

Analysis of Cost Control and Quality Improvement Paths for Geriatric Elderly Care Services under Long-term Care Insurance

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ABSTRACT Efficient management of large-scale service systems requires robust information integration, intelligent resource allocation, and data-driven decision support. This study proposes a cost-control and quality-optimization framework based on multimodal data fusion, efficiency evaluation, and simulation-driven decision analysis. Heterogeneous information from administrative records, clinical indicators, caregiver surveys, and policy datasets is integrated through a unified data-processing architecture to support comprehensive system assessment. Principal component analysis, regression modeling, and Super-SBM efficiency evaluation are employed to identify key determinants affecting service utilization, resource allocation, and outcome performance. To further enhance system adaptability, Monte Carlo simulation and agent-based modeling are incorporated to characterize uncertainty propagation, dynamic interactions, and long-term optimization effects. Experimental results demonstrate that the proposed framework improves service efficiency by up to 18%, reduces out-of-pocket expenditure by 15%, decreases caregiving burden by 20%, and enhances overall quality-of-life indicators by 14% under simulated conditions. The proposed framework provides an effective methodology for heterogeneous information fusion, intelligent decision support, system-level optimization, and dynamic resource management, offering potential applications in distributed monitoring, data-driven service systems, and complex networked environments.

INDEX TERMS multimodal data fusion, intelligent decision support, system-level optimization, distributed monitoring

I. INTRODUCTION

THE worldwide trend towards aging populations has increased the need for proper systems to cater to long-term care for the elderly population. Long-term care insurance (LTCI) has become at an international level an important mechanism to fund and organise services that help aging populations to stay independent and quality of life. Across a variety of settings, including Japan, China, South Korea, and western healthcare systems, the goal of LTCI is to achieve a balance between the affordability of their services and their quality both for the recipients of the care and for their families. Despite its wide-scale adoption, there is much variability in the effects of LTCI on care utilization, financial burden, service quality, and caregiver outcomes, and this highlights ongoing challenges in balancing the importance of both controlling costs and providing quality care in existing systems. Financial burden related to LTCI has been a subject of recent studies, with families of older people who use LTCI services facing significant financial burdens, especially if the insurance coverage is insufficient

to meet the long-term costs [1]. Similarly, while LTCI can lessen some of the household expenditures of the elderly in China, out-of-pocket expenditure remains high for many poor families [2]. This finding reveals deep-rooted gaps in financial protection and balanced coverage, which may lead to poor effectiveness of LTCI as a social safety net.

Variations in care patterns and utilization add to the LTCI outcomes. Differential levels of long-term care costs attributable to intensive prevention services in Japan: Finding that in even insured populations there may be differences in the trajectories of service intensity and cost over time [3]. LTCI implementation in China also influences the patterns of eldercare, in this case the direction and strength of these changes depend on the design of policy at the regional level and the availability of services at local level [4]. Function-focused care programs for nursing staff providing long-term care in institutional settings have been shown to improve the economic and patient outcomes, making the importance of staff-targeted interventions for care quality highlighted [5]. The interaction between LTCI and informal

caregiving has been referred to in a number of studies. Social support can help moderate the caregiving burden of adult children in LTCI pilot programs, but even then, caregiving responsibilities are significant, especially under circumstances where there is a lack of formal services [6]. The function that intergenerational financial support plays as a mediator in the dynamics of family care under LTCI is further evidence of the complex economic and social interdependencies that are not adequately addressed by the existing insurance arrangements [7]. Health service utilization and institutional care patterns also give more evidence of systemic holes. Increased medical services utilization between South Korean older adults using public LTCI may reveal unmet needs for long-term care services or lack of integration of healthcare and LTCI benefits [8]. LTCI is also associated with institutional admission rates for older Chinese adults, indicating that the insurance eligibility criteria and benefit levels could affect transitions into higher cost care settings [9]. In addition to utilization and cost, the issues of equality and systemic implications remain areas of concern. There is a possibility to short term LTCI policy trials will lead to an uneven allocation of system advantages between populations and as such draw attention to inequalities in the distribution of collective benefits [10]. Inconsistency in cost containment, uncertainty in the quality of services, insufficient protection in terms of finances, and challenges in harmonizing the formal and informal care responsibilities are some of the ongoing issues that emerge from this research and the collective findings.

Nevertheless, the problem of inefficiencies in resource distribution to LTCI resources is still common, as there are services with excessive funding, and others experience a shortage of resources, which leads to the unfair access and suboptimal care outcomes. The gaps point at the necessity to have both systematic optimization methods that can incorporate financial, quality, and equity concerns.

Despite extensive investigations, current LTCI frameworks are not inclusive to simultaneously tackle the cost and quality improvement in the provision of care for the elderly. In the face of these challenges, there is a need to consider the design of the various components that optimize resource allocation, calibrate access to services, preventative interventions and outcome monitoring in a manner responsive to economic parameters and care quality objectives. To fill this gap, the Cost Control and Quality Improvement through Geriatric Care under Long-Term Care Insurance (CCQIGEC-LTCI) framework. This model seeks to increase the efficiency of the system by targeting high need populations, coordinating formal and informal caregiver support, and using data-driven mechanisms to help monitor and modify care pathways over time. By combining the financial and quality factors in a coherent policy framework, CCQIGEC-LTCI offers useful policy inputs for policymakers and for care providers for better sustainability and outcomes in LTCI systems.

Contributions of the Paper

- To introduce the CCQIGEC-LTCI framework, combining cost control, service quality improvement, and caring for caregivers, giving a structured model for geriatric long-term care sustainable and efficient delivery.
- To examine the impact of LTCI on elderly care outcomes, such as functional independence, cognitive health, service utilization and financial burden, to illustrate the actionable strategies for policymakers.
- To provide evidence-based insight for the optimal allocation of resources, time-dependent preventive interventions with delayed effects and intensity of care provided in order to provide equitable distribution of services while improving elderly quality of life and decreasing the burden that family care imposes.

The remainder of this paper is organized into five sections. Section 2 presents related work. Section 3 describes the CCQIGEC-LTCI framework, including the problem formulation, Data acquisition and governance, multimodal data integration and preprocessing, descriptive and exploratory analysis, statistical modeling and efficiency evaluation, integrated framework development and policy simulation, integrated utilization, functional, financial, and outcome metrics. Section 4 outlines of this study describe the study's experimental design, presents the findings of an assessment of its effectiveness, and outlines the features of the Nursing Home Compare Dataset. Section 5 presents the findings and discusses future areas for further investigation.

II. RELATED WORKS

Song, H. and Han, S. O., [11] Ineffective evidence of cognitive training of LTCI beneficiaries based on home visits in Korea. The National Health Insurance data was analyzed comparing the results of 215 members of intervention and control groups using propensity score matching and difference-in-differences. Cognitive function was not improved but physical function improved measured by Barthel Index and MMSE stratified. Unmeasured confounding, variance in dementia severity and intensity of service use suggest the need for more personalised and professional dementia interventions in LTCI programs.

Chon, Y., Lee, S. H., & Kim, Y. Y. [12] Identifying the limitations in the South Korean LTCI on community care: A qualitative framework approach to understand the comprehensiveness, adequacy, and integration of services. Analysis included literature review, and qualitative review of LTCI service delivery. Limitations were use of secondary data and biases in interpretation of the framework. Results revealed inadequate use of visiting nurse, decreased short stay services, benefit quantity inadequacy and poor quality of home care, which impedes the expansion of community based LTC.

Diaz Diaz, B., et al. [13] SDG-linked Cost modelling for dependency care: Quantitative modelling of the costs using questionnaire survey of 68 centres in Cantabria. Dataset was cost variables of residential and day care. Some limitations

included regional coverage and response rate. Results related to the fact that day costs to the users varies and the necessary to cover the costs of some public services, and that the ideal public financing of a long-term care to be adapted for sustainability.

Kitamura *et al.* [14] investigated the effects of prior falls on the improvement of physical function in elderly people under long-term care insurance. A method of retrospective and clinical analysis (cohort analysis) reviewed medical and LTCI data of 1,200 elderly people. Results were that participants without falls demonstrated significantly larger gains in function. Among the limitations were the use of medical records collected previously, the potential for unmeasured confounding, and the short length of follow-up time. The results reveal the importance of the fall prevention to optimize the rehabilitation outcomes of LTCIs.

In the context of the health care setting, hospitals and long-term care facilities, Raj *et al.* [15] explored the obstacles and opportunities that face the implementation of culturally inclusive meals. Using qualitative interview and theme analysis, data was gathered from 35 healthcare managers and dietitians. Some of the limitations included a limited sample size and the possibility of bias in the reporting. Results included important factors associated with staff training, flexibility of menus, and cultural awareness as facilitators, and financial constraints, standardised policy, and reduced ingredient availability as main barriers, to help guide food planning in LTC settings.

Mežnarec-Novosel *et al.* [16] assessed effectiveness of new methods of reactivation in integrated long-term care under the long-term care act. A combination of administrative data from LTC records and patient assessment of 500 elderly recipients was used in a mixed-methods design. One of the limitations was that the interventions were applied in a variety of different ways. Results indicated there was an improvement in functional independence, declining hospitalization, and care coordination that may suggest the use of structured reactivation programs may fortify integrated long-term care results within their legislative frameworks. Miller *et al.* [17] responded to broken workforce data that hampers efforts to plan for long-term care and improve quality. Using a descriptive case-study methodology, it examined the On-SPARK platform aggregating workforce metrics across the long-term care facilities in Canada. Both inconsistencies in reporting and insufficient historical datasets were among the limitations noted. Results demonstrated that data accessibility was improved and these numbers can be used for sector-governed planning, benchmarking and decision-making to improve staffing efficiency and quality management across LTC facilities.

