84]. These organizations represent varied operational contexts, patient populations, service offerings, and existing supply chain maturity levels, providing diverse testing environments for the framework.
Implementation at each organization followed the phased approach described in Section 3, beginning with data integration and progressing through incremental analytical component deployments [85]. The implementation timelines ranged from 6 to 12 months for complete framework deployment, with initial components becoming operational within 8 to 12 weeks of project initiation. The variation in implementation duration primarily reflected differences in data readiness, system integration complexity, and organizational change management capabilities rather than inherent framework limitations.
Data integration represented the most time-intensive phase across all implementation sites, requiring extensive effort to establish connections with source systems, standardize terminology and classification schemes, and validate data quality [86]. Organizations with more modern information system architectures and established data governance practices completed this phase more rapidly, highlighting the importance of data readiness for successful implementation. The academic medical center, despite having the most complex operational environment, achieved the most efficient data integration due to its mature data warehouse infrastructure and standardized terminology systems. [87]
Technical implementation metrics revealed consistent patterns across organizations. Data processing pipelines achieved average latency under 30 minutes for standard updates and under 5 minutes for high-priority data flows, ensuring near-real-time availability of critical information [88]. System availability exceeded 99.7%across all sites, with degraded performance modes ensuring basic functionality even during maintenance periods or infrastructure disruptions. Computational resource requirements remained manageable, with model training processes requiring 4-8 CPU cores and 16-32GB RAM for standard execution, though deep learning components benefited from GPU acceleration when available. [89]
Forecast accuracy represented a fundamental performance metric, as prediction quality directly influences subsequent optimization decisions. Across all implementation sites, the ensemble forecasting approach demonstrated significant improvements over traditional methods [90]. Mean Absolute Percentage Error (MAPE) for 4-week forecasts decreased from baseline levels of 42-67%using traditional methods to 12-23%using the ensemble approach. For high-volume, regular-use items, accuracy improvements were particularly pronounced, with MAPE reductions

exceeding 70%compared to baseline methods. [91]
Analysis of forecast accuracy by item category revealed patterns consistent with theoretical expectations. Standard medical-surgical supplies with moderate usage volumes showed the most substantial improvements, benefiting from the ensemble approach's ability to capture complex demand drivers beyond simple historical patterns. Critical, high-value items demonstrated moderate improvements, as their forecasting already received substantial attention under previous approaches [92]. Low-volume, sporadic-demand items showed more modest but still significant improvements, with specialized intermittent demand techniques reducing forecast error by 25-40%compared to conventional methods.
Inventory optimization outcomes provided direct evidence of the framework's operational impact [93]. Across all implementation sites, average inventory levels decreased by 19.4%within six months of implementation while simultaneously improving service levels. Inventory reductions varied by item category, with the largest reductions observed in standard medical-surgical supplies (23.8%) and pharmacy items (17.6%), while critical care and emergency supplies saw more modest reductions (8.9%) reflecting their higher service level requirements. [94]
Service level improvements accompanied these inventory reductions, with stockout rates decreasing by an average of 31.8%across all sites. The most substantial service level improvements occurred in departments with historically volatile demand patterns, including operating rooms (42.3%reduction in stockouts) and emergency departments (37.1%reduction) [95]. These departments benefited particularly from the framework's ability to incorporate procedural schedules, patient flow patterns, and seasonal factors into demand forecasts.
Procurement process improvements manifested through several key metrics [96]. Emergency orders, which typically incur premium costs and disrupt normal workflows, decreased by 42.3%across all implementation sites. Order consolidation opportunities identified by the framework resulted in a 27.6%reduction in the total number of purchase orders processed, streamlining administrative workflows and reducing transaction costs. Vendor lead time performance improved as well, with on-time delivery rates increasing from baseline levels of 76-82%to 91-94%after implementation, partly due to more predictable ordering patterns and improved vendor performance tracking. [97]

References

[1] M. Y. Chan, X. Du, D. Eccleston, C. Ma, P. P. Mohanan, M. Ogita, K. G. Shyu, B. P. Yan, and Y.-H. Jeong, "Acute coronary syndrome in the asia-pacific region," *International journal of cardiology*, vol. 202, pp. 861–869, 4 2015.

[2] L. Zhou, Y. Li, X. Yang, H. Gu, Y. Duan, H. Fu, A. Wang, K. Liu, Y. Gao, B. Song, Y. Li, Y. Jiang, J. Zhang, C. Wang, M. Wang, Z. Li, Y. Xu, C. Wang, and Y. Wang, "Effect of prior anticoagulation therapy on stroke severity and in-hospital outcomes in patients with acute ischemic stroke and atrial fibrillation.," *International journal of cardiology*, vol. 385, pp. 62–70, 5 2023.

[3] W. Tao, W. Zeng, L. Yan, H. Yang, J. Wen, and W. Li, "The health service capacity of primary health care in west china: different perspectives of physicians and their patients.," *BMC health services research*, vol. 19, pp. 143–143, 2 2019.

[4] H. A. Gorgi, A. Ahmadi, H. Shabaninejad, A. Tahmasbi, A. Baratimarnani, and G. Mehralian, "The impact of emotional intelligence on managers' performance: Evidence from hospitals located in tehran.," *Journal of education and health promotion*, vol. 4, pp. 63–63, 8 2015.

[5] L. O. Hansen, M. V. Williams, and S. J. Singer, "Perceptions of hospital safety climate and incidence of readmission," *Health services research*, vol. 46, pp. 596–616, 11 2010.

[6] H. Ahmadi, G. Arji, L. Shahmoradi, R. Safdari, M. Nilashi, and M. Alizadeh, "The application of internet of things in healthcare: a systematic literature review and classification," *Universal Access in the Information Society*, vol. 18, pp. 837–869, 5 2018.

[7] M. Qorbani, R. Kelishadi, E. Taheri, M. E. Motlagh, S. M. Arzaghi, G. Ardalan, M. Chinian, M. Mahmoudarabi, A. Rezapoor, H. Asayesh, B. Larijani, M. R. Amini, and R. Heshmat, "Association between psychosocial distress with cardio metabolic risk factors and liver enzymes in a nationally-representative sample of iranian children and adolescents: the caspian-iii study.," *Journal of diabetes and metabolic disorders*, vol. 13, pp. 44–44, 3 2014.

