Writing Sample / Publications

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Note: This document contains completed manuscripts representing my research portfolio. An extension of Paper 1, incorporating *deep reinforcement learning* methods for patient-centered scheduling optimization, is currently in the final stages of development and available upon request. *Corresponding author.

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Enhancing Efficiency and Workflow in Oncology Outpatient Services Through Simulation-Based Optimization

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Enhancing Efficiency and Workflow in Oncology Outpatient Services Through Simulation-Based Optimization

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Abstract

Outpatient chemotherapy services face growing patient demand and increasing patient dissatisfaction, necessitating efficiency and process improvements to maintain high-quality and efficient care. This study presents an integrative simulation-based approach to enhancing resource efficiency in an oncology infusion center. An agent-based simulation model of an NCI-designated comprehensive cancer center's chemotherapy clinic is developed to evaluate three operational components, including integrating an on-site laboratory, implementing balanced scheduling through simulation optimization, and adjusting nurse staffing levels, under both current and increased patient demand scenarios. The model, calibrated with historical clinical data, captures key performance metrics such as patient visit length and nurse utilization. Results indicate that on-site lab integration and optimized scheduling together can significantly reduce average patient visit length by 80 minutes (by about 30%) while improving nurse utilization by over 10%, effectively smoothing workflow peaks. Notably, combining interventions yields greater performance gains than individual changes alone, highlighting synergistic benefits and underscoring the value of a holistic, multifaceted improvement strategy. Under conditions of sustained demand growth, modest increases in nursing staff further ensure timely patient throughput, maintaining service quality without overstaffing. By leveraging simulation to capture complex interactions, this work provides healthcare managers with data-driven guidance for designing efficient oncology care processes. It also demonstrates a

generalizable process for studying the efficiency improvement in oncology settings via simulation optimization, supporting strategic decisions such as capacity expansion or facility relocation amid rising demand.

Keywords: healthcare process redesign, oncology, process improvement, simulation optimization

1 Introduction

The increasing prevalence of cancer worldwide has sparked a surge in demand for oncology services, including the Outpatient Chemotherapy Process (OCP), a critical component of cancer treatment. In 2018, an estimated 9.8 million patients required first-course chemotherapy annually, which is expected to increase to 15 million by 2040 [1]. This indicates a 53% demand surge for chemotherapy services, corresponding to roughly a 2% annual increase in demand, with many of these patients residing in low-income or middle-income countries [1]. Chemotherapy requires intricate coordination and management due to its profound physical and psychological impacts on patients [2–4], as well as operational challenges like the variability in treatment times, different cancer types, various chemotherapy protocols, and limited resources such as the availability of pharmacists and nurses [5]. The challenge is further complicated by the need to coordinate across multiple departments, such as the administration of chemotherapy drugs in the pharmacy and blood tests in the laboratory, thus necessitating the improvement of operational efficiency for cancer care [6, 7].

Existing research efforts have focused primarily on achieving operational objectives, such as minimizing waiting times, reducing idle time, and improving resource utilization [8]. Mathematical modeling and optimization methods have been employed for scheduling and resource allocation in healthcare settings, guided by well-defined objectives and constraints (typically linear), and underscore the value of optimization in improving oncology clinic operations [9]. However, some empirical research highlights that delays in outpatient chemotherapy are propelled by three structural drivers: volatile appointment scheduling, misaligned resource allocation, and fragmented process design. These weaknesses manifest as slow registration and insurance checks, lengthy laboratory turnaround, drug-compounding queues, nurse shortages, and constrained chair capacity directly erode patient satisfaction [10]. Since these three drivers interact in unpredictable, highly dynamic, and nonlinear ways, optimization models can become intractable for many practical problems [11, 12]. As a result, simulation has emerged as a useful tool for accurately representing these dynamics over time and providing detailed and exploratory insights [13].

Simulation models have demonstrated their effectiveness as analytical tools in healthcare operations, aiding in exploring operational dynamics and patient flow within oncology settings [7, 14]. However, existing simulation studies typically evaluate policies under fixed and steady-state conditions, sidestepping the realities of demand growth and ongoing process drift. This reveals gaps in strategic planning for future demand and operational adjustments, suggesting that more adaptive and forward-looking simulation models can be developed to ensure that oncology clinics meet changing healthcare needs without sacrificing quality or efficiency [15]. Another limitation is to capture human behavior and interactions during simulation. Recent studies have combined agent-based simulation (ABS) with traditional discrete event simulation (DES) by modeling each patient and caregiver as an autonomous entity whose decisions evolve with system state [7]. A third limitation lies in the what-if analysis used in simulation studies to evaluate the impact of various changes on a system's performance. Such analyses often focus on a limited number of hypothetical scenarios, leaving many other potential situations unexplored. This can restrict the comprehensiveness of the analysis and potentially overlook interactions of different components of the system [16].

Addressing the aforementioned gaps in typical simulation studies, this paper presents a comprehensive and general process for studying efficiency and process improvement in oncology clinic settings, illustrated through a real-world case study at the Rutgers Cancer Institute of New Jersey. Specifically, the process involves a detailed examination of clinic processes and analysis of operational data, followed by the development of an agent-based simulation model that mimics current procedures and resource interactions. Subsequently, a simulation optimization approach was employed to evaluate various scenarios and optimize system settings. Furthermore, based on the simulation study and analysis, we offer a set of improvement recommendations, such as the establishment of an on-site laboratory to expedite blood tests, rebalancing appointment schedules, and optimizing nurse staffing levels and assignments. The methodology used to evaluate efficiency and process improvements, along with the recommendations drawn from the case study, ~~offers~~ valuable insights for other oncology outpatient clinics experiencing increased demand in the coming years.

The rest of this paper is organized as follows. Section 2 provides a review of literature on oncology process optimization, highlighting the gaps in current research and the need for improved simulation analysis. Section 3 details the development and specification of our simulation model, including the processes at the Rutgers Cancer Institute of New Jersey and model validation. Section 4 presents experimental settings, the findings of our simulation study, and their implications for improving the operations of oncology outpatient units. Finally, Section 5 concludes the paper, discussing the limitations of our study and suggesting directions for future research.

2 Literature Review

There is ~~a rich~~ body of literature on the use of simulation in healthcare operations. Given that this paper focuses on oncology clinics with unique characteristics, we limit our review to simulation studies on outpatient chemotherapy.

Table 1 illustrates that while simulation research on outpatient chemotherapy has grown steadily, the studies are dispersed across various topics. Researchers have employed what-if analysis to explore improved appointment schedules, optimized staffing plans, and more efficient day-to-day workflows. However, few studies have simultaneously examined all three components holistically and used simulation optimization techniques to search for optimized system designs, particularly in the context of rising patient demand. In the following sections, we review the literature for each component individually.

Table 1 Representative simulation-based studies in oncology clinic operations (2005–2025)

Study (Year)	Scheduling	Resource	Process	Demand	Method
Matta & Pattenson (2007) [17]	✓	✓			DES
Santibáñez *et al.* (2009) [18]	✓		✓		DES
Ahmed *et al.* (2011) [19]	✓	▲			DES
Lu *et al.* (2012) [20]			✓		DES
Masselink *et al.* (2012) [21]			✓		DES
Yokouchi *et al.* (2012) [22]	✓				DES
Woodall *et al.* (2013) [15]	▲	✓		✓	DES+OPT
Liang *et al.* (2015) [9]	✓	✓	▲		DES+OPT
Baril *et al.* (2016) [23]			✓		DES
Alvarado *et al.* (2018) [14]	✓	✓			DES
Suss *et al.* (2018) [24]			✓		DES
Liu *et al.* (2019) [25]	▲	✓		✓	DES
Baril *et al.* (2020) [26]		✓			DES+DOE
Garaix *et al.* (2020) [27]	✓				DES
Lamé *et al.* (2020) [28]			✓		DES
Heshmat & Eltawil (2021) [29]	✓	✓			DES+OPT
Slocum *et al.* (2021) [30]	✓				DES
Hadid *et al.* (2022) [31]	✓	✓			DES+OPT
Corsini *et al.* (2023) [7]		✓	✓	▲	ABS+DOE

✓ indicates that a topic is explicitly addressed in the paper; ▲ indicates that a sensitivity or minor test is conducted in the paper.

DES = discrete-event simulation; ABS = agent-based simulation; DOE = design of experiment; OPT = optimization

Appointment Scheduling. Scheduling of chemotherapy appointments is a complex puzzle, as clinics juggle patient preferences, varying treatment durations, and downstream tasks (labs, pharmacy) that precede each visit. The objective is to create appointment timetables that maximize the utilization of chairs and staff while minimizing patient waiting time. Most studies on this topic use mathematical models to optimize schedules, while simulation remains the principal means to evaluate same-day scheduling rules under real-world variability. Historical data have been used to test alternative templates and recommend a balanced mix of long and short infusions [19]. Staggering start times and capping simultaneous arrivals increased throughput and were implemented in practice [15]. A hybrid study first optimized a timetable and then simulated infusion-time uncertainty, identifying schedules that remained effective under randomness [9]. Heuristics are assessed in the same way: "longest infusion first" rule performs well under random deferrals but is sensitive to pharmacy delays [27], whereas sequencing patients by decreasing infusion length raises efficiency only when arrivals and drug preparation are perfectly on time [24]. In all of these cases, simulation functions mainly as an evaluation stage, validating pre-specified rules rather than driving an iterative search for optimal schedules.

Resource Allocation. Simulation models are widely used to pinpoint bottlenecks in nurses, pharmacists, infusion chairs, and ancillary spaces and then test ways to relieve them. Early work showed that increasing chair–nurse dyads steadily reduces waiting, but with diminishing returns [17]. A comprehensive study of a cancer agency demonstrated that the availability of nurses, chairs, and physicians jointly govern delays, yet the greatest leverage came from rebalancing existing resources rather than adding new capacity [18]. At Duke Cancer Institute, simulation pinpointed nurse unavailability as the dominant bottleneck; coupling a mixed-integer roster with the model identified staggered shifts that were later implemented, improving flow without additional staff [15]. Similar scenario tests revealed that simply hiring more nurses was less effective than adjusting arrival patterns [19], underscoring the interaction between staffing and scheduling. Hybrid optimization–simulation frameworks push the analysis further: one study balanced chair utilization across heterogeneous regimens by jointly choosing schedules and resource mixes [9]; another DES-based model re-assigned nurses dynamically to raise effective capacity [14]. Design-of-experiments map performance across nurse-to-chair ratios and offer robust staffing rules [26], while a capacity-planning tool links nurse–pharmacist mixes to service targets as demand grows [25]. Recent multi-objective studies combined simulation with meta-heuristics or stochastic optimization to simultaneously minimize waiting time, overtime, and cost [29, 31]. These studies confirm that smart rostering and judicious capacity additions can accommodate high volumes more effectively than simple staffing increases, yet most models still evaluate pre-set resource scenarios rather than searching the full design space iteratively.

Process Redesign. Beyond scheduling and staffing, process redesign interventions target the structure and sequence of tasks in the chemotherapy visit. Real-time pharmacy–clinic coordination and parallel tasking reduce the overall length of stay [28]. Pharmacy batching and pre-mix policies further compress compounding time and smooth workload peaks [20, 21]. Lean-oriented studies show that co-locating services and removing redundant steps accelerate patient flow [18, 23]. An agent-based model ~~with interactive agents~~ demonstrates that synchronizing external pharmacy deliveries with chair availability markedly lowers waiting time [7]. Additional redesigns, installing an on-site pharmacy, dedicating pre-treatment nurses, and resequencing lab-consultation-infusion activities also expedite throughput [24]. These studies show that altering task sequencing, information flow, or physical layout can yield substantial, clinic-wide performance gains, yet they are typically evaluated in isolation from scheduling and staffing decisions, ~~reinforcing~~ the need for integrated analysis.

Despite the progress summarized above, two main research gaps continue to limit the practical relevance of simulation studies. First, most simulation studies optimize only one operational component while treating others as fixed parameters. A few papers hint at the value of a broader view, such as evaluating schedules alongside nurse capacity [18], co-optimizing slotting and nurse assignment [14], or jointly tuning slot patterns and staffing in a multi-objective scheme [31]. In addition, global forecasts anticipate a sustained increase in chemotherapy volume over the coming decades [1]; nevertheless, most models tune parameters to current attendance levels and report gains that may erode as caseloads grow. To our knowledge, no existing work integrates all three components while also assessing robustness under increasing demand.

Second, most studies use what-if analysis to evaluate limited scenarios, while some adopt an optimization-then-simulation sequence: a heuristic or mathematical program proposes a schedule, which is further validated through simulation [19, 21, 30]. Only a few papers embed optimization inside the simulation loop, and even then, the search space remains narrow: one calls a mixed-integer model while keeping resources fixed [9], and another optimizes start dates before simulation refines daily slots [29]. As a result, few studies have attempted to realize the full potential of simulation optimization, which can search a large-scale design space and explore multi-objective trade-offs among waiting time, overtime, and cost, particularly subject to prospective demand scenarios.

These omissions are not merely academic: hospital leaders must choose portfolios of interventions that will hold up under future growth and shifting workflows. To fill this gap, the present study develops an ABS model with detailed operational data from the Rutgers Cancer Institute and searches for optimized system designs using simulation optimization. By capturing agent-level interactions and testing policy bundles under demand growth scenarios, the study provides a comprehensive, demand-aware evidence base for outpatient chemotherapy management and offers actionable guidance on which combinations of components deliver resilient improvements.

3 The Simulation Model

In this section, we will present the general process for studying efficiency and process improvement in oncology clinic settings, illustrated through the case study at Rutgers Cancer Institute. We first introduce the background of this case study and then present the three simulation model development steps.

3.1 Background and General Approach

The Rutgers Cancer Institute, affiliated with RWJBarnabas Health (RWJBHealth), is part of the Robert Wood Johnson Medical School. It is one of the nation's 57 National Cancer Institute-designated Comprehensive Cancer Centers and the only one in New Jersey. Through its affiliation with RWJBHealth, the Rutgers Cancer Institute provides adult and pediatric patients access to the most advanced cancer treatment options, including clinical trials, precision medicine, immunotherapy, complex surgical procedures, and sophisticated radiation therapy techniques. This partnership ensures that patients across the RWJBHealth network can benefit from the Rutgers Cancer Institute's specialized oncology services. It manages over 100,000 patient visits annually, reflecting its significant role in cancer care in the region.

The Rutgers Cancer Institute has experienced significant growth over the past several years in terms of patient visits and treatments. Such growth trends are expected to continue in the coming years as the center transitions into New Jersey's first freestanding cancer hospital in a new 12-story, 510,000-square-foot pavilion. However, current service lines face challenges in operational inefficiencies, which lead to long waiting times, understaffing, poor care coordination, and a lack of access to timely appointments. The utilization of resources (e.g., clinic room utilization and infusion chair turnover) has also not reached its potential. To improve patient experience, the Rutgers Cancer Institute leadership, including leading physicians, chief nursing officers, and vice presidents, has recognized that existing workflows are incapable of addressing variations in visit length across providers and service units. They have also recognized the pressing need for standardized operations and compliance with procedures, such as signing chemo orders and lab requests. As a result, the Rutgers Cancer Institute team partnered with Rutgers Business School (RBS) to identify bottlenecks in clinical workflows, aiming to enhance resource utilization, reduce waiting time, and improve the overall patient experience.

We followed a structured approach in developing the simulation model, encompassing three stages: process study, model development, and model validation [32]. The process study stage identifies specific issues and defines the key processes that the model will simulate. The model development stage involves the creation of the simulation model, which includes the design of the environment's layout and the definition of agents and their communication mechanisms to ensure realistic interactions and behaviors. Finally, the model validation phase involves rigorous validation, comparing the model's output against empirical data or theoretical standards to confirm its fidelity to the real-world phenomena it aims to ~~replicate.~~ Later sections will systematically dissect each phase, detailing our approach to model development.

3.2 Process Study

The study focuses on the busiest location at the Rutgers Cancer Institute, the ambulatory unit in East Tower, where all hematologic malignancy and stem cell transplant patients are managed. We aim to enhance its patient treatment processes, measured by patient visit length and nurse utilization. To obtain an accurate picture of patient flows, the RBS team worked closely with the Rutgers Cancer Institute team and spent three months conducting on-site observations and data collection. Specifically, a group of graduate students worked with nurses and the associate chief nursing officer to observe and log patient flows from June to August 2022. They also collected first-hand information on patients' arrival and departure rates, as well as major concerns from patients and feedback from nurses. In addition, the RBS team analyzed Rutgers Electronic Health Record (EHR) data to supplement the field study. Through cross-validation based on the two data sources, we first developed the process flow map. Figure 1 depicts the processes captured for each patient category.

As seen from Figure 1, the patient journey begins at the front desk, where staff record patient information and validate insurance details. Two main categories of patient visits are identified: those involving chemotherapy infusions (termed "routine" visits) and those involving other clinical services without chemotherapy (termed "clinical" visits). Clinical visits refer to appointments for non-chemotherapy care (e.g., consultations or other treatments with physicians), whereas routine visits involve regular chemotherapy infusions or related treatments (such as blood transfusions) administered in chemotherapy chairs. Patients must pass blood tests to prepare for

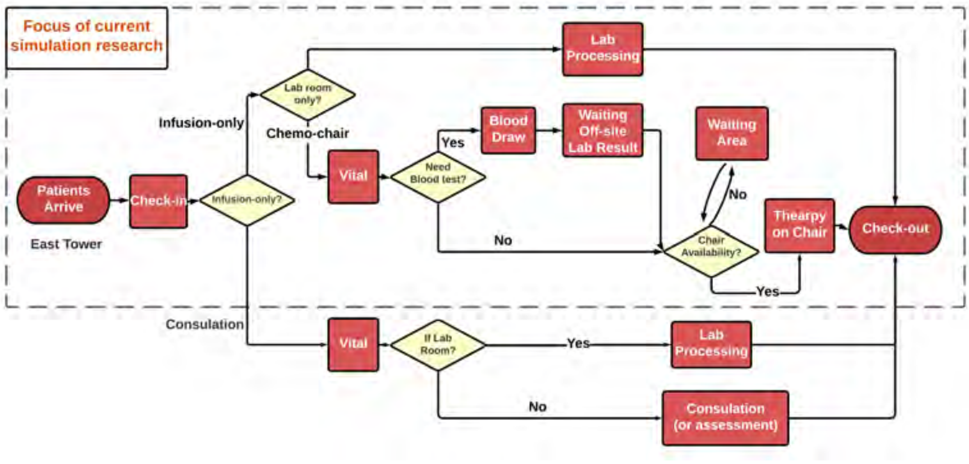


Fig. 1 Flowchart of the patient visiting processes

the upcoming chemotherapy. Based on these requirements, we can categorize patients into three groups, as reflected in the figure:

- Infusion patients (chair visits) who undergo blood tests and chemotherapy on chemo-chairs. They visit a technician in the lab room after checking in for vital signs assessment and blood draw. The blood samples are sent to the laboratory at the hospital, where the Rutgers Cancer Institute is affiliated, for off-site lab processing. Clinicians are notified of the lab results upon completion. Patients wait for the results on their assigned therapy chairs or in the waiting room if available. Once the lab results are received, clinicians coordinate with nurses, who collect the prescribed chemotherapy treatments from the pharmacy and administer them to patients on the therapy chairs. To ensure quality care and patient satisfaction, each nurse is assigned a maximum of two patients. If blood test results indicate that infusion is contraindicated, patients will not proceed to the therapy step. Instead, they exit the queue, and any previously allocated infusion slot, as well as the nursing and chair resources, are released.
- Infusion patients (Lab visits) who only require lab procedures and do not occupy chemo-chairs, such as blood draws or injections, without additional treatments on the same day. This includes patients who come for blood tests for future chemotherapy sessions or routine activities like injections. They are free to leave immediately after their lab procedures.
- Consultations patients who receive clinical services from providers, excluding chemotherapy. They visit doctors for comprehensive assessments and consultations in specific labs or procedure rooms, following a path different from an infusion visit after the department check-in.

To supplement our observations and refine the learned process, we further extracted patient-level timestamps from the institute's electronic health record (EHR) database for all ambulatory encounters between October and December 2022. We utilized data from the first two months for model development and the subsequent month for validation.

Table 2 summarizes the numbers of visits related to infusions (chair visits) and standalone lab visits. Note that visits consisting solely of provider consultations (with no infusion or lab procedure that day) are excluded, as the focus of this study is on the infusion clinic workflow, and consultation patients utilize a distinct set of resources separate from those used for infusion and lab visits. Table 2 also reports the availability of key resources, such as chemotherapy chairs and lab rooms. Specifically, the data reveals that the clinic handled a growing number of monthly patient visits, with 1,074 visits in October, 1,124 in November, and 1,205 in December. The unique patients also increased from 545 in October to 620 in December. Additionally, the clinic was supported by 4 lab rooms and 21 chemotherapy chairs throughout the period. On average, the clinic's daily operations were facilitated by 9 nurses and 2 vital clinicians.

Table 2 Summary statistics of the EHR data from the Rutgers Cancer Institute

Patient Category	**October**	**November**	**December**
Chair Visits	851	893	887
Lab Visits	223	231	318
Total Visits	1,074	1,124	1,205
Unique Patients	545	565	620
Resource Pool	**Numbers**		
Technicians	2		
Nurses (on average)	9		
Chemotherapy Chairs	21		
Lab Rooms	4		

Based on input from the clinical team of the Rutgers Cancer Institute, chair visits/chemotherapy treatments were the main bottleneck in clinic operations. Following their insights, we mapped the EHR data onto the process flow outlined in Figure 1. Specifically, we calculated the distribution of patients across three service categories and the corresponding length of stay. The analysis confirmed that chair visits/chemotherapy treatments account for 45% of total patient encounters and have the longest average length of stay of 246.57 minutes. In comparison, lab visits only account for 29% of total patient encounters, with a shorter average length of stay of 168.72 minutes. The distribution of service categories underscores the importance of simulating patient flow and clinic operations for chair visits/chemotherapy patients.

3.3 Model Development

Based on the flowchart and data learned in the process study, we ~~proceed~~ to develop a simulation model in AnyLogic. AnyLogic is a versatile simulation software that supports agent-based, discrete event, and system dynamics modeling. It ~~allows for~~ the creation of complex models with a user-friendly interface and provides powerful tools for visualizing and analyzing simulation results.

Our AnyLogic model creates a nurse agent pool, where each nurse can handle up to 2 concurrent patients. If all nurses are at capacity, incoming patients wait in the queue. Chairs are modeled as resources with concurrency limited to 21. When a patient completes labs or vital checks, the model checks nurse and chair availability before proceeding to the infusion stage. If resources are unavailable, the patient enters a queue until a nurse agent and a chair resource both become available. In practice, once a pharmacist verifies the order and prepares the chemotherapy, a nurse physically collects the medication and proceeds with the patient's infusion. We therefore incorporate the pharmacy compounding and pick-up time into one combined measure labeled "chemotherapy administration time." This composite duration reflects both drug preparation and nurse infusion activity. Should future demand shifts or operational data reveal that pharmacy is a distinct constraint (e.g., limited compounding hoods), the model can be extended to treat pharmacy as an independent resource pool with capacity parameters.

Figure 2 shows a 3-dimensional view of the simulation developed, illustrating the patient flow through various stages of the healthcare process, including registration, waiting, consultation, and discharge. This 3D visualization helps stakeholders better understand the system dynamics and identify potential areas for improvement.

Fig. 2 3D view of the Rutgers Cancer Institute simulation model

To ensure the reliability and validity of simulations, it is essential to select appropriate probability distributions with accurately estimated parameters to drive the simulation. This is particularly important in systems characterized by significant randomness or uncertainty. For this study, we employed the Python 3 *fitter* library to determine the time distributions for each random process described in Figure 1. The *fitter* package, which leverages SciPy's suite of statistical functions, automates the fitting process by comparing multiple candidate distributions using the following metrics:

- The Akaike Information Criterion (AIC). AIC measures the relative quality of a statistical model for a given set of data, assessing the trade-off between the model's goodness of fit and complexity [33].
- The Bayesian Information Criterion (BIC). BIC is similar to AIC but includes a stronger penalty for models with more parameters, which helps select simpler models with better predictive performance [34].
- ~~The goodness-of-fit tests.~~ Goodness-of-fit tests, such as the Kolmogorov-Smirnov, Chi-square, and Anderson-Darling, evaluate how well the observed data conforms to the expected distribution. Goodness-of-fit tests verify data conformity to a specified distribution, while AIC and BIC assess models by penalizing unnecessary complexity, helping to prevent over-fitting [35]. These metrics help evaluate and compare the suitability and complexity of different models, ensuring they fit well and remain parsimonious and robust in their predictive capabilities.

We evaluated a range of distributions (e.g., Exponential, Gamma, Weibull, Lognormal, Rayleigh, Triangular, etc.) for each random process. We randomly selected 1,578 observations from historical data on patient appointments and service times for parameter fitting, constituting 60% of 2,631 chair appointments. The remaining data are used as the testing group. The best-fit distribution was chosen based on combined AIC/BIC rankings and KS goodness-of-fit tests. For instance, a Rayleigh fit best captured the heavy right tail of off-site laboratory waiting times, while ~~vital~~ collection times aligned more closely with a lognormal pattern.

Table 3 presents several distributions relevant to the critical processes in the simulation. These distributions had the lowest AIC or BIC, balancing goodness of fit with model complexity. If AIC and BIC results ~~contradict~~ each other, priority is given to the goodness-of-fit test results, as they provide the most direct measure of the model's accuracy.

Table 3 Fitted distributions for selected processes in simulation

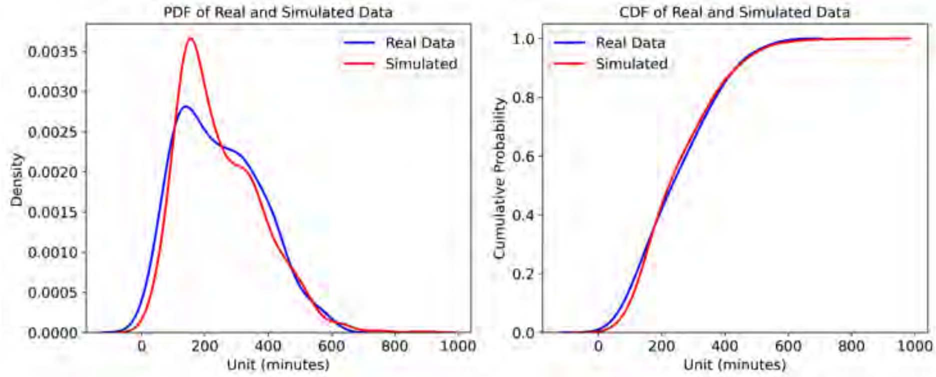
Process	**Distribution**
~~Vital~~ collection	lognormal(2.74,0.77,1.52)
Off-site blood examination	Rayleigh(-0.07,47)
Chemotherapy administration time	gamma(1.34,110.8,0)

3.4 Model ~~Verification~~

In a simulation study, model ~~verification~~ is critical to assess how accurately the model represents the real-world system. We conducted simulations over the testing group (40% of the data) to validate the model. Patient visit length is selected as the primary metric in this study, defined as the ~~total time~~ from a patient's arrival at the front desk to ~~their~~ departure from the system.

To examine the similarity between the simulation results and empirical data in the testing group on patient visit length, we first performed a visual check of the distributions. Figure 3 provides a side-by-side comparison of the probability density function (PDF) and cumulative density function (CDF) for patient visit lengths from the test set and the simulated data. This visual representation illustrates the close ~~alignment~~ between the two distributions, offering a straightforward demonstration of the model's ability to replicate real-world behavior.

Fig. 3 Distributions of visit lengths: real data vs. simulated data



Next, we statistically compared the patient visit lengths produced by the simulation with the empirical data. Table 4 summarizes the descriptive statistics (mean $\pm$ SD) of both samples, as well as the results of a Welch t-test and a Kolmogorov–Smirnov (KS) test, both conducted at a significance level of 0.05.

Table 4 Statistical comparison of empirical and simulated patient visit length

Metric	Empirical	Simulated
Mean $\pm$ SD (min)	246.6 ± 130.5	248.9 ± 129.8
Welch t-test	$t = 0.277$, $p = 0.782$	
	95% CI $= [-14.19, 18.88]$	
Kolmogorov–Smirnov test	$D = 0.066$, $p = 0.235$	

More specifically, it is observed from Table 4 that the mean and SD computed using the simulated data are very close to the counterparts computed using the actual data. A Welch t-test shows that $t = 0.28$ with $p = 0.78$, indicating that we fail to reject the null hypothesis that two samples have equal means. Further, the ~~95 %~~ confidence interval for the difference of means is $[-14.19, 18.88]$, indicating that any practically meaningful deviation is unlikely. Additionally, we employed a two-sample KS test to compare whether two samples (empirical and simulated) come from the same distribution. The results show that the largest absolute difference between two empirical CDFs is relatively small, with $D = 0.066$. Further, the p-value of 0.235 exceeds the chosen significance level of 0.05, indicating that we fail to reject the null hypothesis that the two samples originate from the same underlying distribution. Collectively, these findings show that there are no significant discrepancies between the simulated and empirical data.

In summary, the distribution visualization and statistical analysis results confirm that the simulation model developed ~~is reliable for replicating~~ patient flow at the Rutgers Cancer Institute. The close ~~alignment~~ between the simulated data and the real-world observations demonstrates the model's ~~effectiveness~~ in capturing the essential characteristics of patient visit lengths, providing a robust foundation for further analysis and optimization.

4 Simulation Analysis and Managerial Insights

This section presents our experimental settings, the primary simulation results, and the associated managerial insights.

4.1 Methodologies

We employed both what-if analysis and simulation optimization for the simulation analysis. What-if analysis is used to simulate and compare a limited number of scenarios, which is a typical approach in simulation studies. However, what-if analysis can become overwhelming for complex situations involving multiple independent variables (e.g., hourly visitor arrival rates), where the design space to be tested and compared is large. To this end, simulation optimization techniques can search for the optimal design from a large design space, significantly enhancing the depth and breadth of the analysis. This method helps to understand potential outcomes better and validates a larger space of independent variables, resulting in a more comprehensive and robust analysis. It is necessary to use it in this study since we aim to understand and explore the interactions among several components in the oncology settings, as introduced earlier. By simulating different combinations of variables, simulation optimization provides insights into the best actions to take under uncertainty.

To solve the simulation optimization problem, we used OptQuest, developed by OptTek Systems Inc. OptQuest is a commercial implementation of scatter and tabu search, providing starting points for any gradient-based local solver for nonlinear programming (NLP) problems [36]. These techniques have been identified as outperforming traditional methods such as genetic algorithms and simulated annealing [37, 38]. By integrating OptQuest within our scheduling model, we can explore and optimize appointment schedules more effectively than the current arrival schedule for the schedule balancing dimension.

Our study applied analysis across three dimensions: process redesign, resource level, and schedule balancing. The assumed improvement strategies included: 1) process redesign: establishing an on-site lab to enhance the blood work process and improve visit length performance; 2) resource level: increasing the number of nurses to improve resource availability; and 3) schedule balancing: adjusting the appointment schedule to balance the arrival rate between morning and afternoon hours.

Two performance metrics are of interest: patient visit length and nurse utilization. Here, the visit length is defined as the ~~average~~ time a patient spends from arrival to departure, and nurse utilization measures the workload on nurses, defined by the percentage of time nurses are actively engaged in patient care daily. Note that these metrics are specifically measuring performance for infusions (chair visits) and standalone lab visits, as they directly impact the quality of patient care and operational efficiency of oncology clinics.

Four factors are controlled and varied in the simulation studies:

1. Time Distribution of Blood Test Processing (α): This factor assesses whether each phase of the blood test process should maintain the current off-site time distribution (Level A) or transition to a new on-site time distribution (Level B). The objective is to evaluate the impact of changing the current process on patient time allocation.
2. Number of Nurses per Day (β): This pertains to the daily count of healthcare workers, presently set at 9 (Level A). The aim is to analyze performance changes when considering a variation in the number of nurses. The hospital seeks to understand the effects of adding one nurse (Level B) or two nurses (Level C) at the required time and assess the benefits of altering the healthcare team composition.
3. Schedule Balance (γ): This dimension addresses whether to maintain the current appointment capacity per hour (Level A) or adjust to an optimized number of individuals per hour at the optimized visit time through simulation optimization (Level B). Hospitals aim to understand the impact of schedule balancing and assess the necessity of enhancing this mechanism.
4. Daily Outpatient Volume (δ): This factor encompasses the daily appointment capacity, currently set at the 100% demand level (Level A), as well as 110% (Level B) and 120% (Level C) for demand increases. Considering anticipated demand growth, the hospital will evaluate the effects of process re-engineering and resource realignment in response to higher appointment volumes.

We conducted 500 simulation replications for each scenario to ensure robust statistical analysis using different random seeds to simulate distinct days. The above factors used in the design of experiments are shown in Table 5.

Table 5 Factor levels applied in the design of experiments

Factor	**Level A**	**Level B**	**Level C**
Blood Lab Process Time Distribution (α)	Current: off-site Rayleigh(-0.07,47)	Proposed: on-site triangular(5,10,20)	
Number of Nurses (β)	9	10	11
Schedule Balance (γ)	Current	Optimized	
Daily Outpatient Volume (δ)	100%	110%	120%

4.2 Simulation Results and Analysis

We now present the detailed setup of our experiments and analyze the simulation results.

4.2.1 Impact of On-site Laboratory

Our data analysis and the Rutgers Cancer Institute practices have identified variability and inefficiencies in blood test processing times, primarily caused by the current practice of sending blood samples for off-site processing. Currently, the process involves collecting patient samples at the Rutgers Cancer Institute, sending them to an external laboratory for analysis, and then receiving the results back. Specifically, the historical data shows that the service time for the "Waiting for Report" step at the patient flowchart in Figure 1 closely follows a Rayleigh distribution, as shown in Table 5, with a mean of 58 minutes and a variance of 33.8. In other words, patients wait 58 minutes on average for the blood test results before proceeding to the chemotherapy in a chair. Since a patient may occupy the assigned chair when waiting for the blood test results, such a long and inconsistent waiting time can delay subsequent treatment steps of this patient, as well as remaining patients assigned to the same chair. Thus, the Rutgers Cancer Institute has been seeking a more streamlined process to reduce the blood test turnaround times to resolve this bottleneck. Under consideration, one potential solution is to explore the feasibility of establishing an on-site blood lab to ~~enhance~~ processing speed and reduce overall patient flow time rather than outsourcing blood lab work. Therefore, we use our simulation model to test the effectiveness of an on-site lab compared to the current practice of an outsourced lab.

More specifically, we tested two scenarios in the simulation: one based on the current off-site lab setup and the other on a proposed on-site lab setup. The off-site setup is characterized by the service time distribution shown in Table 5. For the on-site lab, the Rutgers Cancer Institute team anticipates that the proposed on-site process will offer faster turnaround times and more streamlined workflows than the current off-site process. The time duration of the proposed on-site process follows a triangular distribution (5, 10, 20), where 5 is the minimum time, 10 is the most likely time, and 20 is the maximum time. This distribution reflects the anticipated variability, with most process times expected to be around 10 minutes.

We used the aforementioned service time distributions to drive the simulation experiments for two scenarios. Since the Rutgers Cancer Institute is interested in evaluating performance based not only on current patient demand but also on anticipated future demand surges, we drove the simulation under three different levels of daily outpatient volume (δ): 100% (current patient arrival levels), 110%, and 120%. The latter two are achieved by increasing the current hourly average visit rate by 10% and 20%, respectively. This variation in demand is crucial for realistically simulating daily visitor fluctuations rather than applying a uniform visit rate. Evaluating patient visit length and nurse utilization under different demand levels is practically significant for hospital operations, as it helps ensure that our strategies remain effective under future high-demand conditions.

The simulation results are presented in Table 6. It is seen from the table that the on-site blood test processing strategy significantly reduces both patient visit length and nurse utilization rates compared to the off-site strategy. ~~About~~ nurse utilization, the reductions in utilization rates are consistent across different demand levels. Notably, the on-site strategy shows smaller increases in nurse utilization rates as outpatient volume increases from 100% (Level A) to 120% (Level C). Nurse utilization rises from 51.10% to 60.50% with on-site processing, an increase of 9.40%, whereas it jumps from 62.10% to 74.30% with off-site processing, a 12.20% increase.

Table 6 Simulation results: off-site vs. on-site lab

α	δ					
	Level A (100%)		Level B (110%)		Level C (120%)	
	~~Visit Length~~	Utilization	Visit Length	Utilization	Visit Length	Utilization
Off-site lab	262.35	62.10%	270.08	67.70%	284.53	74.30%
On-site lab	222.56	51.10%	237.60	57.20%	246.31	60.50%

Regarding patient visit length, the on-site strategy consistently outperforms the off-site approach across all levels of outpatient volume. The data reveal that, on average, patient visit length decreases by approximately 15% with on-site blood testing compared to off-site testing. This advantage remains stable regardless of changes in outpatient volume, indicating that the demand changes did not significantly influence the advantage of transitioning to on-site blood testing. The predicted visit length reduction between the on-site and off-site strategies is consistent across all three demand levels.

The data strongly suggest~~s~~ that replacing off-site blood testing with an on-site strategy at the Rutgers Cancer Institute would enhance operational efficiency and offer patients a better overall visit experience. The consistent reductions in patient visit length and nurse utilization across varying demand levels indicate that the on-site strategy is well-suited to efficiently manage increased patient volumes. Given the upcoming move~~-in~~ ~~for~~ the Rutgers Cancer Institute to a new free-standing cancer pavilion location ~~(i.e., the Jack and Sheryl Morris Cancer Center)~~, the transition to an on-site blood testing model presents an opportune moment to update workflow processes with relatively low initial implementation difficulty. This proactive change is especially important as the Rutgers Cancer Institute anticipates operational challenges associated with increasing demand. By integrating on-site blood testing into the new facility's design and processes, the Rutgers Cancer Institute can better accommodate a growing patient load, streamline patient care, and reinforce its commitment to delivering high-quality, patient-centered services.