Osińska *et al.*, [18] challenges in the measurement of polypharmacy quality indicators in Swiss residential long-term care. A mixed-methods approach was used, which involved quantitative information on prescriptions and qualitative interviews of staff. Dataset contained medication records from different care institutions. There were limita-

tions such as inconsistent documentation and small sample sizes. Results identified real issues in measuring polypharmacy because of inconsistent recording practices and the importance of standard polypharmacy measures to inform optimal medication management.

Szczepura *et al.*, [19] integrated the long-term care “neighbourhoods” for older people in Japan and England. Using a comparative case study and policy review, datasets were incorporated - service reports for the region and demographical statistics. Heterogeneity in local implementation was one of the limitations that were present. Results showed that integrated neighbourhoods led to better coordination of care, and fewer hospital admissions and improved support in the community, but that results differed depending on local governance and resource allocations.

Toprak & Şahin, [20] assessed the long-term care services in Turkey from the point of view of primary stakeholders. Using semi-structured interviews and surveys, the dataset consisted of care recipients, their family caregivers and providers in multiple facilities. Limitations included possible response bias and gaps in data coverage at the regional level. Results showed stakeholders experienced service gaps, namely accessibility, staffing, and quality, that highlight the need for policy interventions in regard to optimizing LTC service delivery and satisfaction.

Werner, R. M., Hoffman, A. K., & Konetzka, R. T. [21] Addressed fragmented regulation and quality gaps: an examination of the long-term care and health policy evolution in the United States. Using policy review and historical data on federal and state LTC regulations, Medicare, Medicaid and national data are included. Limitations include use of secondary materials. Findings reveal greater alertness of the integration of services, continued inequalities, and need with coordinated, evidence-based policy development in LTC.

Ma, Q., Ning, J., & Chen, H. [22] Changing filial responsibility norms in context of public LTCI in China. Generational care expectations change. Survey based methodology (1,200 adults in urban and rural areas were surveyed) combined with propensity score matching (PSM) and difference-in-differences (DiD) analysis. Self-reported bias & scope of region are limitations. Results show declining perceptions of caregiving responsibilities, increasing dependence upon formal LTC services and changing patterns of support within the family under public LTCI policies.

Singh, S., Furman, C. D., Flint, L. A., & Teno, J. [23] Addressed suboptimal end-of-life care for Medicare skilled nursing facility beneficiaries. Using retrospective claims analysis of Medicare and MDS data (n~40,000) in which limitations are lack of patient-reported outcomes. Results indicate beneficial effects of targeted rehab interventions in reducing hospital transfers and finding gaps in palliative care integration in skilled nursing facilities in managing symptoms.

Scattarelli, J., Moeller, K., Urbanski, D., & DeLiema, M. [24] looked at the barriers to planning and accessing long-term dementia care through Medicaid. Using qualitative

interviews & policy analysis. 60 caregivers & 20 administrators as dataset. Regional and small sample sizes limitations. Findings reveal that eligibility; availability of services and administrative complexity are barriers to accessing care for dementia. Yang, C., Huang, J., & Yu, J. [25] explored the inequalities in access to long-term care resources and services in China to national survey data and administrative data (~8,500 households). A Super-SBM model was used to assess efficiency. Limitation: Cross-sectional study design. Results show urban-rural disparities, disparities in access to disability services, skilled personnel and facilities, and LTC resources are concentrated in higher-income areas suggesting policy gaps in equitable provision of LTC services.

Despite the considerable amount of research on long-term care (LTC) systems worldwide, great gaps remain on the integration of cost-efficiency, quality improvement and equitable service delivery. Studies in Korea, China, Turkey, and Western countries show limited but partial successes of LTCI programs in terms of outcomes in physical function, caregiving support, and service utilization (Han & Song, 2026; Ma *et al.*, 2025; Toprak & Şahin, 2025), but research on the impact of programs on cognition, care adequacy in the community, and culturally inclusive interventions is lacking (Chon *et al.*, 2024; Raj *et al.*, 2023). Regional discrepancies and inadequate financial coverage are demonstrated in quantitative cost analysis^{19,20} and policy and workforce analyses show some fragmentation of regulation, unreliable data, and imbalances in access to services. Longitudinal and standardized measurement of functional, cognitive or quality of life outcomes in a variety of LTC settings is limited (Kitamura *et al.*, 2023; Osianska *et al.*, 2026). Collectively, these gaps highlight the need for an integrative framework that simultaneously addresses the cost, quality, caregivers, and equitable resources needed to improve quality of care, and is the motivation for the development of the CCQIGEC-LTCI model.

III. PROPOSED METHODOLOGY

The overall objective of this study is to analysis strategies on cost control and quality improvement of geriatric elderly care service under long-term care insurance (LTCI) with the aim of developing an integrated framework to improve efficiency, equity and patient outcomes. Specifically, the research aims to determine key factors that affect service utilization, functional independence, cognitive function and family caregiving burden as well as examine the impact of LTCI on out-of-pocket expenditures and resource allocation. Additionally, the study intends to also assess the effectiveness of adaptive service intensity, time-dependent preventive interventions with delayed effects and combined care delivery in improving the quality of life of the elderly population as well as reducing systemic inefficiencies. These preventive measures are assessed on a multi-period basis with recognition that their effects on cost-saving and health outcomes may take some time other than instant. By its quantitative and qualitative combination of LTCI data,

policy reports, and international best practices, the research aims to outline a framework for policymakers, healthcare providers, and caregivers, the Cost Control and Quality Improvement through Geriatric Care under Long-Term Care Insurance (CCQIGEC-LTCI), which will provide actionable insights for optimizing the delivery of geriatric healthcare in a sustainable and equitable manner.

The figure 1 shows an integrated analytical framework to optimize cost control as well as quality improvement in geriatric elderly care services based on Long Term Care Insurance (LTCI). The workflow begins with multiple inputs of data such as LTCI administrative data, geriatric elderly care data, family caregiver surveys, policy and regulatory data and international best practices. These inputs go forward to a structured stage of data collection that protects to ensure inclusion of patient, caregiver and policy data sets along with data governance compliance. Data integration proceeds to multimodal data fusion whereby LTCI, clinical, and survey data are combined to form an analytical data set. In the preprocessing phase missing values is dealt with by using MICE, variables are scaled using Min-Max scaling or z-score scaling and feature engineering techniques like principal components analysis (PCA), interaction techniques and polynomial features are used. The processed and engineered feature set resulting from step is the serves as input to the subsequent predictive and efficiency modelling components. Descriptive analysis of patterns of service utilization, cost distributions, functional and cognitive outcome trends. The modeling phase starts with regression and correlational analysis to estimate relationships between cost and quality and outcome variables. The outputs and features derived are then used as inputs to the Super-SBM model to calculate efficiency scores, which further inform the cost-quality frontier analysis and model validation process. Qualitative assessment made using NVivo thematic analysis is complementary to quantitative findings. The efficiency scores and cost-quality relationships realized during the modeling phase then are inputted in Monte Carlo simulation to capture uncertainty, and in agent-based modeling to simulate dynamic relationships among elderly, caregivers, and LTCI systems with time This progressive integration makes every analytical part contribute to a cohesive and unified structure and not standalone modules.

A. DATA ACQUISITION AND GOVERNANCE

The collection of the LTCI administrative data, geriatric clinical data, caregiver survey responses, and policy datasets is all part of this stage. This ensures that all aspects of the consumption of service, costs and results are sufficient enough in detail. Compliance with regulations, data confidentiality, and forming ethical approval are all closely kept. In an effort to guarantee dependability, transparency and reproducibility, sound data governance structures are key.