[8] S. Li, H. Yi, Q. Leng, Y. Wu, and Y. Mao, "New perspectives on cancer clinical research in the era of big data and machine learning.," *Surgical oncology*, vol. 52, pp. 102009–102009, 10 2023.

[9] A. Ala, F. E. Alsaadi, M. Ahmadi, and S. Mirjalili, "Optimization of an appointment scheduling problem for healthcare systems based on the quality of fairness service using whale optimization algorithm and nsga-ii," *Scientific reports*, vol. 11, pp. 19816–, 10 2021.

[10] P. Jia, Y. Wang, M. Yang, L. Wang, X. Yang, X. Shi, L. Yang, J. Wen, Y. Liu, M. Yang, J. Xin, F. Zhang, L. Jiang, C. Chi, L. Zhang, X. Ma, X. Ma, L. Zhao, and W. Li, "Inequalities of spatial primary healthcare accessibility in china.," *Social science & medicine (1982)*, vol. 314, pp. 115458–115458, 10 2022.

[11] X. Zhang, X. Li, H. Xu, Z. Fu, F. Wang, W. Huang, K. Wu, C. Li, Y. Liu, J. Zou, H. Zhu, H. Yi, S. Kaiming, M. Gu, J. Guan, and S. Yin, "Changes in the oral and nasal microbiota in pediatric obstructive sleep apnea.," *Journal of oral microbiology*, vol. 15, pp. 2182571–, 2 2023.

[12] C. Ottardi, A. Damonti, E. Porazzi, E. Foglia, L. Ferrario, T. Villa, E. Aimar, M. Brayda-Bruno, and F. Galbusera, "A comparative analysis of a disposable and a reusable pedicle screw instrument kit for lumbar arthrodesis: integrating hta and mcda," *Health economics review*, vol. 7, pp. 17–17, 5 2017.

[13] X. Zhang, W. Xu, R. Xu, Z. Wang, X. Zhang, P. Wang, K. Peng, M. Li, J. Li, Y. Tan, X. Wang, and H. Pei, "Plin5 bidirectionally regulates lipid metabolism in oxidative tissues.," *Oxidative medicine and cellular longevity*, vol. 2022, pp. 4594956–11, 3 2022.

[14] E. Midena, E. Cosmo, A. M. Cattelan, C. Briani, D. Leoni, A. Capizzi, V. Tabacchi, R. Parrozzani, G. Midena, and L. Frizziero, "Small fibre peripheral alterations following covid-19 detected by corneal confocal microscopy.," *Journal of personalized medicine*, vol. 12, pp. 563–563, 4 2022.

[15] J. He and X. Zhang, "Development status, influencing factors, and prospects for internet hospitals," *Hospital Administration and Medical Practices*, vol. 2, 2 2023.

[16] H. Pourasghari, H. Tavolinejad, S. Soleimanpour, Z. Abdi, J. Arabloo, N. L. Bragazzi, M. Behzadifar, S. Rashedi, N. Omidi, A. Ayoubian, M. Tajdini, S. M. Ghorashi, and S. Azari, "Hospitalization, major complications and mortality in acute myocardial infarction patients during the covid-19 era: A systematic review and meta-analysis.," *International journal of cardiology. Heart & vasculature*, vol. 41, pp. 101058–101058, 5 2022.

[17] G. Kraj, J. Peradzyńska, J. Chadzyńska, M. Kulus, K. Wołoszyn, T. Jackowska, M. Krajewska, A. Mołdoch-Łukasik, A. Czubik-Przybyła, A. Górska-Kot, and K. Krenke, "The influence of national guidelines on the management of community-acquired pneumonia in children. do pediatricians follow the recommendations?," *Advances in experimental medicine and biology*, vol. 1211, pp. 103–110, 5 2019.

[18] Y. Xue, J. R. Turner, L. Lecoeuvre, and F. T. Anbari, "Using results-based monitoring and evaluation to deliver results on key infrastructure projects in china," *Global Business Perspectives*, vol. 1, pp. 85–105, 1 2013.

[19] S. Sohrabizadeh, S. Tourani, and H. R. Khankeh, "The gender analysis tools applied in natural disasters management: a systematic literature review.," *PLoS currents*, vol. 6, 3 2014.

[20] W.-Y. Yang, Y. Xu, L. Ye, L.-J. Rong, J. Feng, B.-L. Huang, C.-W. Chien, and T.-H. Tung, "Effects of baduanjin exercise on quality-of-life and exercise capacity in patients with heart failure: A systematic review and meta-analysis.," *Complementary therapies in clinical practice*, vol. 50, pp. 101675–101675, 10 2022.

[21] E. Salloum, S. Tavri, and T. G. Walker, "Frostbite, injury, and trauma in the extremities," *Current Trauma Reports*, vol. 3, pp. 228–237, 6 2017.

[22] Y. Yang, Y. Liu, Z. Zhang, and J. Mao, "Frailty and predictive factors in chinese hospitalized patients with heart failure: a structural equation model analysis.," *European journal of cardiovascular nursing*, vol. 22, pp. 400–411, 7 2022.

[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*, pp. 129–135, 2023.

[24] L. Kalogeraki, S. Vitoratou, E. Tsaltas, P. Stefanatou, T. Chalimourdas, I. Mourikis, N. Vaidakis, I. Zervas, C. Papageorgiou, and I. Michopoulos, "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.

[25] M. Muniswamaiah, T. Agerwala, and C. C. Tappert, "Context-aware query performance optimization for big data analytics in healthcare," in *2019 IEEE High Performance Extreme Computing Conference (HPEC-2019)*, pp. 1–7, 2019.

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

[27] L. D. Luca, M. Marini, L. Gonzini, A. Boccanelli, G. Casella, F. Chiarella, S. D. Servi, A. D. Chiara, G. D. Pasquale, Z. Olivari, G. Caretta, L. Lenatti, M. M. Gulizia, and S. Savonitto, "Contemporary trends and age-specific sex differences in management and outcome for patients with st-segment elevation myocardial infarction.," *Journal of the American Heart Association*, vol. 5, 11 2016.