4.2.2 Impact of Increasing Nurse Level

Under the current operational configuration, each nurse can attend to a maximum of two patients simultaneously. However, the average number of on-duty nurses daily is nine, with twenty-one treatment chairs available. This discrepancy indicates that the existing chair needs to have more nursing staff ~~concurrently~~ during peak patient volume periods. Consequently, this can lead to significant waiting times, where patients receive their blood test results but may experience delays in subsequent care due to a lack of available nursing staff. This observation is supported by feedback from the nurses, who have reported experiencing excessive workloads during peak ~~times.~~

Excessive workloads prolong the overall service delivery process and may also detrimentally impact the quality of care provided. In anticipation of the Rutgers Cancer Institute's relocation to a new facility and the expected increase in patient demand, the hospital has proposed testing the feasibility of increasing the nursing staff size. This investigation assesses whether an expanded nursing team can alleviate the anticipated process delays and enhance nurse utilization ~~rates.~~ To this end, we used the simulation model to vary the number of nurses available each day, allowing us to test and compare the effects of different nursing team sizes on patient visit lengths and nurse utilization ~~rates~~. Specifically, we developed three primary scenarios based on varying nurse staffing levels: 9, 10, and 11 nurses. We examined three patient demand levels within each staffing level scenario: 100%, 110%, and 120% of the current demand, similar to the setting in Section 4.2.1.

Table 7 highlights the effects of increasing the number of nurses on visit length and utilization ~~rates~~ under varying outpatient demand levels.

Table 7 Simulation results: varying nurse levels

β	δ					
	Level A (100%)		Level B (110%)		Level C (120%)	
	Visit Length	Utilization	Visit Length	Utilization	Visit Length	Utilization
9	262.35	62.10%	270.08	67.70%	284.53	74.30%
10	256.01	55.00%	267.44	60.80%	283.35	67.10%
11	255.65	51.00%	267.35	55.50%	282.35	61.30%

The simulation results show that at the current demand level (100%), increasing the number of nurses from 9 to 11 results in marginal visit length improvements and significant utilization ~~rate~~ drops. We tested the system's performance when patient demand increased by 10% and 20%. The results indicated that as patient demand increased, adding more nurses yielded consistent outcomes across different demand levels. At a 10% increase in demand, adding more nurses shows improved visit length and utilization, with marginal visit length improvement from 270.08 to 267.44 and utilization drops from 57.20% to 44.60%. At a 20% increase in demand, the impact of additional nurses is more pronounced, although visit length increases are less controlled, ~~utilization rates~~ improve substantially, reaching 61.30% from 74.30% with 11 nurses.

In conclusion, increasing the number of nurses generally drops ~~utilization rates~~ while only slightly mitigating the adverse effects on visit length as patient demand increases. In addition, the analysis underscores that higher demand amplifies nurses' need to maintain efficiency and utilization ~~rates~~.

4.2.3 Impact of Balancing the Schedule

Currently, the Rutgers Cancer Institute schedules patients in the morning to complete daily tasks more quickly and avoid overtime. However, our observations and data indicate that this scheduling approach leads to a high demand for nurses and treatment chairs around noon. This results in significantly longer waiting times for patients arriving around that time. To address the issue of overly concentrated scheduling, the hospital is seeking a potential solution to distribute the number of visits more evenly throughout the day.

Our approach focuses on balancing the schedule to optimize patient flow and nurse workload, aiming to minimize patient visit length while maintaining nurse utilization within a reasonable range. The Rutgers Cancer Institute team recommends that ~~expected~~ nurse utilization should be maintained around 60% at the current outpatient demand level and should not exceed 70% as demand increases to 110% and 120%. This ensures that the quality of treatment remains high even with increased demand. To achieve this, we propose distributing patient appointments more evenly throughout the day, instead of concentrating them during specific periods. This approach aims to minimize peaks and valleys in patient arrivals, resulting in a smoother workflow and better resource management. By distributing appointments evenly, we ensure that nurses are consistently utilized throughout their shifts, which reduces idle time and prevents overburdening during peak hours.

Given the large size of the design space for this problem, we ~~modeled~~ a simulation optimization problem to find the optimal arrival ~~rate distribution~~ across the operating hours, such that the patient's visit length metric is minimized. Specifically, we consider the operating periods in set $T = \{8, 9, \ldots, 15\}$, ~~representing each hour~~ from 8 AM to 3 PM. Our goal is to determine the optimal patient arrival rates x_t for each hour $t \in T$ to maximize efficiency while meeting service constraints. ~~The visit length for the patient i is subject to randomness, captured by $L_i(\mathbf{x}, \omega_j)$, where ω_j represents the random noise observed in the j-th simulation replication~~. The nurse service duration ~~for the patient i in the j-th replication is denoted by $D_i(\mathbf{x}, \omega_j)$~~. We must ensure that the cumulative service time does not exceed the total time available for one nurse in a day, W_{total}, and that the number of patients served is the daily outpatient ~~capacity~~ C. Additionally, the utilization ~~rate~~ of the nursing staff should remain below the threshold U. Our optimization model ~~integrates~~ these factors to find the best $\mathbf{x}$ values that satisfy all constraints while accounting for the variability in service times. The notation used in the model is summarized in Table 8.

Table 8 Notation for the simulation optimization model

Notation	Description
$T = \{8, 9, \ldots, 15\}$	Set of time periods, representing ~~hours~~ from 8 AM to 3 PM
$\mathbf{x} = (x_8, x_9, \ldots, x_{15})$	Decision variable; a vector of patient arrival rates during each operating hour $t \in T$
~~ω_j~~	~~Random noise observed in the j-th replication of the simulation~~
$L_i(\mathbf{x}, \omega_j)$	Visit length ~~for~~ the i-th patient observed in the j-th replication of the simulation, given decision variable $\mathbf{x}$
$D_i(\mathbf{x}, \omega_j)$	Nurse service duration for the i-th patient observed in the j-th replication of the simulation, given decision variable $\mathbf{x}$
W_{total}	Total time workload available for one nurse in a day, ~~which represents~~ the total capacity of a nurse
C	Daily outpatient capacity; $C = C_0$ ~~represents~~ the current daily patient arrival rate (i.e., the summation of current hourly arrival rates)
U	Utilization ~~rate~~ threshold

The respective simulation optimization problem can be expressed mathematically as follows:

$$\min_{\mathbf{x}} \quad \cancel{\mathbb{E}_j\left[\mathbb{E}_i[L_i(\mathbf{x}, \omega_j)]\right]} \tag{1}$$

$$\text{s.t.} \quad \frac{\cancel{\mathbb{E}_j\left[\mathbb{E}_i[D_i(\mathbf{x}, \omega_j)]\right]}}{W_{\text{total}}} \leq U \tag{2}$$

$$\sum_{t \in T} x_t = C \tag{3}$$

$$0 \leq x_t \leq 8 \qquad \forall t \in T \tag{4}$$

Constraint (2) ensures that the expected nurse utilization does not exceed 70% total available time. Constraint (3) ensures that the sum of patient ~~arrivals~~ equals daily outpatient ~~capacity~~ C. Note that C equals the current daily outpatient arrival rate C_0 when $\delta = 100\%$, and $C = \delta C_0$ as we increase δ. Constraint (4) limits the hourly patient arrival rate to the maximum hourly slot in the hospital appointment system. These constraints collectively ensure a balanced workload, controlled arrival rates, and adherence to the system's daily capacity.

To develop balanced schedules, we solved the simulation optimization problem using OptQuest in AnyLogic. Table 9 compares the results of the optimized schedule with the current schedule. The optimized patient scheduling scenario resulted in more consistent and optimized visit length and nurse utilization across scenarios without adding nurses while using an off-site lab. Specifically, in the optimized schedule, the visit length was significantly reduced from 262.35 minutes to 218.80 minutes, and nurse utilization dropped below 60%. This strategy optimizes resource allocation and efficiently handles varying levels of demand, making it an ~~efficient~~ solution for improving patient flow and nurse workload management. Table 10 presents the optimized outpatient appointment schedule ~~described~~ by the hourly arrival rate, which shows a more balanced ~~distribution~~ compared to the previous ~~allocation~~. In addition to the results presented for $\delta = 100\%$, we further optimized the arrival rates for $\delta = 110\%$ and $\delta = 120\%$. Specifically, we first simulated the system by increasing the current hourly arrival rate according to each value of δ, and then ran the simulation-based optimization model (1)–(4) by setting $C = \delta C_0$. The last two columns in Table 9 present the optimized schedule ~~and current schedule~~ for 110% and 120% demand levels. As seen, similar trends have been observed at 110% and 120% demand levels compared to that at the current demand level.

Table 9 Simulation results: current vs. optimized schedule

γ	δ					
	Level A (100%)		Level B (110%)		Level C (120%)	
	Visit Length	Utilization	Visit Length	Utilization	Visit Length	Utilization
Current	262.35	62.10%	270.08	67.70%	284.53	74.30%
Optimized	218.80	<60%	221.56	<70%	234.79	<70%

Table 10 Hourly arrival rates from simulation optimization (α and β set at Level A)

Time	**Optimized**	**Current**
8am	4	8
9am	5	8
10am	5	7
11am	7	5
12pm	2	3
1pm	8	2
2pm	5	2
3pm	0	1

This approach reduces expected visit length and ensures more consistent use of nursing resources throughout the day. As a result, the nurses' workload becomes more manageable, reducing burnout and enhancing job satisfaction. In addition, this strategy is highly cost-effective because it utilizes existing resources more efficiently without incurring additional costs from hiring more staff or restructuring an on-site lab. By optimizing existing resources, the Rutgers Cancer Institute can improve patient care and operational efficiency, making it a sustainable and cost-effective solution for managing patient flow and resource allocation. The results suggest that the Rutgers Cancer Institute should consider implementing a balanced strategy to inform scheduling and resource allocation.

4.3 Managerial Insights

In this study, our research team applied simulation models to evaluate the effectiveness of setting up an onsite lab, increasing nurse staffing, and balancing patient scheduling in addressing ongoing operational challenges and anticipated demand increases at the Rutgers Cancer Institute. The analysis provides insights for the Rutgers Cancer Institute to leverage existing resources to improve its operational efficiency and patient experience.

Currently, as part of the RWJBHealth system, the Rutgers Cancer Institute is using an external lab located in a neighboring RWJBHealth hospital to process all patients' blood samples. Sharing the lab across healthcare facilities might sound economically viable to the healthcare system; ~~mixing~~ blood samples from the ambulatory unit of the Rutgers Cancer Institute with those from the inpatient-based hospital, however, creates a bottleneck as ~~its~~ patients have to wait for the lab results before proceeding with chemotherapies. Our simulation results show that setting up an onsite lab significantly reduces patient visit lengths and nurse utilization ~~rates,~~ suggesting that shifting from a shared lab to a designated lab helps address the bottleneck at the Rutgers Cancer Institute. This approach also demonstrates a more stable response to increasing outpatient demand, indicating a robust system capable of handling fluctuations in patient volume without overburdening resources. Our analyses suggest that healthcare systems should reevaluate their resource-pooling strategies. While such strategies may help maximize resource utilization at the system level, they could also lead to undesirable outcomes for local clinical units.

Traditionally, healthcare providers ~~intend~~ to staff more nurses to address increasing patient demand with the hope of reducing visit lengths and increasing patient turnover ~~rates.~~ While it is logical to assume that adding labor and resources helps speed up ~~throughput,~~ such a relationship is not ~~warranted~~. Our study compares multiple scenarios and shows that the strategy helps reduce utilization rates, yet is less effective in reducing patient visit length. Specifically, increasing the number of nurses appears to be least effective when ~~going~~ from 10 to 11 nurses in our simulation. Adding one nurse only decreases waiting time by around one minute across all three scenarios, suggesting that staffing more nurses can be ineffective in reducing waiting time or improving patient experience. Hospital administrators must evaluate the ~~cost benefits~~ of alternative staffing strategies and choose the optimal strategy per their performance objective ~~(i.e.,~~ reducing utilization ~~rate~~ and shortening visit length are likely to require different strategies).

Currently, the Rutgers Cancer Institute schedules most patient visits in the morning to ensure ~~there is enough~~ buffer time to complete all visits within the same day. While this approach appears ~~lenient~~ and patient-friendly, it creates multiple issues. First, it creates unnecessary crowding ~~effects~~ as patients have to wait extra time due to the above-mentioned resource constraints in the morning. Based on the team's observation, the clinic is busiest between 9 am and 12:30 pm. The clinic appears to have minimal patient visits after 3 pm on weekdays. The imbalance in patient scheduling also creates challenges in staffing. Since nurses work on a shift basis, most are scheduled for the morning shifts, leaving the afternoon time slots underutilized. Our simulation suggests that the Rutgers Cancer Institute should adopt a balanced patient schedule, which involves distributing appointments more evenly throughout the day rather than concentrating ~~on~~ them in the morning. This approach offers significant benefits, including reduced flow time and improved nurse utilization rates. By maintaining consistent and optimal visit length and nurse utilization ~~rates~~ across different scenarios, the balanced schedule strategy proves to be more economical and easier to implement, requiring no additional investment or extra nurses, provided there is cooperation among staff.

The optimal ~~configuration~~ for maximizing performance involves combining the on-site strategy with the updated, balanced schedule, which consistently outperforms merely applying the on-site strategy with the existing schedule at all demand levels—100%, 110%, and 120% (See Table 11). This ~~combination~~ saves 80 minutes of estimated visit length and significantly reduces nurse utilization ~~rates~~ at the current demand (100%). When the updated patient schedule is accepted at the current demand level (100%), it further enhances performance by reducing ~~estimated~~ visit lengths by an additional 39.5 minutes, representing a 17.8% improvement compared to relying solely on the on-site strategy. As demand increases, the time savings become even more substantial: 46.77 minutes at 110% demand and 45.47 minutes at 120% demand. This indicates that the ~~integrated~~ approach is not only the best choice at current demand levels but also becomes increasingly valuable as demand escalates. The more significant ~~time savings~~ under higher demand scenarios highlight that this ~~configuration~~ is better ~~aligned with~~ managing the rising number of patient visits, offering a more robust solution for handling patient surges effectively.

Table 11 ~~Visit~~ length (in minutes) under different configurations across outpatient volumes

Configuration			Daily Outpatient Volume		
On-site Lab	Balanced Schedule	Increase Nurse Staffing	100%	110%	120%
			262.35	270.08	284.53
✓			222.56	237.60	246.31
✓	✓		182.49	190.23	200.53
✓	✓	✓	180.06	186.53	190.26

Interestingly, Table 11 also suggests that merely increasing the number of nurses does not significantly enhance visit length metrics when integrated with these two strategies at current demand levels. Specifically, at 100% demand, adding one nurse only reduces the ~~visit time~~ by 2 minutes, representing a ~~minimal~~ improvement. This challenges the traditional perception that adding nurses necessarily yields the greatest marginal gains in reducing waiting times, suggesting instead that under certain constraints, other strategies (e.g., on-site lab, balanced scheduling) may be more effective in achieving the desired operational outcomes. However, as demand rises, the impact of nurse staffing becomes more substantial. At 110% demand, adding one nurse reduces the visit length by 4 minutes, a more ~~noticeable~~ improvement. At 120% demand, the reduction becomes even more significant, saving an additional 10 minutes. This demonstrates that while increasing nurse levels may not substantially improve efficiency under normal demand conditions, it becomes a critical factor in optimizing performance as patient demand increases beyond current capacity.

This unintuitive finding underscores the complexity of oncology ~~institution~~ operations, where high levels of interaction between different departments result in intricate personnel dynamics. Conventional assumptions may not fully address these complexities, highlighting that ~~surface-level judgments based~~ on experience are insufficient to improve the actual workflow meaningfully. In such settings, staff from various specialties must coordinate closely to manage patient care, often leading to situations where changes in one area, such as increasing nurse staffing, do not yield straightforward improvements in efficiency. Instead, these interactions can produce unexpected outcomes, as the workflows of nurses, doctors, and other healthcare professionals are ~~deeply interconnected~~. This further emphasizes the necessity of simulation-based studies in tackling the challenges of OCP management.

The Rutgers Cancer Institute was highly receptive to our recommendations, and in line with ~~these~~ insights, the clinic has already begun trialing the first phase of improvements by focusing on laboratory efficiency. ~~Particularly,~~ the simulation model ~~performed~~ and the associated data outputs revealed that laboratory services were a prominent pain point. Due to this, a new "fast track" system was developed to expedite laboratory services for patients during their ambulatory visits, which often include infusion of anti-cancer agents in addition to oncology provider visits. The associated intervention led to a significant reduction in patient waiting time, with more than 30% improved productivity for this complex care component at the cancer center. The Rutgers Cancer Institute is evaluating other recommendations for ~~their~~ implementation in the future, particularly as the Rutgers Cancer Institute will be transitioning to the new location. This move will provide an opportunity to introduce a balanced scheduling strategy and make further adjustments as operations stabilize, ensuring that the clinic can continue to meet increasing patient demands efficiently and effectively.

5 Conclusion and Future Research

This study addressed critical issues in process optimization and resource allocation efficiency at the Rutgers Cancer Institute, providing specific improvement strategies through a systematic design of experiments approach. By analyzing factors such as ~~time distribution, the number~~ of nursing staff, appointment schedule balancing, and patient arrival rates, we identified the effectiveness of individual factors and the optimal combination of these factors, considering their interrelationships and synergistic effects.

Unlike previous studies, our approach did not focus solely on the impact of individual factors on process improvement. Instead, we explored potential optimal configurations of factor combinations. Additionally, we tested these recommendations under multiple demand scenarios to ensure the robustness and long-term efficacy of the strategies, ~~guaranteeing~~ that the proposed improvements are effective across different operational settings. Specifically, by implementing on-site lab work, adjusting nursing staff levels, and balancing the appointment schedule, we proposed operational improvements for the Rutgers Cancer Institute. These measures are designed to enhance process efficiency, reduce patient visit length, and maintain nurse utilization within an optimal range (e.g., less than 70%), ultimately improving patient satisfaction and reducing operational costs without compromising quality.

Although we incorporated relevant operational factors and process flows into the simulation and subsequent optimization, we acknowledge that other elements, such as physician preferences, patient preferences, and chemotherapy treatment plans, could potentially influence our results. However, this information was not readily available during our study period or was restricted due to Health Insurance Portability and Accountability Act (HIPAA) considerations. Additionally, specific test results may need to be reviewed by physicians before proceeding with transfusion or infusion, which could further extend the total visit length. Moreover, the assumption of a triangular distribution for on-site lab processing times was based on expert estimates, which may not fully reflect real-world variability once an on-site lab is implemented. Additionally, future changes in medical procedures, technology, or policy might impact the applicability of these findings, necessitating further research and model validation over time. These limitations suggest that ongoing monitoring and potential adjustments to the proposed strategies are required as new data becomes available.

While pharmacy mixing processes can significantly impact patient flow in many oncology clinics, the leadership at our center reported adequate pharmacy resources, with multiple compounding hoods and pharmacists on shift. In the current state, the pharmacy was not identified as a critical bottleneck. However, as volume increases or if operational changes shift workflow timings, pharmacy delays could become more ~~influential.~~ Future expansions of our simulation will explicitly model pharmacy compounding steps and resource constraints to capture their potential effect on overall patient cycle times.

Furthermore, the findings from this study are not only relevant to the Rutgers Cancer Institute but also have broader implications for oncology departments and healthcare institutions worldwide. Many of the challenges identified—such as managing possible patient demand surges, improving resource utilization, and reducing waiting times—are shared across oncology clinics, irrespective of geographic location. The ABS model used in this research can be adapted to various healthcare environments, making it a valuable tool for different oncology clinics, regardless of size or resource level. In settings with limited infrastructure, strategies like balanced scheduling and optimized resource allocation can provide significant improvements without requiring substantial financial investments.

Beyond oncology departments, the principles outlined in this study can also be applied to other areas of healthcare, such as outpatient clinics, emergency departments, and surgical units, where similar operational inefficiencies and resource management challenges exist. By strategically managing resources and patient flows, healthcare administrators can improve service delivery and patient outcomes in various medical environments.

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Empowering Clinicians in Resource-Constrained Dialysis Care: A Triple Aim Perspective on Quality Outcomes and Health Disparities

ABSTRACT

Achieving the Triple Aim in dialysis requires balancing quality, population health, and costs under severe resource constraints. Using a national panel of dialysis facilities and fixed-effects instrumental-variable estimation, we show that expanded clinician labor—the scarcest resource—significantly raises treatment quality. Yet the benefit is smaller in communities facing pronounced social-health disparities. Crucially, empowering clinicians to delegate narrow but critical tasks offsets this penalty and restores quality gains. Our findings offer actionable guidance for allocating clinical labor, mitigating inequities, and advancing Triple Aim goals, while providing a novel composite disparity index for future research.

KEYWORDS: Care Quality, Social Determinants of Health, Triple Aim, Health Disparities, Resource Dependency Theory

INTRODUCTION

The Triple Aim framework has been widely adopted as a strategy for transforming healthcare systems (Berwick et al., 2008). It emphasizes pursuing three interrelated goals: improving patient care outcomes, reducing healthcare costs, and enhancing population health. Addressing the Triple Aim is essential for building a sustainable and efficient healthcare system.

In healthcare, labor expenses are among the most significant drivers of costs due to the labor-intensive nature of care delivery (Health Forum, 2021). Dialysis facilities exemplify this challenge. They rely heavily on skilled personnel, notably registered nurses (RNs), to administer life-sustaining treatments for patients with end-stage renal disease (Centers for Disease Control and Prevention, 2021). Therefore, RN staffing levels are critical to clinical quality and a large component of facility operating costs (Yoder et al., 2013). Compounding the issue, the industry faces workforce shortages and rising wage pressures, which intensify the difficulty of sustaining quality care under constrained budgets (Eliason et al., 2019). These realities create a challenging backdrop for dialysis centers striving to achieve the Triple Aim objectives, underscoring the importance of operational strategies that can optimize resource use without compromising patient outcomes.

Despite extensive research in operations management (OM), few studies have examined the interrelationships among the Triple Aim objectives, such as how improving population health affects patient experience and cost control. Previous OM literature has focused on achieving better resource allocation and service delivery (Dobrzykowski et al., 2014) but overlooked environmental factors that can significantly impact healthcare outcomes (Gaynor & Town, 2011). This oversight represents a critical gap in the literature, which the current study addresses. Guided by resource dependence theory (RDT), which posits that organizations must manage external dependencies to achieve optimal performance (Pfeffer & Salancik, 1978), we explore how population health affects the relationship between resource effectiveness and care quality.

Population health is influenced by many factors, known in the healthcare literature as the social determinants of health (SDoH), which can lead to health disparities (HDs). HDs are defined as systematic differences in health outcomes across different population groups. SDoH is a critical measure of population health and poses a significant barrier to realizing the Triple Aim objectives (Braveman et al., 2011; Koh et al., 2010). For instance, individuals in lower socioeconomic groups may receive delayed or suboptimal healthcare, which worsens their health outcomes over time (Artiga & Hinton, 2018). Therefore, addressing SDoH is crucial for enhancing overall population health; it can also improve patient care experiences and reduce the costs associated with reactive, high-intensity care (Valente et al., 2023). Our study addresses the following key research questions:

1. Do SDoH influence the relationship between resource effectiveness and patient care quality in dialysis centers?
2. What operational strategies can healthcare facilities implement to mitigate the adverse effects of SDoH on clinical outcomes?

These questions are explored using a 5-year nationwide dialysis center operational dataset, combined with a composite factor score of SDoH. The latter encompasses income inequality, housing stability, access to nutritious food, and more.

The dialysis sector has several advantages for this inquiry. First, it is a critical component of the healthcare system that provides life-saving treatment for the approximately 37 million Americans with end-stage renal disease (ESRD) (Centers for Disease Control and Prevention, 2021). It also uses standardized treatment protocols, which allows us to isolate the effects of operational and social factors on healthcare outcomes. The sector also faces serious operational challenges, such as significant reliance on Medicare funding—over $130 billion—and vulnerability to healthcare resource fluctuations, including shortages of skilled healthcare workers and wage inflation (Health Forum, 2021).

Our analysis reveals that SDoH have a measurable negative impact on the quality of care delivered in dialysis centers, aligning with the predictions of RDT. Specifically, higher SDoH index scores weaken the positive relationship between facility staffing levels and clinical outcomes, diminishing the expected improvement in patient care from increased staffing. We then examine how staff empowerment as an operational strategy might mitigate the harmful effects of SDoH. Staff empowerment involves granting clinical staff greater autonomy and flexibility in decision-making, enhancing their ability to adapt to complex and dynamic environments. This approach operationalizes RDT principles by enabling organizations to manage external dependencies more effectively. Our empirical analysis demonstrates that empowerment is an efficient method to weaken the adverse influence of SDoH, effectively reducing its negative impact on resource utilization efficiency and clinical outcomes.

Our findings emphasize that improving population health is both an independent goal and a critical driver for enhancing patient experience and reducing costs. This insight fills a theoretical gap, providing a more systematic strategic planning basis for OM. Moreover, acknowledging that SDoH are complex issues that cannot be resolved in the short term we highlight the need for immediate adoption of operational strategies (e.g., staff empowerment) to address the challenges they pose. While we focused on the dialysis sector, the findings have implications for other sectors and offer valuable insights for healthcare policymakers.

LITERATURE REVIEW

Triple Aim Framework

The Triple Aim is distinguished by its emphasis on population health, advocating for an inclusive model that addresses broader social factors influencing health outcomes beyond clinical quality and healthcare costs. However, while clinical quality and healthcare costs are frequently examined in healthcare research in OM, relatively few studies have addressed population health. Roth et al. (2019) explore the concept of "Triple Aim Performance" (TAP) in hospitals, defined as the simultaneous achievement of high performance on clinical quality, patient experience, and technical efficiency. Although TAP effectively captures internal performance metrics, it does not directly incorporate population health measures. Bonnett and Heim (2024) extended this inquiry by examining how the utilization of nurse practitioners and physician assistants influences TAP in hospitals. Both studies contribute valuable insights; however, neither explicitly addresses population health as a key component of the Triple Aim framework.

Recent OM research has begun to bridge this gap by considering external environmental factors. For example, Ding (2024) investigated how hospitals' market competition and service focus impact their progress toward Triple Aim outcomes. The findings indicated that intense market competition can hinder improvements in cost efficiency, while a focused service strategy enhances performance, albeit with diminishing returns if overly specialized. This study explores this gap further by focusing on dialysis centers. This setting offers a more standardized context than hospitals to examine the interplay among the three Triple Aim dimensions.

HDs and SDoH

HDs reflect the impact of SDoH on health outcomes. SDoH are non-medical factors collectively serving as key population health indicators (Bonnell et al., 2021; Green & Zook, 2019; Marmot et al., 2008). Numerous studies have demonstrated SDoH impacts one's health, overall quality of life, and healthcare costs (Mehboob, 2023; Peltz et al., 2016; Virapongse & Misky, 2018; Zhao et al., 2014). Because the interplay of these factors is dynamic, research underscores the limitations of relying on individual disparity measures and advocates for more comprehensive indicators to capture their impact (Braveman et al., 2005).

The Centers for Medicare and Medicaid Services (CMS) has recognized population health management's importance in aligning incentives with private payers and collaborating with public health and social programs to improve population health and reduce health disparities (Paul, 2016). Organizations like the Urban Population Health Observatory integrate disparity indicators with public health surveillance data to inform health policy. The platform facilitates the development of interventions to address disparity-related issues and improve population health outcomes, demonstrating the practical application of SDoH in management (Brakefield et al., 2021). Similarly, Germany's Integrated Care System incorporates the assessment of HDs in its claims analyses to understand and improve population health outcomes (Unger et al., 2015). These examples illustrate that it is possible to incorporate factors associated with HDs into health management practices. In the OM literature, these disparities are less understood.

Resource Dependency Theory

RDT emphasizes that the success of organizations is highly dependent on effectively controlling and acquiring critical resources (Pfeffer & Salancik, 1978). These resources include tangible assets (e.g., funds and raw materials) and intangible resources (e.g., technology, information, and talent). To achieve their strategic objectives, organizations need to reduce external uncertainties and enhance their power by managing the dependencies on these resources. These actions enable organizations to respond better to environmental changes, ensuring continuous access to critical resources (Ansmann et al., 2021; Casciaro & Piskorski, 2005).

Healthcare organizations face pressure from uncertain access to resources and deploy strategies to secure these resources and achieve high clinical quality, emphasizing the applicability of RDT in healthcare settings (Ansmann et al., 2021). A region's overall level of health resources, such as adequate medical professionals and advanced technological support, directly affects the service capacity and outcomes of organizations in the region. Healthcare organizations rely heavily on these external resources to maintain their service capacity and outcomes (Kash et al., 2014).

As an indicator of regional health, SDoH influence the types and quality of resources organizations can access for their operations (Adler et al., 2016). By addressing SDoH, healthcare organizations can enhance clinical quality within their region. For example, regional shortages in specialized medical talent, unstable supplies of medical equipment, and inadequate educational resources can negatively impact healthcare organizations' operations and service quality (Alexander & Wells, 2008). Therefore, to address uncertainty and improve service quality, healthcare organizations must manage resources according to an area's current SDoH and advocate for long-term improvements.

OM strategies for addressing resource dependency in healthcare include optimizing resource allocation, seeking alternative resources, and improving service efficiency and effectiveness, which help healthcare organizations mitigate the impact of disparities and enhance the quality of service (de Rijk et al., 2007). Figure 1 integrates these OM strategies within the framework of RDT, illustrating how SDoH, representing the external resource level, influences healthcare organizations' resource management practices. The figure demonstrates that by managing these dependencies effectively, healthcare organizations can adapt to external constraints, better allocate resources, and achieve improved clinical outcomes.

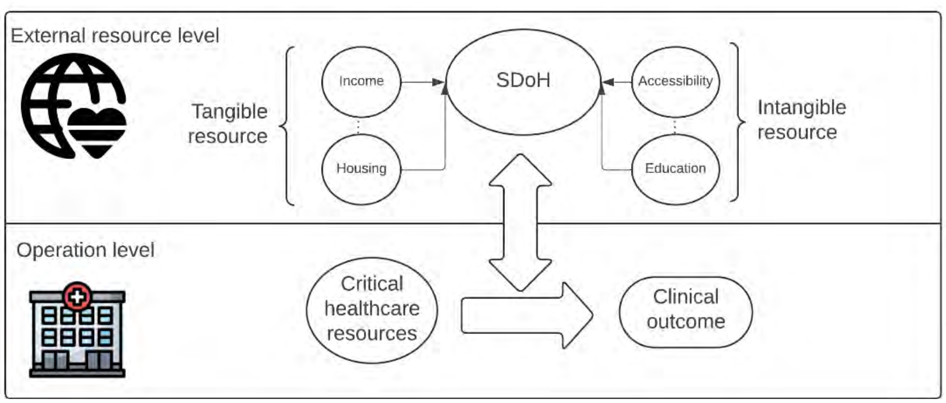


Figure 1: Conceptual Diagram of RDT: An Example in a Healthcare Organization

The current study extends the current body of literature by examining the Triple Aim framework in the context of OM and introducing a composite SDoH measure as an indicator of population health. Secondly, it proposes RDT as an appropriate unifying theoretical framework to explain the interactions between various factors within the context of OM. Finally, it focuses on dialysis facilities, which provide a more standardized and controlled environment than hospitals, to test the model.

HYPOTHESES DEVELOPMENT

Hospital profit margins are generally slim, typically between 1% and 3% (LaPointe, 2021). As a result, hospitals must tightly control costs to survive (Lagasse, 2022). Nonetheless, they must balance cost control with the quality of care. Dialysis facilities operate under similar constraints. Within the Triple Aim's cost-quality balance, RN staffing emerges as a critical factor: investing in additional nurses improves quality but also increases operating costs, requiring careful trade-offs to maintain financial viability.
In alignment with RDT, healthcare organizations can mitigate uncertainty around resource availability by reducing reliance on external environmental constraints, such as shortages in medical personnel, limited access to advanced equipment, and inadequate healthcare infrastructure (Ansmann et al., 2021; Hillman et al., 2009; Yeager et al., 2014). A key strategy to achieve this is internally controlling access to critical resources. This can be done by reallocating spending towards essential healthcare resources, including hiring specialized medical staff and training existing personnel. Additionally, healthcare organizations can consider mergers to internalize resources, improving resource availability and operational outcomes (Alexander & Wells, 2008; Jha et al., 2016).

In the dialysis industry, where service complexity is high, RNs play a pivotal role as core healthcare providers. RNs possess specialized training in nephrology and dialysis procedures, enabling them to manage complex treatments and care for ESRD patients effectively. Their duties in dialysis centers range from assessing patients and monitoring vital signs to identifying potential complications throughout the dialysis process (De Regge et al., 2019; Wheeler et al., 2022; Youn et al., 2022). Moreover, dialysis nurses are responsible for critical clinical decisions, such as adjusting dialysis settings and administering medications, which draw on their advanced expertise. In some states, regulations mandate that only RNs can perform specific clinical operations, further increasing the indispensable role of RNs in dialysis facilities.

Empirical studies have consistently demonstrated a strong correlation between higher RN-to-patient ratios and improved clinical quality outcomes in various healthcare settings (Yoder et al., 2013). Given this, it is reasonable to expect similar positive outcomes in the dialysis industry, where investment in healthcare resources — particularly RNs — should align closely with enhanced clinical quality outcomes.

Hypothesis 1 (H1): A greater number of RNs within a dialysis facility is positively associated with clinical performance.

Differences observed in clinical outcomes are not solely due to the quality of care provided; thus, the skill level of clinicians and the availability of advanced devices at healthcare facilities are not determinative. Research shows that a patient's socioeconomic factors significantly influence their outcomes (Kim et al., 2018; Marmot, 2005; Schultz et al., 2018; Thomas-Hawkins et al., 2019). Adler and Newman (2002) explored how socioeconomic status affects health through material possessions, behaviors, and psychological stressors, suggesting that policy interventions should improve socioeconomic status to enhance overall health. Similarly, Braveman and Gottlieb (2014) emphasized the underlying influence of socioeconomic factors and called for addressing these determinants to improve health outcomes.

Consistent with RDT, SDoH are associated with barriers to accessing health-related resources. In more equitable environmental settings, healthcare organizations and patients have better access to health-related resources and can achieve better quality outcomes. Thus, areas with fewer vulnerabilities in SDoH should have greater health-related resources and better clinical outcomes. Therefore, we propose:

Hypothesis 2 (H2): Higher disparities in SDoH are negatively associated with the clinical performance of dialysis facilities.

RDT posits that an organization's external environment, including its social, economic, and cultural attributes, shape resource acquisition strategies (Pfeffer & Salancik, 1978; Ulrich & Barney, 1984). In the manufacturing sector, RDT demonstrates how companies engage with external entities such as suppliers, customers, and competitors to secure necessary resources, influencing production efficiency and product quality (Hillman et al., 2009; Oliver, 1991). Healthcare institutions, like manufacturing companies, engage with external actors, such as medical equipment suppliers, pharmaceutical suppliers, technology vendors, government agencies, and local communities, to secure resources critical to service delivery. However, research by McGarry et al. (2020) underscored that healthcare organizations face resource shortages in regions with significant health disparities, further compounding the difficulties of acquiring essential materials.

Despite parallels with other industries, traditional applications of RDT do not fully capture healthcare's unique challenges. For instance, socioeconomic factors like income inequality directly affect a healthcare facility's ability to retain qualified staff and access state-of-the-art medical technologies (Braveman & Gottlieb, 2014). Healthcare institutions in low-resource settings may struggle to attract and retain medical professionals due to insufficient compensation or professional development opportunities (Lehmann et al., 2008; Willis-Shattuck et al., 2008). The resulting internal factors, particularly staffing levels, affect patient outcomes, but broader disparities, such as those affecting access to transportation, education, and stable housing, do as well (Berkman et al., 2011). For instance, transportation barriers in underserved communities may prevent patients from accessing timely care, exacerbating disparities and placing additional strain on healthcare providers (Syed et al., 2013). In regions marked by high disparities, institutions must also contend with lower levels of health literacy, requiring greater patient education investments to improve healthcare outcomes (Berkman et al., 2011). In such cases, the external environment, marked by socioeconomic inequality and underfunded healthcare systems, plays a critical role in shaping the quantity and quality of medical resources available. We posit that SDoH interact with resource management strategies, which affect clinical outcomes. And that disparities in SDoH are a key moderating factor in the relationship between internal resource allocation, such as nurse staffing levels, and healthcare facility performance. More specifically, in regions with more equitable SDoH, increases in nurse staffing are expected to yield greater improvements in clinical quality outcomes. Conversely, in regions with greater SDoH vulnerabilities, the benefits of additional staffing may be less pronounced due to persistent external challenges (Braveman & Gottlieb, 2014). Thus, we propose the following hypothesis:

Hypothesis 3 (H3): SDoH moderate the effect of nurse staffing levels on the clinical outcomes of dialysis facilities.

Worker empowerment has gained recognition as a critical management concept within OM, emphasizing the value of enhancing employees' decision-making authority and expanding their access to resources (Chan et al., 2008; Channarika & Serey, 2024). In healthcare settings, worker empowerment enhances employee autonomy and responsibility and strengthens their ability to contribute to organizational goals (Spence Laschinger et al., 2002).

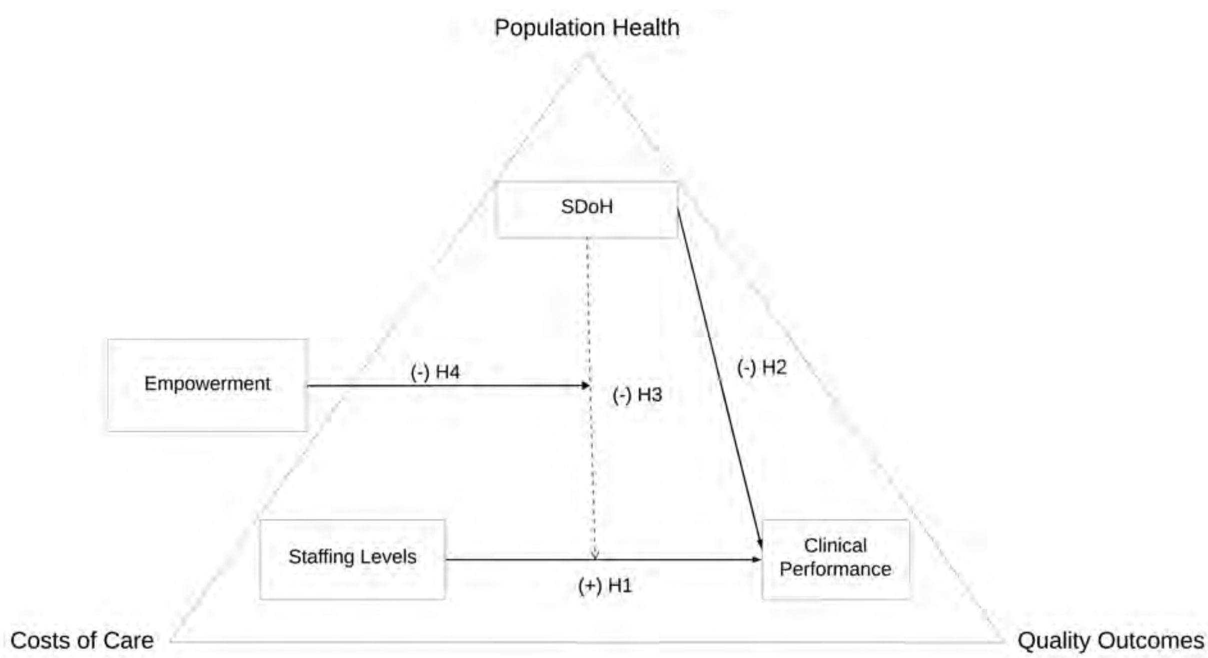
Healthcare is traditionally delivered within a hierarchical structure in which tasks are sorted by their complexity and knowledge intensity. In dialysis facilities, RNs' are at the top of the hierarchy regarding day-to-day operations (Cahill et al., 2021; O'Keefe, 2014). Licensed practical nurses (LPNs), licensed vocational nurses (LVNs), and patient care technicians (PCTs) support RNs by carrying out basic patient care tasks, preparing dialysis equipment, and assisting in patient monitoring. Empowering RNs to delegate some of these responsibilities to LPNs, LVNs, and PCTs enables them to focus on more demanding clinical aspects of care.