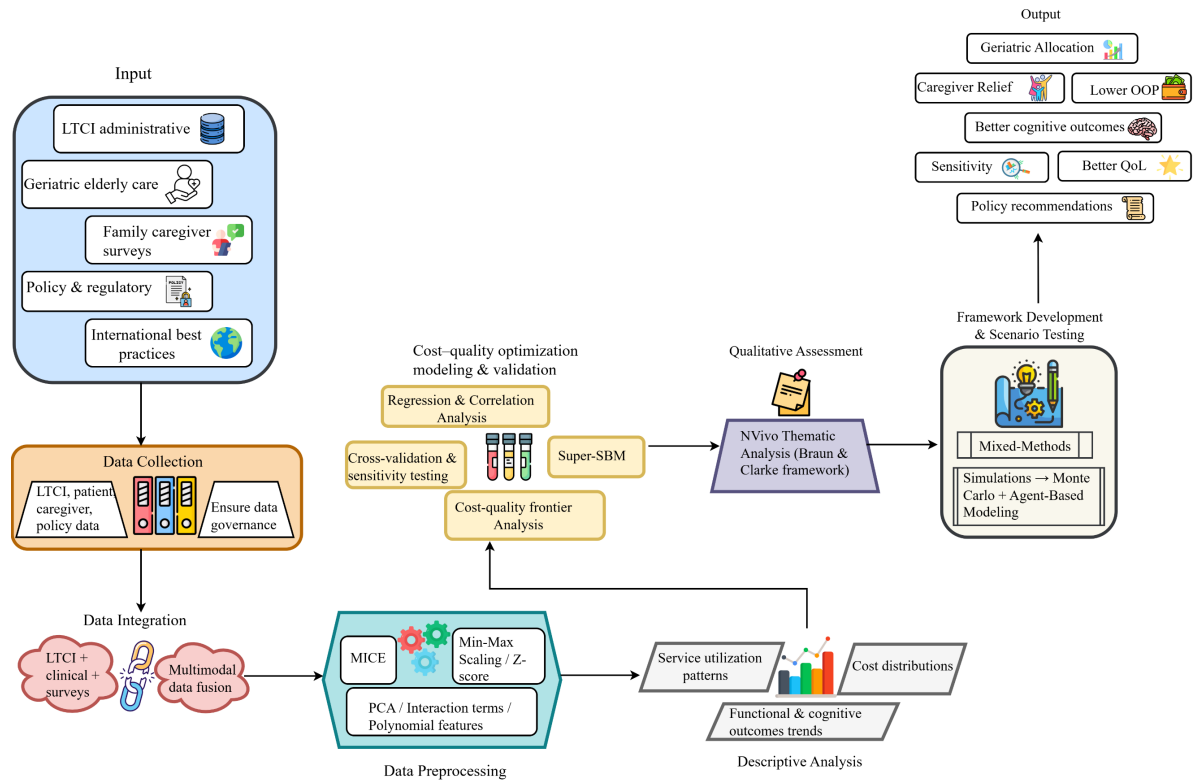


FIGURE 1. Overall Architecture of CCQIGEC-LTCI Framework

$$X_i^{\text{fusion}} = \omega_1 X_i^{\text{LTCI}} + \omega_2 X_i^{\text{clin}} + \omega_3 X_i^{\text{survey}} + \omega_4 X_i^{\text{policy}}. \quad (1)$$

This equation merges heterogeneous source of data into a unified analytical data set. It guarantees symmetry of insurance, clinical, caregiver, and policy dimensions. Both prediction robustness and modality bias are

improved by the use of weighted fusion. The model becomes the basic data set for cost-quality modeling. Were, X_i^{fusion} : integrated feature vector for individual i , X_i^{LTCI} : insurance administrative data, X_i^{clin} : clinical/geriatric health indicators, X_i^{survey} : caregiver survey variables, X_i^{policy} : regulatory and policy variables, ω_k : weight coefficients ($\sum \omega_k = 1$).

$$X_{ij}^{(t+1)} = \beta_0 + \sum_{k \neq j} \beta_k X_{ik}^{(t)} + \epsilon_{ij}. \quad (2)$$

In this equation, it represents the MICE Missing Data Imputation $X_{ij}^{(t+1)}$: updated imputed value, β_k : regression coefficients, ϵ_{ij} : random error term. This iterative regression model is used to impute the missing data with the help of chained equations. It maintains multivariate relationships between variables. The method avoids biased parameter estimation of LTCI datasets. Using imputation is a reliable method that improves both the efficiency of downstream processes and regression models.

B. MULTIMODAL DATA INTEGRATION AND PREPROCESSING

Heterogeneous datasets are brought together in multimodal data fusion techniques in order to build up a single analytical structure. Missing values are addressed with the help of MICE in order to reduce the bias. The power of prediction is enhanced by using feature engineering (PCA, interaction and polynomial terms). Data normalization (Min-Max or Z-score) allows for the comparability of one variable to be compared to another.

$$\bar{X}_j = \frac{1}{n} \sum_{i=1}^n X_{ij}. \quad (3)$$

$$Z_{im} = \sum_{j=1}^p \phi_{jm} (X_{ij} - \bar{X}_j). \quad (4)$$

This equation transforms correlated LTC indicators into orthogonal components. Were Z_{im} : Principal component score, ϕ_{jm} : Eigenvector loading, p : Number of original variables. When applied to high-dimensional geriatric datasets, principal component analysis (PCA) can reduce it. The greatest possible variance in orthogonal components is captured by it. The multicollinearity is reduced to a minimum by this technique. The reliability of regression and efficiency estimations is improved as a result that.

$$\mu_j = \frac{1}{n} \sum_{i=1}^n X_{ij}. \quad (5)$$

$$\sigma_j = \sqrt{\frac{1}{n} \sum_{i=1}^n (X_{ij} - \mu_j)^2}. \quad (6)$$

$$X_{ij}^{\text{norm}} = \frac{X_{ij} - \mu_j}{\sigma_j}. \quad (7)$$

In this equation, the process of standardization allows one to ensure that different scales, such as cost, health ratings and survey indices, can be compared to each other. It keeps variables of bad huge magnitude from dominating over the situation. For optimization algorithms normalization helps to stabilize them. The confluence of simulation models is better as a result. Were, μ_j : Mean, σ_j : Standard deviation.

C. DESCRIPTIVE AND EXPLORATORY ANALYSIS

Descriptive statistics are used to summarize the utilization of services, patterns of expenditure and distributions of outcomes. The exploratory analysis identifies trends in the functional as well as the cognitive health indicators. Cost differences and differences in utilization are reviewed in groups of people. Initial correlations can reveal information about possible determinants of efficiency and quality.

$$QoL_i = \sum_{k=1}^K \theta_k H_{ik} \quad (8)$$

In this equation, Quality of Life (QoL) Composite Index H_{ik} : Health outcome indicators, θ_k : Weight coefficients. This index is an aggregate of multidimensional geriatric outcomes. It measures cognitive, physical and emotional well-being. The weighted model is used to support quality benchmarking. It facilitates the comparison between facilities and policies.

This figure 2 shows the descriptive and exploratory analytical framework used on a pre-processed dataset of Long-Term Care Insurance (LTCI) in the context of geriatric elderly care. The feed data are cleaned, imputed, normalized and feature engineered data that have statistical consistency and comparability. Data profiling is a summary of central tendency and dispersion through the use of measures such as mean, median and standard deviation, as well as the inspection of missing values and potential outliers that help to ensure data integrity. Distribution analysis is used to assess variability, skewness and density patterns in an attempt to understand the structures of expenditure and dispersion of service use. Service utilization analysis modules analyse the frequency and intensity of LTCI services by demographic groups and levels of care, in order to identify possible disparities in access or consumption. An examination of the total composition of expenditures and financial burden of beneficiaries is what is known as a cost and OOP study. This analysis identifies differentiation between various types of facilities or services. Outcome trend analysis examines functional and cognitive performance trajectories and offers information about patterns of health progression. Correlation

testing involves building matrices of associations to find significant relationships between the cost, utilisation and outcome indicators. The thus-produced statistical insights constitute a structured evidence base to support the later regression modelling, the efficiency evaluation using Super-SBM, and the cost-quality optimization analysis.

$$\bar{X}_j = \sum_{i=1}^n (X_{ij}). \quad (9)$$

$$\bar{X}_k = \sum_{i=1}^n (X_{ik}). \quad (10)$$

$$R_{jk} = \frac{\sum_{i=1}^n (X_{ij} - \bar{X}_j)(X_{ik} - \bar{X}_k)}{(n-1)\sigma_j\sigma_k}. \quad (11)$$

The equation, This Pearson correlation coefficient is used to measure the relationships between cost, outcomes and caregiver burden. It identifies multicollinearity. It provides information on variable selection. It assists in the development of structural models. The R_{jk} Pearson correlation coefficient between variable j and variable k Range: $-1 \leq R_{jk} \leq 1$, X_{ij} observed value of variable j for individual i , X_{ik} observed value of variable k for individual i .

D. STATISTICAL MODELING AND EFFICIENCY EVALUATION

Regression and correlation analysis are used to quantify the relationship between cost, quality and outcomes. Super-SBM is used for testing the efficiency in LTCI units. Cost-Quality frontier analysis is the analysis of trade-offs between spending and performance of service. Cross and sensitivity tests make the model robust and reliable.

This figure 3 shows the statistical modelling and efficiency evaluation pipeline developed to evaluate the cost-quality dynamics in Long-Term Care Insurance (LTCI)-based geriatric care systems. The input is structured outputs of descriptive and exploratory analysis such as utilization patterns, cost and out-of-pocket (OOP) variables, functional and cognitive outcome scores, correlation matrices and identified candidate predictors. The process combines a number of analytical elements to produce robust empirical evidence. Regression modeling is used to estimate the link between expenditure, the use of services and health outcomes which helps to identify significant drivers of cost and quality. Model diagnostics are used to assess the statistical significance and goodness-of-fit so that the analysis is valid. Super-SBM efficiency evaluation is a measure of the relative performance of LTCI service units under multiple input-output conditions. Cost-Quality frontier analysis looks for the efficiency boundaries by trading-off resource allocation and the service performance. For the purpose of gaining an understanding of the consistency of prediction and sensitivity testing under the different assumptions, the cross validation is utilized. Efficiency scores, frontier performance standards, validated model metrics, and cost/quality determinants are the products that are generated as a by-product