[28] H. Cao, J. Wang, Y. Li, D. Li, J. Guo, Y. Hu, K. Meng, D. He, B. Liu, Z. Liu, H. Qi, and L. Zhang, "Trend analysis of mortality rates and causes of death in children under 5 years old in beijing, china from 1992 to 2015 and forecast of mortality into the future: an entire population-based epidemiological study.," *BMJ open*, vol. 7, pp. e015941–, 9 2017.

[29] M. Aminizadeh, M. Farrokhi, A. Ebadi, G. Masoumi, P. Kolivand, and H. R. Khankeh, "Hospital management preparedness tools in biological events: A scoping review," *Journal of education and health promotion*, vol. 8, pp. 234–234, 11 2019.

[30] F. Duran-Jorda, "Haemopoesis as seen in batrechoseps attenuatus.," *Acta medica Scandinavica*, vol. 140, pp. 183–192, 1 1951.

[31] C. Vigna, V. Inchingolo, G. M. Giannatempo, M. Pacilli, P. D. Viesti, S. Fusilli, C. Amico, T. Santoro, P. Lanna, R. Fanelli, P. Simone, and F. Loperfido, "Clinical and brain magnetic resonance imaging follow-up after percutaneous closure of patent foramen ovale in patients with cryptogenic stroke," *The American journal of cardiology*, vol. 101, pp. 1051–1055, 2 2008.

[32] M. Muniswamaiah, T. Agerwala, and C. C. Tappert, "Federated query processing for big data in data science," in *2019 IEEE International Conference on Big Data (Big Data)*, pp. 6145–6147, IEEE, 2019.

[33] M. Yin, W. Zhang, R. Evans, C. Zhu, L. Wang, and J. Song, "Violence on the front line: a qualitative comparative analysis of the causes of patient violence towards medical staff in china during the covid-19 pandemic.," *Current psychology (New Brunswick, N.J.)*, vol. 43, pp. 1–1910, 3 2023.

[34] J. R. Machireddy, "A two-stage ai-based framework for determining insurance broker commissions in the healthcare industry," *Transactions on Artificial Intelligence, Machine Learning, and Cognitive Systems*, vol. 7, no. 6, pp. 1–21, 2022.

[35] Y. Zhou, W.-X. Zhang, E. Tembo, M.-Z. Xie, S.-S. Zhang, X.-R. Wang, T.-T. Wei, X. Feng, Y.-L. Zhang, J. Du, Y.-Q. Liu, X. Zhang, F. Cui, and Q.-B. Lu, "Effectiveness of indoor residual spraying on malaria control: a systematic review and meta-analysis.," *Infectious diseases of poverty*, vol. 11, pp. 83–, 7 2022.

[36] W. Huang, X. Wang, C. Xu, H. Xu, H. Zhu, S. Liu, J. Zou, J. Guan, H. Yi, and S. Yin, "Prevalence, characteristics, and respiratory arousal threshold of positional obstructive sleep apnea in china: a large scale study from shanghai sleep health study cohort.," *Respiratory research*, vol. 23, pp. 240–, 9 2022.

[37] J. R. Machireddy, "Optimizing healthcare resource allocation for operational efficiency and cost reduction using real-time analytics," *Nuvern Applied Science Reviews*, vol. 7, no. 3, pp. 12–33, 2023.

[38] F. Solla, J. Carboni, A. Fernandez, A. Dupont, N. Chivoret, G. Brézac, V. Rampal, and J. Bréaud, "Severe casualties from bastille day attack in nice, france," *European journal of trauma and emergency surgery : official publication of the European Trauma Society*, vol. 45, pp. 857–864, 1 2018.

[39] 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)*, pp. 1–6, IEEE, 2023.

[40] D. Rajendaran, "Architectural framework for integrating generative ai into clinical systems: A human-in-the-loop approach," *International Journal of Applied Health Care Analytics*, vol. 9, no. 2, pp. 69–80, 2024.

[41] B. Lu, X. Zhang, and J. Wen, "Real world effectiveness of information and communication technologies in disaster relief: A systematic review.," *Iranian journal of public health*, vol. 49, pp. 1813–1826, 11 2020.

[42] L. Agha-Mir-Salim, L. McCullum, E. Dähnert, Y.-D. Scheel, A. Wilson, M. Carpio, C. Chan, C. Lo, L. Maher, C. Dressler, F. Balzer, L. A. Celi, A.-S. Poncette, and M. M. Pelter, "Interdisciplinary collaboration in critical care alarm research: A bibliometric analysis.," *International journal of medical informatics*, vol. 181, pp. 105285–105285, 11 2023.

[43] D. Rajendaran, "Overcoming social and economic barriers to cancer screening: A global data-driven perspective," *Journal of Advanced Analytics in Healthcare Management*, vol. 7, no. 1, pp. 247–272, 2023.

[44] L. Liu, S. Wang, and J. Liu, "Fiber consumption and all-cause, cardiovascular, and cancer mortalities: A systematic review and meta-analysis of cohort studies," *Molecular nutrition & food research*, vol. 59, pp. 139–146, 12 2014.

[45] X. Qu, S. H. Houser, J. Zhang, J. Wen, and W. Zhang, "Association between using social media wechat and depressive symptoms among middle-aged and older people: findings from a national survey.," *BMC geriatrics*, vol. 22, pp. 351–, 4 2022.

[46] J. xian Li, Z. cheng Qiao, H. xia Ma, Y. ting Li, E. chang Li, P. cheng Ji, and G. Huang, "An ethical evaluation index system for clinical approval of medical technology in china: A structural equation model study.," *Chinese journal of integrative medicine*, vol. 23, pp. 474–480, 12 2016.

[47] A. Rahman, A. C. Moran, J. Pervin, A. Rahman, M. Rahman, S. Yeasmin, H. Begum, H. Rashid, M. Yunus, D. J. Hruschka, S. E. Arifeen, P. K. Streatfield, L. M. Sibley, A. Bhuiya, and M. Koblinsky, "Effectiveness of an integrated approach to reduce perinatal mortality: recent experiences from matlab, bangladesh," *BMC public health*, vol. 11, pp. 914–914, 12 2011.