Recent research supports the view that empowering RNs by delegating responsibilities enhances operational efficiency and clinical outcomes (Bonnett & Heim, 2024). It allows the facility to use lower-level personnel effectively when RNs are scarce or their time is better allocated to critical tasks. These findings align with RDT by demonstrating that granting RNs more authority to distribute and control resources reduces organizational dependency on highly specialized personnel and mitigates the effects of resource shortages. By enhancing RNs' ability to allocate tasks, worker empowerment indirectly boosts productivity, fostering an environment where all healthcare personnel can perform optimally (Bowen & Rd, 1992). Thus, empowering RNs is essential in addressing the challenges of resource scarcity, which can induce stress, reduce performance, and suppress employees' innovative abilities (Bakker et al., 2008; Grant & Parker, 2009; Hobfoll, 1989). Therefore, based on our theoretical foundation and extant literature, we hypothesize:

Hypothesis 4 (H4): Higher levels of worker empowerment will lessen the negative moderating impact of SDoH on the association between the number of RNs and clinical performance.

Figure 2 conceptually presents the hypotheses in relation to the Triple Aim.

Figure 2: Conceptual Diagram



DATA, OPERATIONALIZATION OF VARIABLES, AND SUMMARY STATISTICS

Hemodialysis remains the most common form of dialysis treatment in the United States, and most dialysis facilities offer in-center hemodialysis. Our analyses used data from 33,686 observations of performance measures across 10,568 dialysis facilities registered with CMS and only provided in-center hemodialysis from 2015 to 2019. These data were merged with the Healthcare Cost Report Information System (HCRIS), which provides financial and human resource data on dialysis facilities during the same period.

Over the past decade, the dialysis industry has experienced substantial changes, including establishing new facilities and a wave of mergers and acquisitions. Many small- and medium-sized facilities were either acquired by larger corporations or ceased operations, disrupting the continuity of records for some dialysis centers (Eliason et al., 2019; Parvathareddy & Erickson, 2021). The closure or acquisition of facilities, notably smaller or underperforming ones, has contributed to gaps in data that complicate longitudinal analyses (Wang & Maciejewski, 2019).

Research indicates that missing data can undermine the validity of conclusions in longitudinal studies that rely on panel data models, including fixed-effects models (Hill et al., 2020; Tseng et al., 2016). To address this issue, we retained only those facilities with complete data across all 5 years of the study period. This selection ensured continuity, reducing the risk of confounding results. The final data set consisted of 22,590 observations across 4,149 facilities.

Input – Registered Nurses

RN staffing is a key resource for care quality, and one of the largest patient care costs for a facility. Therefore, RN levels serve as a proxy for resource allocation in our cost-quality analysis. The number of full-time equivalent RNs is calculated by dividing the number of hours all RNs worked by 40 hours per week. The mean value of this indicator for all 5 years is 3.50 RNs. The standard deviation is 5.33.

Moderator – Social Deprivation Index

Given the frequent treatment schedules required by dialysis patients, typically three sessions per week, patients generally select facilities near their home. As such, we included the Social Deprivation Index (SDI) as a moderator that captures the levels of SDoH at the community level (Robert Graham Center, 2018). It is measured at the Zip Code Tabulation Area (ZCTA) level. It includes seven characteristics captured in the U.S. Census Bureau's American Community Survey: the percentage of residents below the poverty threshold, limited educational attainment, prevalence of single-parent households, rates of renter occupancy, housing overcrowding, lack of vehicle ownership, and non-employment among adults under 65. Each characteristic is standardized and then weighted using factor analysis to reflect its relative contribution to overall deprivation. Using the SDI as a community-level measure obviates the need to explicitly control for the proportion of economically disadvantaged individuals within each facility. Due to the inherently local nature of dialysis service delivery, patients at the same facility often share comparable socioeconomic conditions. Thus, employing ZCTA-level SDI offers an effective and balanced representation of how external socioeconomic environments impact dialysis facility operations and patient-related outcomes. By providing a replicable and transparent framework, the SDI has been widely adopted in prior research, enabling robust comparisons across communities (Butler et al., 2013; Phillips et al., 2016; Robert Graham Center, 2018).

Moderator – Clinician Empowerment

In this research, worker empowerment refers to the degree of authority and flexibility RNs possess in delegating key clinical duties to LPNs, LVNs, and PCTs, specifically those involving central venous catheters (CVCs) and administering intravenous medications. This empowerment allows RNs to effectively manage their workload, optimize resource allocation, and enhance the quality of care within dialysis facilities. According to the American Nephrology

Nurses Association (ANNA) and state-level regulatory datasets, in 10 states, RNs are legally permitted to delegate the administration of IV medications through CVCs to LPNs/LVNs under supervision (Cahill et al., 2021; O'Keefe, 2014). Four U.S. states prohibit LPNs/LVNs from accessing or administering intravenous medications via CVCs, indicating a lower level of RN empowerment. In other states, RNs have the autonomy to delegate CVC management fully to LPNs/LVNs. To capture the variations in RN empowerment across different regulatory environments, we developed a discrete, state-level variable to reflect this empowerment:

0: No Delegation Permitted – LPNs/LVNs cannot administer medications through CVCs, indicating minimal RN empowerment.

1: Delegation Under Supervision – RNs cannot delegate medication administration to an LPN/LVN under supervision, indicating moderate RN empowerment.

2: Full Delegation Permitted – RNs can delegate CVC access and medication administration to LPNs/LVNs, indicating high RN empowerment.

The decision to use CVC access delegation as a proxy for RN empowerment is theoretically and practically significant. As key clinical staff in dialysis facilities, RNs manage care delivery and resource utilization, making their level of empowerment a crucial factor in determining the efficiency and effectiveness of care. The flexibility and authority granted to RNs to delegate clinical responsibilities help optimize resource use and reduce the burden on individual RNs.

Output - Clinical Quality Performances

Recent studies highlight the importance of standardized healthcare measures, especially when evaluating dialysis treatment outcomes. CMS' End-Stage Renal Disease Quality Incentive Program (ESRD QIP) is a rigorous and authoritative benchmark, enabling comparison across facilities (Gupta & Wish, 2018). Prior management studies have used QIP scores to measure the performance of dialysis facilities (Dreyfus et al., 2020; Kutner & Zhang, 2017).

Control Variables

This research integrates several control variables to isolate the effects of RN staffing levels, our primary independent variable. In light of the tendency of dialysis facilities managed by large companies to maximize reimbursements through the strategic administration of drugs, we control for drug expenses (Eliason et al., 2019). Supply expenses, which directly relate to the workload of RNs and, consequently, treatment outcomes, are included as a proxy for treatment frequency (Yoder et al., 2013). The number of dialysis stations is included as a physical representation of the facility's capacity and potential patient volume, impacting RN work conditions (Flynn et al., 2009; Thomas-Hawkins et al., 2020). Healthcare services must meet high-quality standards in both for-profit and non-profit institutions, though the two ownership models may prioritize different aspects of care quality (Audi, 2014; Dreyfus et al., 2020). We control for the profit status of dialysis facilities, coding for-profit facilities as 1. Lastly, the Survey and Certification Program certifies ESRD facilities for Medicare by adhering to specified safety and quality standards, referred to as "Conditions for Coverage" (Dreyfus et al., 2020). Longer certification durations are expected to be associated with greater knowledge and potentially improved performance (Dreyfus et al., 2020; Hays & Hill, 2001). Accordingly, we control the number of years a facility has been certified.

Table 1 shows each variable's source and definition. Table 2 provides summary statistics. and the correlation matrix, providing initial evidence of the interrelationships among facility characteristics, workforce variables, and patient outcomes.

Table 1: Origins of Data and Variable Definitions

<table>
<tr><th>Variables</th><th>Definition</th><th>Type</th><th>Source</th></tr>
<tr><td colspan="4">State level</td></tr>
<tr><td>Nurse–patient ratio</td><td>If a state law mandates or recommends minimum nurse staffing levels in healthcare facilities</td><td>Binary</td><td rowspan="2">State Laws and Regulations</td></tr>
<tr><td>Empowerment</td><td>Level of RN empowerment allowed</td><td>Discrete</td></tr>
<tr><td colspan="4">Facility level</td></tr>
<tr><td>Profit status</td><td>For-profit or non-profit</td><td>Binary</td><td rowspan="3">CMS - ICH CAHPS Facility</td></tr>
<tr><td>Dialysis stations</td><td>Number of stations in the facility</td><td rowspan="2">Discrete</td></tr>
<tr><td>Years since certification</td><td>Number of years certified (or re-certified)</td></tr>
<tr><td>Drugs expenses</td><td>Net payments for drugs in fiscal period</td><td rowspan="9">Continuous</td><td rowspan="9">CMS - ESRD Cost Report</td></tr>
<tr><td>Supplies expenses</td><td>Net payments for supplies in fiscal period</td></tr>
<tr><td>Management level</td><td>FTE employment of management staffs</td></tr>
<tr><td>RN</td><td>FTE employment of RNs</td></tr>
<tr><td>LPN</td><td>FTE employment of LPNs</td></tr>
<tr><td>Nurse aides</td><td>FTE employment of nurse aides</td></tr>
<tr><td>Other specify</td><td>FTE employment of other non-clinical staffs</td></tr>
<tr><td>Clinical performance</td><td>Net payments for drugs in fiscal period</td></tr>
</table>

Notes: ICH CAHPS - In-Center Hemodialysis Consumer Assessment of Healthcare Providers and Systems (CAHPS®); FTE – Full-time equivalent. Table 8, in the appendix, provides further description and source details.

Table 2: Correlation Table

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Clinical performance	70.43	13.28	1.000													
(2) RN	4.39	3.45	-0.134***	1.000												
(3) Nurse aides	0.31	1.41	-0.017**	0.031***	1.000											
(4) LPN	0.74	1.09	-0.073***	0.216***	0.014**	1.000										
(5) Management level	0.77	1.31	-0.167***	0.457***	0.006	0.112***	1.000									
(6) Other staff	0.48	0.60	-0.168***	0.346***	-0.115***	0.118***	0.440***	1.000								
(7) Net drug expenses	373,247	256,906	-0.165***	0.589***	0.139***	0.297***	0.088***	0.160***	1.000							
(8) Net supply expenses	285,327	235,691	-0.124***	0.633***	0.052***	0.273***	0.179***	0.295***	0.706***	1.000						
(9) Years since certified	19.38	9.86	-0.045***	0.197***	-0.027***	0.133***	0.113***	0.207***	0.260***	0.240***	1.000					
(10) Profit status	0.93	0.24	0.006	0.035***	-0.017***	0.001	-0.094***	-0.134***	-0.007	-0.039***	0.101***	1.000				
(11) Dialysis stations	18.62	7.49	-0.141***	0.469***	0.088***	0.318***	0.173***	0.324***	0.633***	0.550***	0.388***	0.023***	1.000			
(12) SDI	58.71	26.70	-0.082***	0.088***	0.038***	0.163***	0.031***	0.084***	0.204***	0.104***	0.157***	0.001	0.241***	1.000		
(13) State nurse–patient ratios	0.27	0.44	-0.007	0.086***	0.122***	0.189***	0.073***	-0.032***	0.099***	0.024***	-0.045***	-0.019***	0.085***	0.086***	1.000	
(14) Empowerment	1.67	0.57	0.013**	-0.066***	0.020***	0.097***	0.016**	0.001	-0.014**	-0.036***	0.015**	0.049***	0.032***	0.033***	0.029***	1.000

**** p<0.01, ** p<0.05, * p<0.1*

METHODS

Fixed-Effects Regression

We used a fixed-effects (FE) regression model for several reasons. First, considering the significant differences in disparities by geography, a central challenge is accurately measuring the impact of the independent variables on clinical quality. Our dataset exhibits a mixed structure of cross-sectional and time-series data. According to Wooldridge (2010), FE models can effectively deal with the problem of unobservable individual heterogeneity in panel data, owing to their ability to control for all time-invariant individual characteristics, whether observable or not. Furthermore, Rabe-Hesketh and Skrondal (2012) emphasized that FE models provide more reliable estimates when examining interactions because they control for individual heterogeneity that remains constant over time. The Hausman test supports the preference for the FE model over the random effects (RE) model. The significance of the Hausman test (p-value <0.1) indicates that the assumptions underlying the RE model are violated in this dataset (Hausman, 1978).

The equations below show the empirical models estimated. Equation (1) examines the impacts of RN levels and SDoH on clinical outcomes. Equation (2) examines the effect of SDoH moderation on clinical outcomes. Equation (3) examines the effect of LPN Empowerment on SDoH moderation.

$$(1)\ Clinical\ Outcome_{it} = \alpha + \beta_1 RN_{it} + \beta_2 SDI_{it} + \gamma Z_{it} + \mu_{it} + \lambda_t + \epsilon_{it}$$
$$(2)\ Clinical\ Outcome_{it} = \alpha + \beta_1 RN_{it} + \beta_2 SDI_{it} + \beta_3 (RN_{it} \times SDI_{it}) + \gamma Z_{it} + \mu_{it} + \lambda_t + \epsilon_{it}$$
$$(3)\ Clinical\ Outcome_{it} = \alpha + \beta_1 RN_{it} + \beta_2 SDI_{it} + \beta_3 (RN_{it} \times SDI_{it}) + \beta_4 (Empowerment_{it} \times RN_{it} \times SDI_{it}) + \delta Wit + \gamma Z_{it} + \mu_{it} + \lambda_t + \epsilon_{it}$$

$i: facility$ & $t: year$
$W_{it}: Refers\ to\ the\ two-way\ interaction\ terms\ that\ control\ for\ lower-order\ effects$
$Z_{it}: a\ vector\ of\ additional\ facility-level\ control\ variables$
$\mu_s: county\ fixed\ effects, controlling\ for\ time-invariant\ region\ characteristics$
$\lambda_t: year\ fixed\ effects, controlling\ for\ time\ specific\ effects\ common\ across\ all\ facilities$

We included county-level fixed effects in our regression models to further account for unobserved, time-invariant regional factors. County-level data capture macro-environmental factors such as regional health policies, resource allocations, and socioeconomic conditions that can systematically affect all healthcare facilities within a region (Parker et al., 2017; Shortell et al., 2005). Since counties often serve as administrative units for policy implementation, they are appropriate for examining the impact of these macro-level factors on facility outcomes. For similar reasons, prior studies have employed county-level analyses to examine regional influences on organizational performance (Parker et al., 2017; Shortell et al., 2005). Additionally, we clustered standard errors at the facility level to account for potential within-facility correlations in the error terms, acknowledging that observations within the same facility may be correlated over time.

Next, the variance inflation factors (VIF) and condition indices were assessed to address potential multicollinearity concerns in the models. The VIF values for all variables are below 3, with a mean VIF of 1.65, comfortably within the generally accepted threshold of 10 (Kutner et al., 2005). In addition, the condition indices, with a maximum condition number of 21.84, suggest no critical multicollinearity issues, adhering to the recommendations of Belsley et al. (1980), who proposed that condition indices should not exceed 30. These diagnostics indicate that multicollinearity does not significantly affect the reliability of the regression estimates.

Endogeneity

Like most studies, this one may suffer from endogeneity from measurement errors, omitted controls, and reverse causality (Lu et al., 2018; Peng et al., 2023). The instrumental variable (IV) approach is applied to minimize endogeneity concerns as much as possible. This is accomplished by utilizing a strategy that integrates multiple data sources, diminishing the potential biases of relying on a singular data source. Studies emphasize the importance of diverse data sources in healthcare research to improve study validity (Dreyfus et al., 2020; KC & Terwiesch, 2011). Second, in addressing the issue of omitted variables within the context of nurse staffing levels and treatment outcomes, our model design rigorously incorporates variables identified as potentially influential. A thorough review has informed our approach to previous studies on dialysis treatments, selecting variables that could impact clinical quality as part of our control group. We collect both the facility-level operation and the unit-level control variables, acknowledging these confounding variables' critical role in preserving the validity of causal inferences (Krause & Howard, 2003).

Third, from a staffing and recruitment standpoint, hospitals with superior clinical outcomes might attract more RNs, given the allure of working in institutions with a commendable reputation. Conversely, hospitals with a better reputation may attract more patients, especially those with more critical conditions. Consequently, there is a risk of endogeneity due to this bidirectional causality. Addressing this simultaneity is imperative to ensure the robustness of our findings. Therefore, we introduced an IV regression model to handle endogeneity concerns due to reverse causality and possible omitted controls. IVs are carefully selected to achieve exclusion and relevance criteria (Lu et al., 2018).

The IVs used in this study are the mean hourly pay of RNs and total employment numbers in the state. Conceptually, region-level RN employment and average salaries reflect competition and the region's attraction to RNs but do not directly relate to facilities' other resource levels and expenses. Our approach is consistent with prior empirical research in healthcare management and broader social sciences. Studies by Acemoglu and Angrist (2000) and Kesavan et al. (2014) used demographic characteristics and geographic location as IVs to validate the use of district-level data as an exogenous proxy variable. Studies emphasize the role of salary in attracting and retaining nurses to demonstrate how it affects nursing staffing levels in healthcare organizations (Aiken et al., 2002; Kovner et al., 2009).

Following Lu et al. (2018), we used several diagnostic tools to empirically verify that our instrumental variables (IVs) met both relevance and validity criteria (see Table 3). The under-identification test (p-value < .01) rejects the hypothesis that the instruments are irrelevant (Angrist & Pischke, 2009; Sanderson & Windmeijer, 2016). The F statistic exceeds the conventional threshold of 10, indicating that our instruments are strong and not weakly identified (Stock et al., 2002). Additionally, the Sargan statistic, with a p-value of 0.3469, supports the validity of the overidentifying restrictions (Hansen, 1982; Sargan, 1958). These methodological choices align with best practices established in the literature (Cragg & Donald, 1993; Hansen, 1982; Sargan, 1958; Staiger & Stock, 1997; Stock et al., 2002), supporting the credibility and statistical soundness of the instrumental variables approach. We used a two-stage IV regression model. The first stage uses an ordinary least squares (OLS) FE model and the corresponding IVs to obtain the predicted values and residuals of the endogenous variables (RN). In the second stage, equations (1) (2) (3) are estimated using an FE regression in which we apply the predicted values of the endogenous variables, the residuals obtained in the first stage regression, and interaction terms. This minimizes the bias caused by endogeneity to ensure that our estimates are robust and reliable.

Table 3: Endogeneity Testing Results

Under identification	**P-value**

Sargan-Hansen	<.01
Weak identification	**F statistic**
F statistic	>10
Overidentification	**P-value**
Sargan statistic	>.10

RESULTS

The regression analysis results strongly support the proposed hypotheses (Table 4). RN staffing levels significantly and positively affect clinical performance statistically and substantively. As predicted, higher RN staffing improves clinical quality (Model 1: $\beta = 8.306$, $p < .01$), offering robust support for Hypothesis 1, which posits that greater allocation of RNs enhances clinical performance. Moreover, SDoH exert a significant negative impact on clinical performance (Model 1: $\beta = -.036$, $p < .01$), confirming Hypothesis 2. Higher SDoH (i.e., greater vulnerability) are associated with worse clinical outcomes, underscoring the negative role of SDoH on healthcare facility performance. The negative and significant interaction term (Model 2: $\beta = -.020$, $p < .01$) supports Hypothesis 3, indicating that SDoH weaken the positive effect of RN staffing on clinical performance.

Figure 3 provides a visual representation of the relationships we found. The positive slopes for both low and high SDI indicate that increasing RN staffing improves clinical quality, supporting Hypothesis 1. The findings also validate Hypothesis 2, that the high SDI line is consistently lower than the low SDI line, reflecting the persistent negative impact of greater socioeconomic disparities on clinical performance. The widening gap between Low SDI and High SDI lines under high RN staffing conditions, compared to a narrower gap under low RN staffing conditions, highlights the moderating effect of SDI. This supports Hypothesis 3, which posits that RNs have less ability to improve clinical performance in regions with greater vulnerability.

In Model 3, we introduced the RN Empowerment Index as a moderating variable, incorporating a three-way interaction. The results for Hypothesis 4 are significant (Model 3: $\beta = 0.028$, $p < 0.05$), confirming a positive three-way interaction between RN empowerment, SDoH, and RN staffing levels on clinical performance. The figure illustrating the three-way interaction (Figure 4) shows that the performance gap between low and high SDI facilities narrows in high RN staffing conditions as empowerment increases. This suggests that higher empowerment weakens the negative moderating effect of SDoH. In other words, increased workplace empowerment mitigates the adverse impact of SDoH on RN performance. By increasing empowerment, healthcare managers can better address disparities and resource limitations, ultimately enhancing clinical performance.

Table 4: Main Analyses Regression Estimation Results

	Model 1	Model 2	Model 3	CONTROL
Other specify	-3.319^{***}	2.425	1.546	-3.949^{***}
	(0.176)	(1.600)	(1.230)	(0.239)
Management level	-0.458^{***}	-8.542^{***}	-7.071^{***}	-0.689^{***}
	(0.070)	(2.139)	(1.588)	(0.172)
Drugs net expenses	-0.000	-0.000^{***}	-0.000^{***}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
Supplies net expenses	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Nurses aides	-0.276^{***}	0.544^{**}	0.339^{*}	-0.209^{***}
	(0.058)	(0.241)	(0.177)	(0.076)
LPNs	0.030	-0.804^{***}	-0.433^{**}	0.017
	(0.089)	(0.272)	(0.197)	(0.099)
Years since certi	0.013	0.025	0.025^{*}	0.020^{**}
	(0.009)	(0.016)	(0.013)	(0.010)
Dialysis stations	-0.072^{***}	-0.273^{***}	-0.190^{***}	-0.060^{***}
	(0.016)	(0.062)	(0.044)	(0.018)
Profit status	-1.691^{***}	-7.595^{***}	-6.039^{***}	-2.620^{***}
	(0.367)	(1.636)	(1.178)	(0.510)
State nurse–patient ratio	5.862^{**}	-5.546	-3.590	6.749^{**}
	(2.615)	(5.266)	(4.371)	(2.842)
RNs	8.306^{***}	6.230^{***}	5.203^{**}	
	(2.181)	(1.533)	(2.118)	
SDI	-0.036^{***}	-0.032^{***}	-0.066^{**}	
	(0.006)	(0.005)	(0.026)	
RNs * SDI		-0.020^{***}	-0.044^{**}	
		(0.007)	(0.021)	
Empowerment			2.632	
			(1.853)	
SDI * empowerment			0.026^{*}	
			(0.015)	
RNs * empowerment			-2.382^{**}	
			(0.975)	
Empowerment * RNs * SDI			0.028^{**}	
			(0.012)	
Observations	21961	21961	21961	21961

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3: Two-Way interaction

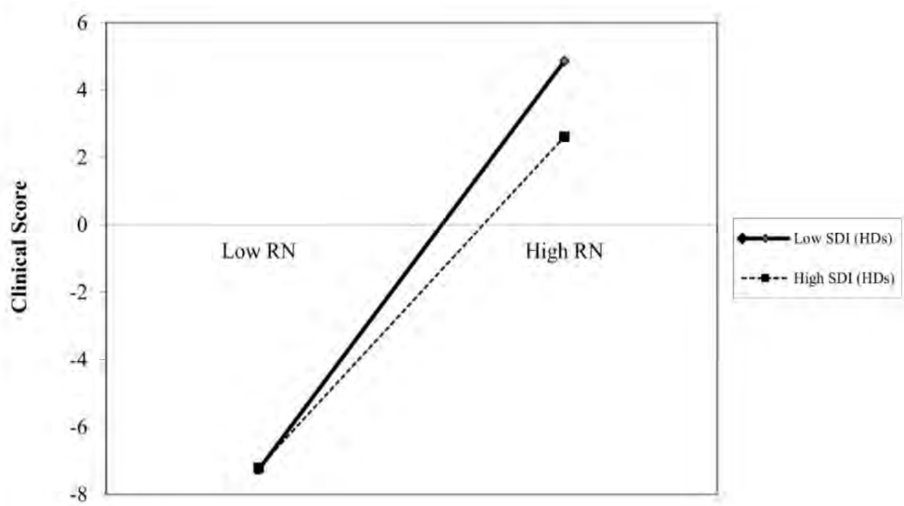
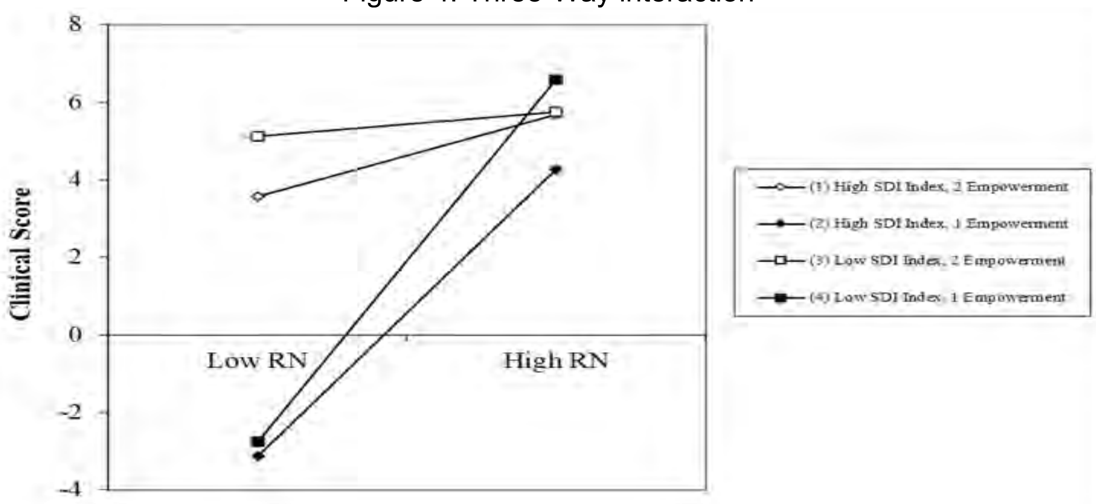


Figure 4: Three-Way interaction



ROBUSTNESS CHECKS

In our robustness tests, we employed three complementary approaches that provide additional theoretical and empirical validation of the relationships observed in the initial model. First, we employed an alternative estimation technique: the generalized method of moments (GMM) (see Table 5 in Appendix Section). GMM is particularly suited for addressing endogeneity, where independent variables may be correlated with error terms, potentially biasing OLS estimates (Hansen, 1982). Our GMM results are consistent with the initial findings.

Second, we replaced the original dependent variable, clinical performance, with a well-established proxy indicator: mortality rates. These indicators are commonly used in healthcare research as direct measures of patient outcomes. The results support all hypotheses and strengthen the robustness of our findings across different clinical outcome metrics (see Table 6 in Appendix Section).

Lastly, we substituted the SDI variable with a poverty index, which reflects the percentage of the population living below 100% of the federal poverty level (FPL). Poverty is a widely recognized SDoH validated by research. Our findings remained consistent when using poverty instead of the SDI (see Table 7 in Appendix Section).

DISCUSSION

This study investigated the interplay between RN staffing levels, SDoH, and clinical quality outcomes in dialysis facilities. Data were analyzed from thousands of observations across 4,149 dialysis facilities throughout the United States. A two-stage instrumented FE regression model was employed, addressing potential endogeneity concerns. Significant relationships were found, underscoring the critical role of staffing and SDoH in determining clinical quality performance. Further, levels of vulnerability in the region, as reflected in the SDoH, moderate the relationship between RN staffing and clinical quality outcomes, such that facilities located in areas with greater vulnerability experience poorer clinical quality performance. Additionally, our study proposes that workplace empowerment strategies are crucial in enhancing clinical quality outcomes, particularly under resource-constrained conditions. Specifically, we found that empowering LPNs can mitigate the adverse moderating effects of poor SDoH on clinical quality performance.

The study findings extend the OM literature by providing a better understanding of the dynamics between workforce composition, socio-environmental influences, and clinical quality outcomes in dialysis facilities. To further contextualize these results, it is essential to delve into the broader theoretical implications, managerial applications, and policy recommendations. By integrating RDT with the Triple Aim framework, we theoretically examine the strategic significance of managing resource dependencies in healthcare settings. Moreover, the practical applications of these insights can guide dialysis facility managers in optimizing operations and policymakers in shaping effective regulations to enhance healthcare delivery.

Theoretical Implications

This research integrates RDT with the Triple Aim framework to better understand healthcare operations management in dialysis facilities. RDT posits that organizations must manage dependencies on critical external resources to survive and succeed. This theory is particularly relevant in healthcare, where resource acquisition and management are pivotal for delivering quality care. The Triple Aim framework emphasizes the need to enhance patient care experience, improve population health, and reduce per capita healthcare costs. Our findings highlight that staffing levels are central to this cost dimension. While vital for quality, RN staffing represents a considerable cost to facilities. Thus, achieving cost reductions cannot be divorced from decisions about RN allocation, a core trade-off between spending and quality underscored by our results.

As this research validates, resource management in service environments, such as dialysis facilities, is critical for achieving higher clinical quality performance. A dialysis facility must achieve high levels of service quality to continue operating. The primary service providers are the RNs employed at a dialysis facility. Thus, managing this constrained resource is imperative for dialysis facility success and survival. This aligns with the Triple Aim's path, which links healthcare costs and quality. The health of the population in an area impacts healthcare outcomes for patients. This link highlights how the environment outside of the dialysis facility may impact healthcare quality within the facility. Efforts to improve and manage the broader

SDoH of a geographic area around a dialysis facility should be explored. The resources deployed towards these efforts will lead to greater clinical quality outcomes within the facility. This may be due to improvement in the patient's environment or through the environment that workers at the facility navigate. Specifically, recruiting and retaining clinicians may be easier when the external environment improves.

RDT offers further insights into how a dialysis facility may manage its resources. Empowering individuals increases job satisfaction (Ahmad & Schroeder, 2003; Anand et al., 2009). This research finds that empowering LPNs to perform RN tasks improves the flexibility of an organization, overcoming some of the detrimental impacts of RN shortages and high levels of social deprivation within the local environment. Furthermore, this research enriches the theoretical discourse by illustrating how RDT can be applied to understand and address the complex interdependencies in healthcare management, particularly within the Triple Aim framework. By pioneering the moderating effect of SDoH on the relationship between healthcare resources and clinical quality performance, this study validates and extends the Triple Aim beyond its suggested direct impact. RDT helps explain how these relationships exist and why workforce empowerment strategies are associated with overcoming resource scarcity issues to improve clinical quality. By including workforce empowerment, this research begins to validate the quadruple aim framework, which additionally considers workforce well-being (Bodenheimer & Sinsky, 2014).

Managerial Implications

The findings offer several practical implications for dialysis facility managers. First, increasing RN staffing levels will improve clinical quality outcomes. Since RNs are expensive to attract and employ, facility managers should prioritize retaining their current RNs. Providing a good work environment, empowering workers, and offering competitive salaries, benefits, and professional development opportunities are strategies to help retain talent (Boudreau et al., 2003).

Second, our study suggests that facilities can increase clinical performance by empowering LPNs and LVNs to perform more advanced tasks. This approach can alleviate some of the burden on RNs. It may help address the chronic shortage of nursing staff that all healthcare facilities face by better utilizing current resources and reducing the impact of external disparities. It offers an alternative to approaches that increase spending by increasing RN staffing levels and to those that rely on the government to implement programs that will address the SDoH.

At the same time, this research highlights the importance of addressing socio-environmental factors in improving patient care. Facilities in areas with greater vulnerability face more challenges in achieving high clinical quality performance as they struggle to attract and retain RNs. These staffing challenges carry financial consequences: facilities in high-SDoH areas may face higher recruitment and labor costs (e.g., bonuses, turnover expenses) to maintain adequate RN levels. Moreover, because disparities in the SDoH dampen the impact of each RN on outcomes, managers are effectively paying more per unit of quality gained. Recognizing this reduced cost-effectiveness in high-SDoH settings is crucial for planning sustainable quality improvement initiatives. Managers should recognize these contextual factors and develop targeted strategies to address them. For instance, partnering with local community organizations to provide additional support services, such as transportation and health education, can help mitigate some of the adverse effects of SDoH.

Policy Implications

Dialysis facility managers and policymakers should recognize the critical role of empowerment in improving healthcare quality. Changes to existing laws should be proposed and passed so that greater empowerment strategies may be achieved. This recommendation aligns with current initiatives to allow nurse practitioners and physician assistants full practice authority. Such approaches provide healthcare clinicians greater autonomy when performing their duties, which may assist with retention and clinical quality performance. State-level policies should also consider the varying impacts of SDoH on healthcare outcomes. Policymakers can support healthcare facilities in disadvantaged areas by providing additional funding, resources, and incentives to address the challenges caused by disparities in SDoH. This can include grants for community health programs, subsidies for transportation services, and funding for educational initiatives to improve health literacy. Additionally, policymakers should promote collaborative approaches integrating healthcare services with community resources. Encouraging partnerships between healthcare facilities and local organizations can enhance the overall support network for patients, addressing broader SDoH that impact health outcomes. Policies facilitating these collaborations, such as joint funding initiatives and shared service agreements, can significantly improve healthcare quality in disadvantaged areas.

Overall, our research illustrates how dialysis centers can strive for the Triple Aim's quality and population health goals in a cost-conscious manner. By understanding where investments in staffing yield the greatest benefit and how empowerment and community factors modify this yield, leaders can make more informed decisions that improve care while controlling costs under varying conditions of HDs.

LIMITATIONS AND CONCLUSION

This study opens several avenues for future research. First, the recent pandemic has significantly altered healthcare operations, workforce dynamics, and patient care priorities, which are not reflected in our dataset. Validating these findings using more recent data to determine how much the results may have changed, if any, may be helpful. Our data only included facilities that were operational throughout all the years of the analyses. Facilities that closed or opened during this time frame may provide more nuance to the results. Also, researchers should extend and generalize these findings to other healthcare settings to determine how the external environment and empowerment strategies may directly and indirectly impact care quality. Furthermore, future research should consider broader applications of RDT in healthcare. Exploring how policy changes, technological advancements, and market dynamics interact with internal and external resources can deepen our understanding of resource dependencies in healthcare. Another potential extension is to explore other forms of empowerment. Future research could investigate the specific mechanisms through which different forms of empowerment impact clinical and operational outcomes.

In conclusion, our study highlights the critical role of staffing levels, social disparities, and empowerment strategies in determining clinical quality outcomes in dialysis facilities. By integrating RDT with the Triple Aim framework, we offer a comprehensive understanding of the complex dynamics between internal and external resources in healthcare. Our findings provide valuable insights for facility managers, policymakers, and researchers, guiding efforts to enhance healthcare quality and equity in resource-constrained settings.