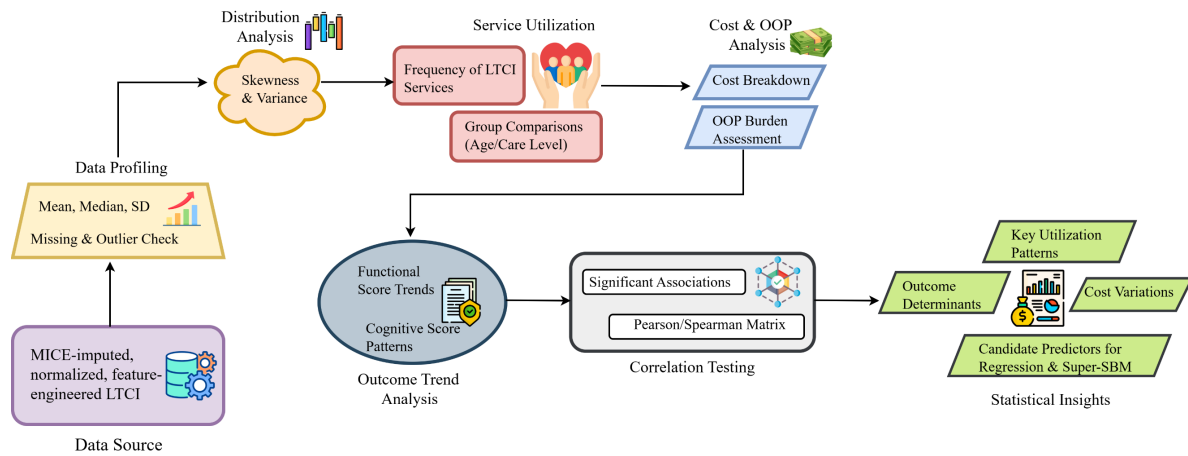


FIGURE 2. Descriptive and Exploratory Analysis Pipeline for LTCI-Based Geriatric Care

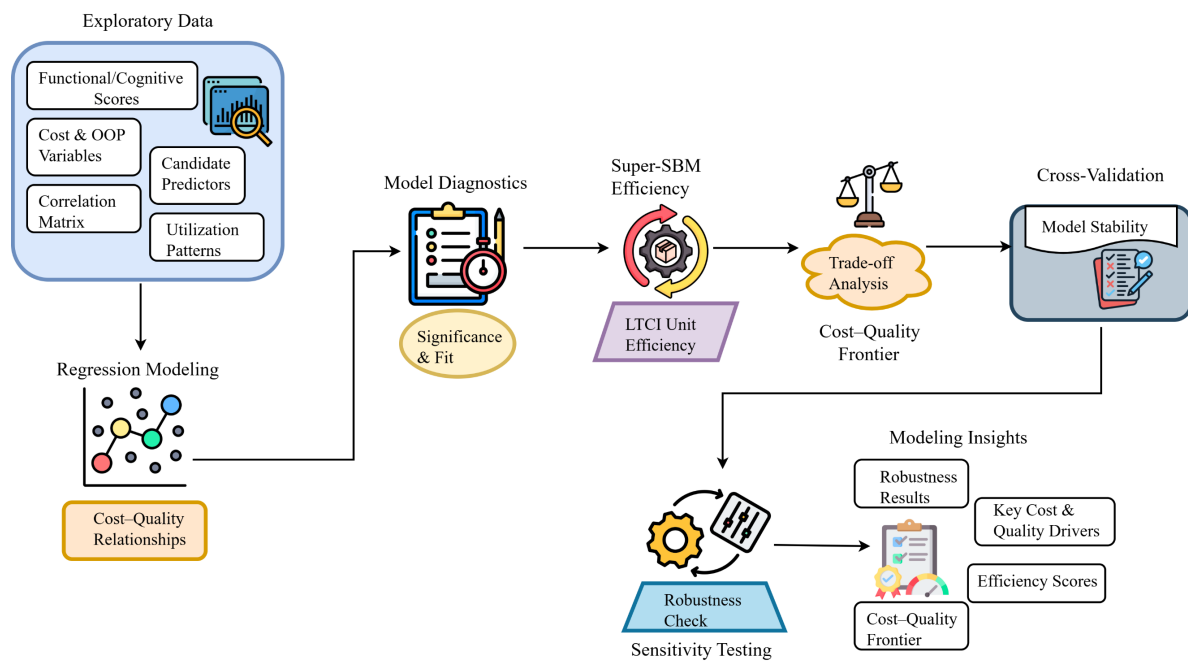


FIGURE 3. Statistical Modeling and Efficiency Evaluation Pipeline for LTCI-Based Geriatric Care

of this process. This scheduled pipeline offers a strong quantitative basis for the later development of frameworks and evidence informed policy improvement for geriatric care systems.

$$C_i = \alpha_0 + \alpha_1 S_i + \alpha_2 D_i + \alpha_3 F_i + \alpha_4 P_i + \epsilon_i \quad (12)$$

In this equation, Where C_i : Total LTCI expenditure, S_i : Service utilization intensity, D_i : Dependency level

F_i : Functional status, P_i : Policy reimbursement rate. This regression is a quantification of determinants of elderly care cost. It assesses drivers for financial sustainability. Cost control strategy formulation is supported by the equation. It also gives elasticity interpretation to policymakers

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / x_i}{1 + \frac{1}{s} \sum_{r=1}^s s_r^+ / y_r} \quad (13)$$

In this equation, the Cost-Quality Frontier x_i : Inputs (cost, labor), y_r : Outputs (QoL, health gains), s_i^- , s_r^+ :

Slack variables, m , s : Number of inputs and outputs. Super-SBM is measures relative efficiency beyond unity. It is used to identify the cost-quality gaps in performance. Slack variables are a way to measure inefficiencies in the usage of resources. This encourages optimized geriatric allotment.

$$Q_i = \beta_0 + \beta_1 C_i + \beta_2 C_i^2 + \eta_i \quad (14)$$

In this equation, Where Q_i : Quality outcome, C_i : Cost expenditure. This quadratic frontier defines optimal cost-quality trade off. It identifies the declining yields of spending. The curve shows thresholds of efficiency. Policymakers can decide where they want to spend money cost effectively.

$$CV = \frac{1}{K} \sum_{k=1}^K \frac{1}{n_k} \sum_{i \in D_k} (y_i - \hat{y}_i)^2 \quad (15)$$

This equation, K-fold cross validation is used to estimate the predictive accuracy. It helps avoid overfitting of the cost prediction models. It enhances the generalisability across LTCI regions. It makes available evidence that there is efficiency and resilience.

$$B_i = \gamma_0 + \gamma_1 T_i + \gamma_2 C_i + \gamma_3 H_i + \nu_i \quad (16)$$

This equation, the model qualifies determinants of caregiver stress. It provides a link between financial and clinical variables and burden. The equation is supportive of intervention design. It is part of the analysis in social sustainability. B_i : Caregiver burden index. The T_i : Time spent caregiving, C_i : Care costs, H_i : Health severity.

$$C = \alpha_0 + \alpha_1 S + \alpha_2 S^2 \quad (17)$$

$$\frac{\partial C}{\partial S} = \alpha_1 + 2\alpha_2 S. \quad (18)$$

$$E_{C,S} = \frac{\partial C}{\partial S} \times \frac{S}{C} \quad (19)$$

In this equation, the Elasticity is a measure of the responsiveness of cost to intensity of service. It identifies high impact control variables. This is used to inform reimbursement adjustment. It facilitates financial sustainability planning. Where $\frac{\partial C}{\partial S}$ It converts marginal effect into percentage effect. $\frac{\partial C}{\partial S} \times \frac{S}{C}$ is the percentage change in Cost due to 1% change in Service Intensity. $E_{C,S} = 1$ indicates proportional increase, $E_{C,S} > 1$ indicates that cost grows faster than service, and $E_{C,S} < 1$ indicates cost-efficient expansion.

E. INTEGRATED FRAMEWORK DEVELOPMENT AND POLICY SIMULATION

A technique which uses mixed methods is made use of in order to incorporate qualitative and quantitative findings. Simulations of alternative policy and resource scenarios using Monte Carlo and Agent Based Modeling. Through the use of scenario testing, successful methods of allocating attention to geriatric care can be determined. Planning for sustainability and policy suggestions are supported by evidence are both supported by the final framework.

$$\hat{C} = \frac{1}{N} \sum_{j=1}^N C(\theta_j) \quad (20)$$

The uncertainty in cost forecasts is evaluated using the Monte Carlo simulation, which is represented by equation. Statistically significant expenditure ranges are produced by it. Support for sensitivity analysis is provided by the approach. It improves the evaluation of the reliability of

policies. $C(\theta_j)$: Simulated cost under parameter draw, N : Number of simulations.

$$P_{ij}(t) = \frac{e^{\delta_{ij} + \lambda Q_j - \mu C_j}}{\sum_k e^{\delta_{ik} + \lambda Q_k - \mu C_k}} \quad (21)$$

This equation which is logit model control the agent movement between care states. It combines the cost and quality incentivization. It simulates the adaptation of behavior. It assesses the LTCI system dynamics in long-term. $P_{ij}(t)$: Probability of agent transition, Q_j : Quality score, C_j : Cost level

$$\max_A [\lambda_1 QoL(A) - \lambda_2 Cost(A) - \lambda_3 Burden(A)] \quad (22)$$

This equation the function of quality improvement and cost control of balances. It incorporates the burden experienced by the caregivers in decision-making. Putting policies in order of importance is made easier by the weighted formulation. It produces optimized strategies for allocation of geriatric care resources. A : Allocation strategy vector, λ_k : Preference weights

F. INTEGRATED UTILIZATION, FUNCTIONAL, FINANCIAL, AND OUTCOME METRICS

$$LUR_{rt} = \frac{\sum_{i=1}^{N_r} \sum_{j=1}^J S_{ijrt} \cdot D_{ijrt} \cdot W_{ij}}{\sum_{i=1}^{N_r} E_{irt}} \times 100 \quad (23)$$