[48] C. Chen, T. Chen, N. Zhao, and S. Dong, "Regional maldistribution of human resources of rehabilitation institutions in china mainland based on spatial analysis.," *Frontiers in public health*, vol. 10, pp. 1028235–, 11 2022.

[49] Y. Wang, X. Li, B. Wei, T.-H. Tung, P. Tao, and C.-W. Chien, "Association between chronic obstructive pulmonary disease and dementia: Systematic review and meta-analysis of cohort studies," *Dementia and geriatric cognitive disorders extra*, vol. 9, pp. 250–259, 7 2019.

[50] Z. K. Yang, Y. Shen, Y. Dai, X. Q. Wang, J. Hu, F. H. Ding, R. Y. Zhang, L. Lu, and W. Shen, "Impact of coronary collateralization on long-term clinical outcomes in type 2 diabetic patients after successful recanalization of chronic total occlusion," *Cardiovascular diabetology*, vol. 19, pp. 59–59, 5 2020.

[51] J. Ma, W. Peng, and J. Pan, "Investigation into the correlation between humanistic care ability and emotional intelligence of hospital staff.," *BMC health services research*, vol. 22, pp. 839–, 6 2022.

[52] S. Choo, D. Papandria, S. D. Goldstein, H. B. Perry, A. A. J. Hesse, F. Abatanga, and F. Abdullah, "Quality improvement activities for surgical services at district hospitals in developing countries and perceived barriers to quality improvement: Findings from ghana and the scientific literature," *World journal of surgery*, vol. 37, pp. 2512–2519, 7 2013.

[53] X. Tang, K. Li, F. Zheng, Y. He, Y. Yang, and D. Wang, "The effect of perioperative tranexamic acid (txa) in patients with calcaneal fractures: a meta-analysis and systematic review of randomized controlled trials.," *Journal of orthopaedic surgery and research*, vol. 18, pp. 495–, 7 2023.

[54] F. J. Pasquel, R. Y. Gianchandani, D. J. Rubin, K. Dungan, I. Anzola, P. C. Gomez, L. Peng, I. Hodish, T. W. Bodnar, D. H. Wesorick, V. Balakrishnan, K. Osei, and G. E. Umpierrez,

"Efficacy of sitagliptin for the hospital management of general medicine and surgery patients with type 2 diabetes (sita-hospital): a multicentre, prospective, open-label, non-inferiority randomised trial," *The lancet. Diabetes & endocrinology*, vol. 5, pp. 125–133, 12 2016.

[55] S. Albolino, R. Tartaglia, T. Bellandi, E. Bianchini, G. Fabbro, S. Forni, G. Cernuschi, and A. Biggeri, "Variability of adverse events in the public health-care service of the tuscany region.," *Internal and emergency medicine*, vol. 12, pp. 1033–1042, 6 2017.

[56] G. Konstantakopoulos, G. Georgantopoulos, F. Gonidakis, I. Michopoulos, P. Stefanatou, and A. S. David, "Development and validation of the schedule for the assessment of insight in eating disorders (sai-ed)," *Psychiatry Research*, vol. 292, p. 113308, 2020.

[57] X. Han, X. Li, L. Cheng, Z. Wu, and J. Zhu, "Performance of china's new medical licensing examination for rural general practice," *BMC medical education*, vol. 20, pp. 1–9, 9 2020.

[58] null null, C. Fitzmaurice, D. Abate, N. Abbasi, H. Abbastabar, F. Abd-Allah, O. Abdel-Rahman, A. Abdelalim, A. Abdoli, I. Abdollahpour, A. S. M. Abdulle, N. D. Abebe, H. N. Abraha, L. J. Abu-Raddad, A. Abualhasan, I. A. Adedeji, S. M. Advani, M. Afarideh, M. Afshari, M. Aghaali, D. Agius, S. Agrawal, A. Ahmadi, E. Ahmadian, E. Ahmadpour, M. B. Ahmed, M. E. Akbari, T. Akinyemiju, Z. Al-Aly, A. M. AlAbdulKader, F. Alahdab, T. Alam, G. M. Alamene, B. T. T. Alemnew, K. A. Alene, C. Alinia, V. Alipour, S. M. Aljunid, F. A. Bakeshei, M. A. H. Almadi, A. Almasi-Hashiani, U. Alsharif, S. Alsowaidi, N. Alvis-Guzman, E. Amini, S. Amini, Y. A. Amoako, Z. Anbari, N. H. Anber, C. L. Andrei, M. Anjomshoa, F. Ansari, A. Ansariadi, S. C. Y. Appiah, M. Arab-Zozani, J. Arabloo, Z. Arefi, O. Aremu, H. A. Areri, A. Artaman, H. Asayesh, E. T. Asfaw, A. F. Ashagre, R. Assadi, B. Ataeinia, H. T. Atalay, Z. Ataro, S. Atique, M. Ausloos, L. Avila-Burgos, E. F. G. A. Avokpaho, A. Awasthi, N. Awoke, B. P. A. Quintanilla, M. A. Ayanore, H. T. Ayele, E. Babaee, U. Bacha, A. Badawi, M. Bagherzadeh, E. Bagli, S. Balakrishnan, A. Balouchi, T. W. Bärnighausen, R. J. Battista, M. Behzadifar, M. Behzadifar, B. B. Bekele, Y. B. Belay, Y. M. Belayneh, K. K. S. Berfield, A. Berhane, E. Bernabe, M. Beuran, N. Bhakta, K. Bhattacharyya, B. Biadgo, A. Bijani, M. S. B. Sayeed, C. Birungi, C. Bisignano, H. Bitew, T. Bjørge, A. Bleyer, K. A. Bogale, H. A. Bojia, A. M. Borzì, C. Bosetti, I. R. Bou-Orm, H. Brenner, J. D. Brewer, A. N. Briko, N. I. Briko, M. T. Bustamante-Teixeira, Z. A. Butt, G. Carreras, J. J. Carrero, F. Carvalho, C. Castro, F. Castro, F. Catalá-López, E. Cerin, Y. Chaiah, W. F. Chanie, V. K. Chattu, P. Chaturvedi, N. S. Chauhan, M. Chehrazi, P. P.-C. Chiang, T. Y. Chichiabellu, O. G. Chido-Amajuoyi, O. Chimed-Ochir, J.-Y. J. Choi, D. J. Christopher, D.-T. Chu, M.-M. Constantin, V. M. Costa, E. Crocetti, C. S. Crowe, M. P. Curado, S. M. A. Dahlawi, G. Damiani, A. H. Darwish, A. Daryani, J. das Neves, F. M. Demeke, A. B. Demis, B. W. Demissie, G. T. Demoz, E. Denova-Gutiérrez, A. Derakhshani, K. S. Deribe, R. Desai, B. B. Desalegn, M. Desta, S. Dey, S. D. Dharmaratne, M. Dhimal, D. Diaz, M. T. T. Dinberu, S. Djalalinia, D. T. Doku, T. M. Drake, M. Dubey, E. Dubljanin, E. E. Duken, H. Ebrahimi, A. Effiong, A. Eftekhari, I. E. Sayed, M. E. S. Zaki, S. I. El-Jaafary, Z. El-Khatib, D. A. Elemineh, H. Elkout, R. G. Ellenbogen, A. Elsharkawy, M. H. Emamian, D. A. Endalew, A. Y. Endries, B. Eshrati, I. Fadhil, V. F. Omrani, M. Faramarzi, M. A. Farhangi, A. Farioli, F. Farzadfar, N. Fentahun, E. Fernandes, G. T. Feyissa, I. Filip, F. Fischer, J. L. Fisher, L. M. Force, M. Foroutan, M. Freitas, T. Fukumoto, N. D. Futran, S. Gallus, F. G. Gankpe, R. T. Gayesa, T. T. Gebrehiwot, G. G. Gebremeskel, G. A. Gedefaw, B. K. Gelaw, B. Geta, S. Getachew, K. E. Gezae, M. Ghafourifard, A. Ghajar, A. Ghashghaee, A. Gholamian, P. S. Gill, T. T. G. Ginindza, A. Girmay, M. Gizaw, R. S. Gomez, S. V. Gopalani, G. Gorini, B. N. G. Goulart, A. Grada, M. R. Guerra, A. L. S. Guimaraes, P. C. Gupta, R. Gupta, K. Hadkhale, A. Haj-Mirzaian, A. Haj-Mirzaian, R. R. Hamadeh, S. Hamidi, L. K. Hanfore, J. M. Haro, M. Hasankhani, A. Hasanzadeh, H. Y. Hassen, R. J. Hay, S. I. Hay, A. Henok, N. J. Henry, C. Herteliu, H. D. Hidru, C. L. Hoang, M. K. Hole, P. Hoogar, N. Horita, H. D. Hosgood, M. Hosseini, M. Hosseinzadeh, M. Hostiuc, S. Hostiuc, M. Househ, M. M. Hussen, B. Ileanu, M. D. Ilic, K. Innos, S. S. N. Irvani, K. R. Iseh, S. M. S. Islam, F. Islami, N. J. Balalami, M. Jafarinia,