APPENDIX

Table 5: Summary of Regression Analysis by GMM

	Model 1	Model 2	Model 3
RN	8.306*** (2.181)	6.230*** (1.533)	5.203** (2.118)
SDI	−0.036*** (0.006)	−0.032*** (0.005)	−0.066*** (0.026)
Other specify	2.425 (1.600)	1.546 (1.230)	−3.949*** (0.239)
Management level	−8.542*** (2.139)	−7.071*** (1.588)	−0.689*** (0.172)
Drug net exp	−0.000*** (0.000)	−0.000*** (0.000)	−0.000** (0.000)
Supplies net exp	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)
Nurse aides	0.544** (0.241)	0.339* (0.177)	−0.209*** (0.076)
LPNs	−0.804*** (0.272)	−0.433** (0.197)	0.017 (0.099)
Years since certi.	0.025 (0.016)	0.025* (0.013)	0.020** (0.010)
No. dialysis sta.	−0.273*** (0.062)	−0.190*** (0.044)	−0.060*** (0.018)
Profit/nonprofit	−7.595*** (1.636)	−6.039*** (1.178)	−2.620*** (0.510)
State nurse–patient ratio	−5.546 (5.266)	−3.590 (4.371)	6.749** (2.842)
RNs * SDI		−0.020*** (0.007)	−0.044** (0.021)
Empowerment			2.632 (1.853)
SDI * empowerment			0.026* (0.015)
Empowerment*RN* SDI			0.028** (0.012)
RNs * empowerment			−2.382** (0.975)
Observations	21961	21961	21961

Table 6: Summary of Regression Analysis for Mortality

	Model 1	Model 2	Model 3
RNs	−2.218***	−2.340***	−2.293**
	(0.288)	(0.315)	(0.950)
SDI	0.007***	0.007**	0.040***
	(0.003)	(0.003)	(0.012)
Other specify	−1.838***	−2.247***	0.248
	(0.232)	(0.321)	(0.199)
Management level	2.649***	3.045***	0.132*
	(0.321)	(0.402)	(0.078)
Drug net exp	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Supplies net exp	0.000***	0.000***	0.000*
	(0.000)	(0.000)	(0.000)
Nurse aides	−0.247***	−0.265***	−0.024
	(0.056)	(0.060)	(0.039)
LPNs	0.020	−0.054	−0.040
	(0.069)	(0.080)	(0.054)
Years since certi.	0.008	0.007	0.011**
	(0.007)	(0.007)	(0.005)
No. dialysis sta.	0.005	−0.003	−0.040***
	(0.013)	(0.014)	(0.009)
Profit/nonprofit	−0.317	−0.331	−0.378*
	(0.265)	(0.281)	(0.214)
State nurse–patient ratio	1.064***	1.176***	1.155***
	(0.287)	(0.308)	(0.235)
SDI * RNs		0.008**	0.012
		(0.003)	(0.011)
Empowerment			0.807***
			(0.183)
SDI * empowerment			−0.021***
			(0.007)
Empowerment * RNs * SDI			−0.010*
			(0.006)
RNs * empowerment			1.092**
			(0.437)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Summary of Regression Analysis for SDI-Poverty

	Model 1	Model 2	Model 3
RNs	8.218***	5.667***	4.062**
	(2.157)	(1.417)	(1.988)
SDI	-0.038***	-0.034***	-0.042**
	(0.007)	(0.005)	(0.020)
Other specify	2.353	1.398	-3.974***
	(1.582)	(1.183)	(0.261)
Management level	-8.457***	-6.792***	-0.569***
	(2.115)	(1.510)	(0.140)
Drug net exp	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)
Supplies net exp	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)
Nurse aides	0.539**	0.320*	-0.229**
	(0.239)	(0.169)	(0.072)
LPNs	-0.791**	-0.315*	0.035
	(0.269)	(0.187)	(0.098)
Years since certi.	0.026*	0.027**	0.020**
	(0.016)	(0.013)	(0.010)
No. dialysis sta.	-0.272***	-0.170***	-0.059***
	(0.062)	(0.041)	(0.017)
Profit/nonprofit	-7.530***	-5.572***	-2.494***
	(1.619)	(1.093)	(0.506)
State nurse–patient ratio	-18.400***	-14.490***	0.369
	(5.174)	(3.835)	(2.004)
SDI * RNs		-0.023**	-0.041**
		(0.008)	(0.020)
Empowerment			3.406*
			(1.798)
RNs * empowerment			-1.844**
			(0.907)
SDI * empowerment			0.012
			(0.011)
RNs * empowerment * SDI			0.026**
			(0.011)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Detailed Data Source and Description

Level	Data - relative variable(s)	Time-variant	Title	Source
State	RN employment - Job market statistics	Yes	29-1141 Registered Nurses	BLS - Occupational Employment and Wage Statistics https://www.bls.gov/oes/current/oes291141.htm#st
	Nurse-to-patient	No	Nurse-to-Patient Staffing Ratio Laws and Regulations by State	Nurse Journal https://www.nursingworld.org/practice-policy/nurse-staffing/nurse-staffing-advocacy/
	LPN Access	No	The Authority for Certain Clinical Tasks Performed by Unlicensed Patient Care Technicians and LPNs/LVNs in the Hemodialysis Setting: An Update and Invitation to Take Action	American Nephrology Nurses' Association https://doi.org/10.37526/1526-744X.2021.48.2.119
Zip (ZCTA5)	SDI	Yes	SDI at the ZCTA level	Robert Graham Center https://www.graham-center.org/maps-data-tools/social-deprivation-index.html
Facility	Ownership and certification	No	ICH CAHPS	CMS - Dialysis Compare database https://data.cms.gov/provider-data/topics/dialysis-facilities
	Staffing level and net payment	Yes	Cost Report	
	Metrics of clinical performance	Yes	QIP Reports	

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Health Care Management Science

Enhancing healthcare operation in disadvantaged communities: The role of chain affiliation and dynamic capabilities

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Abstract:	Healthcare organizations operating in socially disadvantaged communities often struggle to deliver high-quality care due to challenges like limited health literacy, unstable transportation, and cultural mistrust. This study examines how chain affiliation in dialysis centers serving socially disadvantaged populations impacts clinical outcomes. Drawing on Dynamic Capabilities Theory, we propose that being part of a chain network enables facilities to adapt and improve quality of care in low-resource environments. We empirically test this hypothesis using a five-year panel dataset of dialysis facilities and apply robust econometric techniques—instrumental variable generalized method of moments (IV-GMM), two-stage least squares (2SLS), and limited-information maximum likelihood (LIML)—to address endogeneity. The analysis reveals that chain-affiliated facilities maintain higher quality scores and experience a smaller decline in performance due to social disadvantage compared to independent centers. Our findings suggest that chain networks confer dynamic capabilities that enhance resilience and quality in underserved settings. This work contributes to healthcare management science by demonstrating the value of chain affiliation as a strategy for quality improvement and by informing health policy on strengthening care delivery in resource-constrained settings.

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Enhancing healthcare operation in disadvantaged communities: The role of chain affiliation and dynamic capabilities

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Abstract

Healthcare organizations operating in socially disadvantaged communities often struggle to deliver high-quality care due to challenges like limited health literacy, unstable transportation, and cultural mistrust. This study examines how chain affiliation in dialysis centers serving socially disadvantaged populations impacts clinical outcomes. Drawing on Dynamic Capabilities Theory, we propose that being part of a chain network enables facilities to adapt and improve quality of care in low-resource environments. We empirically test this hypothesis using a five-year panel dataset of dialysis facilities and apply robust econometric techniques—instrumental variable generalized method of moments (IV-GMM), two-stage least squares (2SLS), and limited-information maximum likelihood (LIML)—to address endogeneity. The analysis reveals that chain-affiliated facilities maintain higher quality scores and experience a smaller decline in performance due to social disadvantage compared to independent centers. Our findings suggest that chain networks confer dynamic capabilities that enhance resilience and quality in underserved settings. This work contributes to healthcare management science by demonstrating the value of chain affiliation as a strategy for quality improvement and by informing health policy on strengthening care delivery in resource-constrained settings.

Highlights

1. Social disadvantage significantly undermines clinical quality in dialysis centers.
2. Dynamic capabilities from chain networks enable rapid adaptation amid high social disadvantage.
3. Robust analyses show that chain networks mitigate quality declines from socioeconomic challenges.
4. These findings inform policy and management strategies in resource-constrained settings, with implications for broader healthcare systems.

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Keywords: Dynamic capabilities, social disadvantage, chain, health care quality, underserved populations

1 Introduction

In the early 2020s, DaVita, a leading U.S. dialysis chain, announces plans to expand its network of centers by over 20% within five years. It is Davita's second major expansion following a similar initiative a decade earlier. The announcement sparked significant discussions in industry reports and specialized media [1]. Unlike the past one, which centered on acquiring and merging existing facilities in urban areas, the current expansion more emphasizes acquiring or establishing new facilities in rural, underserved regions. Underdeveloped regions often grapple with economic constraints, cultural and linguistic diversity, and limited educational resources—factors contributing to these communities being described as socially disadvantaged [2]. Suffering from these disadvantages, patients in underdeveloped areas frequently lack access to adequate health services. Therefore, this new expansion raises a new debate: Can a dialysis chain achieve profitability while addressing social and ethical issues, such as delivering high-quality healthcare services to underserved populations in these regions? Or will such expansion efforts unintentionally worsen existing disparities?

Dialysis centers provide essential support for patients with end-stage renal disease (ESRD), the most advanced stage of kidney disease, by facilitating the removal of waste and excess water from the blood. Such treatment requires coordinating resources across multiple departments and adhering to stable, standardized procedures. However, ESRD patients in socially disadvantaged communities face persistent challenges, including low adherence to dialysis treatments, difficulties in managing complex comorbidities, high rates of complications, and significantly elevated healthcare costs [3]. Over the past decade, the U.S. Centers for Medicare & Medicaid Services (CMS) has introduced various payment reforms and value-based incentive programs to improve dialysis care quality and equity [2]. However, these measures have struggled to address structural inequalities rooted in socioeconomic factors. Disadvantaged communities experience disproportionately high readmission rates, healthcare expenditures, and lagging patient satisfaction [4, 3]. The results imply that conventional quality improvement (QI) initiatives—such as disseminating standardized clinical guidelines, forming isolated QI teams, or implementing limited patient education programs—often yield marginal benefits in complex and resource-constrained environments.

The independent facility, the other organizational structure, faces more significant challenges in securing timely resources and maintaining effective operations than more structured organizations in these communities [5, 6]. The COVID-19 pandemic has exacerbated the inequalities caused by strained resources, limited mobility, and personnel shortages, which has resulted in frequent disruptions to daily care services and delays in routine treatments for local patients during supply chain interruptions [7, 8]. Reports highlighted reduced dialysis frequency and rising late-stage complications, underscoring the fragility of care delivery under these adverse conditions [9]. Given these difficulties, questions raised from the expansion of chain organizations can be further described as how their affiliated facilities will perform in these regions following such integration of independent facilities in underdeveloped areas.

Traditional empirical research on chain organizations has primarily focused on examining whether joining a chain organization or expanding the scale of chains contributes to improving performance (e.g., quality outcomes, efficiency) at the operational level. In the healthcare context, numerous studies have demonstrated that chain organizations offer significant advantages in enhancing healthcare outcomes and efficiency [10, 11, 12]. However, the following research finds that these advantages are not always observed in healthcare chain organizations [13, 14, 15]. The emerging phenomena of expansion in different areas led to a new conjecture about inconsistency: the benefits of chain organizations are affected by the external environment. However, few studies have explored the impact of chain organizations when considering differences in the external environment. This gap is mainly due to the lack of theoretical frameworks and existing data's narrow temporal and spatial scopes. Addressing this research gap is particularly critical given the ongoing expansion of healthcare chain organizations into increasingly diverse regions, such as DaVita's growth in the dialysis sector.

Therefore, our research aims to address the gap by exploring the question: Will these chain organizations reshape dialysis care with organizational resilience and adaptability in areas with different social disadvantage levels? To answer the problem, theoretically, we initiate the insight from Dynamic Capabilities Theory (DCT) to examine how chain organizations mitigate the challenges faced by facilities in underdeveloped regions. Empirically, we apply a 5-year CMS dataset (2015–2019), which includes detailed facility-level operational, clinical, and patient outcome metrics, providing a robust basis for empirical analysis. Our findings confirm the detrimental impact of social disadvantages on dialysis facility performance. Secondly, they demonstrate that the chain structure moderates these adverse effects, enhancing facility quality outcomes despite the challenges of socially disadvantaged contexts.

Our findings contribute to addressing the theoretical gap regarding the mechanisms underlying the effects of chain organization through the lens of DCT. These theoretical contributions offer valuable insights into strategic decision-making, enabling large dialysis chains and other healthcare organizations to better assess the risks and benefits of expanding into underserved communities. Furthermore, our analysis demonstrates that expanding chain organizations yields a win-win outcome, benefiting both facilities and socially disadvantaged ESRD patients. The emerging chain affiliations enhance health outcomes and improve the quality of life for countless underserved ESRD patients. From a policy standpoint, we highlight an alternative strategy to enhance the quality of health instead of long-term investing in improving socially disadvantaged environments.

In the following sections, we focus on the dialysis industry as our empirical context to explore the expansion and practices of chain organizations through the theoretical lens of dynamic capabilities. In Section 2, we conduct a literature review and propose our hypotheses. Section 3 describes the data sources and processing methods, while Section 4 explains the model construction. Section 5 presents and discusses the results, and Section 6 conducts sensitivity analyses to test the robustness of our findings. Finally, Section 7 summarizes key insights and implications for healthcare policy and management strategies.

2 Literature Review and Hypotheses Development

2.1 The relationship between social disadvantage and facility performance

Socially disadvantaged communities are an integrated concept, including measuring multiple indicators. For example, such communities usually face challenges from entrenched poverty, limited educational opportunities, cultural and linguistic barriers, inadequate housing, and insufficient preventive care resources [16, 17]. In healthcare, these disadvantages lead to patients' low health literacy, unstable insurance coverage, and weak trust in healthcare providers. As a result, these patients cannot seek timely care and preventive health behaviors, frequently encounter advanced disease states, complex comorbidities, and lower adherence to recommended treatments [18, 19]. Meanwhile, providers can hardly deliver effective and complete services due to a lack of patient cooperation. These situations are aggravated by the lack of skilled clinicians, unreliable supply chains, and fragmented referral networks [20, 21].

The challenges are especially pronounced in managing chronic conditions that demand ongoing patient engagement, strict adherence to care plans, and reliable coordination of complex treatment regimens. For example, effective dialysis delivery depends on precise treatment protocols, adherence to thrice-weekly sessions, integrated dietary counseling, and vigilant monitoring of vascular access [22, 23, 24]. In disadvantaged communities, ESRD patients may need more consistent transportation, face language barriers that limit comprehension of nutritional guidelines, or distrust the health system due to historical and cultural factors. Also, the facility may hardly understand patients' difficulties, only find patients often experience irregular attendance, suboptimal adherence, and frequent complications [18, 25, 26]. In more serious cases, it may be difficult for the facility to diagnose or treat patients with related conditions. Given these challenges, the interactions among various disadvantageous factors are complex and cumulative. Therefore, integrated measures of social disadvantages are essential for exploring mechanisms. Recent studies also have noted that focusing on isolated factors potentially leads to biased conclusions [27, 28]. With a comprehensive measurement of the socially disadvantaged factors, we have the following assumption in dialysis industry context:

Hypothesis 1. Healthcare organizations will be associated with lower clinical quality performances in socially disadvantaged contexts, ceteris paribus.

2.2 Chain – the moderating effect

Chain organizations, often called multi-unit enterprises, are structured networks of facilities or service providers operating under centralized management and standardized protocols. These organizations aim to leverage economies of scale, resource centralization, and standardized care protocols to improve efficiency, reduce costs, and enhance service delivery consistency across locations. In the healthcare industry, chain organizations are defined as networks of healthcare facilities unified under centralized public or private management, often sharing a familiar brand. These organizations exhibit characteristics such as centralized strategic direction, standardized governance structures, and centralized back-end functions like human resources, finance, procurement, and legal services. They operate with standardized protocols to ensure consistent service delivery and pursue shared goals, including improving patient outcomes, optimizing resource utilization, and achieving operational efficiency. By leveraging economies of scale, resource centralization, and efficient governance, chain organizations aim to enhance efficiency, reduce costs, and deliver high-quality, consistent care across multiple locations [29, 30].

Several studies have discussed the effectiveness of chain organizations, but their conclusions remain mixed. On the positive side, some studies emphasize that chain organizations centralize resource pooling, integrate supply chain management with lower costs, and ensure reliable access to essential medications, equipment, and technological infrastructures [31, 32]. Also, chain-based learning networks enable rapid dissemination of best practices and targeted interventions across multiple sites [33]. Conversely, some studies show that chain organizations cannot help much in the efficiency and quality of dialysis treatment. Large chain organizations (LGOs) in the dialysis industry can face challenges such as organizational inertia, which limits their ability to make swift decisions [13]. Market consolidation may also reduce the personalization of patient care, prioritizing standardized operations instead [34].

Additionally, geographical clustering by chain organizations can limit localized flexibility in service provision [35]. We summarized both sides of existing research in Table 1. Recent studies have pointed out that existing research often has limited attention to analyzing chain organizations across diverse regions. This oversight may contribute to inconsistent conclusions, as much of the research only examines the applicability of chains in specific areas. Although some works have recognized these differences, they remain constrained by the temporal and geographical boundaries of data collection. They lack a sound theoretical basis to explain and validate the underlying mechanisms through empirical investigations.

The DCT, introduced by David Teece et al. [43], offers a valuable framework to address this theoretical gap. The DCT shows that organizations with stronger ability to sense environmental changes, seize improvement opportunities, and reconfigure internal and external resources can better deliver the outcomes in volatile and various environments [43, 44, 45]. In the healthcare context, socially disadvantaged communities represent a unique and challenging environment. Patients' needs in these areas are often harder to identify due to irregularities in service availability and limitations in data collection. Uncertainty surrounding patient conditions is exacerbated by poor public health infrastructure and more complex complication profiles. Furthermore, healthcare facilities face resource scarcity, including limited access to medical supplies and institutional support [17, 46]. From the perspective of DCT, these barriers significantly hinder the ability of healthcare organizations to sense patient needs, seize opportunities for care improvement, and reconfigure care processes effectively. Factors such as unstable institutional support and insufficient community engagement further amplify these challenges [44, 45, 47].

Under such conditions, more than static clinical guidelines and traditional process optimization

Table 1: Summary of Studies on Hospital Consolidations and Dialysis Facilities

Author	Title	Year	Focus	Results	Limitations	Region
Luke et al.	Local Markets and Systems: Hospital Consolidations in Metropolitan Areas [36]	1995	Formation of local hospital systems (LHSs) and market consolidation among metropolitan hospitals	Chain organizations and local hospital systems enhance market power and resource control. LHSs improve efficiencies through shared infrastructure and market positioning yet face challenges balancing consolidation with service accessibility.	Focuses on data from the early 1990s, limiting insights into post-1992 changes; findings may not generalize to rural or non-metropolitan contexts.	×
Hirth et al.	Practice Patterns, Case Mix, Medicare Payment Policy, and Dialysis Facility Costs [37]	1999	Cost implications of dialysis practice patterns, Medicare payment policies, and facility characteristics	Dialysis practice patterns and Medicare payment policies have significant cost impacts; hospital-based units have higher costs; economies vary among chain sizes.	Case mix data limited by census measures; endogeneity issues in estimating cost drivers.	×
Ozgen and Ozcan	A National Study of Efficiency for Dialysis Centers: An Examination of Market Competition and Facility Characteristics [38]	2002	Technical efficiency in freestanding dialysis facilities under different market and organizational conditions	Ownership form, market competition, and affiliation with dialysis chains significantly affect efficiency; for-profits generally outperform non-profits in mixed markets.	Cross-sectional design limits causal inferences; quality measures were not directly assessed.	×
Burns and Pauly	Integrated Delivery Networks: A Detour on the Road to Integrated Health Care [30]	2002	The rationales, performance, and lessons learned from vertical and horizontal integration of hospitals	Vertical and horizontal integration generally failed to improve economic performance. Key lessons include misaligned assumptions, poor management, and ineffective execution.	Studies are primarily based on data from the 1990s; insights are limited by the maturity and scope of integrated delivery networks during this period.	×
Grabowski and Hirth	Competitive Spillovers Across Non-profit and For-profit Nursing Homes [33]	2003	Examines quality differences and spillover effects between non-profit and for-profit nursing homes	Chain-affiliated facilities showed differentiated quality outcomes. Non-profit chains provide a quality spillover to for-profit chains, improving overall market quality. The presence of chains enhances inter-organizational competition, contributing to quality dynamics.	Limited to data from the mid-1990s. Spillover effects require further study to confirm underlying mechanisms.	×

Table 1 (continued)

Author	Title	Year	Focus	Results	Limitations	Region
Ozgen and Sahin	Measurement of Efficiency of the Dialysis Sector in Turkey Using Data Envelopment Analysis [39]	2010	Factors influencing the efficiency of Turkey dialysis centers	Chain-affiliated facilities, especially those linked to international chains, demonstrate higher efficiency compared to independent facilities. Facilities in national chains also show better utilization of resources than non-chains. Efficiency is influenced by scale and geographic location.	Cross-sectional study with 2008 data limits longitudinal insights; excludes potential case-mix adjustments and structural quality indicators; Turkey-specific context may not generalize globally.	✓
Saunders et al.	Variation in Dialysis Quality Measures by Facility, Neighborhood and Region [40]	2013	The effects of facility characteristics, neighborhood, region and chain on dialysis outcomes.	The proportion of African Americans in the dialysis facility neighborhood is strongly and consistently associated with lower facility quality.	Separately consider several isolated factors of social environment. Results come from facility-level.	✓
Shreay et al.	Efficiency of U.S. Dialysis Centers: An Updated Examination of Facility Characteristics [41]	2014	Factors influencing the efficiency of U.S. dialysis centers	Chain-affiliated facilities, particularly large chains, are less efficient compared to smaller or independent organizations. Efficiency appears negatively correlated with chain size.	analysis is based on 2010 cross-sectional data; excludes hospital-based dialysAnalysisities and lacks direct quality-of-care measures.	×
Shay and Mick	Clustered and Distinct: A Taxonomy of Local Multihospital Systems [42]	2017	Local multihospital systems (LMSs), focusing on their differentiation, integration, and spatial configurations	Chain organizations, as part of LMSs, demonstrate distinct taxonomy based on integration and differentiation. Highly integrated systems are most efficient but less common; configurations vary significantly based on market characteristics.	study relies on data from six U.S. states, limiting generalizability; temporal inconsistencies in datasets (2010–2012) may affect accuracy.	×
Dreyfus et al.	The Impact of Chain Organization Size on Efficiency and Quality of Affiliated Facilities—Implications for Multi-Unit Organizational Forms [13]	2020	The effects of chain organization size on dialysis quality and efficiency.	There is a U-shaped relationship between chain organization size and quality, as well as efficiency.	The differences between regional chain organizations are not captured.	×

Table 1 (continued 2)

Author	Title	Year	Focus	Results	Limitations	Region
Aghili et al.	Chain Hospitals in the Health Industry: A Scoping Review of Principles and Definitions [29]	2023	The concepts, principles, and definitions of chain hospitals and their organizational structures	Defined 55 different definitions for chain hospitals, presenting 6 main components (e.g., governance, organization) and 16 subcomponents; emphasized clarity in defining hospital types before implementation.	study limited to English-language articles and five databases; findings rely on interpretation of existing studies and exclude direct assessment of chain hospital effectiveness.	×

are needed [3, 4]. Conversely, by leveraging the structure property of chain networks, chain organizations can improve the corresponding abilities of the independent facilities. Chains provide governance structures, dedicated QI specialists, and roving clinical informatics teams that guide facilities through iterative changes in practice. These shared capabilities reduce the risk of "organizational inertia," helping to update care processes as local conditions differ [25, 18]. This approach significantly aids facilities in establishing effective patient information databases, thereby improving their ability to sense and respond to patient needs. Moreover, chain networks facilitate knowledge transfer: if one affiliated dialysis clinic successfully implements a culturally tailored patient education program to enhance treatment adherence among low-income, linguistically diverse patients, other chain facilities can rapidly learn from this pilot's success [13]. A deeper understanding of diverse patient populations enables facilities to precisely assess patient conditions and seize opportunities to deliver timely, appropriate treatments. Furthermore, chain affiliation enables a more fluid reallocation of resources and staff. Affiliated facilities can rapidly implement evidence-based interventions by pooling strategic decision-making and financial resources at the chain level, preventing further deterioration in quality outcomes [48, 49]. This capacity to reconfigure resources effectively addresses challenges stemming from resource scarcity. In summary, according to DCT, though disadvantaged environment exerts a direct, negative pressure on healthcare quality, organizational affiliation by a chain should help mitigate these effects.

These mitigation mechanisms are especially applicable in dialysis care. Large dialysis organizations (LDOs) employ centralized quality monitoring platforms and QI teams that continuously assess performance metrics, identify underperforming sites, and promote successful interventions with a proven track record [23, 22]. Shared clinical protocols, such as standardized vascular access management or anemia control strategies, ensure consistent adherence to evidence-based practices. Additionally, bulk purchasing and pre-negotiated supplier contracts secure steady access to essential resources, including dialyzers and pharmaceuticals, which are critical for maintaining treatment quality. A chain-affiliated dialysis center operating in a low-income, ethnically diverse neighborhood can leverage system-wide cultural competence training, patient navigation strategies, and telehealth education platforms perfected at another facility serving similar populations. Centralized QI teams can swiftly tailor these initiatives, ensuring that disadvantaged sites can approximate the quality performance of better-resourced settings. Collectively, these networked efforts enhance chain-affiliated clinics' ability to sense evolving needs, seize opportunities for improvement, and reconfigure processes to consistently deliver high-quality care, even under challenging external conditions. Based on the perspectives mentioned before, we assume in the dialysis industry:

Hypothesis 2. The positive effect of chain affiliation on clinical quality performance will be more pronounced in socially disadvantaged contexts, ceteris paribus.

3 Data, Operationalization of Variables, and Summary Statistics

3.1 Data sources and sample selection

The dialysis industry has experienced substantial consolidation in recent decades, driven in part by cost pressures, regulatory changes, and increased competition [24]. Federal initiatives, including the Medicare Improvements for Patients and Providers Act, require public reporting of facility-level performance metrics, thereby enhancing transparency and accountability [50]. The data used in this study reflect these broader industry conditions, providing a setting conducive to examining the drivers of performance and quality.

This study employs a comprehensive panel dataset from the year 2015–2019, drawn primarily from publicly available administrative sources maintained by the Centers for Medicare & Medicaid Services (CMS). Under federally mandated conditions of coverage, dialysis facilities must report detailed operational, clinical, and patient outcome metrics at regular intervals [51]. This requirement fosters consistent and transparent data, enabling large-scale empirical analyses of facility-level quality and operational efficiency [22, 26, 50].

The initial dataset includes 33,686 facility-year observations from 10,568 CMS-registered dialysis facilities over five years. To improve comparability, we restrict the sample to facilities offering only hemodialysis, thereby mitigating confounding effects arising from varying treatment modalities [23, 22]. Next, we merge these facility-level clinical data with information from the Healthcare Cost Report Information System (HCRIS), which provides standardized financial and human resource indicators. This integration follows established research practices that combine clinical and financial data to identify determinants of healthcare quality [13, 48, 49]. The final merged sample comprises 25,974 observations through 5,748 centers, forming a robust basis for investigating drivers of quality performance in a rapidly evolving industry.

3.2 Social disadvantage

Prior empirical research has frequently focused on single socioeconomic indicators—such as household income—to characterize community-level advantages [52, 53]. More recent work, however, has underscored the limitations of such narrow approaches and emphasized the need for more comprehensive measures that capture the broader array of social determinants influencing health outcomes [54, 55].

In this study, we employ the Social Vulnerability Index (SVI), a composite metric developed by the U.S. Centers for Disease Control and Prevention (CDC), which integrates socioeconomic, demographic, and housing indicators into a single measure of community-level social disadvantage [56, 57, 58]. By reflecting the multifaceted factors that shape a population's resilience to health-related threats, the SVI has gained widespread recognition in healthcare research as an effective tool for understanding disparities in health outcomes, healthcare access, and quality of care [59, 60]. The SVI ranges from 0 to 1, with higher values indicating greater social disadvantage. In our dataset, the mean SVI for communities in which the institutions are located is 0.57 (SD = 0.25).

3.3 Chain status

Chain affiliation reflects whether a dialysis facility is part of a larger organizational network or operating as an independent entity [30, 61]. Chain-affiliated facilities often benefit from shared governance, centralized procurement, standardized clinical protocols, and well-developed internal knowledge networks [31, 32]. We operationalize Chain as a binary indicator, coded as 1 if the facility is affiliated with a chain and 0 otherwise. The proportion of chain-affiliated facilities in our dataset increases steadily from 4,671 in 2015 to 5,618 in 2019. This growth aligns with broader consolidation patterns in the dialysis industry and enhances our capacity to examine whether chain affiliation moderates the impact of social disadvantage on quality performance.

3.4 Quality outcomes

We measure clinical quality performance using the CMS Quality Incentive Program (QIP), a federal pay-for-performance initiative that links reimbursement adjustments to dialysis facility outcomes [51]. The QIP consolidates multiple clinical indicators designed to encourage adherence to evidence-based practices, enhance patient safety, and improve treatment effectiveness. Among these indicators are measures of dialysis adequacy (e.g., Kt/V, which captures toxin and fluid removal effectiveness) and vascular access management (e.g., increased use of arteriovenous fistulas and grafts over catheters), as well as other relevant quality measures.

Importantly, the QIP's comprehensive, nationally benchmarked framework confers credibility and consistency to our measures. Public reporting of QIP outcomes further induces facilities to maintain or improve quality, thereby capturing both the clinical execution of dialysis care and providers' responsiveness to institutional pressures. Prior studies have employed the QIP as a key measure of dialysis performance, demonstrating its utility in assessing facility-level quality improvements, guiding payment reforms, and examining the effects of incentives on clinical outcomes [13, 62, 63]. The QIP composite score ranges from 0 to 100. In our sample, the mean QIP score over the five-year period is 70.46 (SD = 13.70), indicating substantial variation in quality performance across dialysis providers. By employing the QIP composite metric, we adopt a policy-relevant, multi-dimensional score of dialysis care quality.

3.5 Control variables and operationalization

In addition to chain affiliation and social disadvantage, we include several facility-level controls to address potential confounding influences on clinical quality performance. Prior research in health services and organizational studies indicates that an institution's ownership structure, operational experience, scale of operations, resource availability, and staffing configuration can affect outcomes by shaping managerial priorities, patient care processes, and the implementation of improvement initiatives [64, 65, 66].

First, we control facility ownership form by including a binary indicator coded as 1 if the facility is for-profit and 0 otherwise. Ownership status may influence decision-making horizons, efficiency goals, and the emphasis placed on quality-improvement activities [67]. The dialysis sector features a high proportion of for-profit providers, and accounting for this characteristic helps isolate the effects of other organizational and environmental factors.

Second, we incorporate a measure of the facility's operational experience using the number of years since its initial certification under Medicare conditions. Greater operational tenure is often associated with accumulated expertise, more refined care protocols, and enhanced capacity to address clinical complexity, all of which may foster quality improvement over time [68, 69]. This variable offers insight into the learning curve that facilities undergo as they gain familiarity with patient populations, treatment technologies, and regulatory expectations.

We also include variables that capture the facility's scale and resource intensity. The number of dialysis stations serves as an indicator of physical capacity and scope, potentially influencing both the efficiency of care delivery and the ability to maintain high standards under varying patient loads [70]. Additionally, drug-related expenses, expressed in logged form to mitigate skewness, proxy for the complexity and breadth of clinical services. Facilities with higher drug expenditures may treat more clinically challenging patient populations or utilize a broader set of therapeutic interventions, potentially affecting outcomes and the feasibility of quality enhancement.

Further, we control overall patient volume, represented by the number of treatments. Patient volume can influence operational performance through learning-by-doing effects, scale economies, or strain on resources, as higher volumes may drive efficiency gains or intensify workload pressures [71, 72]. Recognizing these potential countervailing forces, including treatment volume allows us to discern whether higher patient throughput correlates with improved or diminished quality in the dialysis setting.

Finally, workforce composition can shape the delivery of clinical care and the facility's capacity to implement new initiatives. We include variables capturing the total number of clinical staff (physicians & registered nurses), and non-clinical

Table 2: Correlation Matrix

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Quality outcomes	70.46	13.71	1.000										
(2) Social disadvantages	58.83	26.73	-0.085**	1.000									
(3) Chain status	0.93	0.26	0.117**	-0.030**	1.000								
(4) Profit status	0.93	0.26	-0.005	-0.044**	-0.031**	1.000							
(5) Years certified	18.80	10.12	-0.066**	0.103**	0.079**	0.097**	1.000						
(6) Number of Station	18.49	7.85	-0.140**	0.183**	0.030**	0.058**	0.380**	1.000					
(7) Lab net-expenses†	10.59	0.75	0.012*	0.105**	-0.025**	0.052**	0.224**	0.516**	1.000				
(8) Drug net-expenses†	12.64	0.74	-0.076**	0.170**	-0.024**	0.067**	0.241**	0.635**	0.633**	1.000			
(9) Treatment numbers†	9.17	0.63	-0.102**	0.183**	-0.010	0.013*	0.289**	0.703**	0.725**	0.835**	1.000		
(10) Clinical Staff	5.75	4.05	-0.098**	0.112**	-0.098**	0.078**	0.205**	0.544**	0.571**	0.711**	0.767**	1.000	
(11) Nonclinical Staff	10.72	6.97	-0.115**	0.168**	-0.025**	0.057**	0.295**	0.665**	0.616**	0.717**	0.832**	0.602**	1.000

** $p<0.01$, * $p<0.05$

†Denotes log-transformed variable.

staff. Adequate and well-trained nursing personnel are known to be associated with better patient outcomes and safer practices, whereas administrative and support staff may facilitate smoother operations and patient coordination [73, 66]. We log-transform select staffing variables to achieve more stable distributions and improve estimation reliability.

Collectively, these controls help ensure that our analyses more accurately isolate the effects of chain affiliation and social disadvantage on clinical quality performance (See, Table 2). By incorporating a diverse set of organizational, financial, and human resource metrics, we acknowledge the complexity of health care service delivery and better account for the multifaceted nature of quality improvement efforts in the dialysis sector.

4 Method

4.1 Fixed effects models

Our empirical analyses examine how social disadvantage influences clinical quality performance and whether chain affiliation moderates this relationship. We employ fixed effects (FE) regressions to address unobserved, time-invariant facility attributes and year-specific shocks common to all facilities. To verify that the fixed-effects (FE) specification is superior to the alternative estimations, we conduct serial standard statistical tests (See, Table 3). Specifically, we use the Braasch-Pagan Lagrange multiplier and the Hausman test to determine that the random-effects (RE) model is superior to ordinary least squares (OLS) and that the fixed-effects (FE) model is preferable to the RE model. To avoid potential multicollinearity errors, we evaluate the variance inflation factor (VIF). The VIF values for all variables are below 10, with a mean VIF below 2.7 for all models, indicating that collinearity remained within an acceptable range of below 5 (Kutner et al., 2005). Specifically, we estimate the following models (1)–(2).

Here, i indexes facilities and t indexes years. $QualityOutcomes_{it}$ is the clinical quality performance measure for facility i in year t. SD_{it} measures social disadvantage, and $Chain_{it}$ indicates chain affiliation. The parameters α_i and δ_t are facility and year fixed effects, respectively, capturing unobserved, time-invariant facility characteristics and common temporal shocks. X_{it} is a vector of control variables (e.g., profit status, years since certification, facility size, expenditure levels, treatment volume, staffing composition), and ϵ_{it} is the error term.

4.2 Endogeneity

Although we include a range of facility- and community-level controls—such as facility size, profit status, local economic conditions, and regional health system characteristics—to mitigate potential omitted variable bias, three sources of endogeneity may still persist: measurement errors, confounding factors, and reverse causality [74]. Measurement errors are less concerning in this context, given the rigorous data collection protocols of the Centers for Medicare & Medicaid Services (CMS), the Census Bureau, and the Bureau of Labor Statistics (BLS) [75]. However, the Social Vulnerability Index (SVI)—which captures social disadvantage—may not be strictly exogenous due to the remaining two sources of endogeneity.

Table 3: Model Selection Tests

Test	Purpose	Metric
Breusch–Pagan Lagrange Multiplier	RE model is preferable to pooled OLS model if $p < 0.01$	$p < 0.001$
Hausman	FE model is preferable to RE model if $p < 0.01$	$p < 0.01$
Multicollinearity	Evaluates potential multicollinearity if VIF > 5	VIF $= 2.7$

$$\text{Quality Outcomes}_{it} = \alpha_i + \delta_t + \beta_1\, SD_{it} + \beta_2\, \text{Chain}_{it} + X_{it}\,\Phi + \epsilon_{it} \tag{1}$$

$$\text{Quality Outcomes}_{it} = \alpha_i + \delta_t + \beta_1\, SD_{it} + \beta_2\, \text{Chain}_{it} + \beta_3\big(\text{Chain}_{it} \times SD_{it}\big) + X_{it}\,\Phi + \epsilon_{it} \tag{2}$$

Table 4: Model Selection Tests

Test	Purpose	Metric
Under identification	Instruments are relevant if $p < 0.05$	$p < .001$
Sargan-Hansen (over identification)	Instruments are exogenous if $p > 0.1$	$p = .31$
Weak identification	Instruments are not weak if $F > 10$ & critical values*	$F = 57$

Notes* : critical values = 16.87 (Stock-Yogo weak ID test 10% maximal IV size)

First, confounding factors (e.g., insufficient public infrastructure, limited educational opportunities, and weak social support) can simultaneously influence patient behaviors and provider outcomes [16, 76, 54, 25]. For instance, communities lacking reliable transportation or facing widespread language barriers often exhibit lower adherence to recommended treatments, thereby biasing performance metrics. Second, reverse causality may arise if improvements in local healthcare services attract higher-socioeconomic-status individuals, leading to a decline in a community's SVI and triggering a feedback loop.

To address these concerns, we employ an instrumental variable (IV) regression model [74]. We select two instruments theorized to correlate with social disadvantage yet exert minimal direct influence on facility-level decisions. The first instrument— mean RN hourly salary at the state level — reflects broader economic conditions and resource costs that shape social vulnerability. Because RNs form the core workforce in dialysis centers, higher RN wages often indicate better regional employment opportunities and greater wealth, both of which can affect local socioeconomic conditions [76, 54]. The second instrument—the population aged 16 and over at the county level—captures local demographic characteristics commonly associated with social disadvantages, such as potential workforce size and educational attainment [16]. However, these measures do not present individual facility-level resource allocation or clinical processes, thereby minimizing direct endogeneity with facility performance [74]. In this study, we log-transform the population variable to improve precision and address potential non-linearities.

Interaction effects that include endogenous variables can complicate estimation further. As established by Angrist and Pischke [77] and Wooldridge [78], when interaction terms involve at least one endogenous variable, constructing additional instrumental variables becomes necessary. Specifically, this requires multiplying the original instruments by the second level interacting variable ($Chain$) to form a set of interaction instruments. Therefore, the interaction terms, $Chain \times \overline{RNSalary}$ and $Chain \times \log(Population_{16+})$, are constructed to improve identification by capturing the interaction-driven variation in the endogenous regressor while maintaining exclusion criteria. The approach enhances the robustness of our IV framework.

While fixed-effects modeling helps mitigate time-invariant unobserved heterogeneity, we employ an IV Generalized Method of Moments (GMM) approach for the potential heteroskedasticity and within-group error correlation, thereby further enabling robustness in estimation. Notably, the frequently used IV two-stage least squares (2SLS) estimator is essentially a special case of GMM, relying on assumptions of homoscedastic and serially uncorrelated errors. By contrast, IV-GMM offers a more flexible variance-covariance matrix, potentially yielding greater efficiency. As shown in Table 4, the selected instruments meet both relevance and exclusion criteria, confirming their validity for resolving endogeneity.

5 Results

In Model 1, the coefficient on SD is negative and statistically significant (-100.036, p¡0.01), indicating that higher levels of social disadvantage are associated with lower clinical quality scores. The results support Hypothesis 1. This finding aligns with previous studies [18, 25] showing social disadvantage communities pose challenges that inhibit consistent delivery of high-quality care. This finding supports Hypothesis 2, which posited that chain-affiliated facilities, benefiting from economies of scale, standardized clinical protocols, and internal knowledge sharing, achieve more stable and higher clinical quality levels [61, 23, 49]. In Model 2, the coefficient on the interaction is positive and statistically significant (82.839, $p < 0.05$), indicating that as SD intensifies, chain affiliation mitigates the downward pressure on quality performance. In other words, chain-affiliated facilities do not experience as steep a decline in clinical quality in response to increasing SD as non-chain facilities do. The result validates Hypothesis 2. This finding supports the DCT, which posited that chain-affiliated facilities, benefiting from economies of scale, standardized clinical protocols, and internal knowledge sharing, achieve more stable and higher clinical quality levels [61, 23, 49].