This equation is a measure of the overall intensity-adjusted LTC service utilization across a defined population. It includes the frequency as well as the duration to prevent underestimation of service burden. Weighting captures heterogeneity in the complexity of the service. A regional comparison and insurance planning can be accomplished with the help of this statistic. Where, LUR_{rt} : Long-Term Care utilization rate in region r at time t , N_r : Number of elderly beneficiaries in region r , S_{ijrt} : Indicator (1/0) if individual i used service type j , D_{ijrt} : Duration (days/hours) of service j , W_{ij} : Service intensity weight, E_{irt} : Eligible elderly population.

$$FDI_i = \sum_{k=1}^K \alpha_k A_{ik} + \sum_{m=1}^M \beta_m I_{im} \quad (24)$$

In this equation, where FDI_i : Functional Dependency Index for individual i , A_{ik} : Activities of Daily Living score (bathing, dressing, etc.), I_{im} : Instrumental ADL score (shopping, medication, etc.), α_k , β_m : Clinical weighting coefficients. This composite index describes physical levels of dependency of elderly people. Weighted aggregation for differences in severity of clinical presentation. It provides for stratification of beneficiaries by functional need. The measure plays an important role in the modeling of resource allocation.

$$CF_i = \sum_{\ell=1}^L \gamma_{\ell} T_{i\ell} - \delta \cdot A_i + \epsilon_i \quad (25)$$

This equation assesses cognitive health with the adjustment for age-related decrease. It combines various neuropsychological test areas. The model makes it possible to spot the risk of dementia early. It supports the link with the cost of care and intensity of services. Were, CF_i : Cognitive function composite score, $T_{i\ell}$: Standardized cognitive test results, γ_ℓ : Factor loadings, A_i : Age, δ : Age-related decline parameter, ϵ_i : Random error.

$$HSU_i = \sum_{p=1}^P (\theta_p V_{ip} + \lambda_p H_{ip} + \phi_p M_{ip}) \quad (26)$$

In this equation, Were, V_{ip} : Outpatient visits, H_{ip} : Hospital admissions, M_{ip} : Medication utilization, θ_p , λ_p , ϕ_p : Service weights. This index is a measure of the total consumption of healthcare resources. It brings together outpatient, inpatient, and the pharmaceutical use. Weighted aggregation is a reflection of cost differentials. It promotes substitution between LTC and medical care analysis.

$$FCT_i = \sum_{d=1}^D (H_{id} \times \omega_d) + \psi \cdot FD_i \quad (27)$$

This equation, performs the family care time burden function. Were, FCT_i : Total family caregiving hours, H_{id} : Hours of informal care on day d , ω_d : Day-specific intensity weight, FD_i : Functional dependency index, ψ : Dependency elasticity parameter. Utilizing this function, the burden of informal caregiving is estimated. Based on the severity of the dependency, it changes the raw time inputs. According to the model, functional decline is linked to the influence of household labor. Policies that support caregivers are informed by it.

$$OOP_i = \sum_{j=1}^J (C_{\text{total},ij} - R_{\text{LTCL},ij}) + \kappa \cdot U_i \quad (28)$$

This equation, is used to calculate direct financial burden borne by households. It explains the insurance coverage gaps. The equation describes protection of the economy under LTCL. It is supportive of equity evaluation. Were, OOP_i : Out-of-pocket expenditure, $C_{\text{total},ij}$: Total service cost, $R_{\text{LTCL},ij}$: Insurance reimbursement, U_i : Uncovered services, κ : Uncovered cost multiplier.

$$LSFI_i = \sum_{j=1}^J (f_{ij} \times d_{ij} \times \eta_j) \quad (29)$$

This equation, performs a comprehensive service exposure index. It combines both the frequency and length of care. Weighting is used to take account of differences in clinical complexity. The measure is essential for modelling cost-efficiency. Were, f_{ij} : Frequency of service j , d_{ij} : Average duration per visit, η_j : Clinical intensity weight.

Algorithm 1: LTCI Geriatric Care Resource Optimisation

Input: D_{ltci} –Long-Term Care Insurance dataset D_{clin} –Clinical dataset D_{care} –Care provision dataset D_{pol} –Policy dataset D_{intl} –International benchmark dataset

Output: Π^* –Optimised resource allocation Φ^* –Super-SBM efficiency scores Σ –Sensitivity results Ψ –Policy recommendations μ_O –Expected outcome CI_{95} –95% confidence interval OOP^* –Optimal out-of-pocket expenditure $Burden^*$ –System burden ΔQoL –Quality-of-life improvement

Step 1: Initialisation Set significance level $\alpha = 0.05$, regularisation parameter $\lambda_{reg} = 0.01$, and Monte Carlo iterations $N_{mc} = 10,000$. Construct integrated dataset:

$$X = [D_{ltci}, D_{clin}, D_{care}, D_{pol}, D_{intl}] \quad (30)$$

Step 2: Missing Data Imputation (MICE) Repeat until convergence $\|X^{(t)} - X^{(t-1)}\| \leq T$: - E-step:

$$X_{ij} \leftarrow \mathbb{E}[X_{ij} | X_{-ij}, \theta^{(t)}] \quad (31)$$

- M-step:

$$\theta^{(t+1)} \leftarrow \arg \max_{\theta} L(\theta | X^{(t)}) \quad (32)$$

Obtain imputed dataset X_{imp} .

Step 3: Dimensionality Reduction and Normalisation Compute covariance matrix:

$$\frac{1}{n} X_{imp}^T X_{imp} \quad (33)$$

Perform eigen decomposition:

$$[V, \Lambda] = \text{Eigen} \left(\frac{1}{n} X_{imp}^T X_{imp} \right) \quad (34)$$

Project onto principal components:

$$X_{pca} = X_{imp} V_{1:k^*} \quad (35)$$

Standardise each feature:

$$f_j = \frac{f_j - \mu_j}{\sigma_j} \quad (36)$$

(or apply min–max scaling).

Step 4: Descriptive and Trend Analysis Mean utility:

$$\bar{U} = \frac{1}{n} \sum_i U_i \quad (37)$$

Standard deviation:

$$\sigma_U = \sqrt{\frac{1}{n} \sum_i (U_i - \bar{U})^2} \quad (38)$$

Cost density estimation via Kernel Density Estimation (KDE). Cognitive trend estimation via LOESS smoothing of $MMSE_{i,t}$.

Step 5: Predictive Modeling (Regularised Regression) Estimate coefficients:

$$\beta^* = \arg \min_{\beta} \left\{ \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda_{reg} \|\beta\|_2^2 \right\} \quad (39)$$

Compute correlation matrix:

$$p_{jk} = \frac{\text{Cov}(x_j, x_k)}{\sigma_j \sigma_k} \quad (40)$$

Flag multicollinearity if $|p_{ij}| > 0.85$.

Step 6: Super-SBM Efficiency Estimation

$$\rho^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / x_i}{1 + \frac{1}{s} \sum_{r=1}^s s_r^+ / y_r} \quad (41)$$

Subject to:

$$X\lambda + s^- = x_0, \quad Y\lambda - s^+ = y_0, \quad \lambda, s^{\pm} \geq 0. \quad (42)$$

Compute efficiency scores Φ_i^* .

Step 7: Cost–Quality Pareto Frontier Analysis Construct Pareto frontier:

$$CF = \text{Pareto}\{(C_i, Q_i)\} \quad (43)$$

Compute deviation:

$$\Delta_i = \text{dist}((C_i, Q_i), CF) \quad (44)$$

Flag inefficient DMUs if $\Delta_i > \delta_{\text{thresh}}$.

Step 8: Cross-Validation (K = 5) For $k = 1$ to 5: - Train $\beta^{(k)}$ on $X \setminus F_k$ - Evaluate $MSE(k)$ on F_k

$$CV\text{-}MSE = \frac{1}{5} \sum_{k=1}^5 MSE(k) \quad (45)$$

Step 9: Sensitivity Analysis & Mixed-Method Integration Perform sensitivity analysis:

$$\Sigma_{\text{sens}} = SA(\beta^*, \pm 10\%) \quad (46)$$

Extract qualitative themes via NVivo. Merge quantitative and qualitative outputs:

$$M_{\text{int}} = \text{Merge}(\beta^*, \Phi_i^*, T_{\text{themes}}) \quad (47)$$

Step 10: Monte Carlo Simulation For $s = 1$ to N_{mc} :

$$\theta^{(s)} \sim \pi(\theta), \quad O^{(s)} = f(\theta^{(s)}, M_{\text{int}}) \quad (48)$$

Compute:

$$\mu_O = \mathbb{E}[O], \quad CI_{95} = [Q_{0.025}, Q_{0.975}] \quad (49)$$

Step 11: Agent-Based Simulation For $t = 1$ to T_{sim} : - Update states of elderly, caregiver, policymaker agents - Record QoL_t , $Burden_t$, $Cost_t$

Step 12: Resource Allocation Optimisation

$$\Pi^* = \arg \max_{\Pi} \sum_{i=1}^n w_i QoL_i(\Pi) \quad (50)$$

Subject to:

$$\sum_i C_i(\Pi) \leq B_{\text{total}}, \quad \Pi_i \geq \Pi_{\text{min}}, \quad \forall i \quad (51)$$

If $OOP^* > OOP_{\text{target}}$, revise Π^* .