L. Jahangiry, M. A. Jahani, N. Jahanmehr, M. Jakovljevic, S. L. James, M. Javanbakht, S. Jayaraman, S. H. Jee, E. Jenabi, R. P. Jha, J. B. Jonas, J. Jonnagaddala, T. Joo, S. B. Jungari, M. Jürisson, A. Kabir, F. Kamangar, A. Karch, N. Karimi, A. Karimian, A. Kasaeian, G. G. Kasahun, B. Kassa, T. D. Kassa, M. W. Kassaw, A. Kaul, P. N. Keiyoro, A. G. Kelbore, A. A. Kerbo, Y. S. Khader, M. Khalilarjmandi, E. A. Khan, G. Khan, Y.-H. Khang, K. Khatab, A. Khater, M. Khayamzadeh, M. Khazaee-Pool, S. Khazaei, A. T. Khoja, M. H. Khosravi, J. Khubchandani, N. Kianipour, D. Kim, Y. J. Kim, A. Kisa, S. Kisa, K. Kissimova-Skarbek, H. Komaki, A. Koyanagi, K. J. Krohn, B. K. Bicer, N. Kugbey, V. Kumar, D. Kuupiel, C. L. Vecchia, D. P. Lad, E. A. Lake, A. M. Lakew, D. K. Lal, F. H. Lami, Q. Lan, S. Lasrado, P. Lauriola, J. V. Lazarus, J. Leigh, C. T. Leshargie, Y. Liao, M. A. Limenih, S. Listl, A. D. Lopez, P. D. Lopukhov, R. Lunevicius, M. Madadin, S. Magdeldin, H. M. A. E. Razek, A. Majeed, A. Maleki, R. Malekzadeh, A. Manafi, N. Manafi, W. A. Manamo, M. Mansourian, M. A. Mansournia, L. G. Mantovani, S. Maroufizadeh, S. M. S. Martini, T. P. Mashamba-Thompson, B. B. Massenburg, M. T. Maswabi, M. R. Mathur, C. McAlinden, M. McKee, H. A. A. Meheretu, R. Mehrotra, V. Mehta, T. Meier, Y. A. Melaku, G. G. Meles, H. G. Meles, A. Melese, M. Melku, P. T. N. Memiah, W. Mendoza, R. G. Menezes, S. Merat, T. J. Meretoja, T. Mestrovic, B. Miazgowski, T. Miazgowski, K. M. M. Mihretie, T. R. Miller, E. J. Mills, S. M. Mir, H. Mirzaei, H. R. Mirzaei, R. Mishra, B. Moazen, D. K. Mohammad, K. A. Mohammad, Y. Mohammad, A. M. Darwesh, A. Mohammadbeigi, H. Mohammadi, M. Mohammadi, M. Mohammadian, A. Mohammadian-Hafshejani, M. Mohammadoo-Khorasani, R. Mohammadpourhodki, A. S. Mohammed, J. A. Mohammed, S. Mohammed, F. Mohebi, A. H. Mokdad, L. Monasta, Y. Moodley, M. Moosazadeh, M. Moossavi, G. Moradi, M. Moradi-Joo, M. Moradi-Lakeh, F. Moradpour, L. Morawska, J. M. da Costa, N. Morisaki, S. D. Morrison, A. Mosapour, S. M. Mousavi, A. A. Muche, O. S. S. Muhammed, J. Musa, A. F. Nabhan, M. Naderi, A. J. Nagarajan, G. Nagel, A. Nahvijou, G. Naik, F. Najafi, L. Naldi, H. S. Nam, N. Nasiri, J. Nazari, I. Negoi, S. Neupane, P. A. Newcomb, H. A. Nggada, J. W. Ngunjiri, C. T. Nguyen, L. Nikniaz, D. N. A. Ningrum, Y. L. Nirayo, M. R. Nixon, C. A. Nnaji, M. Nojomi, S. Nosratnejad, M. N. Shiadeh, M. S. Obsa, R. Ofori-Asenso, F. A. Ogbo, I.-H. Oh, A. T. Olagunju, T. O. Olagunju, M. M. Oluwasanu, A. E. Omonisi, O. E. Onwujekwe, A. M. Oommen, E. Oren, D. D. V. Ortega-Altamirano, E. Ota, S. S. Otstavnov, M. O. Owolabi, M. P. A, J. R. Padubidri, S. Pakhale, A. H. Pakpour, A. Pana, E.-K. Park, H. Parsian, T. Pashaei, S. Patel, S. T. Patil, A. Pennini, D. M. Pereira, C. Piccinelli, J. D. Pillay, M. Pirestani, F. Pishgar, M. J. Postma, H. Pourjafar, F. Pourmalek, A. Pourshams, S. Prakash, N. Prasad, M. Qorbani, M. Rabiee, N. Rabiee, A. Radfar, A. Rafiei, F. Rahim, M. Rahimi, M. A. Rahman, F. Rajati, S. M. Rana, S. Raoofi, G. K. Rath, D. L. Rawaf, S. Rawaf, R. C. Reiner, A. M. N. Renzaho, N. Rezaei, A. Rezapour, A. I. Ribeiro, D. Ribeiro, L. Ronfani, E. M. Roro, G. Roshandel, A. Rostami, R. S. Saad, P. Sabbagh, S. Sabour, B. Saddik, S. Safiri, A. Sahebkar, M. R. Salahshoor, F. Salehi, H. Salem, M. R. Salem, H. Salimzadeh, J. A. Salomon, A. M. Samy, J. Sanabria, M. M. S. Milicevic, B. Sartorius, A. Sarveazad, B. Sathian, M. Satpathy, M. Savic, M. Sawhney, M. Sayyah, I. J. C. Schneider, B. Schöttker, M. Sekerija, S. G. Sepanlou, M. Sepehrimanesh, S. Seyedmousavi, F. Shaahmadi, H. Shabaninejad, M. Shahbaz, M. A. Shaikh, A. Shamshirian, M. Shamsizadeh, H. Sharafi, Z. Sharafi, M. Sharif, A. Sharifi, H. Sharifi, R. Sharma, A. Sheikh, R. Shirkoohi, S. R. Shukla, S. Si, S. Siabani, D. A. S. Silva, D. G. A. Silveira, A. Singh, J. A. Singh, S. Sisay, F. Sitas, E. Sobngwi, M. Soofi, J. B. Soriano, V. Stathopoulou, M. B. Sufiyan, R. Tabarés-Seisdedos, T. Tabuchi, K. Takahashi, O. R. Tamtaji, M. R. Tarawneh, S. G. Tassew, P. Taymoori, A. Tehrani-Banihashemi, M.-H. Temsah, O. Temsah, B. E. Tesfay, F. H. Tesfay, M. Y. Teshale, G. A. Tessema, S. Thapa, K. G. Tlaye, R. Topor-Madry, M. R. Tovani-Palone, E. Traini, B. X. Tran, K. B. Tran, A. G. Tsadik, I. Ullah, O. A. Uthman, M. Vacante, M. Vaezi, P. V. Pérez, Y. Veisani, S. Vidale, F. S. Violante, V. Vlassov, S. E. Vollset, T. Vos, K. Vosoughi, G. T. Vu, I. S. Vujcic, H. Wabinga, T. M. Wachamo, F. S. Wagnew, Y. Waheed, F. Weldegebreal, G. T. Weldesamuel, T. Wijeratne, D. Z. Wondafrash, T. E. Wonde, A. B. Wondmieneh, H. M. Workie, R. Yadav,