Table 5: IV-GMM Estimation Results

	(1)	(2)
Social disadvantages	-100.036***	-157.270***
	(30.420)	(44.984)
Chain	-0.057	2.604
	(1.025)	(2.106)
Social disadvantage × Chain		82.839**
		(40.231)
Profit status	-0.671	-0.415
	(1.798)	(1.652)
Years certified†	-4.365**	-4.179**
	(2.033)	(1.904)
Dialysis stations†	-2.033	-2.331*
	(1.446)	(1.410)
Laboratory expenses†	3.062***	3.034***
	(0.267)	(0.266)
Drug expenses†	1.910***	1.790***
	(0.396)	(0.406)
Number of treatments†	-3.399***	-3.101***
	(0.686)	(0.709)
Clinical staff†	0.779**	0.892**
	(0.358)	(0.374)
Nonclinical staff†	1.728***	1.702***
	(0.470)	(0.473)
F-statistic	615***	598***
R-squared (within)	0.342	0.328
State FE	✓	✓
Year FE	✓	✓
N of facilities	5,748	
N of observations	25,974	

Robust clustered standard errors are reported.
†Denotes log-transformed variable. *p <0.10, **p <0.05, ***p <0.01.

In Figure 1, as local social disadvantage deepens; non-chain healthcare facilities experience sharper declines in quality than chain-affiliated facilities. While community-level improvements—such as enhanced education, transportation, and preventive care—take substantial time, chain networks can implement organizational interventions rapidly. Chain affiliation fosters resource reallocation scaled best practices, and staff training, yielding meaningful quality gains even in the face of entrenched social challenges. The evidence suggests that chain networks can offset disadvantages more effectively in the short term than waiting for broader socioeconomic reforms. Rather than viewing local conditions as fixed barriers, supporting collaborative networks and chain structures can serve as a strategic stopgap—if not a long-term solution—to improve healthcare quality amid persistent socioeconomic constraints.

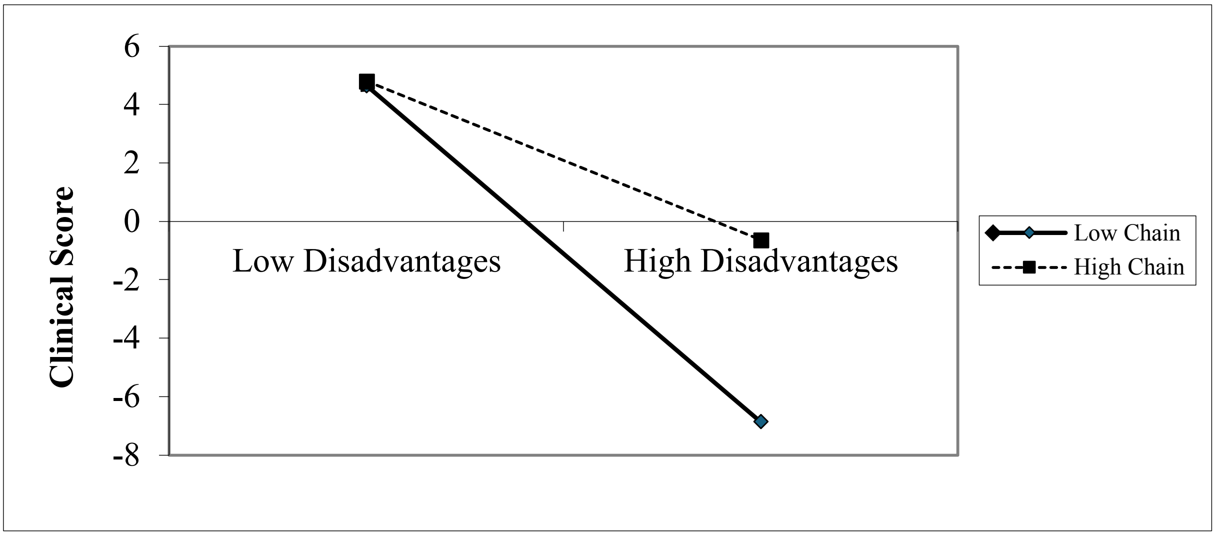
6 Robustness

6.1 Alternative method approach

To ensure the robustness of the findings obtained using the IV-GMM approach, this study employs two additional IV estimation methods: 2SLS and Limited Information Maximum Likelihood (LIML). These methods effectively address methodological concerns and offer complementary strengths.

First, 2SLS is effective in handling endogeneity through instrumental variables. This method separates the endogenous variable, such as the SVI, from the error term using a two-stage process. In the first stage, instruments predict the endogenous variable, which is then used in the second stage to estimate the outcome. While 2SLS assumes homoscedasticity and can be sensitive to weak instruments, it provides reliable results under appropriate conditions. Second, LIML is

Fig. 1: Two-way linear interaction effects estimated via regression analysis



employed as an alternative method to address potential instrument weaknesses, while IVs are not weak in our study. LIML is particularly robust in the presence of weak instruments and produces consistent estimates under more flexible assumptions than 2SLS. This makes LIML a valuable complement to 2SLS, especially in cases of uncertain instrument strength.

The results from these methods, as shown in Table 7, closely align with the statistics from IV-GMM, demonstrating the robustness of the findings. Specifically, 2SLS (Model 3) and LIML (Model 5) both show that higher social disadvantage, as measured by SVI, is associated with lower clinical quality scores. The coefficients for SD are negative and statistically significant (-95.805, $p < 0.01$ in 2SLS; -96.165, $p < 0.01$ in LIML). Similarly, chain affiliation exhibits positive effects in both methods, with slightly smaller coefficients observed in 2SLS (2.162 in Model 4) than in LIML (2.271 in Model 6). Both 2SLS and LIML confirm that chain affiliation mitigates the negative impact of social disadvantage on clinical quality. The interaction term between SD and chain affiliation is positive and statistically significant (62.653, $p < 0.05$ in 2SLS Model 4; 65.188, $p < 0.10$ in LIML Model 6), reinforcing the hypothesis that chain-affiliated facilities better sustain quality performance under challenging socioeconomic conditions. These findings highlight the robustness and reliability of the results.

6.2 Alternative subgroup analysis

To further validate the moderating role of chain affiliation in the relationship between social disadvantage and clinical quality performance, we conduct a subgroup analysis based on the Social Vulnerability Index (SVI). Subgroup analysis is widely recognized as a robust method to address heterogeneity across contexts, particularly in studies of socioeconomic disparities (Diez Roux, 2012; Braveman et al., 2011). By categorizing regions into low, medium, and high SVI groups using the mean and ± 1 standard deviation, we capture potential contextual variations that may be masked in aggregate analysis.

The results presented in Table 8 align with our main findings. Among the three subgroups, the coefficient for chain affiliation is highest (7.954, $p < 0.01$) in the high SVI group and lowest (3.395, $p < 0.01$) in the low SVI group. This pattern confirms that the moderating effect of chain affiliation is significantly stronger in regions characterized by higher levels of social disadvantage. These findings reinforce the importance of chain structures in addressing clinical quality disparities, particularly in socioeconomically vulnerable areas.

6.3 Alternative independent – the unscaled SVI

The main analysis relies on the Rescaled Percentile Rank (RPL), a normalized version of SVI, widely employed in empirical research to facilitate cross-regional comparability [79, 57]. Bonnett and Heim [80] indicate that the scaling variables may cause inconsistent results and, in this way, validate their main results using the raw measures in the robustness section. To mitigate potential scaling effects, we incorporate the Summed Percentile Rank (SPL), an unscaled version of SVI. Table 6 indicates Model (10)-(11) results. The findings based on SPL align closely with those derived from RPL, with no changes in the direction or significance of the results. The regressions ensure robustness and validate the consistency of the analyses, irrespective of scaling [81].

7 Post Hoc Analysis

In the main analysis, we treat chain status as a binary feature, distinguishing between chain and independent facilities. This approach aligns with prior research on integrated delivery systems and LDOs [61, 32]. However, other studies suggest that chain size can significantly influence organizational quality and efficiency, with its impact shaped by the heterogeneity in the chain scale. Based on our preceding analysis, the mitigating effects of chain affiliation should consistently benefit, especially as larger chains possess more substantial dynamic capabilities, including extensive internal learning networks, broader managerial expertise, and more flexible resource pools [44, 45].

To test this extrapolation, we re-estimated our models by grouping chain affiliation into three categories: small chains (fewer than 100 facilities), mid-sized chains (100–1,000 facilities), and large chains (more than 1,000 facilities). This categorization aligns with the observed structure of the U.S. dialysis market, where two dominant organizations each manage more than 1,000 units, while other chains remain smaller (see Table 6). Table 9 (models 7–9), the core patterns persist by comparing the social disadvantage impacts through different chain size groups. Specifically, large chains display the highest coefficient on social disadvantage ($-51.348, p < 0.1$) compared to mid-sized ($-180.694, p < 0.05$) and small ($-209.227, p < 0.1$) chains.

More specifically, these findings broaden our conclusions in two important ways. First, compared with our second hypothesis in the main analysis, which only distinguishes between independent facilities (chain scale $= 1$) and chain-affiliated facilities (chain scale $\neq 1$), these results reveal a more nuanced continuum: of the larger the chain, the more effectively it can mitigate the impact of social disadvantages. This finding extends beyond a simple dichotomy and underscores the importance of chain scale in moderating the relationship between social disadvantages and organizational outcomes. The enhancement of facilities' resilience depends on the scale of chain affiliations, which means a larger scale of chain organization will provide greater capability to against the adverse external conditions. Facilities joining a larger chain absorb best practices, specialized training, and supply chain efficiencies that they could not access independently.

Second, the observed scale-based effects imply *collective* benefits for both newly affiliated sites and the broader chain community. Specifically, the larger chain also gains from the diverse experiences and patient populations at newly integrated sites, enhancing the network's collective capacity for sensing emergent needs and experimenting with culturally tailored interventions [13, 44]. In other words, these newly affiliated sites broaden the chain's overall network capacity and scale, benefiting themselves and existing affiliates. This reciprocal dynamic strengthens the chain's collective ability to sense emergent needs and experiment with culturally tailored interventions, as well as enhances its resilience against adverse socioeconomic pressures.

8 Discussion

The findings suggest that chain affiliation can meaningfully moderate the negative relationship between social disadvantage and clinical quality in the dialysis sector. Our empirical results show that, on average, facilities operating in higher-disadvantage communities scored 6–8% lower on core quality measures, reflecting the substantial challenges posed by socioeconomic barriers such as low health literacy, limited transportation,

Table 6: Distribution of Chain Sizes

Chain size	Range of scale	Number of organizations	Approx. % of observations
Small	1 – 100	71	10%
Medium	101 – 1000	19	20%
Large	> 1000	2	70%

and cultural mistrust. Crucially, however, chain-affiliated facilities maintain higher baseline quality and experience significantly less performance deterioration as social disadvantage intensifies. The results answer the debates about the social and ethical effects of chain organizations in disadvantaged areas, proving that ESRD patients would achieve better care after expansion. Also, our study contributes to three other aspects: theoretical basis, managerial, and policy-making insights.

Initiated from DCT, we demonstrate how chain affiliation provides a structural platform for adaptation, thus mitigating the negative impacts of socially disadvantaged environments. We can conclude that the benefits come from three essential abilities: sensing needs, seizing opportunities, and reconfiguring resources. In disadvantaged contexts, independent facilities often encounter severe constraints in seizing the needs and conditions of patients, which limit their ability to implement new interventions swiftly or sustain continuous improvement. In contrast, chain-owned sites can leverage internal data analytics systems to identify emergent care gaps, mobilize specialized staff from other locations to address resource bottlenecks and replicate successful culturally tailored education campaigns initially tested in a similar low-literacy community. This internal "innovation marketplace," where proven interventions travel quickly through chain networks, effectively amplifies dynamic capabilities—turning a challenging environment from a persistent liability into a scenario where quality improvements are still attainable.

Moreover, the study provides actionable insights for healthcare management, highlighting strategies for optimizing operations in underserved communities. By applying DCT, chain organization managers can better evaluate the risks and opportunities associated with expanding into socially disadvantaged areas and operate their structures to offer essential resources to facilities facing disadvantaged environments. Specifically, LDOs should focus on developing robust internal communication platforms to ensure seamless information sharing, adopting a flexible staffing model to deploy specialized expertise where it is most needed, and implementing advanced resource allocation tools to fully leverage the value chain.

Additionally, the post hoc analysis underscores that *not all chain affiliations are created equal.* Larger chains, with more extensive organizational capabilities, exhibit stronger inter-facility knowledge flows and a more powerful capacity to flexibly allocate resources where needed most. Consequently, if an independent dialysis center located in a highly disadvantaged region is considering acquisition or partnership, alignment with a larger chain may yield more substantial improvements in clinical quality. For the chain side, acquiring or establishing new facilities in underdeveloped areas is not merely a cost or philanthropic gesture; it also enriches the chain's ability to handle diverse challenges and patient populations. The result is a "win-win" dynamic in which new affiliates gain operational resilience, while the entire network benefits from fresh insights into serving marginalized communities.

Lastly, the findings provide policymakers with practical steps to improve the quality of care delivery for underserved populations. Policymakers can draw on this evidence to design incentives that support chain-based solutions or encourage independent providers to form collaborative networks. Consider a chain-affiliated dialysis center located in a predominantly Hispanic, low-income urban neighborhood. Independent facilities might struggle to improve adherence if patients cannot easily attend thrice-weekly sessions or understand dietary recommendations. The local clinic can rapidly adopt these strategies by drawing on another chain facility's successful pilot program—such as using bilingual community health workers, partnering with a nearby food bank for nutrition education, and using a mobile app to coordinate patient transportation. Centralized QI

Table 7: Alternative IV estimation - 2SLS and LIML approach

	2SLS		LIML	
	(3)	(4)	(5)	(6)
Social disadvantage	-95.805***	-121.582***	-96.165***	-127.816***
	(26.708)	(38.974)	(26.816)	(41.497)
Chain	-0.082	2.162	-0.081	2.271
	(0.886)	(1.573)	(0.886)	(1.639)
Social disadvantage × Chain		62.653**		65.188*
		(31.706)		(33.818)
Profit status	-0.644	-0.342	-0.645	-0.343
	(1.746)	(1.649)	(1.747)	(1.657)
Years certified†	-4.592**	-4.151**	-4.595**	-4.183**
	(1.859)	(1.735)	(1.861)	(1.758)
Dialysis stations†	-1.986	-2.238*	-1.985	-2.233*
	(1.275)	(1.256)	(1.276)	(1.259)
Laboratory expenses†	3.068***	3.078***	3.068***	3.071***
	(0.261)	(0.261)	(0.261)	(0.263)
Drug expenses†	1.912***	1.829***	1.912***	1.824***
	(0.369)	(0.378)	(0.370)	(0.380)
Number of treatments†	-3.389***	-3.273***	-3.389***	-3.271***
	(0.647)	(0.669)	(0.647)	(0.673)
Clinical staff†	0.779**	0.927***	0.778**	0.923***
	(0.337)	(0.353)	(0.337)	(0.355)
Nonclinical staff†	1.720***	1.681***	1.721***	1.686***
	(0.438)	(0.442)	(0.438)	(0.444)
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Robust standard errors are reported. *p <0.10, **p <0.05, ***p <0.01.
†Denotes log-transformed variable.

Table 8: Alternative independents — region groups and unscaled SVI

	Region groups			Raw SVI	
	(7)	(8)	(9)	(10)	(11)
Social disadvantage				-8.962***	-26.645***
				(2.920)	(5.752)
Chain	3.395***	5.834***	7.954***	-0.709	-168.802***
	(1.256)	(0.692)	(1.178)	(0.798)	(47.773)
Social disadvantage × Chain					21.500***
					(6.103)
Profit status	-2.318**	-0.569	1.098	-0.089	-0.825
	(0.930)	(0.555)	(0.976)	(1.591)	(1.589)
Years certified†	0.666	0.189	0.843*	-2.518**	-1.351
	(0.415)	(0.263)	(0.473)	(1.229)	(1.238)
Dialysis stations†	-1.442	-2.101***	-2.807**	-2.251*	-2.410*
	(0.910)	(0.524)	(1.135)	(1.267)	(1.262)
Laboratory expenses†	1.304***	2.519***	1.924***	3.060***	2.873***
	(0.480)	(0.299)	(0.428)	(0.245)	(0.252)
Drug expenses†	1.842***	0.673*	2.038***	1.847***	1.396***
	(0.643)	(0.391)	(0.636)	(0.345)	(0.370)
Number of treatments†	-5.224***	-3.492***	-3.277***	-3.322***	-2.811***
	(1.076)	(0.625)	(1.145)	(0.595)	(0.618)
Clinical staff†	0.105	0.029	0.520	0.497	0.644**
	(0.471)	(0.308)	(0.577)	(0.321)	(0.325)
Nonclinical staff†	0.067	-0.048	-0.941	1.727***	1.886***
	(0.572)	(0.385)	(0.585)	(0.411)	(0.411)
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Robust standard errors are reported. *$p<0.10$, **$p<0.05$, ***$p<0.01$.
†Denotes log-transformed variable.

Table 9: Post Hoc analysis — chain size

	Chain size		
	(12)	(13)	(14)
Social disadvantage	-209.227*	-180.694**	-51.348*
	(111.045)	(83.832)	(28.606)
Profit status	5.917***	-2.911	1.934
	(1.438)	(6.565)	(2.295)
Years certified†	6.247**	-83.567***	-3.273***
	(2.799)	(5.417)	(1.259)
Dialysis stations†	6.461	-3.814	-2.737
	(6.115)	(3.944)	(1.685)
Laboratory expenses†	0.070	3.007***	5.941***
	(1.504)	(0.972)	(0.488)
Drug expenses†	0.205	-1.052	3.444***
	(1.268)	(1.411)	(0.674)
Number of treatments†	-1.280	0.276	-8.204***
	(2.273)	(1.787)	(1.211)
Clinical staff†	-0.813	-0.837	1.507**
	(1.438)	(0.938)	(0.703)
Nonclinical staff†	0.401	0.909	3.939**
	(1.739)	(1.104)	(1.597)
State FE	✓	✓	✓
Year FE	✓	✓	✓

Robust standard errors are reported. *p <0.10, **p <0.05, ***p <0.01.
†Denotes log-transformed variable.

teams and standardized training modules streamline this knowledge transfer, ensuring the disadvantaged site benefits from network-level learning.

The global health landscape, as articulated in the United Nations Sustainable Development Goals and ongoing CMS health equity initiatives, calls for reducing disparities in access and outcomes. The evidence presented here suggests that chain-affiliated organizations can be strategic allies in achieving these goals. In rural dialysis centers with sparse specialist availability, or facilities serving predominantly minority populations that face linguistic and cultural barriers, chain structures support the rapid diffusion of context-specific solutions. By complementing broader public health reforms and targeted policy interventions, chain organizations—through their internal learning networks—can help level the playing field and advance equity in care quality.

9 Conclusion

This study demonstrates that chain affiliation plays a moderating role in mitigating the negative effects of social disadvantage on dialysis facility quality. Chain-affiliated facilities exhibit stronger resilience and adaptability in challenging socioeconomic contexts by leveraging dynamic capabilities—namely, enhanced sensing of patient needs, seizing improvement opportunities, and reconfiguring resources. Our findings indicate that chain networks can help overcome socioeconomic barriers in underserved areas by disseminating best practices, reallocating resources, and proactively refining care delivery processes.

Despite these contributions, several limitations warrant caution. First, our study relies on secondary data compiled from CMS sources and other publicly available datasets. Although these sources are standardized and widely used, we cannot entirely exclude potential coding errors or biases inherent in large administrative databases. Second, our measurement of social disadvantage employs composite indices (e.g., SVI), while capturing the multi-dimensional of social adversity—do not distinguish among specific barriers, such as linguistic isolation or transportation insecurity. Future research could use more granular data (e.g., household-level socioeconomic measures) to better capture localized nuances. Third, although we used multiple robustness checks and an instrumental variables approach, endogeneity issues may persist if unobserved factors (e.g., local policy interventions, unique community assets) systematically affect both social disadvantage and facility performance. Finally, this study focuses exclusively on dialysis facilities in the U.S.; thus, the generalizability of our findings to other healthcare contexts or countries with different regulatory and reimbursement frameworks may be limited.

Future studies can build on our findings by examining how chain affiliation operates in other healthcare domains—particularly in chronic care settings where patient engagement is critical but socioeconomic constraints are pervasive. Incorporating finer-grained data, such as patient-level adherence metrics and localized social determinants of health, could shed light on the underlying mechanisms through which organizational capabilities specifically address different types of disadvantages. Comparative analyses of multiple health system structures (e.g., accountable care organizations and regional health cooperatives) may also clarify whether these governance forms exhibit similar advantages—or face similar constraints—as large chain organizations. Further, researchers could explore the interplay between chain affiliation and emerging management science techniques (e.g., simulation, optimization, machine learning) to determine which interventions most effectively enhance dynamic capabilities in the face of variable socioeconomic risks. Ultimately, extending these lines of inquiry will refine our understanding of how organizational strategies and network-based structures can promote health equity across an even wider range of healthcare settings.

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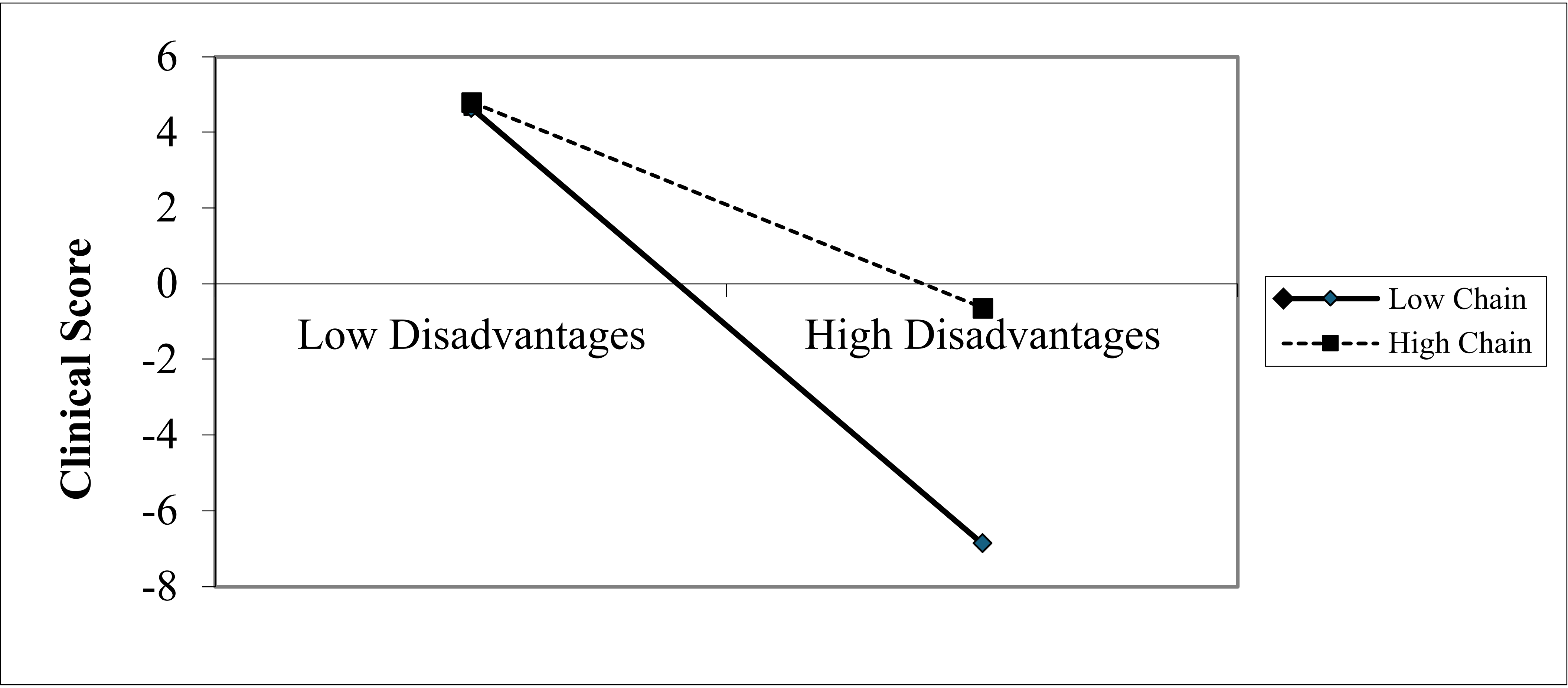
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Balancing Workforce Fissuring and Service Quality: Evidence from Dialysis Operations

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The growing reliance on contract workers in core operational roles challenges traditional assumptions about workforce design and service quality. Using panel data from 3,792 U.S. dialysis facilities (2015–2023), we examine how the ratio of contract registered nurses (RNs) affects care quality in outpatient hemodialysis centers. Drawing on team-based learning and relational coordination theories, we hypothesize an inverted U-shaped relationship between the contract RN ratio and quality performance, moderated by support staff intensity and patient severity. After addressing endogeneity with instrument variables, we find that moderate workforce fissuring, when supported by strong auxiliary staffing, can enhance rather than compromise service quality, whereas high patient severity reduces tolerance for fissuring. These results challenge the traditional core/non-core dichotomy in outsourcing decisions and demonstrate that fissured workforces can be strategically deployed even in high-skill, quality-critical operations. Our findings also offer practical guidance for healthcare and other industries grappling with workforce shortages.

KEYWORDS
dialysis operations, fissured workforce, healthcare operations, service quality, team coordination

1 | INTRODUCTION

Over the past decade, healthcare organizations have increasingly relied on contract nurses to mitigate workforce shortages. For example, the proportion of care facilities employing contract nurses through staffing agencies doubled from 23% in 2018 to nearly 50% in 2022 (Bowblis et al., 2024). This trend reflects a broader shift towards fissured workforce arrangements, in which organizations outsource core activities to third-party providers while maintaining control over standards and accountability for outcomes (Weil, 2014). Using a fissured workforce gives organizations greater staffing flexibility and access to specialized expertise, enabling them to respond quickly to fluctuations in demand and skill requirements, particularly in industries with seasonal or volatile workloads such as healthcare and hospitality. However, this model also introduces significant challenges, including coordination difficulties, loss of organizational knowledge, and potential declines in service quality. These risks are particularly pronounced in healthcare, where care delivery relies heavily on specialized skills and team-based collaboration. As the healthcare industry increasingly embraces a fissured workforce, healthcare organizations face challenges such as high turnover and fragmented employment relationships, which can weaken team cohesion and impede the sharing of critical knowledge about organizational processes and individual patients. Hence, understanding how a fissured workforce affects service quality is essential in contexts that require specialized expertise (i.e., high skill) and complex coordination (Handley and Benton Jr, 2009).

Other than non-core functions such as administrative support, catering, and logistics, fissured workers can also perform core business activities and be heavily involved in an organization's internal processes and team collaborations. However, studies in Operations Management (OM) literature have primarily focused on outsourcing/contracting non-core functions, and research on how fissuring core functions affects service quality in high-skill work settings remains limited (Weil, 2014). This gap is particularly salient in healthcare operations, where care delivery depends on continuous coordination between specialized professionals, real-time adaptation to patient conditions, and the preservation of facility-specific knowledge (Mishra et al., 2020; Tucker et al., 2007). This paper addresses this gap by investigating the relationship between contract registered nurse (RN) ratio (i.e., the share of contract RNs among all RNs) and service quality, while examining the moderating roles of support staff intensity (i.e., the number of patient care technicians, or PCTs, per dialysis station) and patient severity in dialysis facilities.

We chose to study dialysis operations because it provides an ideal setting to examine the operational consequences of a fissured workforce. Dialysis facilities frequently employ contract RNs, a highly skilled segment of the fissured workforce, who serve as integral members of the core clinical team alongside physicians. According to our panel data of U.S. dialysis facilities from 2015 to 2023, these facilities exhibit substantial variation in their reliance on a fissured workforce, ranging from an exclusive use of employed RNs to a complete dependence on contract RNs, providing a solid foundation for robust statistical analysis. Furthermore, dialysis treatment itself is characterized by high technical complexity and requires intensive coordination between RNs and PCTs, with the former providing clinical oversight and the latter performing routine support tasks. The interdependence creates a natural context for studying team coordination and cross-role effects (Havens et al., 2018). Finally, the dataset encompasses detailed staffing configurations and standardized quality metrics, allowing us to assess quality performance across facilities (Centers for Medicare & Medicaid Services, 2023).

Our results suggest that the contract RN ratio and service quality follow an inverted U-shaped relationship, with optimal quality occurring at moderate contracting levels (approximately 14%). Drawing on team-based learning and knowledge transfer literature, adding new members to a team can introduce complementary skills and fresh perspectives, while also challenging entrenched routines, thereby increasing cognitive diversity and stimulating learning (March, 1991; Tjosvold et al., 2004). When strong integration processes are in place, moderate turnover can refresh the collective knowledge base, foster innovation, and improve performance (O'Connor et al., 1993; Li and van Knippenberg, 2021). However, knowledge accumulation and retention depend on stable membership and repeated interactions, both of which are likely to be disrupted when organizations rely heavily on contract personnel (Argote and Guo, 2016). Relational coordination theory suggests that effective service delivery in interdependent settings requires shared goals, mutual knowledge, timely communication, and capacities that develop through sustained collaboration (Hoffer Gittell, 2002; Havens et al., 2018). Excessive reliance on contract labor undermines these mechanisms, depleting the knowledge base and coordination, hence compromises the quality of dialysis treatments. The observed inverted U-shaped relationship between the contract RN ratio and service quality reflects the interplay of these dynamics.

Our results also show that the support staff intensity and patient severity further moderate the relationship between the contract RN ratio and service quality. Specifically, as the support staff intensity increases, the inverted U shape becomes more pronounced. The results suggest that PCTs preserve operational continuity and facility-specific knowledge, thus mitigating the potential adverse effects of contract RNs and enabling facilities to sustain quality even with higher contract RN ratios. In addition, the U-shaped relationship is also moderated by patient severity as the curvature flattens and the turning point of the curve shifts to the left for patients with higher severity. This pattern reflects an increasing need for team-based communication and facility-specific expertise in more complex patient care, capabilities that become harder to achieve as the proportion of contract labor rises (Huckman and Pisano, 2006; KC and Terwiesch, 2011). These findings collectively demonstrate that the value of contract labor in healthcare operations is not uniform, but rather contingent upon the intensity of organizational support structures and the coordination complexity of the service context.

This study makes several contributions to the literature. First, it empirically demonstrates that the quality outcome of contract labor follows a curvilinear pattern, challenging linear assumptions about outsourcing benefits and highlighting the operational trade-offs of a fissured workforce (Weil, 2014; Boudreau, 2019). Second, it identifies organizational conditions that enable effective use of contract labor in high-skill contexts, showing that support staff act as critical safeguards against knowledge loss and coordination breakdown. Finally, the study also reveals that patient severity, an indicator of the resources required to treat patient symptoms, significantly reduces the effective use of contract labor. The findings advance our understanding of how firms can design resilient operations despite fragmentation of the workforce and respond to calls for research on managing capability erosion in outsourced settings (Handley, 2012; Mishra et al., 2020; Peng et al., 2023).

2 | LITERATURE REVIEW

This section develops the theoretical foundation for understanding how fissuring in core, high-skill roles affects performance in team-based operations. We draw on team learning and relational coordination theories to identify mechanisms that shape knowledge retention and team coordination. These mechanisms form the foundation of our conceptual framework, which we apply to the dialysis context to develop hypothesized relationships in the next section.

2.1 | Fissured Workforce in Core, High-Skill Operations

The fissured workforce refers to organizational arrangements in which firms outsource significant activities to external providers, loosening traditional employer-employee relationships for cost savings and flexibility (Weil, 2014). While this model initially emerged in low-skill, peripheral roles, such as cleaning, maintenance, and food service (Kalleberg, 2000), it has increasingly penetrated the core of organizations. Firms now contract out high-skill roles, including professional services, R&D, IT, and even clinical services, with non-employed personnel blended into core workflows and teams (Weil, 2014; Boston-Leary et al., 2024).

This shift brings strategic and operational benefits. By leveraging a fissured workforce, organizations gain flexibility in scaling capacity and reducing labor costs while having access to expertise that would have been costly to develop internally (Holcomb and Hitt, 2007). Managers, under pressure to prioritize core competencies, often consider fissuring even complex tasks to focus internal resources on what the firm does best (Weil, 2014; Abraham and Taylor, 1996). Furthermore, combining internal employees' institutional knowledge with contractors' fresh skills and perspectives can, in theory, create complementarities that promote innovation and responsiveness (Parmigiani, 2007).

However, embedding fissured workers in core, high-skill functions introduces significant risks. A primary concern is the loss of critical capabilities and tacit knowledge traditionally housed within internal teams, leading to reliance on external expertise and increasing organizational vulnerability (Anderson Jr and Parker, 2002; Handley, 2012). For example, empirical studies link prolonged contracting of R&D to declines in innovative capacity (Holcomb and Hitt, 2007; Kotabe and Mol, 2009). In addition, challenges in coordinating with fissured workers further compound these risks. Unlike peripheral tasks that can be governed through contracts and oversight, high-skill work depends on ongoing communication, trust, and shared understanding, all of which are more difficult to foster in fissured workforce structures (Huckman and Pisano, 2006; Mishra et al., 2020). Contract professionals often lack established social ties and familiarity with local routines and culture, which can disrupt workflows and impede knowledge transfer. Traditional governance mechanisms, such as contract agreements and oversight, are often inadequate in these contexts (Williamson, 1981; Ellram et al., 2008).

To mitigate these risks, organizations must design safeguards that preserve institutional tacit knowledge and support coordination capabilities when managing high-skill core activities (Handley, 2012; Parmigiani, 2007). An effective approach is to maintain a stable internal core that acts as a knowledge repository and integration hubs for rotating contractors (Handley, 2012). These internal anchors support the assimilation of external expertise into organizational routines, allowing organizations to leverage the benefits of a fissured workforce without compromising quality outcomes. While OM research has traditionally focused on outsourcing peripheral functions, it has paid limited attention to how safeguards work in high-skill core operations. As fissuring has progressed from a peripheral cost-saving tactic to an integral component of high-skill core work, understanding how to balance the flexibility offered by contractors with the preservation of institutional knowledge and relational coordination becomes increasingly important for managing complex, interdependent, and quality-critical work systems.

2.2 | Knowledge and Coordination Mechanisms

High-skill, team-based operations depend on two interrelated capabilities: the ability to retain and integrate knowledge over time and the ability to coordinate actions in real time (Tucker et al., 2007). Workforce fissuring disrupts both. To investigate these dynamics, we draw on two complementary theoretical perspectives: team-based learning and relational coordination, which together explain how fissuring affects performance in complex service systems.

Team-Based Learning

Organizational learning is the process through which organizations acquire, retain, and transfer knowledge derived from experience. This process enables organizations to adapt to changing environments, improve their operations over time, and sustain long-term performance and competitiveness (Argote and Miron-Spektor, 2011). Within organizations, teams are the primary locus of this learning (Argote and Ingram, 2000; Guzzo and Dickson, 1996; Tucker et al., 2007), which emerges through the integration of specialized knowledge held by different members and is strengthened by repeated collaboration over time. Through repeated collaboration, teams develop transactive memory systems, shared cognitive maps of "who knows what," and establish routines that enable efficient knowledge sharing and adaptation within the team (Wegner, 1987; Argote and Ingram, 2000). In cohesive teams, close working relationships and repeated interactions reinforce these cognitive maps, enabling the transfer of tacit knowledge even across distinct functional roles. This reciprocal knowledge sharing is a core mechanism of team-based learning, allowing collective know-how to be preserved and adapted as circumstances change. Consequently, teams with greater continuity and familiarity often perform better in coordinated tasks, as shared experience enhances communication efficiency, facilitates coordination, and builds a richer base of collective knowledge that extends beyond individual expertise (Reagans et al., 2005; Huckman et al., 2009; Lewis, 2003).

However, the rise of the fissured workforce introduces frequent membership changes that destabilize these learning processes. When experienced members leave, they carry away tacit knowledge that is difficult to codify, while new members face steep learning curves to adapt to local practices and norms. These disruptions weaken the trust and transactive memory that form the social and cognitive foundations of teamwork, especially when changes are abrupt, excessive, or poorly managed (Arrow and McGrath, 1993; Smith et al., 2017; Li and van Knippenberg, 2021). Empirical research shows that teams often experience performance shortfalls after membership loss until routines and shared understandings are reestablished (Fleishman and Harris, 1962; Guillaume et al., 2012). Furthermore, the impacts of membership changes are amplified when tasks are more complex and interdependent, given their reliance on tacit coordination and shared institutional memory.

While membership changes can disrupt learning, it can also catalyze renewal and infusion of new ideas under the right conditions. The same mechanisms that cause knowledge loss can enable knowledge infusion. New members may bring complementary skills, fresh perspectives, and cognitive diversity, which can challenge complacent routines and foster innovation (March, 1991; Tjosvold et al., 2004). When supported by strong integration processes, moderate turnover can refresh the collective knowledge base and improve performance (O'Connor et al., 1993; Li and van Knippenberg, 2021). Thus, from a team learning perspective, the challenge is to strike a balance between incorporating external expertise and preserving the continuity of team knowledge.

Relational Coordination

Beyond knowledge retention, high-skill operations demand real-time coordination among interdependent roles. Relational coordination theory posits that in work systems characterized by high interdependence, uncertainty, or time sensitivity, success depends not only on formal processes and individual skills, but also on the quality of the relationships among team members (Hoffer Gittell, 2002; Gittell et al., 2010). High levels of relational coordination are characterized by shared goals, shared knowledge, and mutual respect, which are reinforced through frequent, timely, and solution-oriented communication. These relational foundations build trust and shared understanding that allow team members to synchronize their actions and adapt to changing environments rapidly. However, contractors often lack social ties and contextual knowledge, leading to communication that is more transactional and less anticipatory (Health Services Safety Investigations Body, 2024; Wilkin et al., 2018). As relational coordination weakens, the likelihood of misaligned actions, delayed responses, and safety lapses increases, especially in complex, high-stakes settings such as dialysis facilities, where patient conditions can change rapidly and errors carry serious consequences (Mishra et al., 2020).

Furthermore, the complexity of tasks and the degree of interdependence influence the extent to which relational coordination impacts team performance. When work is standardized or modular, team performance relies less on intensive interpersonal communication (Teekens et al., 2023; Lazar et al., 2022). In such settings, teams can operate effectively through formal, transactional interactions and experience less disruption from personnel turnover. This contrasts drastically with high-complexity, interdependent work, where strong relational ties and shared context are essential. In complex environments such as acute healthcare or advanced R&D, replacing seasoned core employees with contract staff can undermine performance by disrupting trust networks and nuanced communication channels necessary for effective communication. Research shows that when tasks are complex or tightly coupled, teams with strong relational coordination are more resilient to disruptions, as members proactively fill gaps for one another, communicate emergent issues promptly, and coordinate responses smoothly through shared understanding (Faraj and Xiao, 2006; Huckman et al., 2009).