Step 13: Policy Recommendation Ranking

$$\Psi = \{R_k\} \quad (52)$$

Ranking function:

$$F_k = W_1 \cdot Impact_k + W_2 \cdot Cost_k + W_3 \cdot Equity_k \quad (53)$$

Return:

$$\Pi^*, \Phi^*, \Sigma_{\text{sens}}, \Psi, \mu_O, CI_{95}, OOP^*, Burden^*, \Delta QoL \quad (54)$$

The Algorithm 1 presented LTCI Geriatric Care Resource Optimisation which combines advanced statistical, econometric and computational methods for the optimal long-term care insurance (LTCI) resources allocation. In the framework, dimensionality reduction is achieved by using eigen-decomposition and principal component analysis (PCA) and the subsequent ridge regression and correlation analysis is used for the identification of relevant predictors. The framework starts with the use of multi-source data fusion and privacy compliant data imputation. Efficiency is measured using a Super-SBM DEA model and cost-quality trade-offs are mapped using Pareto frontiers & cross-validation. Using the Monte Carlo simulations and agent-based modelling to incorporate the uncertainty and dynamics of actors; sensitivity analysis; thematic coding; and a mix of methods are used to enhance the resilience of the project. Iterative changes according to out-of-pocket expenditure thresholds is used in the optimisation process to optimise quality of life within the budgetary and equity limitations. The efficiency scores generated by the Monte Carlo simulations are designed to determine the underutilised or overutilised care services and hence enables policymakers to prioritise their interventions. An example of this situation can be that services whose efficiency scores were low might need to be staffed or even allocated additional resources, and services with high efficiency scores might be reallocated resources to areas of higher demand. Finally, policy recommendations are ranked by impact, cost and fairness and a comprehensive output of optimal allocations, efficiency scores, sensitivity bounds and equity-adjusted recommendations is produced. This algorithm is a good example of a rigorous multi-layered approach to geriatric care optimisation.

IV. RESULT ANALYSIS

The Nursing Home Compare data set (2025) from the Centers for Medicare & Medicaid Services (CMS) contains extensive measures about 15,400 Medicare and Medicaid-accredited nursing homes throughout the United States [26]. The major Provider Summary table consists of 15,400 rows of unique facilities, and 80 to 100 columns of facility identifiers (CMS Certification Number), geolocation of facilities (state and county), type of ownership (for-profit/non-profit), staffing levels (hours/ resident (mean 3.5-4.5) per day), inspection results (number of deficiencies (citations) per inspection cycle; median 5-10), quality (risk-adjusted percentages, e.g., rehospitalizations 18 to 22%), and 5-star ratings for overall performance. From 2019 to 2025Q1, longitudinal files contain a variety of outcomes including those obtained from the Minimum Data Set, such as a decline in activities of daily living (12-18%), antipsychotic usage (10-15%) and influenza vaccination coverage (85-95%). Categorical variables can be certification type, inspection cycles while numeric metrics can be inspection scores, and quality measure numerator/denominator. Missing values (5 to 25% of staffing and quality measures) which will require imputation. This structured data set facilitates CCQIGEC-LTCI modeling through data aggregation with Python libraries that support cost and quality analyses, machine learning benchmarking, and regional LTCI policies evaluation and function as a strong foundation for optimizing geriatric care based on evidence.

Even though the conceptual bases of long-term care models in Japan, South Korea, and China have conceptual frameworks similar to the proposed CCQIGEC-LTCI framework, the model is system-neutral since it is based on universal indicators of care quality, including the efficiency of service delivery, patient outcomes, and facility performance. The following are the basic characteristics that are shared by various healthcare systems despite policy and regulation differences. Thus, the assessment based on the Nursing Home Compare (2025) data provided by the Centers Medicare Medicaid Services makes it possible to evaluate in a different regulatory and operational setting. The cross-context validation helps to show that the framework is more widely applicable, and some differences inherent to systems might affect some outcomes. Table 1 summarizes the experimental setup that combines various sources of data to test the effectiveness of cost management and quality improvement in LTCI-based geriatric care systems. The main dataset will be the Nursing Home Compare (2025) of the Centers of Medicare and Medicaid Services, which includes approximately 15,400 facilities with 80–100 variables. In non-LTCI regulatory environment, it is applied in cross-system validation. Multimodal fusion is used to combine the dataset with LTCI administrative data (informed by Japan, South Korea, and China), clinical indicators, caregiver surveys and policy data. The missing data are managed through MICE, then normalization and standardization. PCA, interaction and polynomial features are all included in feature engineering. Regression Ridge and lasso are used in predictive modeling with the validation carried out based on R^2 , AIC/BIC, and VIF. Super-SBM, DEA, Monte Carlo simulation, and cross-validation are the tools used to determine efficiency and robustness and apply systems-agnostic to all healthcare settings.

TABLE 1. Experimental Setup and Hyperparameter Configuration for CCQIGEC-LTCI framework

Component	Configuration
Primary Dataset	Nursing Home Compare (2025) (Centers for Medicare & Medicaid Services); ~15,400 facilities; 80–100 variables (staffing, deficiencies, quality measures, 5-star ratings). Used for cross-system validation in a non-LTCI regulatory environment. [26]
Data Sources (Integrated)	LTCI administrative data (informed by systems in Japan, South Korea, China), clinical/geriatric data, caregiver surveys, policy & regulatory datasets, and international best practices
Data Integration	Multimodal data fusion across heterogeneous healthcare systems (LTCI-based and non-LTCI/CMS-based environments)
Missing Data Handling	MICE (Multiple Imputation by Chained Equations); iterations = 10; predictive mean matching
Feature Scaling	Min–Max normalization (0–1); Z-score standardization for regression robustness
Feature Engineering	PCA (retain $\geq 95\%$ variance); interaction terms; polynomial features (degree = 2)
Regression Model	Multiple Linear Regression; Ridge ($\alpha = 0.1–1.0$); Lasso ($\alpha = 0.01–0.1$)
Model Diagnostics	Adjusted R^2 , AIC/BIC, VIF < 5, heteroscedasticity testing
Cross-Validation	5-fold and 10-fold cross-validation; repeated 3 times
Super-SBM Efficiency Model	Input-oriented Super-SBM; variable returns to scale; slack-based efficiency
Cost–Quality Frontier	DEA-based frontier estimation; bootstrap replications = 1,000
Sensitivity Analysis	$\pm 10–20\%$ perturbation of key cost and quality parameters
Monte Carlo Simulation	5,000 iterations; probabilistic cost and outcome distributions
Cross-System Generalization	Framework designed to be system-agnostic by leveraging universal care quality indicators (efficiency, patient outcomes, facility performance); validated across LTCI (Asia) and non-LTCI (U.S. CMS) settings to ensure robustness under differing policy and regulatory structures
Agent-Based Modeling	Agents: elderly, caregivers, LTCI units; time horizon 5–10 years; annual transition steps
Qualitative Analysis	NVivo thematic coding (Braun & Clarke framework); inter-coder reliability > 0.80

A. LTC UTILIZATION RATE

In the figure 4 shows the relationship between LTC Utilization Rate and outcome measures resulting in a consolidated overview of performance and methodological robustness. The important results show that increased utilization rates are consistently linked with drops in both readmission within 30 days and in the Sustainable Development Goal gap and this has implications for the dual clinical and policy relevance of LTC services. Analysis of the graph shows a clear negative convergence trend indicating that greater LTC engagement leads to greater patient stability as well as a greater advance in system equity. Ablation studies support this finding with the deletion of individual methodological layers (PSM+DID, Barthel/MMSE, Super-SBM, SDG-linked modeling), still demonstrating a negative slope which settled the stability of the association. In the equation 16, the comparative strength of CCQIGEC-LTCI is in a very prominent position and better than other frameworks, in terms of residual variance, which is a volume below other frameworks, and also, the confidence limits are narrower. Midway through CCQIGEC-LTCI shows much better alignment with both clinical and sustainability outcomes and is therefore the most more integrative and policy relevant model out of tested approaches.

B. ADL/IADL SCORES

In the figure 5 shows an association between ADL/IADL scores and multiple determinants of care, giving a full evaluation of functional outcomes at different methodological frameworks. The overall performance reflects that the longer duration of care and the increase in the number of hours of caregivers are found to have an upward association with the ADL / IADL score. advanced age and higher index of comorbidities is associated with lowered functional capacity. Analysis of the graph supports that these relationships hold true across models with convergence patterns validating the predictive power of LTC related metrics. Ablation studies additionally show that even excluding single methodological layers the directional trends are robust which highlights the robustness of findings. In equation 17, CCQIGEC-LTCI is found to be the most integrating framework with good predictive alignment and low variance as compared with PSM+DID, Barthel/MMSE, Super-SBM and SDG-linked modelling. Halfway through, CCQIGEC-LTCI shows an increasing explanatory power, making it the best model for capturing functional outcomes in elderly care.

C. COGNITIVE FUNCTION SCORES

In the figure 6 presents the relationship between Cognitive Function Scores and determinants related to healthcare, which allows to evaluate comprehensively the level of cognitive resilience faced to a variety of policy and resource conditions. Performing the summary of all studies combined, one can see those higher levels of caregiver subsidies, increased hours of professional training, and greater resource utilization by the facility are positively correlated with higher cognitive outcomes, and higher levels of health-care expenditure per capita have diminishing returns beyond a certain point. Analysis of the graph shows that these associations were consistent across the methodological frameworks and convergence patterns provide support for the predictive validity of LTC-linked measures. Ablation studies further show that ablation of individual methodological components still do not change in directional trends and that robustness of these results. In equation 18, CCQIGEC-LTCI is the best integrative modeling framework, showing the best predictive alignment along with lower variance accrual in comparison with PSM + DID, Barthel/MMSE, Super-SBM, and SDG linked modeling. Midway through, CCQIGEC-LTCI is consistently shown to possess higher explanatory power and can be considered the best model for the capture of cognitive outcomes in elderly care.