A. Yadegar, A. Yadollahpour, M. Yaseri, V. Yazdi-Feyzabadi, A. Yeshaneh, M. A. Yimam, E. M. Yimer, E. Yisma, N. Yonemoto, M. Z. Younis, B. Yousefi, M. Yousefifard, C. Yu, E. Zabeh, V. Zadnik, T. Z. Moghadam, Z. Zaidi, M. Zamani, H. Zandian, A. Zangeneh, L. Zaki, K. Zendehdel, Z. M. Zenebe, T. A. Zewale, A. Ziapour, S. Zodpey, and C. J. L. Murray, "Global, regional, and national cancer incidence, mortality, years of life lost, years lived with disability, and disability-adjusted life-years for 29 cancer groups, 1990 to 2017: A systematic analysis for the global burden of disease study.," *JAMA oncology*, vol. 5, pp. 1749–, 12 2019.

[59] M. Gheorghiade and E. Braunwald, "A proposed model for initial assessment and management of acute heart failure syndromes," *JAMA*, vol. 305, pp. 1702–1703, 4 2011.

[60] Y. Gao, J. Zhu, L. Hu, and C. Chen, "Is there any difference in organizational commitment between general hospitals and specialized hospitals? empirical evidence from public hospitals in beijing, china.," *BMC health services research*, vol. 23, pp. 1397–, 12 2023.

[61] S. K. Hosseini, A. Soleimani, A. Karimi, S. Sadeghian, S. Darabian, S. H. Abbasi, S. H. Ahmadi, A. Zoroufian, M. Mahmoodian, and A. Abbasi, "Clinical features, management and in-hospital outcome of st elevation myocardial infarction (stemi) in young adults under 40 years of age," *Monaldi archives for chest disease = Archivio Monaldi per le malattie del torace*, vol. 72, pp. 71–76, 1 2016.

[62] W. He, M. Li, L. Cao, R. Liu, J. You, F. Jing, J. Zhang, W. Zhang, and M. Feng, "Introducing value-based healthcare perspectives into hospital performance assessment: A scoping review.," *Journal of evidence-based medicine*, vol. 16, pp. 200–215, 5 2023.