Together, these theories illustrate why fissuring in core roles is not simply a staffing issue but a potential disruption to the social-cognitive infrastructure of teams. Team-based learning explains the gradual erosion of knowledge continuity, while relational coordination explains the immediate breakdown of real-time collaboration. Both mechanisms are amplified in environments with high task interdependence and uncertainty, such as dialysis care, where success depends on both accumulated experience and coordinated action. This dual perspective forms the basis for our hypotheses regarding how workforce composition influences service quality and how organizational supports (i.e., support staffing) and contextual factors (i.e., task complexity) interact to influence quality outcomes in a fissured workforce.

3 | HYPOTHESES DEVELOPMENT

Building on the theoretical mechanisms outlined in Section 2, we now develop hypotheses that link the fissured workforce to service quality in a high-skill, team-based setting. We focus on outpatient hemodialysis centers, where care delivery depends on tightly coordinated teams and the preservation of tacit knowledge. We begin by describing the empirical setting and then articulate three sets of hypotheses.

3.1 | Empirical Context: Outpatient Hemodialysis Centers

Outpatient hemodialysis centers provide life-sustaining treatment to patients with end-stage renal disease through a standardized process that requires intensive coordination among members of the care team. While physicians prescribe treatment protocols, conduct weekly rounds, and oversee overall patient care plans, they are not continuously present during routine treatments. As a result, the daily operational workflow depends primarily on the coordinated efforts of RNs and PCTs, making the RN-PCT pair the operational core of daily care delivery. Regulations require that at least one RN be present and on duty whenever dialysis patients are treated (Centers for Medicare & Medicaid Services, 2008). RNs initiate and supervise dialysis treatments and occasionally perform critical hands-on tasks, while PCTs provide technical support. Specifically, during each treatment session, RNs are responsible for clinical assessment, medication administration, and oversight, while PCTs perform routine technical tasks such as machine setup, vascular access cannulation, and continuous monitoring under RN supervision (Cahill et al., 2021; Plantinga et al., 2024). In addition to PCTs, certified nursing assistants (or nurse aides) serve as the primary assistive personnel in dialysis centers. Their responsibilities focus on activities of daily living and other non-assessment tasks, and they are generally not permitted to engage in clinical procedures across states. Consequently, they are not considered part of the core clinical team in dialysis operations and are not considered in our analysis (Centers for Medicare & Medicaid Services, 2008; Cahill et al., 2021).

Figure 1 illustrates the typical workflow of an outpatient hemodialysis session, highlighting the roles of an RN and a PCT and their interactions. At the start of a treatment session, the RN assesses the patient's pretreatment condition and carries out the dialysis prescription, such as ultrafiltration parameters and medication administration, according to physician orders. Meanwhile, the PCT prepares the dialysis machine and supplies. Under the supervision of the RN, the PCT cannulates vascular access and initiates treatment (Plantinga et al., 2024). During dialysis, the PCT monitors vital signs and machine settings, makes routine adjustments, and documents care, while the RN oversees progress and intervenes if complications arise (Cahill et al., 2021). After treatment, the PCT disconnects the patient and secures the access site, followed by the RN's post-treatment evaluation. The shaded area in Figure 1 highlights urgent situations where complications, such as sudden hypotension, vascular access problems, or machine alarms, require immediate intervention of the RN.

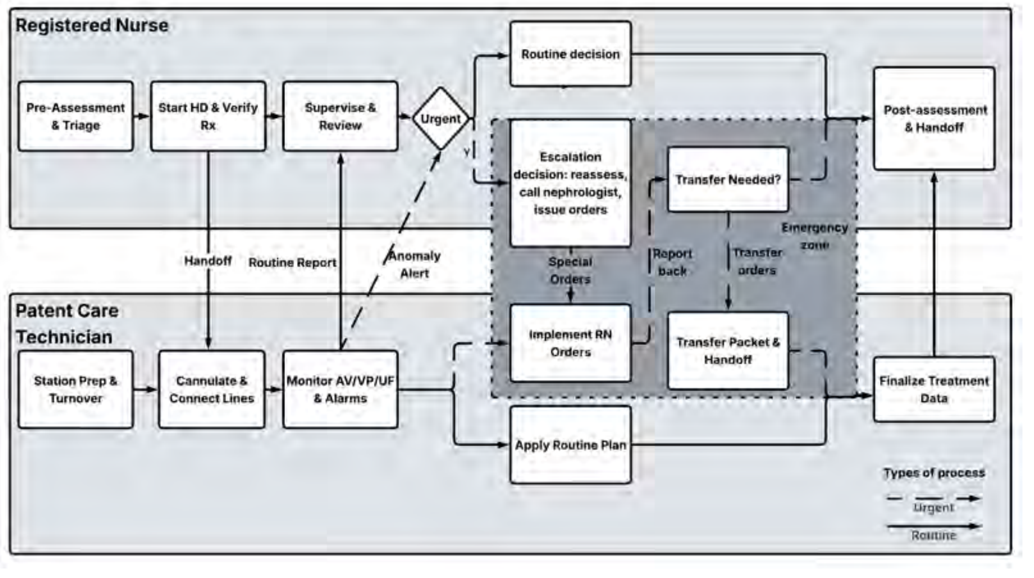

FIGURE 1 Typical Workflow of an Outpatient Hemodialysis Session

This division of labor creates a tightly coupled workflow where RNs initiate and supervise dialysis treatments while PCTs provide essential support. This workflow requires multiple handoffs and continuous information exchange between RNs and PCTs, demanding synchronized coordination and shared tacit knowledge to ensure patient safety and treatment effectiveness. In urgent situations, the need for rapid RN-PCT coordination and efficient handoffs becomes even more critical (Yu and Wijesekera, 2013). Because patients typically undergo hemodialysis three times per week (National Kidney Foundation, 2025), stable RN-PCT pairings foster trust, accrue shared knowledge, and strengthen team coordination over time (Hayes et al., 2015). The stability is crucial for consistent treatment adherence and overall compliance (Gittell et al., 2008).

However, high rates of burnout and turnover with employed RNs (Plantinga et al., 2024) drive many centers to hire contract RNs to meet staffing needs and maintain operations. While contract RNs bring fresh practices and alleviate staffing shortages, their limited familiarity with local clinic protocols or PCT workflow can slow their responses to urgent situations and elevate the risk of medical errors (Thomas-Hawkins et al., 2008). Therefore, as noted in Section 1, the combination of high technical complexity, frequent team interactions, and stringent safety requirements in dialysis care makes it an ideal context for studying how workforce composition affects service quality across varying levels of fissuring (Pisano et al., 2001; Tucker et al., 2007).

3.2 | Impact of the Contract RN Ratio on Care Quality

We argue that the effect of the contract RN ratio on care quality is nonlinear. As illustrated in Figure 2, the inverted U-shaped pattern emerges from two opposing forces, which we discuss next.

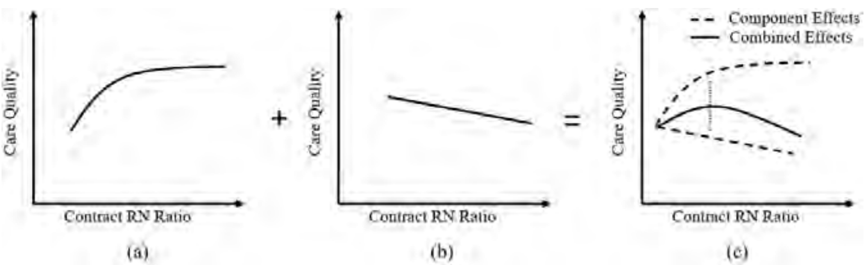

FIGURE 2 Hypothesized Effect of the Contract RN Ratio on Care Quality

On the positive side, contract RNs can contribute more than simply filling staffing gaps: they bring new clinical practices and operational insights gained from other facilities. These external perspectives can stimulate learning and process improvements without undermining the stability of existing routines. This aligns with organizational learning theory, which suggests that a limited infusion of new knowledge can enhance the exploration of new opportunities while preserving the exploitation of established capabilities (March, 1991). Empirical evidence from acute care supports this view: hospital units with 5-15% of nursing hours delivered by contract nurses reported lower medication error rates than those staffed exclusively with permanent employees (Bae et al., 2010). Similarly, in dialysis settings, a low-to-moderate presence of contract RNs can introduce best practices and innovations from other institutions while preserving team stability and cohesion, enriching collective knowledge without disrupting established workflows. However, these benefits do not scale linearly: as the proportion of contract RNs rises, marginal gains diminish as new practices can disrupt established routines and assimilation is constrained by the team's capacity to absorb external knowledge, resulting in a concave relationship. Figure 2(a) illustrates this positive yet diminishing effect of new knowledge infusion, showing that gains taper as the contract RN ratio increases.

When the contract RN ratio exceeds a certain threshold, the drawbacks of workforce fissuring begin to outweigh its benefits. Increased reliance on contract RNs can disrupt the social and cognitive foundations that underpin teamwork. High contract RN ratio erodes transactive memory systems and shared cognitive maps of "who knows what," making handoffs more error-prone and slowing responses to complications. Dialysis care relies heavily on tacit knowledge embedded in clinical practices, such as the ability to anticipate atypical patterns like a blunted nocturnal decline in systolic blood pressure among certain hemodialysis patients, which is difficult to codify and easily lost when team continuity is compromised (Kooman et al., 1992). Empirical studies link frequent RN turnovers to higher rates of intradialytic hypotension, treatment interruptions, blood pressure instability, and other complications, ultimately increasing patient complaints (Thomas-Hawkins et al., 2008; Jeong, 2023). Heavy reliance on contract RNs also strains employed RNs, who must repeatedly orient newcomers, adding to their workload and stress. For instance, patient falls tend to increase, and staff are more susceptible to stress and fatigue when contract RNs account for more than 15% of total unit hours (Bae et al., 2010). Furthermore, patients often value the trust built through consistent interactions with familiar nurses. Rapid RN turnover undermines this trust, reducing patient satisfaction (Argentero et al., 2008). These adverse effects continue to grow as the contract RN ratio increases. Figure 2(b) illustrates this negative impact of increasing contract RN ratios, driven by growing disruptions to team cohesion and diminishment of shared knowledge.

Combining these two opposing forces, we suggest an inverted U-shaped relationship between the contract RN ratio and care quality, as illustrated in Figure 2(c): quality initially improves with low-to-moderate contract RN ratios, peaks when fissuring benefits are maximized, and then declines as its negative effects outweigh the gains. Accordingly, we hypothesize:

Hypothesis 1 (H1) There is an inverted U-shaped relationship between the contract RN ratio and dialysis care quality; that is, quality first increases and then decreases, ceteris paribus.

3.3 | Support Intensity as a Knowledge–Coordination Buffer

Building on Hypothesis 1, we posit that support intensity, defined as the ratio of PCTs to dialysis stations, moderates the inverted U-shaped relationship, as illustrated in Figure 3 and discussed next.

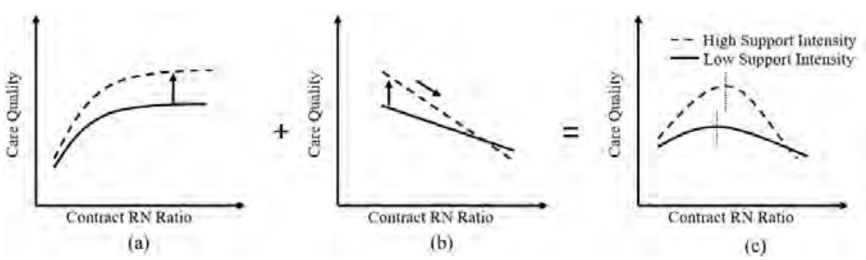

FIGURE 3 Hypothesized Effect of the Contract RN Ratio on Care Quality Moderated by Support Intensity

In dialysis care, PCTs serve as the operational backbone through their unique roles between patients and RNs. They perform routine yet critical tasks, handle direct patient care, and remain present with patients throughout each dialysis session, as noted in Section 3.1. This continuous involvement gives PCTs an intimate understanding of patient needs and facility operations, positioning them as natural bridges within the care team. This bridging role becomes particularly critical in the context of workforce fissuring. Building on team-based learning theory, stable team members with accumulated tacit knowledge serve as anchors for integrating new members (Argote and Miron-Spektor, 2011). PCTs fulfill this anchoring function through their collaborative working relationships with both employed and contract RNs. The nature of dialysis care requires PCTs and RNs to work side-by-side during procedures, creating conditions for "coactive vicarious learning" (Myers, 2018). In this arrangement, PCTs work under RN supervision while simultaneously providing ground-level support and patient-specific insights.

The effectiveness of this knowledge transfer mechanism stems from the continuous, hands-on nature of PCT–RN collaboration. When contract RNs join the facility, they collaborate closely with PCTs who hold deep institutional knowledge of facility setups, patient histories, preferences, and subtle clinical indicators that are difficult to codify. Through these interactions, PCTs transfer tacit knowledge to contract RNs, maintaining continuity of patient-specific care despite staff rotations. At the same time, contract RNs introduce external practices from other facilities, which PCTs can absorb and relay to employed RNs, creating a bidirectional information flow. This positions PCTs as “knowledge keepers” who preserve institutional memory while facilitating the integration of new practices into established workflows. Their role aligns with the concept of boundary spanners in organizational theory (Handley, 2012; Tushman, 1977), individuals who bridge organizational gaps and enable knowledge transfer across role boundaries. A stable PCT team provides the absorptive capacity needed to incorporate external knowledge without disrupting established routines (Argote and Miron-Spektor, 2011; Parmigiani, 2007). Figure 3(a) illustrates this effect, showing the upward shift of the quality curve as support intensity increases.

However, this buffering capacity has limits. As support teams expand, they can inadvertently amplify the coordination burdens created by contract RNs. From the RN’s perspective, a larger PCT team increases interdependencies and elevates supervision needs, which in turn heighten coordination costs (Hoffer Gittell, 2002). Furthermore, as team size expands, responsibility diffuses and process inefficiencies emerge: vigilance and error-catching are shared among more personnel, and peer learning slows as it shifts toward sequential interactions, impeding efficient cooperative learning (Arrow and McGrath, 1993; Smith et al., 2017; Li and van Knippenberg, 2021). Prior research indicates that as the size of the nursing unit increases, relational quality and shared mental models often deteriorate, leading to inefficiencies and errors (Kalisch et al., 2013). Figure 3(b) illustrates this dynamic, showing that greater support intensity enhances care quality under low-to-moderate fissuring but accelerates quality decline once the contract RN ratio surpasses a critical threshold.

Combining these effects together, we argue that support intensity moderates the inverted U-shaped relationship in two ways, as shown in Figure 3(c): (1) by sharpening the inverted U shape, magnifying gains at low-to-moderate contract RN ratios and losses at high ratios, and (2) by shifting the turning point to the right, enabling facilities with stronger support teams to accommodate higher levels of fissuring before quality declines. Accordingly, we hypothesize:

Hypothesis 2a (H2a) Higher support intensity amplifies the inverted U-shaped relationship between the contract RN ratio and dialysis care quality, ceteris paribus.

Hypothesis 2b (H2b) Higher support intensity shifts the turning point of the inverted U-shaped relationship to the right, ceteris paribus.

3.4 | Patient Severity as a Performance Constraint

In hemodialysis, patients’ hemoglobin levels usually fall inside the clinically recommended range (10–12 g/dl) (Kidney Disease: Improving Global Outcomes (KDIGO) Anemia Work Group, 2012). We conceptualize patient severity as the proportion of patients whose hemoglobin levels fall outside this range, which signals greater clinical complexity and coordination demand. Higher patient severity increases the frequency and urgency of interventions, compresses decision windows, and tightens role interdependencies, thereby elevating the need for rapid, error-free communication and shared situational awareness (Hoffer Gittell, 2002; Gittell et al., 2013). In dialysis, this dynamic is particularly salient during the urgent, time-sensitive events highlighted in Section 3.1. Greater severity amplifies the frequency and stakes of these critical junctures, directly increasing task complexity and coordination demands while further compressing decision windows and tightening cross-role coupling (Galbraith, 1974; Manser, 2009; Yu and Wijesekera, 2013). Such high-severity conditions attenuate the benefits of knowledge infusion from contract RNs: when teams operate under constant time pressure and heightened vigilance, they lack the cognitive slack needed to incorporate new practices or adapt workflows introduced by external personnel (Argote and Miron-Spektor, 2011). Figure 4(a) illustrates this effect, showing a downward shift in the quality curve as patient severity rises, diminishing the positive impact of knowledge infusion.

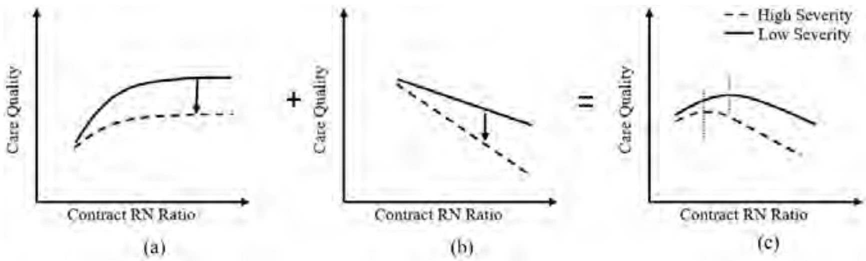

FIGURE 4 Hypothesized Effect of Contract RN Ratio on Care Quality Moderated by Patient Severity

Furthermore, high patient severity amplifies the costs of unfamiliarity introduced by contract RNs. Dialysis care for medically complex patients often hinges on tacit knowledge, such as anticipating blood pressure drops or detecting subtle vascular access issues, that develops through repeated interactions. Contract RNs, lacking this embedded knowledge and relational familiarity, are more likely to miss early warning signs or misinterpret implicit cues from experienced PCTs (Thomas-Hawkins et al., 2020). In such high-severity contexts, even minor coordination failures can escalate into serious adverse events, as reflected in failure-to-rescue rates, a nursing-sensitive outcome that worsens with higher contract RN ratios (Needleman et al., 2002). Figure 4(b) illustrates this effect, showing a steeper decline in quality as patient severity increases, driven by the erosion of tacit knowledge and team cohesion, which amplifies the consequences of coordinated failures.

These mechanisms suggest that as patient severity rises, the inverted U-shaped curve between the contract RN ratio and care quality becomes compressed and suppressed, as shown in Figure 4(c): the turning point occurs earlier, and the overall performance gain from moderate fissuring is smaller. In other words, high patient severity reduces the tolerance for fissuring and increases the penalty for excessive reliance on contract RNs. Accordingly, we hypothesize:

Hypothesis 3a (H3a) Higher patient severity attenuates the inverted U-shaped relationship between the contract RNs ratio and dialysis care quality, ceteris paribus.

Hypothesis 3b (H3b) Higher patient severity shifts the turning point of the inverted U-shaped relationship to the left, ceteris paribus.

4 | DATA SOURCES AND RESEARCH DESIGN

This section outlines data sources, sample construction, and variables used to test proposed hypotheses in the outpatient hemodialysis setting.

4.1 | Data Sources and Sample Construction

The End-Stage Renal Disease Quality Incentive Program (ESRD QIP) was created under the 2008 Medicare Improvements for Patients and Providers Act (MIPPA) and implemented beginning with the 2012 payment year, making it Medicare's first pay-for-performance initiative (Weiner and Watnick, 2017). The program requires facilities to publicly report performance metrics while conditioning a portion of Medicare reimbursement on compliance with quality standards (Centers for Medicare & Medicaid Services, 2023). In addition, dialysis centers must regularly submit detailed reports to the Centers for Medicare & Medicaid Services (CMS) on workflows, treatment protocols, and patient outcomes as a condition of participation (Centers for Medicare & Medicaid Services, 2008). These mandates have produced extensive, standardized datasets that enable rigorous analysis of how variations in staffing models influence care quality.

Our empirical analysis draws on a comprehensive panel dataset of U.S. outpatient dialysis facilities spanning 2015–2023, constructed by integrating multiple administrative sources maintained by CMS. These sources provide standardized, facility-level information on operations, staffing, and quality performance, enabling longitudinal analysis of workforce composition and service outcomes.

- *CMS's Dialysis Facility Reports & Care Compare database* provides facility-level operational data, including facility ownership (independent vs. chain-affiliated), treatment modality, capacity (number of dialysis stations), and patient volumes.
- *Healthcare Cost Report Information System* (HCRIS) contains annual Medicare cost reports submitted by all certified dialysis facilities. These reports detail financial expenditures and staffing configurations, including full-time equivalent (FTE) counts for both employed and contracted personnel across clinical and administrative roles. This source enables the precise calculation of the contract RN ratio.
- *End-Stage Renal Disease Quality Incentive Program* (ESRD QIP) publishes standardized quality performance scores based on clinical and reporting measures. These scores serve as our primary outcome variable and are updated annually for all participating facilities.

The analysis uses the facility-year as the unit of observation, with each dialysis center uniquely identified by its CMS Certification Number. The CMS Dialysis Facility Reports provided 65,328 observations from 8,773 facilities, HCRIS contained 56,387 observations from 8,068 facilities, and the ESRD QIP data included 55,959 observations from 8,859 facilities for the 2015–2023 period. Through merging facility-level data above three sources, we compiled an initial sample of 68,321 unique facility-year observations from 8,961 distinct facilities. Then, we applied the following screening criteria: (1) we dropped data from 2021 and 2022 due to suppressed reporting of key variables (e.g., QIP quality scores, dialysis station counts) during COVID-19 disruptions (Centers for Medicare & Medicaid Services, 2020, 2021), which would otherwise bias longitudinal estimates; (2) we included only outpatient clinics providing in-center hemodialysis as their primary service, excluding facilities focused on home or peritoneal dialysis; (3) we deleted data with missing values for key variables. Table 1 details these sample construction steps.

The final analytical sample comprises 17,611 facility-year observations from 3,792 dialysis centers. The panel is unbalanced due to facility openings, closures, and pandemic-related gaps, but offers broad coverage of the U.S. dialysis industry. On average, each facility contributes 5–6 years of observations. This sample closely mirrors the national dialysis landscape as most facilities in the sample are freestanding (as opposed to hospital-affiliated), for-profit clinics, consistent with industry norms. This integrated dataset provides a robust foundation for examining how variations in workforce composition, particularly the reliance on contract RNs, affect quality outcomes under different organizational and clinical conditions.

4.2 | Variable Construction

This section details the operationalization of key constructs, including the dependent variable, the independent variable, moderators, and control variables used in our models.

TABLE 1 Sample Construction Steps

Part A: Data Sources	**Observations**	**Facilities**
CMS Dialysis Facility Reports	65, 328	8, 773
HCRIS	56, 387	8, 068
ESRD QIP	55, 959	8, 859
Part B: Selection Criteria	**Observations**	**Facilities**
Initial facility-year observations from 2015–2023	68, 321	8, 961
Dropped observations from 2021–2022 due to data suppression during COVID-19	−15, 914	−12
Excluded facilities not providing in-center hemodialysis as their primary service	−14, 313	−1, 713
Deleted observations with missing values for key variables (RN, PCT, etc.)	−20, 483	−3, 444
Final analytical sample (facility-years)	17, 611	3, 792

4.2.1 | Dependent Variable: Quality Performance

The dependent variable in our analysis is the Quality Performance (QP) score assigned to each dialysis facility under the ESRD QIP. The QP score is a composite quality score that aggregates performance across multiple clinical and reporting measures in a given year. Higher QP scores reflect better performance and can lead to increased Medicare reimbursement, while facilities with scores below a threshold may incur financial penalties (Reaves and Weiner, 2021). CMS publishes these scores annually for all certified facilities, which are widely used as quality benchmarks for research and policy evaluations (Weiner and Watnick, 2017; Ajmal, 2017).

4.2.2 | Independent Variable: Contract RN Ratio

Our primary independent variable is the Contract RN Ratio (CRR), defined as the proportion of the share of contract RN FTEs relative to the total RN FTEs in a facility:

$$\text{CRR} = \frac{\text{Contract RN FTEs}}{\text{Total RN FTEs}}.$$

RNs represent core, high-skill personnel in dialysis care, who are responsible for clinical oversight, medication administration, and emergency response, as explained in detail in Section 3.1. The ratio of contract FTE labor is commonly used as an indicator of the degree of fissuring (Weil, 2014; Senek et al., 2020; Ajmal, 2017). Therefore, the CRR measure reflects the extent to which a dialysis facility relies on fissured RNs for core clinical operations.

4.2.3 | Moderators

We incorporate two moderators, Support Intensity (SI) and Patient Severity (PS), to capture organizational and clinical conditions that shape the relationship between the contract RN ratio and quality performance.

Support Intensity (SI)

Support intensity is defined as the FTEs of on-staff and facility-employed PCTs divided by the total number of dialysis stations within each facility:

$$\mathrm{SI} = \frac{\text{PCT FTEs}}{\text{Number of Dialysis Stations}},$$

where a dialysis station typically includes a dialysis machine, a comfortable chair or bed for the patient, and monitoring equipment.

The numerator reflects the level of support staffing in dialysis care, with PCTs functioning as key support personnel for RNs. The denominator serves as a proxy for a facility's fixed treatment capacity, which is not affected by daily census fluctuations or shift patterns. Previous studies suggest that station-based normalization provides a more stable, capacity-representative measure than patient-based ratios, as the number of stations changes infrequently and better reflects structural support intensity (Plantinga et al., 2024).

This capacity-normalized SI metric reflects the intensity of structural support personnel underpinning routine dialysis operations. National benchmarks indicate a median of roughly three stations per PCT (SI $\approx$ 0.33) (Plantinga et al., 2024). Higher SI values signal greater buffering capacity and learning bandwidth, enabling facilities to absorb variability introduced by contract RNs. As such, SI serves as a robust indicator of frontline support, encompassing both operational resilience and the ability to sustain quality performance under variable fissuring configurations.

Patient Severity (PS)

Patient severity is defined as the percentage of patients whose hemoglobin (Hgb) levels fall outside the clinically recommended range of 10–12 g/dL:

$$\mathrm{PS} = \frac{\text{Patients with Hgb} <10 \text{ or } >12 \text{ g/dL}}{\text{Total Patients}}.$$

We use the degree of deviation of patient hemoglobin (Hgb) from the recommended clinical range (10–12 g/dL) as a proxy for patient severity, reflecting the complexity of care and coordination demands for out-of-range patients (Kidney Disease: Improving Global Outcomes (KDIGO) Anemia Work Group, 2012). Patients with low Hgb (< 10 g/dL) require intensified care, including frequent laboratory monitoring, Erythropoiesis-Stimulating Agent (ESA) administration, intravenous iron adjustments, and potentially red blood cell transfusions. These interventions increase coordination demands across clinical, pharmacy, and laboratory teams (Kidney Disease: Improving Global Outcomes (KDIGO) Anemia Work Group, 2012). In contract, elevated Hgb (>12 g/dL) often signals ESA overuse, which raises risks of vascular access clots and stroke in patients with chronic kidney disease. These cases require rapid ESA dose reductions and timely coordination with imaging and interventional services (Besarab et al., 1998; Pfeffer et al., 2009). Table 2 summarizes these scenarios and associated tasks, illustrating how deviations from the target range translate into heightened facility-level coordination needs.

This PS measure is consistent with prior healthcare OM studies that uses it to capture facility-level patient severity (Dreyfus et al., 2020). Deviations from the target range trigger additional interventions that require precise, real-time coordination among clinical team members. As a result, higher PS signals greater operational interdependence and urgency, intensifying the risks associated with workforce fissuring.

4.2.4 | Controls

To isolate the effect of the contract RN ratio and moderators on quality outcome, we include a comprehensive set of control variables to account for facility characteristics, resource availability, staffing composition, and contextual factors known to influence dialysis performance:

TABLE 2 Clinical Scenarios and Coordination Tasks for Out-of-Range Hemoglobin

Scenario (Hgb)	Operational Response	Coordination Requirements	Local Execution Factors
Low (<10 g/dL)	Trigger re-test and increase monitoring; adjust medicines (ESA/Intravenous iron); escalate for transfusion if criteria are met.	Ensure lab results flow into the monitoring system; confirm supply and scheduling of blood products; track and log any adverse events.	Lab turnaround times; transfusion process steps; patient compliance and attendance patterns.
High (>12 g/dL)	Hold or reduce ESA order; monitor blood pressure and vascular access; escalate for imaging or procedure if thrombosis is suspected; adjust dialysis timing around the procedure.	Maintain a fast communication loop between orders, labs, and scheduling; secure imaging or procedure slots; align treatment sessions with interventions.	Availability of imaging or procedure slots; transport and caregiver logistics; dialysis sequencing rules; local access-protection protocols.

- *Total Nurse Aides*: FTE nurse aides (scaled), representing additional support staff who assist with basic patient care tasks. These personnel help maintain continuity in routine care (Webb and Wish, 2024; O'Keefe, 2014).
- *Total Social Workers*: FTE social workers who handle psychosocial support, care coordination, and discharge planning. Their presence reflects the facility's investment in non-clinical support services that may compensate for or complement variations in the contract RNs ratio (Pun et al., 2022; Friedman and Bernell, 2006).
- *Total Physicians*: FTE physicians, capturing medical director involvement and physician oversight intensity. Greater physician presence may influence how effectively facilities integrate contract RNs into clinical workflows and maintain quality standards (Weiner and Watnick, 2017; Mishra et al., 2020).
- *Drugs Expense*: Annual pharmaceutical spending, representing medication management demands and clinical complexity. This variable captures the treatment intensity that affects nursing workload and coordination requirements, particularly relevant when contract RNs must navigate facility-specific drug protocols (Kidney Disease: Improving Global Outcomes (KDIGO) Anemia Work Group, 2012; Pfeffer et al., 2009).
- *Laboratory Expenses*: Annual laboratory spending, serving as a proxy for resource intensity and diagnostic capacity (Piri, 2024; Reaves and Weiner, 2021).
- *Week Shift*: Average number of days per week the facility operates (scaled), reflecting operational intensity and scheduling complexity. Facilities with extended weekly schedules face different staffing pressures and may rely differently on contract RNs to maintain coverage across additional shifts (Plantinga et al., 2024; Thomas-Hawkins et al., 2020).
- *Years Since Certification*: Continuous measure of facility age (scaled), reflecting organizational experience and process maturity (Ajmal, 2017; Pisano et al., 2001).
- *Ownership*: Indicator for whether the facility is part of a large dialysis organization or an independent clinic. Chain-affiliated centers may benefit from standardized protocols and resource sharing, which can affect quality outcomes (Weiner and Watnick, 2017; Ajmal, 2017; Erickson et al., 2017).
- *In-center Hemodialysis*: Indicator for facilities primarily providing in-center treatment. While our sample is restricted to facilities offering in-center hemodialysis as their primary service, this control captures variations in the extent of in-center focus, as some facilities may offer other services that affect staffing practices (Plantinga et al., 2024; Yoder et al., 2013).
- *State Fixed Effects*: State-level indicators that capture geographic variation in regulatory environments, labor market conditions, and Medicaid policies affecting dialysis operations (Ajmal, 2017; Weiner and Watnick, 2017).
- *Year Fixed Effects*: Temporal indicators that control for industry-wide shocks such as policy changes, reimbursement adjustments, or secular trends in care delivery (Centers for Medicare & Medicaid Services, 2023; Reaves and Weiner, 2021).

These controls align with prior research and ensure that estimated effects of workforce fissuring are not confounded by structural, staffing, or resource-related differences across facilities (Weiner and Watnick, 2017; Ajmal, 2017; Reaves and Weiner, 2021; Plantinga et al., 2024). Table 3 reports descriptive statistics and pairwise correlations for all variables.

5 | MODELS & METHODOLOGY

This section outlines the framework and estimation approaches used to test the hypothesized nonlinear and moderated effects, addressing model specification, endogeneity, and instrument validity.

5.1 | Panel Models

To test our hypotheses, we estimate a series of panel data models linking workforce composition to dialysis facility quality performance. We log-transform QP and CRR as follows:

$$\begin{aligned}\widetilde{\mathrm{QP}} &= \log_{10}(\mathrm{QP}),\\ \widetilde{\mathrm{CRR}} &= \log_{10}(\mathrm{CRR}+1),\end{aligned}$$

where adding 1 to CRR prevents undefined values for facilities with zero contract RNs. This transformation reduces skewness, stabilizes variance, and mitigates the influence of extreme values. It also makes the coefficients easier to interpret in relative terms (e.g., percentage changes) and mitigates the influence of extreme values, which is especially important when testing nonlinear effects.

The dependent variable in our models is the log-transformed QIP composite score ($\widetilde{\mathrm{QP}}_{it}$), and the primary independent variable is the log-transformed contract RN ratio ($\widetilde{\mathrm{CRR}}_{it}$), where i denotes the facility and t the year. We also include quadratic and interaction terms to capture hypothesized nonlinear and moderating effects, where SI_{it} denotes support intensity and PS_{it} denotes patient severity for facility i in year t.

Model Specification

The baseline model evaluates the inverted U-shaped relationship between the contract RN ratio and quality outcome (H1):

$$\widetilde{\mathrm{QP}}_{it} = \beta_{10} + \beta_{11}\,\widetilde{\mathrm{CRR}}_{it} + \beta_{12}\,\widetilde{\mathrm{CRR}}_{it}^{2} + \beta_{13}\,\mathrm{SI}_{it} + \beta_{14}\,\mathrm{PS}_{it} + \mathbf{X}_{it}^{\top}\gamma + \alpha_i + \delta_t + \varepsilon_{it}, \tag{1}$$

where $\mathbf{X}_{it}$ denotes the vector of control variables, α_i and δ_t represent facility and year fixed effects, respectively, and ε_{it} captures the idiosyncratic error term. Support for H1 requires a statistically significant positive coefficient on the linear term ($\beta_{11} > 0$) and a significant negative coefficient for the quadratic term ($\beta_{12} < 0$), which jointly describe an inverted U-shaped relationship between $\widetilde{\mathrm{QP}}$ and $\widetilde{\mathrm{CRR}}$.

To test moderation hypotheses (H2a/b and H3a/b), we extend the model to include interactions of $\widetilde{\mathrm{CRR}}$ and its squared term with the moderators (SI and PS):

$$\begin{aligned}\widetilde{\mathrm{QP}}_{it} = \beta_{20} &+ \beta_{21}\,\widetilde{\mathrm{CRR}}_{it} + \beta_{22}\,\widetilde{\mathrm{CRR}}_{it}^{2} + \beta_{23}\,\mathrm{SI}_{it} + \beta_{24}\,\mathrm{PS}_{it}\\ &+ \beta_{25}\left(\widetilde{\mathrm{CRR}}_{it}\cdot\mathrm{SI}_{it}\right) + \beta_{26}\left(\widetilde{\mathrm{CRR}}_{it}^{2}\cdot\mathrm{SI}_{it}\right)\\ &+ \beta_{27}\left(\widetilde{\mathrm{CRR}}_{it}\cdot\mathrm{PS}_{it}\right) + \beta_{28}\left(\widetilde{\mathrm{CRR}}_{it}^{2}\cdot\mathrm{PS}_{it}\right)\\ &+ \mathbf{X}_{it}^{\top}\gamma + \alpha_i + \delta_t + \varepsilon_{it}.\end{aligned} \tag{2}$$

TABLE 3 Statistic Summary and Pairwise Correlations

	Mean	SD	Min	Max	Correlations												
					(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) QP	72.672	14.954	5.00	100.00	1.000												
(2) CRR†	0.03	0.132	0.00	1.00	-0.056^{***}	1.000											
(3) SI	0.336	0.474	0.00	38.22	-0.015^{*}	-0.007	1.000										
(4) PS	0.166	0.114	0.00	1.00	-0.180^{***}	0.008	0.009	1.000									
(5) Total Nurse Aides	0.375	1.65	0.00	27.33	0.021^{***}	-0.020^{**}	-0.137^{***}	-0.057^{***}	1.000								
(6) Total Social Workers	0.721	0.509	0.01	20.00	-0.066^{***}	0.010	0.523^{***}	-0.039^{***}	0.153^{***}	1.000							
(7) Total Physicians	0.167	0.488	0.00	35.00	-0.022^{***}	0.023^{***}	0.695^{***}	0.087^{***}	0.017^{**}	0.417^{***}	1.000						
(8) Drugs Expense	364.537	245.978	0.19	2969.27	-0.144^{***}	0.034^{***}	0.138^{***}	-0.072^{***}	0.135^{***}	0.590^{***}	0.027^{***}	1.000					
(9) Laboratory Expense	50.03	39.102	0.01	580.89	0.108^{***}	-0.011	0.137^{*}	-0.133^{***}	0.088^{***}	0.493^{***}	-0.005	0.618^{***}	1.000				
(10) Week Shift	9.828	9.39	1.00	758.00	-0.023^{***}	0.003	0.043^{***}	-0.025^{***}	0.140^{***}	0.154^{***}	-0.030^{***}	0.135^{***}	0.209^{***}	1.000			
(11) Years Since Certification	17.26	9.969	2.00	52.00	0.014^{*}	-0.007	0.015^{*}	-0.076^{***}	-0.033^{***}	0.167^{***}	-0.039^{***}	0.153^{***}	0.134^{***}	0.032^{***}	1.000		
(12) Ownership	0.952	0.215	0.00	1.00	0.079^{***}	-0.067^{***}	-0.036^{***}	-0.101^{***}	-0.041^{***}	-0.082^{***}	-0.164^{***}	-0.054^{***}	-0.045^{***}	0.000	0.034^{**}	1.000	
(13) In-center Hemodialysis	0.998	0.043	0.00	1.00	0.017^{***}	0.005	-0.013^{*}	-0.017^{**}	0.002	-0.002	0.006	0.012^{*}	0.014^{*}	-0.002	0.028^{***}	0.021^{***}	1.000

Notes:

1. $N = 17{,}611$ facility–years and 3,792 unique facilities. Correlations are pairwise (lower triangle) with two-tailed tests: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.
2. † The CRR summary stats are provided to show the distribution among ever-contracted facilities (N = 1,004) and do not imply that subsequent analyses are restricted to this subsample.

This specification allows us to test whether support intensity amplifies the curvature (H2a) or shifts the turning point rightward (H2b), and whether patient severity flattens the curve (H3a) or shifts the turning point leftward (H3b). We include both moderators (support intensity and patient severity) in a single model (2), as both moderators might operate simultaneously rather than independently. As suggested by (Ozer Balli and Sørensen, 2013; Montoya, 2019), excluding one moderator while testing the other risks omitted variable bias and confounded inference. By estimating the effects of both moderators in the same model, we capture boundary conditions and avoid attributing variance in the focal relationship to the wrong contingency factor. In addition, we also tested each moderator in separate models, which reported results consistent with model (2).