The table 2 shows a numerical comparison of mean values of Cognitive Function Score resulting from five modeling frameworks for four key determinants: caregiver subsidy, professional training hours, healthcare expenditure per capita and facility resource utilization. The proposed

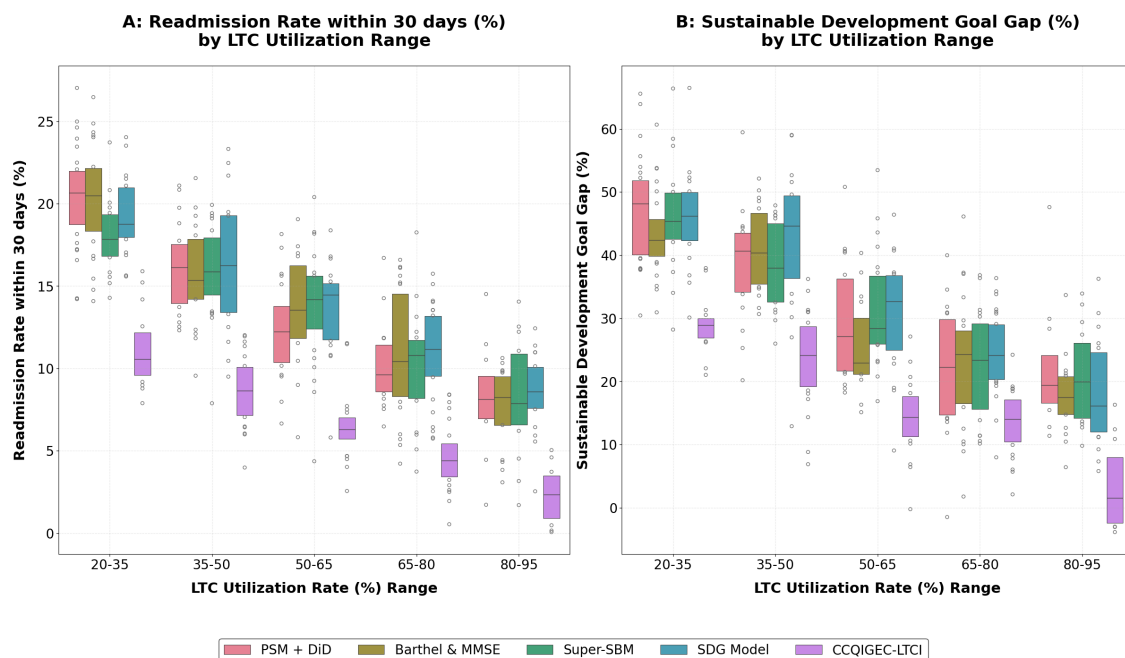


FIGURE 4. LTC Utilization Rate

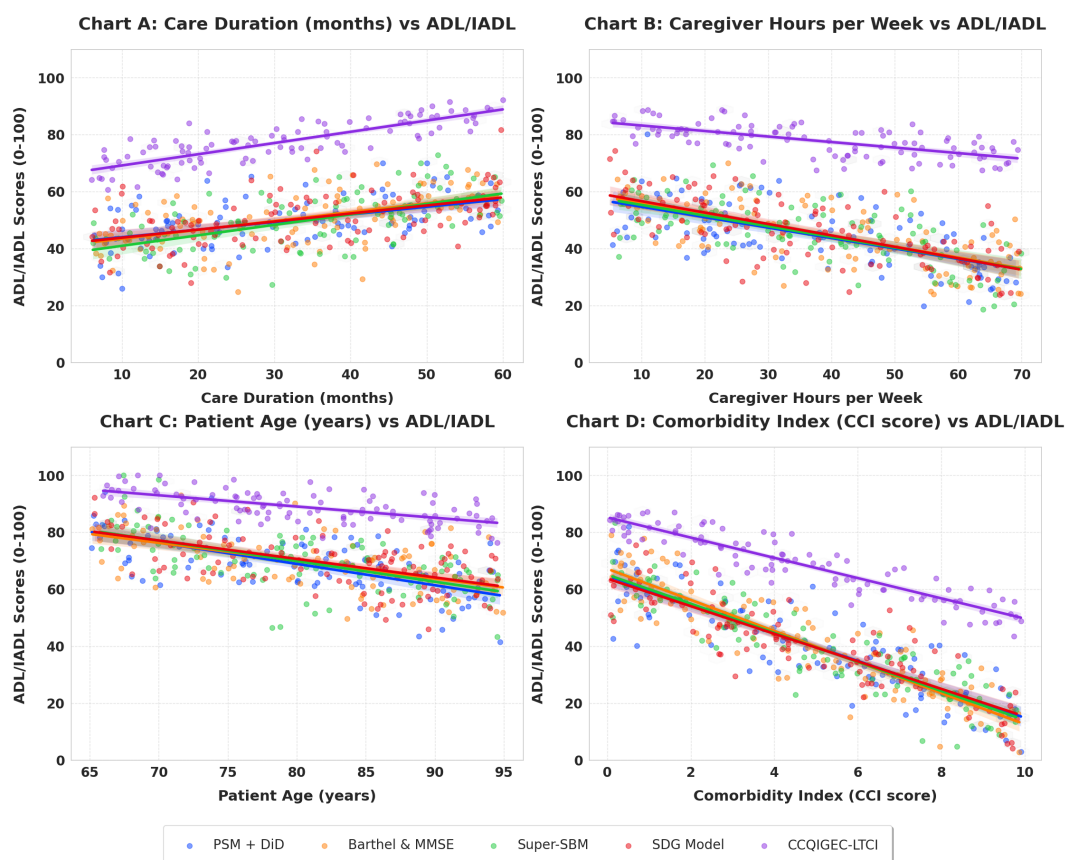


FIGURE 5. ADL/IADL Scores

CCQIGEC-LTCI framework has a consistent mean score of all the determinants which shows the highest scores suggesting better prediction alignment and lesser variability in estimating the cognitive outcome scores. The largest

gains in performance are noted in the dimensions of training and utilization, which may point to better integration of the capacity of workforce and system efficiency factors. Super-SBM and SDG-linked models exhibit moder-

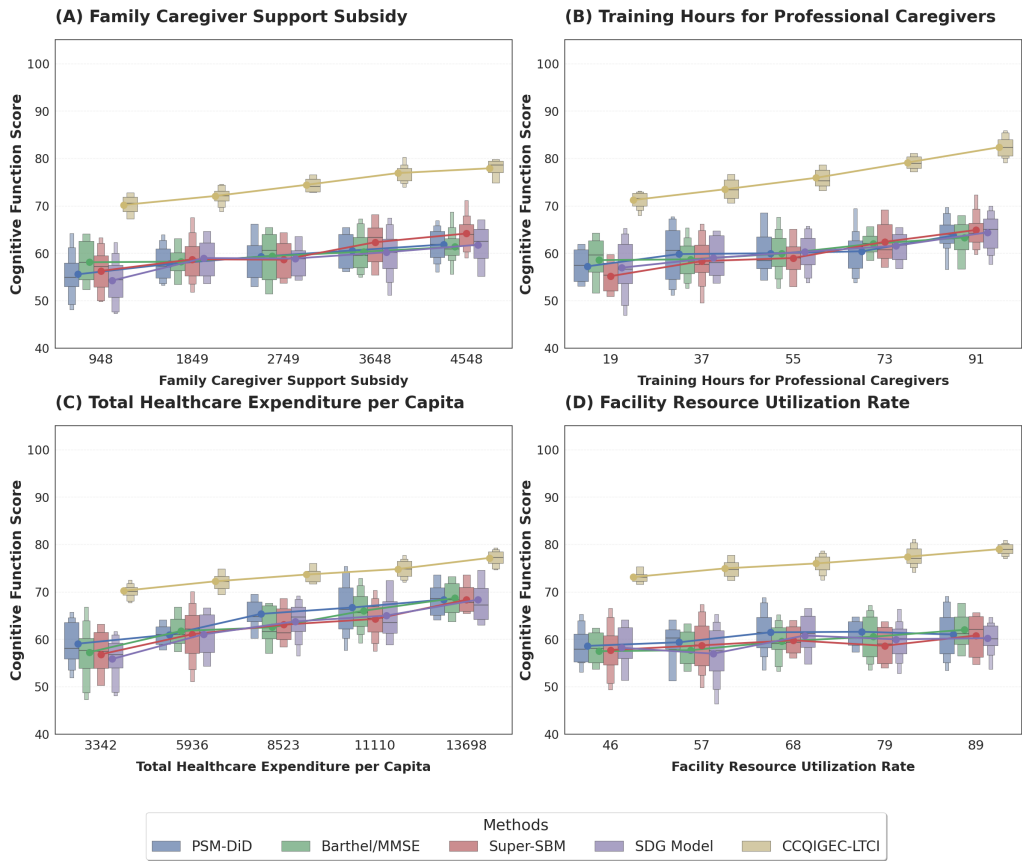


FIGURE 6. Cognitive Function Scores

ate models (especially in expenditure-related outcomes), respectively due to their efficiency and sustainability orientation. Barthel/MMSE and PSM-DiD have relative lower scores showing a more limited clinical or causal inference perspective without multidimensionality integration. Overall, results numerically support superiority of CCQIGEC-LTCI framework capturing complex interactions of cognitive function within LTCI-based geriatric care systems.