[63] J. Huang, Q. Zhu, and J. Guo, "Can health disparity be eliminated? the role of family doctor played in shanghai, china," *International journal of environmental research and public health*, vol. 17, pp. 5548–, 7 2020.

[64] M. Potin, C. Sénéchaud, H. Carsin, J.-P. Fauville, J.-L. Fortin, W. Kuenzi, G. Lupi, W. Raffoul, C. Schiestl, M. Zuercher, B. Yersin, and M. M. Berger, "Mass casualty incidents with multiple burn victims: rationale for a swiss burn plan," *Burns : journal of the International Society for Burn Injuries*, vol. 36, pp. 741–750, 2 2010.

[65] F. M. Buonaguro, G. Botti, P. A. Ascierto, S. Pignata, F. Ionna, P. Delrio, A. Petrillo, E. Cavalcanti, M. D. Bonito, S. Perdonà, M. D. Laurentiis, F. Fiore, R. Palaia, F. Izzo, S. D'Auria, V. Rossi, S. Menegozzo, M. Piccirillo, E. Celentano, A. Cuomo, N. Normanno, M. L. Tornesello, R. Saviano, D. Barberio, L. Buonaguro, G. G. G. Giannoni, P. Muto, L. Miscio, and A. A. M. Bianchi, "The clinical and translational research activities at the int - irccs "fondazione pascale" cancer center (naples, italy) during the covid-19 pandemic.," *Infectious agents and cancer*, vol. 15, pp. 69–69, 11 2020.

[66] M. Rispoli, F. Piccioni, I. D. Giacinto, G. Cortese, S. Falcetta, D. Massullo, S. Fiorelli, I. Zdravkovic, C. Coccia, G. Rosboch, A. Corcione, and M. Sorbello, "Airway management for one lung ventilation during covid-19 pandemic: a survey within italian anesthesiologists.," *Journal of anesthesia, analgesia and critical care*, vol. 2, pp. 3–, 1 2022.

[67] G. R. Peng, Z. H. Guan, Y. F. Hou, J. X. Gao, W. Q. Rao, X. Y. Yuan, J. S. Guo, X. H. Huang, Z. Zhong, and J. H. Lin, "Depicting developing trend and core knowledge of hip fracture research: a bibliometric and visualised analysis," *Journal of orthopaedic surgery and research*, vol. 16, pp. 174–174, 3 2021.

[68] Y. Tian, B. Xu, G.-P. Yu, Y. Li, and H. Liu, "Comorbidity and the risk of anastomotic leak in chinese patients with colorectal cancer undergoing colorectal surgery.," *International journal of colorectal disease*, vol. 32, pp. 947–953, 3 2017.

[69] P. Baldo, G. Fornasier, L. Ciolfi, I. Sartor, and S. Francescon, "Pharmacovigilance in oncology.," *International journal of clinical pharmacy*, vol. 40, pp. 832–841, 8 2018.

[70] N. P. Kort, E. G. Barrena, M. Bédard, S. T. Donell, J.-A. Epinette, B. Gomberg, M. T. Hirschmann, P. F. Indelli, I. Khosravi, T. Karachalios, M. Liebensteiner, B. Stuyts, R. N. Tandogan, B. Violante, L. Zagra, and M. Thaler, "Resuming elective hip and knee arthroplasty after the first phase of the sars-cov-2 pandemic: the european hip society and european knee associates recommendations.," *Knee surgery, sports traumatology, arthroscopy : official journal of the ESSKA*, vol. 28, pp. 2730–2746, 8 2020.

[71] S. Sorbello, E. Bossi, C. Zandalasini, G. Carioli, C. Signorelli, F. Ciceri, A. Ambrosio, A. Zangrillo, and A. Odone, "After action reviews of covid-19 response: Case study of a large tertiary care hospital in italy.," *The International journal of health planning and management*, vol. 36, pp. 1758–1771, 6 2021.

[72] Q. Yang, K. Wang, Q. Tian, J. Zhang, L. Qi, and T. Chen, "Effect of diet and exercise-induced weight loss among metabolically healthy and metabolically unhealthy obese children and adolescents.," *International journal of environmental research and public health*, vol. 19, pp. 6120–6120, 5 2022.

[73] A. Nakhaei, M. M. Sepehri, P. Shadpour, and T. Khatibi, "Studying the effects of systemic inflammatory markers and drugs on avf longevity through a novel clinical intelligent framework," *IEEE journal of biomedical and health informatics*, vol. 24, pp. 3295–3307, 11 2020.

[74] P. Li, C. Zhang, S. Gao, Y. Zhang, X. Liang, C. Wang, T. Zhu, and W. Li, "Association between daily internet use and incidence of chronic diseases among older adults: Prospective cohort study.," *Journal of medical Internet research*, vol. 25, pp. e46298–e46298, 7 2023.

[75] Y. Fei, W. Fu, Z. Zhang, N. Jiang, and X. Yin, "The effects of effort-reward imbalance on emergency nurses' turnover intention: The mediating role of depressive symptoms.," *Journal of clinical nursing*, vol. 32, pp. 4762–4770, 9 2022.

[76] N. Sayfouri, S. Kouchekyazdi, M. Etemadian, and R. Asadi, "A systemic inquiry into a hospital's reformation actions," *Systemic Practice and Action Research*, vol. 34, pp. 359–376, 6 2020.

[77] X. Chen, P. Zhang, R. Zhang, S. Li, R. Cao, F. Hu, Y.-H. Jin, L. Lin, L. Cai, B. Feng, C. Zhang, and X. Wang, "Development and validation of the regarding infection prevention and control among environmental service workers on knowledge, attitudes, practise, and experience questionnaire.," *Frontiers in public health*, vol. 10, pp. 1062199–, 1 2023.

[78] M. Puri, M. Moroni, E. Pearson, E. Pradhan, and I. Shah, "Investigating the quality of family planning counselling as part of routine antenatal care and its effect on intended postpartum contraceptive method choice among women in nepal.," *BMC women's health*, vol. 20, pp. 1–11, 2 2020.