Estimation Approach

To confirm that panel models outperform alternative structural models, we first check if the dependent variable is stationary using a Fisher-type panel unit root test based on Augmented Dickey-Fuller statistics. The results reject non-stationarity ($p < 0.01$), confirming that the outcome variable is suitable for panel regression without additional differencing (see Table 4). After establishing stationarity, we assess the model specification and estimation methods. We checked for multicollinearity by computing Variance Inflation Factors (VIFs) and the Condition Index (CI), revealing all VIFs below 5 and CI below 30, indicating that multicollinearity is not a significant concern. We then compare the pooled ordinary least squares (OLS), random effects (RE), and fixed effects (FE) models. The Breusch-Pagan test shows significant unobserved heterogeneity ($p < 0.10$), which favors RE over OLS. The Hausman test ($p < 0.10$) further suggests that FE is preferable, as it addresses bias arising from correlation with regressors. See Table 5 for a summary.

TABLE 4 Fisher-Type Panel Unit-Root Test (Augmented Dickey–Fuller)

Statistic	p-value
Inverse χ^2 (P)	< 0.01
Inverse Normal (Z)	< 0.01
Inverse Logit t (L^*)	< 0.01
Modified Inverse χ^2 (P_m)	< 0.01

Notes. H_0: all panels contain unit roots; H_a: at least one panel is stationary.

Our panel is unbalanced. As explained in Section 4.1, we dropped data from 2021 to 2022 due to missing key variables such as QIP quality scores during COVID-19 pandemic. This pattern does not compromise the validity of our fixed-effects (FE) estimators. FE models remain consistent with unbalanced panels as they rely on within-facility variation over time (Hsiao, 2003; Wooldridge, 2010; Baltagi, 2008). The FE estimator handles unbalanced panels by applying within transformations to the available observations (Sta, 2019). Including above two years to force balance would reduce efficiency, inflate standard errors, and potentially introduce bias if the missingness is not random (Allison, 2001; Cameron and Miller, 2015). We use cluster-robust standard errors to ensure valid inference, maintaining both consistency and efficiency in the presence of unbalanced data (Cameron and Miller, 2015; Ibragimov and Müller, 2016).

5.2 | Endogeneity and Instrument Variables

A key empirical concern is the potential reverse causality between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$. Facilities experiencing deterioration of quality can react by increasing the contract RN ratio to address staff shortages, meet regulatory expectations, or recover from performance penalties. In this case, lower quality drives higher reliance on contract RNs rather than the other way around, leading to estimation biases. This issue is well documented in the literature on temporary nurse staffing and care outcomes (see, e.g., Senek et al. 2020; Vander Weerdt et al. 2023; Peng et al. 2023; Lu et al. 2018), underscoring the importance of addressing endogeneity arising from

TABLE 5 Model-Selection and Specification Diagnostics

Test	Decision Rule / Purpose	Result
Collinearity Diagnostics		
Variance Inflation Factors (VIF)	Multicollinearity a concern if VIF > 10	< 5
Condition Index (CI))	Multicollinearity a concern if CI > 30	< 30
Model Diagnostics		
Breusch-Pagan LM	Prefer RE to pooled OLS if $p < 0.10$	$p < 0.10$
Hausman	Prefer FE to RE if $p < 0.10$	$p < 0.10$

potential reverse causality.

5.2.1 | Instrumental Variable Estimation with Control Functions (IV-CF)

We address endogeneity using a control function (CF) estimator (also referred to as two-stage residual inclusion, 2SRI), following Terza et al. (2008) and Wooldridge (2015). This methodology is particularly well-suited for our context as it accommodates the multiple endogenous regressors arising from our nonlinear specification, including quadratic terms and interactions. The CF approach allows us to isolate the exogenous regressor in $\widetilde{\mathrm{CRR}}$ while accounting for unobserved factors that might simultaneously influence both staffing decisions and $\widetilde{\mathrm{QP}}$.

First Stage: Reduced-Form Equations

In our specification, we treat $\widetilde{\mathrm{CRR}}$ and its interactions with two moderating variables as potentially endogenous. Let each endogenous regressor be denoted as $X_{j,it}$ for $j \in \{1, \dots, M\}$, where M represents the total number of endogenous regressors. For each endogenous regressor, we estimate a first-stage reduced-form regression:

$$X_{j,it} = \pi_{j0} + \sum_{k=1}^{K} \pi_{jk} Z_{k,it} + \mathbf{W}_{it}^{\top} \boldsymbol{\pi}_j + \alpha_i + \delta_t + \upsilon_{j,it} \tag{3}$$

where $Z_{k,it}$ denotes the k-th excluded instrument with K representing the total number of instruments, $\mathbf{W}_{it}$ represents the vector of all exogenous variables including moderators and control variables, π_{j0} is the intercept for the j-th first-stage equation, π_{jk} captures the coefficient on the k-th instrument, $\boldsymbol{\pi}_j$ is the coefficient vector for exogenous controls, α_i and δ_t represent facility and year fixed effects respectively, and $\upsilon_{j,it}$ represents the first-stage residuals capturing unobserved factors affecting the endogenous regressor.

Structural Equation with CF

The second stage augments the structural equation with the first-stage residuals as control functions:

$$\widetilde{\mathrm{QP}}_{it} = \beta_0 + \sum_{j=1}^{M} \beta_j X_{j,it} + \sum_{j=1}^{M} \eta_j \hat{\upsilon}_{j,it} + \mathbf{W}_{it}^{\top} \gamma + \alpha_i + \delta_t + \varepsilon_{it} \tag{4}$$

where $\hat{\upsilon}_{j,it}$ denotes the fitted residuals from the j-th first-stage equation, η_j represents the control function coefficient for the j-th endogenous regressor, β_j captures the structural parameter of interest for each endogenous variable, γ contains coefficients for the exogenous variables, α_i and δ_t represent facility and year fixed effects respectively, and ε_{it} is the idiosyncratic error term.

A statistically significant coefficient η_j provides direct evidence of endogeneity for the corresponding regressor $X_{j,it}$. Under the control function approach, the structural parameters β_j are consistently estimated even in the presence of endogeneity, as the residuals $\hat{v}_{j,it}$ control for the correlation between the endogenous regressors and the error term. This specification ensures that our estimates of the inverted U-shaped relationship and moderating effects remain unbiased despite the potential reverse causality between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$.

5.3 | IV Selection

To address potential endogeneity in our estimation models, we employ the administrative contract ratio as an instrumental variable. This ratio captures the proportion of FTE administrative staff employed through contracts, derived from Medicare cost reports. Federal guidelines require the reporting of FTEs from both contracted and employed staff for key roles, including administration, with detailed logging of hours for personnel serving in each role (Cen, 2022). This uniform reporting ensures that the administrative contract ratio accurately measures each dialysis center's reliance on contracted administrative personnel. Facilities that employ contract RNs for clinical work have already adopted a flexible, outsourced staffing approach (i.e., an "outsourcing culture"). Extending this model to administrative functions represents a natural progression consistent with their overall staffing philosophy. Consequently, the administrative contract ratio is expected to correlate with the contract RN ratio, thereby meeting the instrument relevance criterion. Furthermore, administrative FTEs focus predominantly on supervision and management, not direct patient care. Hence, the administrative contract ratio is likely independent of quality outcomes, satisfying the exogeneity requirement.

Our second instrument is the average wage for RNs in corresponding regions (RN wage). This variable captures local labor market conditions and the cost of employed RNs. When RN wages are high, facilities often face challenges in recruiting and retaining employed RNs and may consequently rely heavily on contract RNs, even at increased cost (Bourbonniere et al., 2006). At the same time, contract RNs themselves are also drawn to higher-wage regions, which reinforces the relationship between the RN wage and the use of contract RNs. In addition, RN wages are primarily driven by local patient volumes and competition among healthcare providers rather than the performance or quality of individual facilities, making them a highly relevant and clearly exogenous instrument for the contract RN ratio. Although few studies directly quantify whether contract nurses prefer high-wage regions, existing evidence suggests that temporary nurses are highly sensitive to wage levels. Higher RN wages serve as a much stronger incentive for nurses to choose temporary positions (Bellemore, 1998). Industry reports also suggest that areas with higher RN wages or greater RN shortages are more likely to attract contract or temporary nurses (Sorelle, 2015).

All endogenous models are estimated using a CF approach in Stata 19 with fixed effects estimators (`xtreg, fe` and `xtivreg, fe`). Results from Durbin–Wu–Hausman tests reject exogeneity, confirming the need for IV/CF estimation in our context (Durbin, 1954; Wu, 1973; Hausman, 1978). For each endogenous regressor, we fit a separate first-stage model and include its residual in the outcome equation; the significance of these residual terms constitutes a direct control-function test of endogeneity (Rivers and Vuong, 1988; Terza et al., 2008; Wooldridge, 2015). To assess instrument strength, we report the first-stage model's *excluded-instruments* F-statistic for each endogenous variable separately. Consistent with conventional practice, values at or above 10 indicate that weak-instrument bias is unlikely (Staiger and Stock, 1994; Stock and Yogo, 2002). In our specifications, all first-stage models' F-statistics exceed 10. The Sargan–Hansen test does not reject the exclusion restriction ($p > 0.10$), supporting that the instruments satisfy the validity requirement in Eq. (3). Under-identification tests strongly reject the null hypothesis ($p < 0.001$), indicating that the instruments are sufficiently correlated with the endogenous variable. The excluded-instruments F-statistic consistently exceeds conventional thresholds, demonstrating strong instrument relevance (**?**).

Table 6 reports the first-stage diagnostics for the linear, quadratic, and interaction specifications used to test our hypotheses, specifically presenting $\widetilde{\text{CRR}}$, $\widetilde{\text{CRR}}^2$, and their interactions with SI and PS. Because conventional Cragg–Donald and Stock–Yogo statistics are not valid in the presence of heteroskedasticity, clustering, or more than three endogenous regressors, we rely instead on Kleibergen–Paap LM and Wald tests, which remain appropriate in this context. These tests confirm identification at the 5% level and do not indicate weak instruments.

TABLE 6 Instrumental Variable Diagnostics

Panel A. IV Tests (p-values)	Main Model	Full Model
Anderson–Rubin Wald	< 0.01	< 0.01
Stock–Wright LM S	< 0.01	< 0.01
Under-identification (overall)	< 0.05	< 0.01
Over-identification (Hansen J)	> 0.10	> 0.10
DWH test	< 0.10	< 0.10
Panel B. First-Stage Diagnostics		
Excluded instruments (F-statistic)	> 100	> 100
First-stage residual (p-value)	$p < 0.10$	$p < 0.10$

Notes: Panel B summarizes diagnostics for all first-stage regressions; all excluded-instrument F-statistics and first-stage (CF approach) residuals meet the prespecified diagnostic criteria.

6 | RESULTS

This section presents the empirical results from our panel models and instrumental variable estimations. Table 7 reports three specifications: (0) a baseline model with controls only, (1) a quadratic model in Eq. (1) testing the inverted U-shaped effect of the contract RN ratio (H1), and (2) a fully interacted model in Eq. (2) incorporating support intensity and patient severity as moderators (H2a/b and H3a/b). We first examine the primary effect of contract RN ratio (Section 6.1), followed by moderation effects (Sections 6.2 and 6.3), and conclude with an extended cost-quality efficiency analysis (Section 6.4).

6.1 | Inverted U-Shaped Relationship Between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$

Model (1) in Table 7 shows that the coefficient of $\widetilde{\text{CRR}}$ is positive and significant ($\beta_{11} = 9.211$, $p < 0.01$), while the coefficient of the squared term is negative and significant ($\beta_{12} = -33.940$, $p < 0.01$), suggesting an inverted U-shaped relationship between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$.

To further validate the curvature, Lind and Mehlum (2010) proposed a three-step validation test: (1) test whether the quadratic term is significant and has the expected sign; (2) ensure the turning point lies within the observed range of the independent variable (Fieller, 1954); and (3) verify that the slope is significantly positive at the lower bound and significantly negative at the upper bound. Haans et al. (2016) extended this approach by adding an additional step: (4) a local slope robustness test to confirm that the marginal effect changes sign in the immediate neighborhood of the turning point. The purpose of this localized slope test is to detect rare but consequential violations of U-shaped patterns, such as flattening near the extremum or misleading curvature driven by sparse data.

The three-step procedure proposed by Lind and Mehlum (2010) has been applied in prior OM research to test U-shaped relationships (Pal et al., 2024). To strengthen our analysis, we adopt the extended four-step approach and implement it using the IV-FE quadratic specification of Model (1), with the results shown in Table 8. The results pass all these steps and jointly support the inverted U-shaped relationship between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$ (H1).

TABLE 7 Main Specification: Fixed-Effects Instrumental Variables Estimates

Variable	(0)	(1)	(2)
$\widetilde{\text{CRR}} \mid \beta_{11}/\beta_{21}$	0.362 ***	9.211 ***	10.900 ***
	(0.096)	(3.379)	(3.723)
$\widetilde{\text{CRR}}^2 \mid \beta_{12}/\beta_{22}$		−33.940 ***	−97.714 ***
		(12.980)	(34.720)
$\widetilde{\text{CRR}} \cdot \text{SI} \mid \beta_{25}$			36.396 ***
			(7.402)
$\widetilde{\text{CRR}}^2 \cdot \text{SI} \mid \beta_{26}$			−291.278 ***
			(80.530)
$\widetilde{\text{CRR}} \cdot \text{PS} \mid \beta_{27}$			−49.611 ***
			(14.630)
$\widetilde{\text{CRR}}^2 \cdot \text{PS} \mid \beta_{28}$			169.212 ***
			(53.750)
$\text{SI} \mid \beta_{13}/\beta_{23}$	0.042 ***	0.042 ***	0.073 ***
	(0.008)	(0.008)	(0.010)
$\text{PS} \mid \beta_{14}/\beta_{24}$	−0.085 ***	−0.082 ***	−0.111 ***
	(0.009)	(0.009)	(0.011)
Total Nurse Aides†	0.109	−1.100	−1.934 *
	(0.906)	(0.993)	(1.120)
Total Social Workers	−0.003	−0.001	−0.005
	(0.003)	(0.004)	(0.003)
Total Physicians	0.002	−0.001	0.004
	(0.003)	(0.003)	(0.003)
Drugs Expense	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Laboratory Expense†	0.245 ***	0.277 ***	0.324 ***
	(0.019)	(0.022)	(0.026)
Week Shift†	−0.038	−0.040	−0.016
	(0.042)	(0.042)	(0.041)
Years Since Certification†	0.152	−0.089	0.448
	(2.900)	(2.920)	(2.910)
Ownership	−0.001	0.001	−0.004
	(0.004)	(0.004)	(0.004)
In-center Hemodialysis	0.046 ***	0.041 ***	0.038 ***
	(0.015)	(0.015)	(0.016)
F-statistic	684.80	623.83	457.60
R^2-statistic	0.5431	0.5433	0.5441
State FE	✓	✓	✓
Year FE	✓	✓	✓
N of facilities		3,792	
N of observations		17,611	

Clustered robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

† Variable scaled (e.g., times 1,000) for presentation purposes.

TABLE 8 Four-Step Validation Test for Inverted U-Shaped Relationship

Step	Test Name	Thresholds	Result
1	Quadratic Term Significance Test	β_{12} must be negative and significant at $p < 0.10$.	$\beta_{12} = -33.940$, $p < 0.01$
2	Fieller Confidence Interval	Turning point confidence interval must lie within observed range, tested at $p < 0.10$.	Turning point = 0.136 95% CI: [0.127, 0.144] Observed range: [0.0, 0.2]
3	Boundary Slope Sign Test (U-test)	Slopes at X_{min} and X_{max} must be significant and of opposite sign at $p < 0.10$).	At X_{min}: positive slope, $p < 0.05$ At X_{max}: negative slope, $p < 0.05$
4	Local Derivative Sign Test	Slopes around $x^* \pm 5\%$ must be significant and of opposite sign at $p < 0.10$).	At $x^*-5\%$: positive slope ($t = 4.53$, $p < 0.05$). At $x^*+5\%$: negative slope ($t = 2.94$, $p < 0.10$).

Notes. Steps follow Lind and Mehlum (2010) and Haans et al. (2016). x^* = turning point.

6.2 | The Moderation Effect of Support Intensity

We next evaluate whether Support Intensity (SI) moderates the relationship between the contract RN ratio and quality performance, as predicted in H2a and H2b. The fully interacted quadratic model in Eq. (2) (Model (2) in Table 7) introduces interaction terms between $\widetilde{\text{CRR}}/\widetilde{\text{CRR}}^2$ and SI.

Results for H2a: Evidence Supports Curvature Amplification

The results in Table 7 show that the linear interaction term ($\widetilde{\text{CRR}} \cdot \text{SI}$) has a positive coefficient that is marginally significant ($\beta_{25} = 36.396$, $p < 0.10$), suggesting that SI strengthens the positive marginal effect of $\widetilde{\text{CRR}}$. The quadratic interaction term ($\widetilde{\text{CRR}}^2 \cdot \text{SI}$) has a negative coefficient that is highly significant ($\beta_{26} = -291.278$, $p < 0.01$), indicating that SI steepens the curvature of the inverted U-shaped relationship (Haans et al., 2016; Pal et al., 2024). Together, these coefficients imply that facilities with stronger PCT support experience larger quality gains at low-to-moderate $\widetilde{\text{CRR}}$ but also faster quality deterioration at high $\widetilde{\text{CRR}}$. This pattern supports H2a, which predicts that SI amplifies the curvature of the $\widetilde{\text{CRR}}$–$\widetilde{\text{QP}}$ relationship.

Together, these coefficients imply that facilities with stronger PCT support experience larger quality gains at low-to-moderate $\widetilde{\text{CRR}}$ but also faster quality deterioration at high $\widetilde{\text{CRR}}$. This pattern supports H2a, which predicts that SI amplifies the curvature of the $\widetilde{\text{CRR}}$–$\widetilde{\text{QP}}$ relationship.

Results for H2b: No Evidence of Turning Point Shift

We next examine whether SI shifts the turning point using the conditional optimum formula by computing the first derivative of the model (Haans et al., 2016):

$$\widetilde{\text{CRR}}^* = -\frac{\beta_{21} + \beta_{25} \cdot \text{SI} + \beta_{27} \cdot \text{PS}}{2 \cdot (\beta_{22} + \beta_{26} \cdot \text{SI} + \beta_{28} \cdot \text{PS})}. \tag{5}$$

To test whether the turning point changes significantly with the moderator, we derive the derivative of Eq. (5) with respect to SI. The rate of change of the turning point with respect to the moderator is as follows (Haans et al., 2016):

$$\frac{\partial \widetilde{\text{CRR}}^*}{\partial \text{SI}} = \frac{(\beta_{21} \cdot \beta_{26} - \beta_{22} \cdot \beta_{25}) + (\beta_{26} \cdot \beta_{27} - \beta_{25} \cdot \beta_{28}) \cdot \text{PS}}{2 \cdot (\beta_{22} + \beta_{26} \cdot \text{SI} + \beta_{28} \cdot \text{PS})^2}. \tag{6}$$

Since the denominator in Eq. (6) is always positive, a necessary and sufficient condition for a rightward shift of turning point is that $(\beta_{21} \cdot \beta_{26} - \beta_{22} \cdot \beta_{25}) + (\beta_{26} \cdot \beta_{27} - \beta_{25} \cdot \beta_{28}) \cdot \text{PS}$ is significantly greater than 0. Evaluating this expression at the mean level of PS, we find that this term is positive but not significantly different from 0 (coefficient = 381.457, $p = 0.224 > 0.10$). This indicates that the location of the turning point remains stable and the observed shift is not statistically significant, providing no support for H2b.

The top subfigure of Figure 5 illustrates the moderating effects of support intensity on the curvilinear relationship between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$. This plot is generated using the coefficients from Model (2) in Table 7, with PS held at its mean value. The results indicate that higher support intensity amplifies the curvilinear effect of $\widetilde{\text{CRR}}$ within its empirically relevant range (0.0 to 0.1). In practical terms, facilities with stronger support staff presence consistently achieve higher quality outcomes at comparable levels of fissuring. A strong PCT presence enhances a facility's ability to integrate contract RNs and realize early gains in quality. However, it also intensifies coordination burdens as fissuring increases, steepening the curve. Although the turning point of the curve appears to shift rightward visually, this shift is not statistically significant.

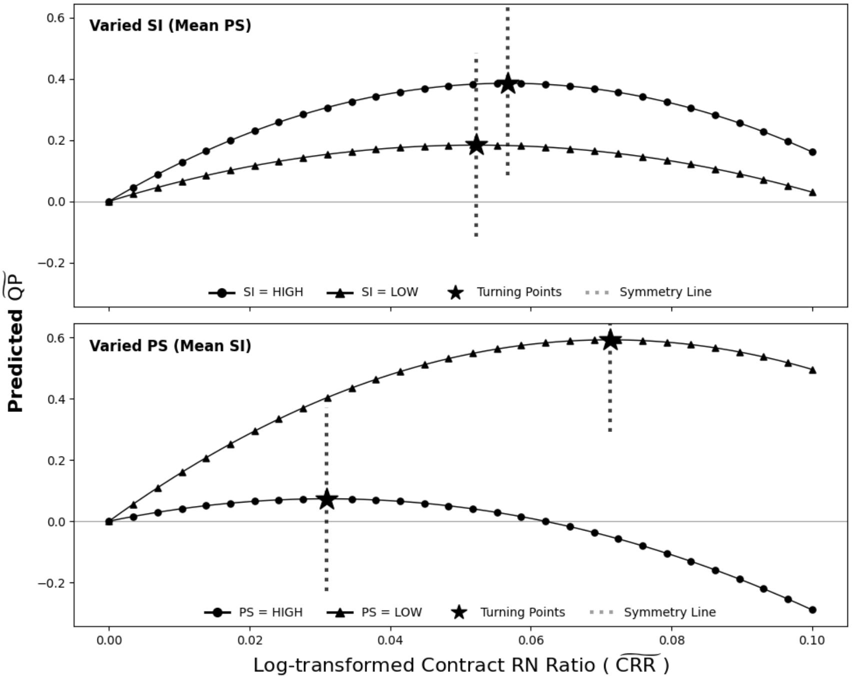

FIGURE 5 Moderating Effects of Support Intensity and Patient Severity

6.3 | The Moderation Effect of Patient Severity

We now evaluate whether Patient Severity (PS) moderates the relationship between the contract RN ratio and quality performance, as predicted in H3a and H3b. The model in Eq. (2) (Model (2) in Table 7) includes interaction terms between $\widetilde{\text{CRR}}/\widetilde{\text{CRR}}^2$ and SI.

Results for H3a: Evidence Supports Curvature Compression

The results in Table 7 show that the linear interaction term ($\widetilde{\text{CRR}} \cdot \text{PS}$) has a negative and significant coefficient ($\beta_{27} = -49.611$, $p < 0.01$), and the quadratic interaction term ($\widetilde{\text{CRR}}^2 \cdot \text{SI}$) has a positive and significant coefficient ($\beta_{28} = 169.212$, $p < 0.01$). This pattern indicates that patient severity flattens the inverted U-shaped relationship by reducing quality gains at low $\widetilde{\text{CRR}}$ and quality losses at high $\widetilde{\text{CRR}}$, consistent with H3a.

Results for H3b: Evidence Supports Leftward Shift of Turning Point

We next examine whether PS shifts the turning point using the derivative of Eq. (5) with respect to PS, as follows:

$$\frac{\partial \widetilde{\text{CRR}}^*}{\partial \text{PS}} = \frac{(\beta_{21} \cdot \beta_{28} - \beta_{22} \cdot \beta_{27}) + (\beta_{25} \cdot \beta_{28} - \beta_{26} \cdot \beta_{27}) \cdot \text{SI}}{2 \cdot (\beta_{22} + \beta_{26} \cdot \text{SI} + \beta_{28} \cdot \text{PS})^2}. \tag{7}$$

Since the denominator in Eq. (7) is always positive, a necessary and sufficient condition for a leftward shift of turning point is that $(\beta_{21} \cdot \beta_{28} - \beta_{22} \cdot \beta_{27}) + (\beta_{25} \cdot \beta_{28} - \beta_{26} \cdot \beta_{27}) \cdot \text{SI}$ is significantly smaller than 0. Evaluating this expression at the mean level of PS, we find that this term is negative and marginally statistically significant (coefficient $= -3003.297$, $p = 0.075 < 0.10$). This suggests that the location of the turning point does shift toward the left, thereby supporting H3b.

The bottom subfigure of Figure 5 visually summarizes the above moderating effects of patient severity on the curvilinear relationship between $\widetilde{\text{CRR}}$ and $\widetilde{\text{QP}}$. This plot is generated using the coefficients from Model (2) in Table 7, with IS held at its mean value. As seen, the curve for high patient severity facilities is significantly flatter and suppressed, reflecting reduced potential benefits from $\widetilde{\text{CRR}}$. Meanwhile, the peak of the curve shifts leftward, suggesting lower tolerance for contract staffing under greater patient complexity. In practical terms, facilities serving sicker patients should adopt a more conservative approach to fissuring, as even moderate reliance on contract RNs can erode quality when coordination requirements are intense.

To estimate the optimal CRR, we use the full specification from Model (2) and evaluate it at the mean values of SI and PS. The resulting turning point for the log-transformed $\widetilde{\text{CRR}}$ is 0.0558, which corresponds to an optimal CRR of approximately 13.8% on the original scale. In other words, Model (2) suggests that, under average conditions of SI and PS, the ideal contract RN ratio is about 14%. Naturally, this optimal point will shift as SI and PS vary across facilities.

6.4 | Extended Study: Cost-Quality Analysis

To complement our quality-focused analysis, we explore the cost implications of alternative staffing configurations. This extended study evaluates how varying levels of contract RN ratio (CRR) and Support Intensity (SI) jointly influence both quality performance and labor costs, providing a practical decision-making perspective for dialysis facility managers.

To achieve this, we conceptualize a representative facility using sample means: $\overline{N} = 5$ essential clinical staff (sample mean = 4.99) and $\overline{S} = 19$ dialysis stations (sample mean = 19.35). Using the Bureau of Labor Statistics for 2023-2024 and industry benchmarks (U.S. Bureau of Labor Statistics, 2024; Advisory Board, 2022), we estimate annual salaries of $w_{PRN} = 89,000$ for each permanent RN, $w_{PCT} = 47,000$ for each PCT, and $w_{CRN} = 178,000$ for each contract RN.

Using these inputs, we calculate both quality outcomes and total labor costs as functions of CRR and SI. Specifically, we vary CRR from 0 to 0.2 in increments of 0.01 and SI from 0 to 0.12 in increments of 0.01. For each point on the grid, the quality is calculated using Model (2) in Table 7 with SI held at its mean value, and the total labor cost is computed by:

$$\text{Cost} = \overline{N} \cdot \text{CRR} \cdot w_{CRN} + \overline{N} \cdot (1 - \text{CRR}) \cdot w_{PRN} + \overline{S} \cdot \text{SI} \cdot w_{PCT}. \tag{8}$$

For interpretation, a 0.01 increase in CRR corresponds to \$4,450 in additional cost, and a 0.01 increase in SI corresponds to \$8,930.

Figure 6 plots isoquality contours (curved lines) and isocost lines (straight lines), illustrating trade-offs between quality and cost. As seen, multiple staffing mixes can achieve the same quality target, but cost efficiency varies substantially across configurations. For example, a QP of 2.2 can be achieved by (1) a low-CRR and high-SI (CRR ≈ 0.075 and SI ≈ 0.12) or (2) a high-CRR and low-SI (CRR ≈ 0.175 and SI ≈ 0.05). Both deliver similar quality, but the first option is much more expensive.

The most cost-efficient point to achieve a QP of 2.2 lies near CRR ≈ 0.12 and SI ≈ 0.035, balancing moderate fissuring with lean support staffing. Beyond CRR ≈ 0.12, marginal cost escalates sharply, and additional SI becomes the primary lever for quality improvement.

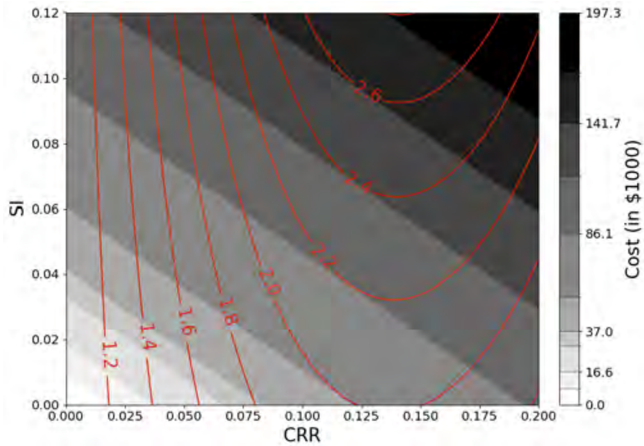

FIGURE 6 Cost–Quality Efficiency Analysis

These results underscore that cost efficiency and quality optimization require joint calibration of CRR and SI. Over-reliance on contract RNs or excessive investment in support staff yields diminishing returns. Instead, a moderate fissuring strategy, complemented by targeted support, achieves superior cost–quality balance. Facilities should periodically reassess this balance as labor market conditions and patient complexity evolve.

7 | ROBUSTNESS CHECKS

We conducted a series of robustness checks to verify that our findings reflect underlying structural relationships rather than methodological artifacts, and to address potential concerns about temporal stability stemming from pandemic-related data gaps in the main analysis (Leamer, 1983; Lu and White, 2014).

7.1 | Alternative IV Models

Although our main analysis employs two-stage residual inclusion (2SRI) to accommodate the nonlinear specifications, the validity of our findings should not depend on this particular estimation choice. Hence, we re-estimated our models using alternative IV approaches with results presented in Table 9.

The two-stage least squares (2SLS) results presented in Column (1) of Table 9 confirm our main findings. The inverted U-shaped relationship remains significant with $\beta_{21} = 10.900$ ($p < 0.05$) and $\beta_{22} = -97.710$ ($p < 0.05$). In addition, all interaction terms remain consistent with main analysis results, with support intensity interactions of $\beta_{25} = 36.400$ ($p < 0.01$) and $\beta_{26} = -291.300$ ($p < 0.01$), as well as patient severity interactions of $\beta_{27} = -49.610$ ($p < 0.01$) and $\beta_{28} = 169.200$ ($p < 0.05$).

The limited information maximum likelihood (LIML) results in Column (2) of Table 9 address weak instrument bias, a common challenge in models with multiple endogenous variables. Although the coefficient magnitudes increase slightly under LIML estimation, the results are consistent with the main analysis, confirming the inverted U-shape with $\beta_{21} = 22.300$ ($p < 0.05$)

and $\beta_{22} = -204.300$ ($p < 0.05$). All moderating effects retain hypothesized directions and significance.

7.2 | Random-Effects Models

The random effects IV regression in Column (3) of Table 9 exploits both within-facility and between-facility variations, providing insight into whether our findings depend solely on temporal changes within facilities or also reflect differences across facilities (Hsiao, 2003; Wooldridge, 2010). While some coefficients become insignificant under random effects (e.g., contract RN ratio of $\beta_{21} = 11.41$ ($p > 0.1$)), other coefficients largely hold the same directions. The quadratic contract RN ratio maintains marginal significance with $\beta_{22} = -141.800$ ($p < 0.10$), and the patient severity interactions remain significant with $\beta_{27} = -44.660$ ($p < 0.05$) and $\beta_{28} = 170.100$ ($p < 0.05$). These smaller coefficients from random-effects models align with our Hausman tests favoring fixed effects, suggesting that unobserved facility characteristics might affect staffing choices.

7.3 | Alternative Quality Metrics and Temporal Validation

To test the robustness of our results, we further used alternative clinical quality measures spanning different time periods. This approach addresses two critical concerns simultaneously: whether our findings depend on the specific composite quality measure used in the main analysis, and whether the relationships hold consistently across different temporal contexts despite the pandemic-related data gap.

In Column (4) of Table 9, we present results with the dialysis adequacy (Kt/V), which measures the efficiency of toxin removal during dialysis, representing the most direct clinical indicator of treatment effectiveness. The results were derived from 2015–2020 data, providing an uninterrupted pre-pandemic window that complements our main analysis period. The results confirm the inverted U-shaped relationship with $\beta_{21} = 48.900$ ($p < 0.01$) and $\beta_{22} = -312.600$ ($p < 0.05$), as well as moderating effects of support intensity and patient severity. This continuous six-year span offers important evidence that our findings are robust and not influenced by the missing observations from 2021 to 2022.

In Column (5) of Table 9, we present results with the standardized transfusion ratio (STR), which is defined as the observed transfusions relative to expected transfusions at the focal dialysis center. It reflects clinical practice patterns that can be affected by both clinical management quality and care coordination. As the STR data is only available from 2019 onward, it provides complementary temporal coverage to the Kt/V analysis. Results wiith STR also confirm the inverted U-shape with $\beta_{21} = 38.210$ ($p < 0.01$) and $\beta_{22} = -310.500$ ($p < 0.01$) with consistent supports to moderating effects.

Collectively, these robustness checks address the primary threats to our model specifications. The consistency across alternative IV models mitigates concerns over weak instruments or misspecification in addressing endogeneity. Although the random-effects models show some attenuation, they confirm that our findings reflect operational relationships within each facility rather than spurious between-facility variations. Most importantly, the use of alternative quality metrics across different time periods provides compelling evidence of our core insights. Specifically, the inverted U-shaped relationship and moderation effects of support intensity/patient severity reflect how a fissured workforce affects care delivery in dialysis settings.

8 | DISCUSSION

This section brings together our findings to highlight their practical and theoretical significance. We first translate the results into actionable guidance for managers designing hybrid workforces in high-skill, quality-critical settings. We then examine the theoretical contributions that refine OM perspectives on outsourcing and workforce design. Next, we consider broader implications for industries where fissured workforces are prevalent. Finally, we acknowledge the study's limitations and propose

TABLE 9 Robustness Check Results

Variable	(1)	(2)	(3)	(4)	(5)
$\widetilde{\text{CRR}} \mid \beta_{21}$	10.900 **	22.300 **	11.410	48.900 ***	38.210 ***
	(5.009)	(10.640)	(8.204)	(16.630)	(4.823)
$\widetilde{\text{CRR}}^2 \mid \beta_{22}$	−97.710 **	−204.300 **	−141.800 *	−312.600 **	−310.500 ***
	(45.140)	(98.430)	(82.840)	(137.800)	(43.750)
$\widetilde{\text{CRR}} \cdot \text{SI} \mid \beta_{25}$	36.400 ***	52.220 ***	13.300	105.400 ***	56.550 ***
	(11.170)	(19.590)	(15.450)	(28.910)	(13.510)
$\widetilde{\text{CRR}}^2 \cdot \text{SI} \mid \beta_{26}$	−291.300 ***	−526.800 **	−323.800 **	−747.100 **	−683.700 ***
	(104.100)	(219.600)	(160.900)	(298.300)	(110.700)
$\widetilde{\text{CRR}} \cdot \text{PS} \mid \beta_{27}$	−49.610 ***	−77.650 **	−44.660 **	−121.800 **	−64.160 ***
	(18.610)	(33.390)	(19.310)	(52.050)	(17.510)
$\widetilde{\text{CRR}}^2 \cdot \text{PS} \mid \beta_{28}$	169.200 **	279.800 **	170.100 **	410.700 **	285.700 ***
	(71.090)	(129.200)	(74.130)	(199.700)	(74.550)
$\text{SI} \mid \beta_{23}$	0.073 ***	0.098 ***	0.037 *	0.253 ***	0.076 ***
	(0.013)	(0.026)	(0.021)	(0.036)	(0.015)
Severity $\mid \beta_{24}$	−0.111 ***	−0.128 ***	−0.115 ***	−0.284 ***	−0.140 ***
	(0.013)	(0.023)	(0.015)	(0.035)	(0.015)
F-statistic	375.80	375.80	5936.39	29.74	236.29
Controls	✓	✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N of observations		17,611		14,849	8,513

Clustered robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

† Variable scaled (e.g., times 1,000) for presentation purposes.

directions for future research.

8.1 | Managerial Insights

Our evidence shows that fissuring in core, high-skill roles can be viable and even performance-enhancing with the right mix of contract RNs and the right organizational structures. In dialysis centers, contracted RNs are deeply embedded in the heart of clinical care. Achieving this balance requires facilities to closely monitor quality outcomes and continuously adjust operational practices to identify the optimal mix. While our study and prior research suggest that this "sweet spot" occurs at roughly a 14% contract RN ratio, each organization must account for its unique operational characteristics and fine-tune staffing levels to sustain quality performance.

In tightly coupled service settings such as dialysis care, RNs and PCTs work closely to co-deliver care, though they are responsible for different parts of the care delivery process. Facilities that maintained adequate auxiliary PCT staffing preserved local knowledge and tacit coordination, creating the conditions for contracted RNs to bring added flexibility and new expertise to clinical care. Compared with RNs, PCTs are largely employed by dialysis centers at a lower pay scale. To address the shortage and hence frequent turnovers of RNs, organizations can increasingly use PCTs as buffer and institutionalize tacit knowledge to retain critical expertise despite RN turnovers.

Patient severity adds another layer of nuance. Facilities serving patients with higher clinical severity face compressed decision windows and heightened coordination demands, which reduce tolerance for fissuring. In these environments, even moderate reliance on contract RNs can erode quality unless offset by strong relational and structural supports. Conversely, facilities with less severe case mixes have greater flexibility to leverage fissuring without compromising outcomes. This means that fissuring decisions cannot be based on cost considerations alone; they must account for the interplay between workforce design, support intensity, and patient severity.

These findings underscore that cost savings from fissuring cannot be evaluated in isolation. If support to RNs is underfunded, apparent efficiencies are offset by reliability losses and rework, patterns consistent with capability-erosion mechanisms documented in prior OM research (Handley, 2012). In contrast, when organizations deliberately allocate resources to support roles, fissuring becomes a lever for expanding capacity and enriching knowledge without compromising dependability. Therefore, the managerial task is to choose a fissuring-support combination that balances collaboration demand, budget constraints, and service-level requirements. As case mix, volumes, and technology continue to evolve, the balance between fissuring and support must adapt. The efficient frontier is not fixed but shifts over time, underscoring the need for continuous monitoring and periodic recalibration rather than relying on a one-time organizational design. Facilities serving patients with higher clinical severity should adopt a more conservative approach to fissuring, as their narrower margin for coordination errors makes strong support structures and lower contract ratios essential for sustaining quality.

8.2 | Theoretical Insights

This study contributes to OM theory by advancing our understanding of fissured workforces in high-skill, quality-critical settings. First, it challenges the traditional core/non-core dichotomy that has long guided outsourcing decisions (Weil, 2014; Abraham and Taylor, 1996). Our findings show that even core roles can be partially outsourced without compromising performance, provided that coordination capacity and support structure are in place. This perspective is aligned with research on leveraging complementarities between governance and capability (Parmigiani, 2007; Holcomb and Hitt, 2007), positioning platform-enabled and on-demand labor as integral components of the operating system rather than as ancillary add-ons (Benjaafar and Hu, 2020; Altman et al., 2023).

Second, we establish an inverted U-shaped relationship between fissuring and quality outcomes. Moderate fissuring can relieve workload, introduce fresh expertise, and enhance flexibility. However, beyond an optimal range, these benefits diminish and reverse as excessive reliance on a fissured workforce erodes team cohesion, tacit knowledge, and process stability. This curvilinear pattern refines capability-loss arguments in outsourcing literature by specifying where benefits peak and why they decline (Handley, 2012). It echoes evidence that safety/quality can remain stable up to moderate agency use but deteriorate past a certain threshold (see, e.g., Bae et al. 2010). As such, our work aligns with OM research demonstrating that hybrid and on-demand workforces create value only when supported by careful allocation and coordination (Lu et al., 2023). Our study also complements recent observations that fissuring has moved beyond traditional low-skill, peripheral, or franchise contexts (Weil, 2014; Massimino and Lawrence, 2019; Handley et al., 2022; Mishra et al., 2020).

Third, we identify the organizational mechanisms that moderate the effects of fissuring. Support intensity, embodied in stable auxiliary roles and integration routines, buffers the coordination costs associated with rotating contractors, preserves local knowledge, and sustains tacit coordination. These mechanisms explain how fissuring can coexist with operational reliability, extending relational coordination and team-learning theories into the domain of workforce design. By articulating how coordination capacity conditions fissuring outcomes in high-skill, quality-critical settings, we extend the fissured-workplace concept into the core of operations (Weil, 2014) and advance a boundary-spanning view of capability retention alongside dual/concurrent sourcing logics (Parmigiani, 2007; Holcomb and Hitt, 2007; Handley, 2012). Collectively, these insights support an emerging paradigm that treats the workforce as a flexible resource configured across organizational boundaries to optimize performance (Benjaafar and Hu, 2020).

8.3 | Extended Implications

The implications of our findings extend beyond healthcare to other industries where fissured workforces are common, such as IT services, consulting, manufacturing, and franchising (Altman et al., 2023). The central principle is that fissuring, even in core roles, is not inherently detrimental. Its success depends on whether organizations create conditions that preserve continuity and coordination under varying collaboration demands. While the specific form of support will differ by industry, the underlying mechanism remains the same: structured onboarding to accelerate alignment with local routines (Klein and Heuser, 2008), cross-role training to build shared knowledge and flexibility (Olivella and Nembhard, 2016), and standardized communication protocols or digital platforms to reduce interface frictions and maintain cohesion across organizational boundaries (Faraj and Xiao, 2006; Bjørn et al., 2014).

Viewed through a decision-making lens, these mechanisms are not optional add-ons but strategic investments that enable firms to capture the benefits of a fissured workforce without hollowing out critical capabilities (Handley, 2012). This perspective considers fissuring as part of a broader workforce ecosystem rather than a cost-cutting tactic, aligning with emerging OM research that treats labor as a configurable resource spanning organizational boundaries. As fissured work arrangements proliferate globally, the challenge for both managers and scholars is to identify governance choices and integration practices that convert flexibility into dependable performance. Our findings provide a foundation for this agenda by specifying the conditions under which fissuring enhances rather than undermines operational reliability. Future research should also explore additional moderators and examine how advanced training programs, knowledge retention systems, and cultural initiatives that integrate external workers can expand the conditions under which fissuring remains effective.

8.4 | Limitations and Future Research

Similar to other empirical studies, our study is subject to limitations. In the following, we discuss several key limitations that warrant attention and open avenues for future research.

First, our empirical context focuses on the RN-PCT pair in outpatient dialysis centers. Although this setting offers ideal conditions for studying fissured workforces in high-skill, team-based operations, the coordination mechanisms and knowledge transfer patterns observed here may not generalize to other healthcare domains or industries with different team structures. Future research should examine whether similar patterns emerge in contexts, such as physician-nurse collaborations in acute care or engineer-technician teams in manufacturing.

Second, our quality measure, while comprehensive and standardized through the CMS QIP scoring system, primarily captures clinical and operational outcomes. It does not directly reflect patient satisfaction or employee well-being, which may respond differently to fissuring. Incorporating perspectives from multiple stakeholders could provide a more holistic understanding of fissuring's consequences.

Third, our measurement of contract staffing relies on FTE-based ratios from Medicare cost reports, which cannot fully capture nuances such as contract duration, experience level, or agency affiliation and pay rate. These factors could likely influence how quickly contract staff integrate into local routines and how much tacit knowledge is lost or retained. Future studies should leverage richer data sources or mixed-method approaches to capture these dynamics.

Finally, the two-year gap in our panel due to COVID-19 disruptions limits our ability to assess how extreme shocks affect fissuring dynamics. The pandemic likely altered both the reliance on contract labor and the operational environment in ways that merit dedicated study. Future research should also explore additional moderators and examine how advanced training programs, knowledge retention systems, and cultural initiatives that integrate external workers can expand the conditions under which fissuring remains effective.

Despite these limitations, our findings provide strong evidence that moderate fissuring, when supported by robust coordination mechanisms, can enhance rather than compromise service quality in high-skill operations. This insight lays the groundwork for a broader research agenda on how organizations can balance flexibility and reliability in increasingly fissured workforce ecosystems.

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Quantitative Investment Strategy Analysis based on Machine Learning for Share Dealing

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Abstract

In the fluctuated stock market, the maximum profits cannot be guaranteed by long-term holding stocks. Applying a quantitative investment strategy for frequent trading could increase investors' profits effectively. In this paper, the machine learning model is used to predict stock prices, and an experiment is conducted to compare the effectiveness of different share dealing strategies, including a variety of quantitative investment frequent trading strategies and long-term holding strategies. The experiment results show that the frequent trading strategy can increase stock profits effectively, while the real profits will be affected by the prices changing trend of stocks, the prediction accuracy of the simulation and the strategies of investors.

Keywords: machine learning, stocks, quantitative investment, frequent trading

1 Introduction

Driven by the wave of Reform and Opening and economic globalization, the Chinese market has been built and developed prosperously starting from scratch after over three-decades' development. It has become an important part of the national economy. The scale of the securities market has been enlarged gradually, and regulations have been improved step by step accordingly. As a consequence, the securities market developed healthily nowadays based on the right regulations after the comprehensive revolution [1,2]. As an important part of the securities market, the price fluctuation shows the trend of macroeconomic development to a certain extent, such as operating status, periodic changes, etc. Therefore, the securities market is also known as the "barometer" of the economy. The healthy development of the stock market could stimulate the social economy effectively by pushing the realization of China's grand financial goal, which has profound significance for national rejuvenation [3].

The prosperity of the stock market brought some profits to some investors in a short term; hence it attracts tremendous investors to blindly invest all they have had into the stock market. However, as we know, high-profit return always accompanies by high risk. Therefore, most of the investors encountered stock loss due to a lack of prediction on stock market risks. There are many factors influence stock market risks, including politics and military affairs, economic status, natural disasters and so on. These out-of-control factors may bring the price fluctuation of the stock market. It is worth mentioning that the risks in the stock market are inevitable in all capital markets and exist generally. Meanwhile, lots of researchers are attracted to analyze and predict the fluctuation of the stock market and explore the hidden economic pattern to avoid risks as much as possible and then profit from it [4]

In the mid-term of the last century, computer-based automatic trading began to be popular overseas. This kind of trade tends to assist with the automatic decision completion of buying or selling [5]. In this way, the effectiveness of applying computers to research and financial data analysis has been proved. To keep financial data standardized, researchers use mathematical methods during the data analysis phase to find out the connections between economic phenomena and data, which is called quantitative investment [6].The formed strategies in quantitative investment are based on the complicated financial model which combined with financial data, personal experience, mathematical model, and computer science. This is called a quantitative financial investment strategy.

Quantitative investment-related technologies and professional software gradually emerged, and they are commonly used like Python, Matlab, SPSS and so on [7]. The key point of these technologies is that quantitative investment is not able to lower the risk of stock investment while showing it mathematically. As

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a brand-new investment method, the quantitative investment method is developed based on data and investment strategies, focusing on models with stable investment return rates and excellent risk control abilities. It attracts increasing attention from researchers and marketers. However, the internal quantitative investment is still in the early development phase, which is not trustworthy by most investors [8,9].

In recent years, many investigators conducted researches on quantitative investment in the stock market to expose the economic development pattern, apply mathematic models and then make a profit from it. These researches applied the following three kinds of methods mainly:

a. They use economics regulation as the standard of quantitative investment, and *Turtle Trading Rules* are commonly used. Yan Xiaoling proposed a quantitative investment strategy using *Turtle Trading Rules* to complete empirical testing and strategy optimization towards specific stocks [1]. Yang Zhikun conducted a quantitative investment strategy based on timing strategy and stock selection with *Turtle Trading Rules* to analyze the adaptability of strategy for investors [10]. Hu Boran completed quantitative strategy research in combination with Bollinger bands and KDJ [8]. Zhou Hao selected some stocks based on multi-factors quantitative investment strategy and the specialties of stocks market itself to prevent investment risks, provide the empirical research experience and set an example for asset pricing in China [11]. Dang Xiaoli analyzed the stocks market based on financial factors, utilizing MA and MACD to construct an automatic trading investment strategy with python.
b. They summarize the numerical characteristics of financial data, construct mathematic models, predict and analyze stock prices. For example, Ding Qi developed the technology factor, value factor and multi-factor stock selection strategies after completing the significance analysis and principal component analysis [12]. Dong Xiaobo designed a quantitative investment strategy and constructed a multi-factor stock selection strategy based on the results of empirical analysis [13]. Li Junhao deduced the prediction model for specific stock prices based on multiple linear regression [6]. Lu Wanbo brought out a joint moment component analysis weight setting based on element value and constructed a quantitative strategy based on the high-order moment correlation structure of the stock market [2].
c. They also apply AI technologies like machine learning and deep learning to enable quantitative investment. For example, Jiang Peng selected 38 significant factors with data standardization and principal component analysis to predict stock prices and complete investment decisions based on a support vector machine [9]. Combined with a random forest algorithm and a multi-factor stock selection model, Li Jie built an effective investment portfolio model [15]. Zhan Yu uses the factor analysis method, decision tree, random forest, support vector machine method respectively to make the fundamental stock selection and technical stock selection in two stages, which has significantly influenced the diversity of stock investment strategies [16]. Zhang Hongyong improved the features and effectiveness of the algorithm based on deep learning and strengthened learning-oriented investment as well [17]. By applying machine learning technology based on anomalous factors and applied multiple machine learning algorithms, Li Bin constructed stocks profits prediction model [18].

Machine learning and deep learning have advantages in the quantitative investment field. However, we cannot make sure that the algorithm could bring a better prediction result before having the predicted test results of the machine learning model. Therefore, applying a machine-learning algorithm to predict stock prices will be a system still having an empirical problem [18].

In summary, according to the prediction results, this paper was conducted based on multiple widely used machine learning algorithms and real stock data to build corresponding machine learning models for stocks prices prediction and bring the quantitative investment strategies for frequent trading. During the prediction phase, this paper assessed multiple machine learning models, figured out the best working machine learning model, predict the stock prices on top of that, and help people to make a decision when to buy stocks. Following the strategy, this paper also applied programs to simulate the stocks trading, estimated the stock profits, made a comparison on long-term holding situations, and finally draw some conclusions of quantitative investment frequent trading strategies.

2 Analysis Methods

2.1 Overall analysis frame

Some financial information of the stock which was analyzed from public Internet information was collected firstly, including the opening price, highest price, lowest price, closing price, and transaction of all

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trading days between the stock. It was analyzed from the beginning of listing to December 31, 2019.

Then, other financial information on awaiting analysis stocks was collected from open online information, including opening price, highest price, lowest price, closing price and trading volume on all trading dates since listing date till 31st December 2019.

Constructed machine learning requires data set based on multiple stocks information (opening price, highest price, lowest price, closing price and trading volume) as sample characteristics. The data can be predicted after N days as sample labels and these samples can be divided into a training set and testing set.

We can find out which machine learning model has a better prediction result by applying the training set and testing set into multiple typical machine learning models, respectively. In the end, we can also estimate the investment profits for quantitative investment frequent trading strategies according to this machine learning model's prediction results. The overall analysis flow chart shows in Fig.1.

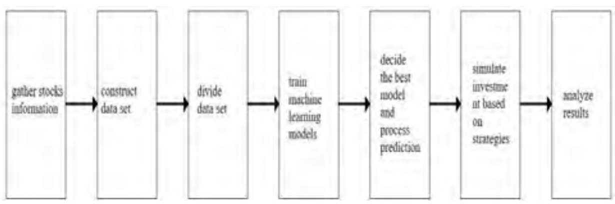

Fig. 1. overall analysis flow.

2.2 Data acquisition and preprocessing

Even though we collected multi-aspects stocks information online, we mainly pay attention to the information like opening price, highest price, lowest price, closing price and trading volume of awaiting stocks. During the data analysis phase, we firstly removed invalid data and then added one more column after each row. The specific values on this column are supposed to be relative with the prediction days "N". If the next day's data needs to be predicted, then this column will be the closing price of the next trading date.

On top of the previous data analysis, a sample would be formed for each row. After managing those samples in chronological order, we would divide them into two sections according to time slots. The former section would be the training set (X_{train}, Y_{train}) for machine learning models, the latter one would be the prediction set(X_{test}, Y_{test}) for machine learning models.

2.3 Machine learning models' overview

The effect of machine learning models on stock prediction has been proved by many researchers. This paper selected multiple classical machine learning models training and prediction analysis data, including decision tree algorithm, linear regression algorithm, K nearest neighbor algorithm, random forest algorithm, AdaBoost algorithm, support vector machine, GradientBoosting algorithm, Bagging algorithm and ExactTree algorithm. These algorithms accept the sample characteristics from the training set and adjust inner parameters and structure until the end of the training. During the prediction stage, sample characteristics would be input from the testing set by applying trained models and predict the sample labels from the testing set, marked as $\widehat{Y} = (\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n)$. Compared with real value $Y = (y_1, y_2, \cdots, y_n)$, the advantages and disadvantages of models for further analysis need to be confirmed.

We apply root mean square error (RMSE) as an important basis to estimate machine learning algorism. RMSE shows the model's overall offset situation between the predicted value and real value. The smaller the RMSE value model, the better prediction results. The calculation method is calculating the square of error of each sample's real value and then predicting value, summing up and re-averaging. The equation is shown below (2-1).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}$$

Before estimating the model's prediction results, we are not able to confirm which machine learning model performs the best on awaiting stocks. Therefore, we have to exhaustively try every machine learning model and compare it thoroughly to conclude the smallest RMSE value model. The final model will be the one to predict stock prices nicely. According to the prediction results of model selection, we would further simulate and analyze them based on quantitative investment frequent trading strategies.

2.4 Quantitative investment frequent trading strategy

Quantitative investment frequent trading strategy is based on the basic hypothesis as the stock price does not deviate too much from its actual value but fluctuates around the actual value. The stock price decreases greatly when it deviates much higher than the real price while it increases when it deviates much lower than the real price. The core ideology of the frequent trading strategy is to aim at trading at an appropriate time, buy the stocks when the price is low

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and tend to rise them. In addition, sell them when the stock price tends to drop to earn the difference. Through manipulating and profiting from competitive frequent trading process, though the single profit of each trading is limited, more profit could be accumulated through the long-term frequent process. The ideology of quantitative trading is shown in Fig. 2.

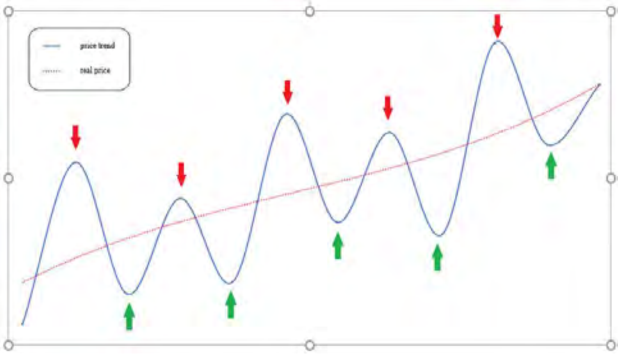

Fig. 2. quantitative investment frequent trading ideology.

Fig. 2. shows that the stock's price always fluctuates its real price. The red arrow represents the bestselling time, which is the local peak price, while the green arrow represents the most ideal purchasing time which is the local off-peak price. From one aspect, the prediction of frequent buying and selling can increase the number of holding shares to remain the same total cost; from the other aspect, buying at a low price and selling at a high price could transform the added value into visible income. Therefore, theoretically analyzing the quantitative investment frequent trading strategy could bring more profits.

The difficulties of achieving substantial profits are how to predict the highest and lowest stock price. On top of the previous machine learning model predicted results, we present the following trading strategies, and in the next part, we will combine the real stocks information and analyze the following trading strategies:

Trading strategy 1(long-term holding strategy): this refers to purchasing in the beginning and selling in the end without other processes during a specific period.

Trading strategy 2(trust the model's frequent trading strategy): this refers predicting the next day's stock price, purchasing when the next day's price is higher than today's closing price if possible and selling them when the next day's price is lower than today's closing price during a specific period.

Trading strategy 3(conservative frequent trading strategy): this refers predicting the next day's stock price, purchasing when the next day's price increasing rate is 0.1% higher than today's closing price and selling them if the next day's price is lower than today's closing price during a specific period.

Trading strategy 4 (risky frequent trading strategy): this refers predicting the next day's stock price, purchasing when the next day's price increasing rate is 0.1% higher than today's closing price and selling them when the next day's price decreasing rate is 0.1% higher than today's closing price during a specific period,

Trading strategy 5 (long-term frequent trading strategy): this refers predicting the price in 3 days; if there is a rising tendency, trying to sell them in 3 days and keep predicting during the 3 days; if the price keeps rising, then continue keeping until the sign of dropping. You need to start a new buying round after selling at a dropping price.

Trading strategy 6 (long-term conservative frequent trading strategy): this refers predicting the price in 3 days; if the rising rate is 0.1% higher than the closing price, keep and sell them in 3 days; keep predicting in the 3 days; if the price keeps rising and the increasing rate is 0.1% higher than predicted price, continue keeping till the sign of dropping tendency, start a new buying round after selling at dropping price.

Among the previous strategies, trading strategy 1 is a long-term holding strategy; trading strategy 2 is the simplest frequent trading strategy, which trusts machine learning models completely and requires higher accuracy of models. To offset the influence from machine learning model's accuracy, hence present the trading strategies with threshold consideration, trading strategy 3 is comparatively "conservative" sell immediately after the model predicting a dropping sign; while strategy 4 is comparatively "risky" sell after a specific dropping threshold value showing up. Strategy 5 and 6 extend the period of each trade properly, which is supposed to confirm the possibility of profits through long-term observation. Overall, strategy 5 and 6 are more "conservative".

3 Empirical Analysis

3.1 Data collection and preparation

On top of the previous analysis, four real shares had been selected as samples, including Link Real Estate (code: 0823), Tsinghua Unisplendour (code: 000938), Huamao Textile (code:000850), BDStar Navigation (code:002151). To collect valid listing data from 2000 to 2019, the data before 2019 were put into training samples and the data after 2019 were put into testing samples. After data processing and analysis, we applied a training set to train multiple machine learning models and RMSE value as an important standard to estimate models training quality to predict the data after 2019 with the best model.

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3.2 Models training and prediction

Take Link Real Estate as an example. We applied the machine learning model and tested the RMSE value after each model training. This is showed in chart 1.

Table 1. Link Real Estate machine learning model RMSE value.

model	RMSE value (keep 3 decimal places)
decision tree algorithm	10.242
linear regression algorithm	1.138
K nearest neighbour algorithm	11.201
random forest algorithm	10.690
AdaBoost algorithm	12.507
support vector machine	21.924
GradientBoosting algorithm	10.541
Bagging algorithm	10.596
ExactTree algorithm	10.555

The linear regression algorithm predicted best towards this share from RMSE value and we selected a linear regression algorithm to predict this share in the end. After the completion of the prediction on the other 3 shares in a similar way, we show the predicted results of each share in Fig. 3.-6.

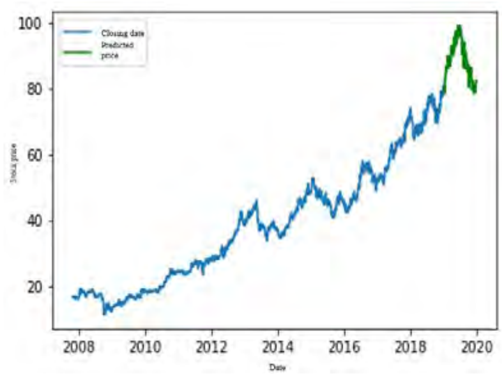

Fig. 3. Link Real estate predicted tendency

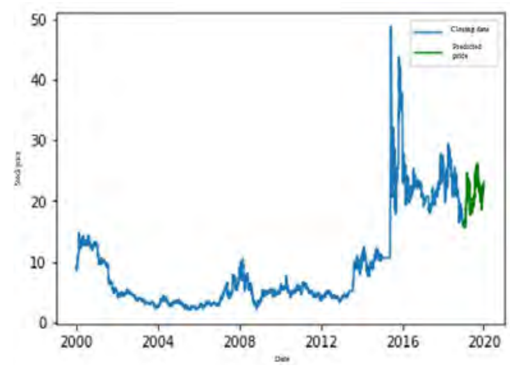

Fig. 4. Tsinghua Unisplendour

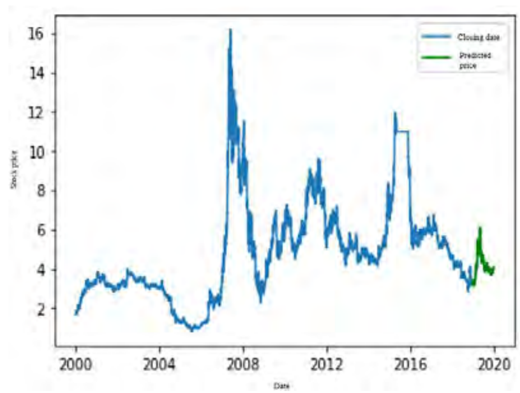

Fig. 5 Huamao Textile

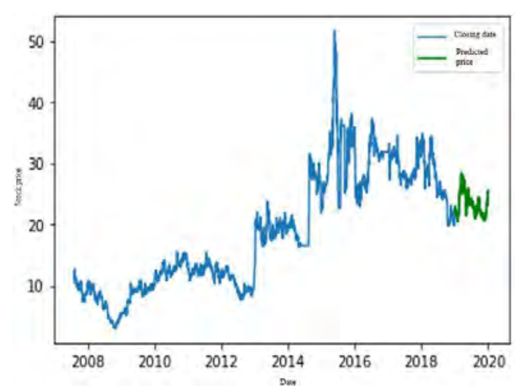

Fig. 6 BDStar Navigation

The prediction results showed that machine learning models have good prediction results on general stock prices. The stock prices predicted by machine learning models are preferable to a certain extent.

3.3 Simulation trading estimation and analysis

After the prediction process using the previous methods, the simulation trading process is shared in 2 and 3 part respectively and the annualized rate of return result is shown in table 2.

Table 2. annualized rate of return under different trading strategy purchasing.

	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6
Link Real Estate	3.78%	5.96%	5.14%	8.08%	2.11%	11.55 %

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Tsinghua Unigroup	42.59%	56.08%	58.46%	48.72%	5.97%	6.67%
Huamao shares	22.52%	36.68%	36.20%	19.65%	15.15%	14.85%
Big Dipper	14.04%	30.84%	40.06%	25.76%	11.60%	4.45%

The process from buying to selling share is called one trading. The trades number of executed processes under each strategy is showed in table 3.

Table 3. trading number under different trading strategy purchasing.

	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6
Link Real Estate	1	48	41	22	49	49
Tsinghua Unigroup	1	51	45	40	43	42
Huamao shares	1	60	41	29	46	47
Big Dipper	1	24	24	12	57	58

After analyzing the results, we could draw the following conclusions: (1) generally speaking, the frequent trading strategy is more profitable than the long-term holding strategy; (2) frequent trading strategy is more likely bringing profits to some extent for the stocks in fierce, short-periodic and frequent fluctuation situation; (3) profits through long-term frequent trading strategy is comparatively less than short-term probably due to low accuracy during the model prediction phase on long-term stock prices change. The growing error would result in deviation of trading range selection; (4) when applying the threshold value to manage the buying and selling time, the difference generated from the system could be offset and then increase the profits; (5) applying risky strategy and comparing with conservative strategy are more likely to decrease the profits of the stock; (6) there is no significant connection between trading numbers and profits. Stock profits normally are related to trading time.

4 Conclusion

As the stock market is developing prosperously, an increasing number of investors join in the stocks market with tremendous capital to receive benefits and profits. However, the stock market fluctuates fiercely, and obviously, long-term holding shares is not the best profitable strategy. The best profitable strategy is selling the stocks at the highest local price and buying the stocks at the lowest local price. For example, repetitive frequent trades could be able to keep stable growth profits. The key point of profits is to aim at the right time. Also, this paper is applied to machine learning models to train and predict the best model based on real stocks data. Using quantitative investment frequent trading strategy is a good way to simulate trading, analyze the simulation results. The analysis results showed that frequent trading strategy does help to increase investors' profits effectively, but the final profits are closely related to the price changing tendency of stocks itself. The accuracy of model prediction and the choice of risky or conservative strategy is still determined by the clients.

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House price prediction using polynomial regression with Particle Swarm Optimization

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Abstract. This paper combines the characteristics of the real Washington DC house price estate market and the theoretical model of housing prices to conduct an empirical analysis and comparison of the current mainstream housing price index prediction models. It is found that the current mainstream model only studies the trend of the housing price index itself, and is not sensitive to the characteristics of the house itself. Therefore, this paper uses a multiple regression model to integrate the advantages of external factors and use the improved housing price composition establishing a multiple regression prediction model with the particle swarm optimization. It not only makes up for the disadvantages of poorly determined housing price regression indicators and lack of statistical data in multiple regression prediction, but also enables the model to reflect the inflection point of housing prices in advance. PSO is used for selection of affect variables and regression analysis is used to determine the optimal coefficient in prediction.

Keywords. Washington DC house price, Regression Analysis, Particle Swarm Optimization.

1. Introduction

With the process of urbanization and the arrival of new immigrants in the US, more and more cities and gathering areas are created, and a series of new problems are brought with them. The most serious of these is the huge rise in house prices caused by increased population density. According to the information, the average home price was approximately $27,000 in the 1970s. (1970s Prices - Looking Back at 1970s Prices) However, the same amount of money can only buy one bedroom in some undeveloped states today. As a result, it is increasingly vital to forecast the determinants and future trends of house prices, not only for government fiscal policy makings, but also for our living environments and individual investments. Washington is a beautiful and livable state with a booming economy in recent years. Also, Washington state, home to many high-tech companies such as Microsoft, is also attracting a growing number of new immigrants. In this way, studying the influence factors of housing prices in Washington state is instructive to guide us make a better decision in house purchasing and property investment.[1]

There are several approaches that can be used to determine the price of the house, one of them is the prediction analysis. The first approach is a quantitative prediction. A quantitative approach is an approach that utilizes time-series data. Quantitative prediction models are used to forecast future data

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as a function of past data. They are appropriate to use when past numerical data is available and when it is reasonable to assume that some of the patterns in the data are expected to continue into the future. These methods are usually applied to short or intermediate-range predictions. The second approach is to use linear regression based on house pricing. There are a couple of variants to it in the form of simple and multiple linear regression. Simple Linear regression is applicable when we have a single input variable and will be extended to Multiple linear regression when we start dealing with multiple input variables. In linear regression, determining coefficients generally using the least square method, but it takes a long time to get the best formula.

Particle swarm optimization (PSO) is proposed to find the coefficients aimed at obtaining optimal results. PSO is one of the most well-known metaheuristics; it was proposed by Kennedy and Eberhart.[2] This algorithm is inspired from swarm behavior such as bird flocking and schooling in nature. PSO has been widely used and it is the inspiration for a new research area called swarm intelligence. On the optimization problem the value of the variable on the regression equation can find a maximum solution using PSO.

2. House Data Profiling

We utilize house data from Washington DC, one of the largest cities in the United States, as an example to understand the domain situation. Initially selected 21613 sets of data, containing a total of 22 features from Kaggle, "House Sales in King County, USA". In order to summarize a large amount of features and find out which features have high correlations with the price, we use correlation matrix which is a table showing correlation coefficients between variables. Each cell in the table shows the correlation between two variables.

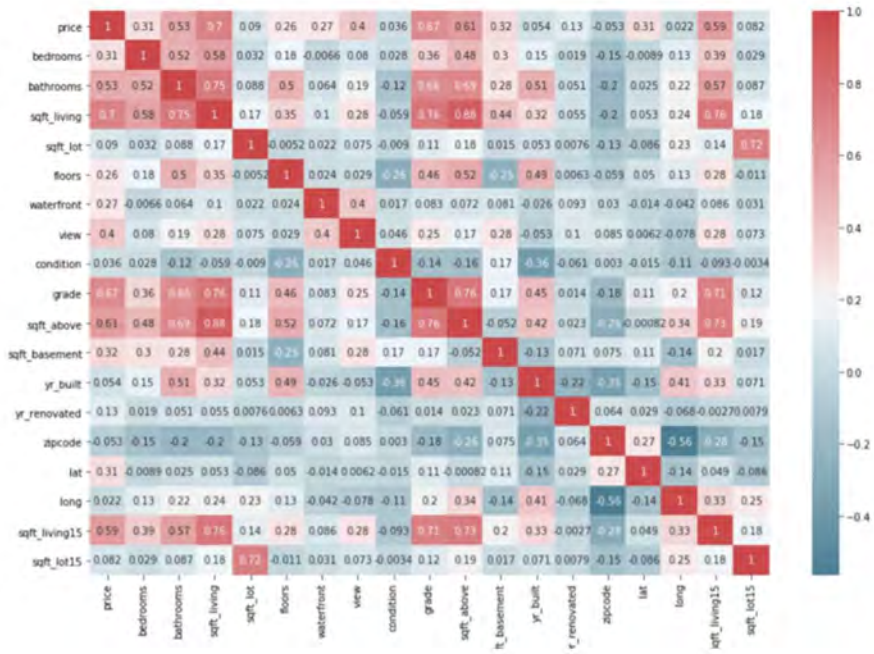

Figure 1. Correlation heatmap

And we find out there are four features that have high correlations with the price, which are sqft_livings, grade, sqft_above and sqft_living15.

Explanation of main features: sqft_living: square footage of the apartment interior living space; grade: an index from 1 to 13, where 1-3 falls short of building construction and design, 7 has an average level of construction and design, and 11-13 has a high level of construction and design; sqft_above: square footage of the apartment interior housing space that is above the ground level; sqft_living15: square footage of the apartment interior living space for the nearest 15 neighbors; bedrooms: number of bedrooms in the house; lat: year of house; bathrooms: number of bathrooms in the house; waterfront: number of waterfronts in the house; grade: rating of the house from customers.

3. Regression analysis and Particle Swarm Optimization

3.1. Prepare work

By adding the high correlation variables into the regression. After trying several times, there are two regressions shown high R-squared. Regression model 1 uses variables 'bathrooms', 'sqft_living', 'grade', 'sqft_above' and 'sqft_living15'. And find out that R-Square in regression model 1 nearly 60%. And then turn to regression model 2 uses variables 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', ’floors', 'waterfront', 'view', 'grade', 'sqft_abov e', 'sqft_basement' and 'lat','sqft_living15'. But R-Squared in regression model 2 is still nearly 60%. However, in order to acquire a more precise model, continue work on a polynomial regression model based on the variables in regression 2.

3.2. Polynomial Regression

In statistics, polynomial regression is a form of regression analysis in which the relationship between the independent variable x and the dependent variable y is modelled as an nth degree polynomial in x.[4]

The model’s performance using Polynomial Regression:

```
                            OLS Regression Results
=======================================================================================
Dep. Variable:                  price   R-squared (uncentered):                   0.870
Model:                            OLS   Adj. R-squared (uncentered):              0.870
Method:                 Least Squares   F-statistic:                          1.053e+04
Date:                Thu, 14 May 2020   Prob (F-statistic):                        0.00
Time:                        18:01:21   Log-Likelihood:                     -2.3842e+05
No. Observations:               17290   AIC:                                  4.769e+05
Df Residuals:                   17279   BIC:                                  4.769e+05
Df Model:                          11
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
bedrooms      -3.235e+04   2426.445    -13.331      0.000   -3.71e+04   -2.76e+04
bathrooms      -1.73e+04   3986.024     -4.340      0.000   -2.51e+04   -9485.196
sqft_living     141.2306      2.899     48.718      0.000     135.548     146.913
sqft_lot         -0.3286      0.044     -7.404      0.000      -0.416      -0.242
floors        -1.528e+04   4507.981     -3.389      0.001   -2.41e+04   -6440.736
waterfront     5.472e+05   2.25e+04     24.290      0.000    5.03e+05    5.91e+05
view           6.415e+04   2750.852     23.321      0.000    5.88e+04    6.95e+04
grade          9.628e+04   2713.355     35.482      0.000     9.1e+04    1.02e+05
sqft_above       49.8759      2.870     17.380      0.000      44.251      55.501
sqft_basement    91.3547      3.331     27.426      0.000      84.826      97.884
lat           -9755.7918    343.133    -28.432      0.000   -1.04e+04   -9083.217
sqft_living15     6.0576      4.365      1.388      0.165      -2.498      14.613
==============================================================================
Omnibus:                    12630.582   Durbin-Watson:                   2.003
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           756497.595
Skew:                           2.933   Prob(JB):                         0.00
Kurtosis:                      34.870   Cond. No.                     2.67e+17
==============================================================================
```

Figure 2. Polynomial regression model OLS result summary output

R-square for the polynomial regression is appropriate 0.80, which shows it works very well to estimate the price of housing in Kings county including 12 variables and the degree of this regression is 12. The variables are 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'view', 'grade', 'sqft _above', 'sqft_basement', 'lat', and 'sqft_living15'.

3.3. Particle Swarm Optimization

PSO is a stochastic optimization method that represents solutions as particles [5]. The goal of particle swarm optimization is to make all particles find the optimal solution in a multi-dimensional hyper-volume. First, assign initial random positions and initial random speeds to all particles in the space. Then advance the position of each particle in turn according to the speed of each particle, the best global position known in the problem space, and the best known position of the particle. As the calculation progresses, by exploring and using the known vantage points in the search space, the particles gather or aggregate around one or more best points. The mystery of the algorithm design is that it retains the two information of the optimal global position and the optimal position known to the particles. Subsequent experiments found that retaining these two information has a better effect on faster convergence and avoiding prematurely falling into the local optimal solution. This also laid the foundation for the subsequent improvement of the particle swarm algorithm.[6]

A number of particles are generated randomly, where each particle consists of some dimensions of xi position and velocity vi. Each particle will measure its fitness value which is shown in below: f (x) = Ɛ from prediction.[7]

Where, f (x) is the fitness value of each particle that indicates the error prediction value. Each particle will explore the solution search space to get optimal results. The displacement from one position to another is greatly influenced by the speed of each particle, to obtain the best position requires a dynamic speed formulation using vi.[8]

From the speed update formula of PSO, we can find that if the algorithm needs to converge quickly, we need to increase the acceleration constant. But doing so may cause the algorithm to appear "premature". If the inertia weight is adjusted to a large value, it can increase the “enthusiasm” of the particles to detect new positions, avoid falling into the local optimum too early, but it will also reduce the convergence speed of the algorithm. For some improved algorithms, a random term is added to the last term of the speed update formula to balance the convergence speed and avoid "premature". And according to the characteristics of the position update formula, the particle swarm algorithm is more suitable for solving continuous optimization problems.[9]

Calculation cycle of velocity values vi and updated position xi will be repeated until maximum iteration is achieved. When the iteration is over, the best particles come out as the optimum solution.

4. Result

The experimental process examines the parameters used on particle swarm optimization such as particle test, iteration test, and also inertia weight combination test. The PSO algorithm generates population and initial velocity in the range of [0-100]. The range used has been tested from the number -1000 to 1000 and obtained that range 0-100 can provide highest fitness solutions. Particle test and iteration test for each model use a multiple of 100 in which the maximum particle test lies in 3000 particles, if the particles tested over 3000 require longer computation time. For each testing run 5 times, and the fitness value obtained from the average test results. The last test was a combination of inertia weight, performed to know the displacement velocity of each particle, inertia weight is tested in a range [0,1-0,9]. The result of each variable testing is shown in Table1. Combined with previous polynomial regression and the R-square for the model is 0.88.

Table 1. Test results of parameters

Variables	Test paraticles	Fitness	Iteration test	Fitness	Inertia weight		Fitness
bedrooms	800	940	1000	27939	0.8	0.4	864
bathrooms	800	8490	1000	3787	0.8	0.2	2420
sqft_living	800	3880	1000	9308	0.8	0.7	8369
sqft_lot	1000	877	1000	2198	0.4	0.8	7040
floors	1000	672	1000	2698	0.8	0.3	6869
waterfront	1000	2930	1000	7839	0.2	0.6	370
view	800	3788	1000	3987	0.6	0.4	3932
grade	800	12578	1000	72091	0.8	0.4	12730
sqft _above	800	3704	1000	3747	0.2	0.6	3480
sqft_basement	800	2703	1000	2083	0.2	0.5	3704
lat	1000	308	1000	720	0.2	0.8	1570
sqft_living15	1000	8872	1000	7032	0.2	0.8	3702

5. Conclusion

In this paper, several tests have been performed using polynomial regression and particle swarm optimization methods to perform house price prediction. Based on the Washington DC house pricing data, the system is modeling house price predictions into 11 variables which of them represents one feature. But the Particle Swarm Optimization also has many disadvantages, such as poor local search ability, easy to fall into local extreme value, low search accuracy and so on. In response to these problems, the particle swarm algorithm has the following two categories of improvement directions in the coming research: The first type of improvement method is to change the topological structure of particle relations. The second type of improvement method is the introduction of new mechanisms. By introducing a new particle control mechanism to speed up the convergence speed, and avoid falling into the local optimum.

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