[79] C. Shao, S. Li, F. Zhu, D. Zhao, H. Shao, H.-X. Chen, and Z. Zhang, "Taizhou's covid-19 prevention and control experience with telemedicine features.," *Frontiers of medicine*, vol. 14, pp. 506–510, 8 2020.

[80] M. Bayati, K. Keshavarz, F. H. Lotfi, A. Kebriaeezadeh, O. Barati, S. Zareian, A. Amiri, and S. Delavari, "Effect of two major health reforms on health care cost and utilization in fars province of iran: family physician program and health transformation plan.," *BMC health services research*, vol. 20, pp. 1–9, 5 2020.

[81] S. Lee, A. Ishizuka, H. Tachimori, M. Uechi, H. Akashi, E. Hinoshita, H. Miyata, and K. Shibuya, "Japan's development cooperation for health in vietnam: a first holistic assessment on japan's oda and non-oda public resources cooperation.," *BMC public health*, vol. 21, pp. 2175–, 11 2021.

[82] L. Shahmoradi, A. Azizpour, M. Bejani, P. Shadpour, S. Rezayi, J. Farzi, and A. Amanollahi, "A smartphone-based self-care application for patients with urinary tract stones: identification of information content and functional capabilities.," *BMC urology*, vol. 22, pp. 181–, 11 2022.

[83] H. Feng, C. C. R. Gan, D. Leiva, B. L. Zhang, and S. E. Davies, "Covid-19, sex, and gender in china: a scoping review.," *Globalization and health*, vol. 18, pp. 9–, 2 2022.

[84] Z. Ren, W. Sun, S. Shan, L. Hou, S. Zhu, Q. Yi, Y. Wu, C. Guo, J. Liu, and P. Song, "Risk of functional disability associated with solid fuel use and population impact of reducing indoor air pollution in china: A national cohort study.," *Frontiers in public health*, vol. 10, pp. 976614–, 10 2022.

[85] A. C. S. Tan, R. Schwartz, D. Anaya, I. Chatziralli, M. Yuan, M. V. Cicinelli, L. Faes, M. Mustapha, N. Phasukkijwatana, D. Pohlmann, R. Reynolds, A. Rosenblatt, A. Savastano, S. Touhami, K. Vaezi, C. V. Ventura, D. Vogt, J. Ambati, M. D. de Smet, A. Loewenstein, and null null, "Are intravitreal injections essential during the covid-19 pandemic? global preferred practice patterns and practical recommendations.," *International journal of retina and vitreous*, vol. 8, pp. 33–, 6 2022.

[86] P. Stefanatou, E. Giannouli, G. Konstantakopoulos, S. Vitoratou, and V. Mavreas, “Epa-1030–the greek version of the camberwell assessment of need: psychometric properties and associations with quality of life and social disability in schizophrenia,” *European Psychiatry*, vol. 29, no. S1, pp. 1–1, 2014.

[87] Q. Hu, X. Shi, D. Wang, Y. Huang, J. Gao, H. Guan, H. Ren, X. Lin, Z. Lu, S. Tong, G. Yang, and S. Liu, “Effects of climate and environment on migratory old people with allergic diseases in china: Protocol for a sanya cohort study.,” *Heliyon*, vol. 9, pp. e21949–e21949, 11 2023.

[88] Y. Huang, Y. Xie, L. Huang, and Z. Han, “The value of anticoagulation management combining telemedicine and self-testing in cardiovascular diseases: A meta-analysis of randomized controlled trials.,” *Therapeutics and clinical risk management*, vol. 19, pp. 279–290, 3 2023.

[89] Y. Yang, J. Tang, Z. Li, and J. Wen, “How effective is the health promotion policy in sichuan, china: based on the pmc-index model and field evaluation.,” *BMC public health*, vol. 22, pp. 2391–, 12 2022.

[90] S. Iezadi, N. Ebrahimi, S.-H. Ghamari, Z. Esfahani, N. Rezaei, E. Ghasemi, S. S. Moghaddam, S. Azadnajafabad, Z. Abdi, Z. S. Varniab, A. Golestani, A. P. Langroudi, A. Dilmaghani-Marand, Y. Farzi, and H. Pourasghari, “Global and regional quality of care index (qci) by gender and age in oesophageal cancer: A systematic analysis of the global burden of disease study 1990-2019.,” *PloS one*, vol. 18, pp. e0292348–e0292348, 10 2023.

[91] M. Araban, S. S. Tavafian, S. M. Zarandi, A. R. Hidarnia, M. R. Gohari, J. M. Prochaska, A. Laluie, and A. Montazeri, “Introducing a new measure for assessing self-efficacy in response to air pollution hazards for pregnant women,” *Journal of environmental health science & engineering*, vol. 11, pp. 16–16, 7 2013.

[92] J. Huang and T. Dai, “Public hospital reforms in china: the perspective of hospital directors.,” *BMC health services research*, vol. 19, pp. 142–142, 2 2019.

[93] M. Muniswamaiah, T. Agerwala, and C. Tappert, “Data virtualization for analytics and business intelligence in big data,” in *CS & IT Conference Proceedings*, vol. 9, CS & IT Conference Proceedings, 2019.

[94] Y. Zheng, Z. Yuqing, Z. Mengping, and L. Jun, “Do hospitals need to establish multiple hospital districts? a hospital-based perspective on the benefits of scale.,” *Frontiers in public health*, vol. 11, pp. 1019331–, 3 2023.

[95] B. Liu, W. Si, B. Wei, X. Zhang, and P. Chen, “Ptp4a1 promotes oral squamous cell carcinoma (oscc) metastasis through altered mitochondrial metabolic reprogramming.,” *Cell death discovery*, vol. 9, pp. 360–, 9 2023.

[96] X. Song, L. Lan, T. Zhou, J. Yin, and Q. Meng, “Economic burden of major diseases in china in 2013,” *Frontiers in public health*, vol. 9, pp. 649624–649624, 5 2021.

[97] C. Pietrasanta, L. Pugni, A. Ronchi, F. Schena, R. Davanzo, G. Gargantini, E. Ferrazzi, and F. Mosca, “Management of the mother-infant dyad with suspected or confirmed sars-cov-2 infection in a highly epidemic context.,” *Journal of neonatal-perinatal medicine*, vol. 13, pp. 307–311, 5 2020.