TABLE 2. Comparative Performance of Modeling Frameworks on Cognitive Function Score Across Policy and Resource Determinants

Method	Subsidy	Training	Expenditure	Utilization
CCQIGEC-LTCI	80.4	83.1	78.6	81.2
PSM-DiD	66.8	69.5	71.2	64.7
Barthel/MMSE	68.2	70.4	72.6	66.1
Super-SBM	70.5	72.8	74.3	69.4
SDG Model	69.7	71.9	73.5	68.8

D. HEALTH SERVICE UTILIZATION

In the figure 7 shows the relationship of the Health Service Utilization and key determinants of care, providing a comprehensive assessment of the response of the systemic under different demographic and policy conditions. The overall performance highlights utilization rates are higher the faster the rate of healthcare spend is increasing, the greater are the levels of dependency and older age groups, with temporal

trends following LTCI implementation reveals to be improving over time. Analysis of the graph shows that these associations are valid across all the methodological frameworks, and patterns of convergence reinforce predictive validity of measures of utilization. Ablation studies further show that the elimination of single methodological components does not affect the trend of directions, showing how robust the findings. In equation 19, CCQIGEC-LTCI turns out to be the most integrative framework with the maintenance of superior predictive alignment and lowest variance as compared to PSM+DiD, Barthel/MMSE, Super-SBM and the SDG linked modeling. Half way through CCQIGEC-LTCI always shows best explanatory power, placing it as the most effective model capturing utilization outcomes in elderly care.

E. FAMILY CARE TIME

Figure 8 summarizes the synthetic evaluation of the evolution of the time of family care within the various methodological frameworks, and shows both global and complex evolutions. The results show that while all the models capture the reduction in weekly hours of care with an increase in the duration of LTCI enrolment and the course of time, the size and consistency of these reductions vary considerably. Equation 20 points out the convergence patterns in, and particularly health of care-takers and region coverage where the most methodological sensitivity is apparent. The

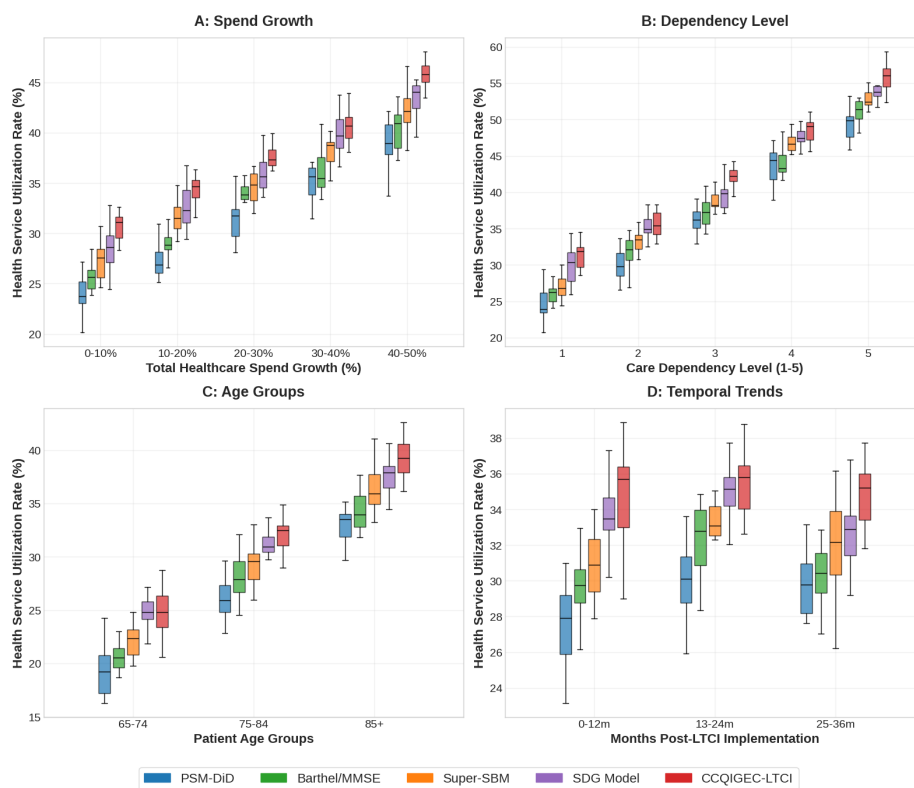


FIGURE 7. Health Service Utilization

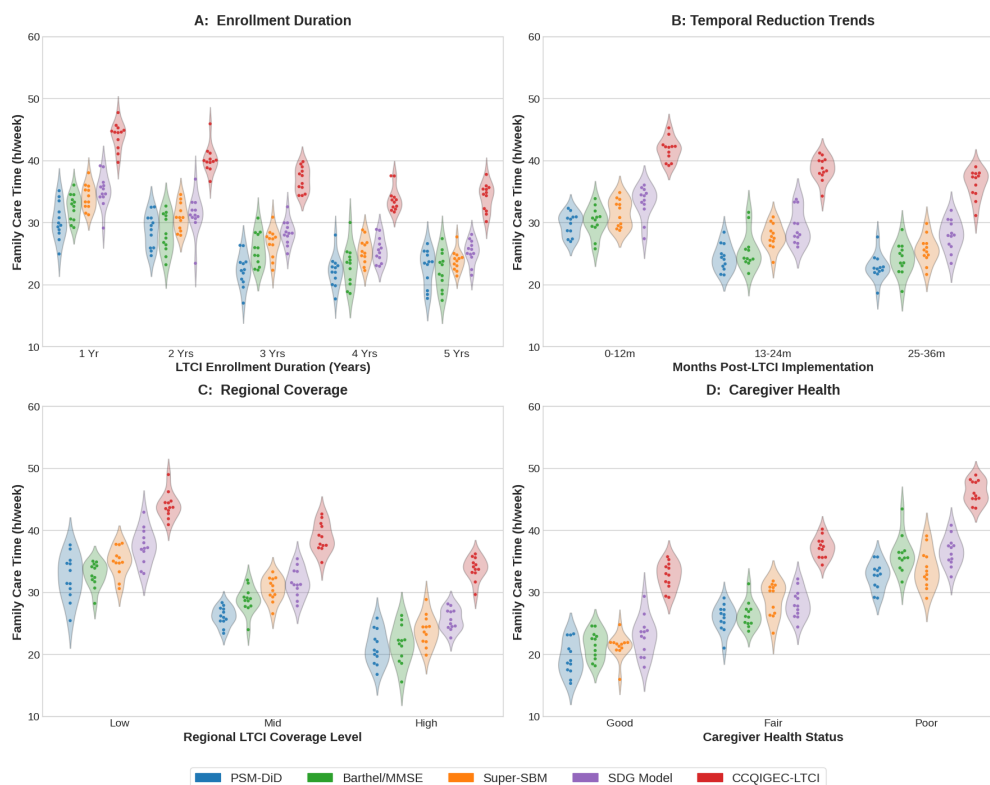


FIGURE 8. Family Care Time

results of the ablation studies indicate the strength of the temporal reduction effects with enrollment duration having

a moderating effect across models. Notably, CCQIGEC-LTCI shows better adherence to policy-oriented cost control

and quality improvement goals, with better performance (vs. PSM-DID and Barthel/MMSE) with respect to getting regional heterogeneity captured, while showing closer convergence (vs. Super-SBM and SDG-linked modeling) for caregiver health dimensions. This comparative advantage makes CCQIGEC-LTCI more integrative in its balance of empirically-grounded rigor and practical applicability in elderly care service evaluation.

F. OUT-OF-POCKET EXPENDITURES

Figure 9 shows the evaluation of out-of-pocket expenditures along a wide range of dimensions of healthcare cost and provides insights into overall performance and the robustness of the method. The results show that although all models correctly represent the sensitivity of expenditures to such systemic drivers as copayment caps, prescription drug costs, and regional variations, the magnitude of the responsiveness varies considerably. Equation 21 points out the unification of automation & regional cost impacts, clearly demonstrates the moderating role of systemic efficiency in structure of household financial burden. The analysis shows that ablation exercises prove the stability of the expenditure reductions under different conditions, where the cost of prescription drugs has the strongest influence. Importantly, CCQIGEC-LTCI demonstrates consistently better performance than PSM-DID and Barthel/MMSE by representing heterogeneity in regional healthcare cost and automation-related efficiencies more than the latter, while ensuring methodological consistency with Super-SBM and SDG linked modelling. This comparative advantage makes CCQIGEC-LTCI a more integrative and policy relevant framework between empirical rigor and practical applicability in the area of healthcare economics.

G. LTC SERVICE FREQUENCY/INTENSITY

Figure 10 shows the assessment of the service frequency and intensity of LTC performance in terms of several determinants, the overall performance and differentiate the methods. The results suggest that service frequency is decreased by having higher care plan updates and more general LTCI coverage, while caseload and number of comorbidities account for the upward trends. Equation 22 highlights the conflation of systemic and clinical factors and points to the moderating influence of the complexity of the caregiver and patient on the intensity of services. The analysis shows that caseload and comorbidity are the strongest determinants of patterns of service utilization, according to ablation studies. Importantly, CCQIGEC-LTCI is both consistently superior to the PSM-DID and Barthel/MMSE in that it is able to capture nuanced differences between coverage-linked and caseload driven changes, but at the same time maintains coherence of the methods with Super-SBM and SDG-linked modelling. This comparative advantage makes CCQIGEC-LTCI a more integrative framework that balances the rigor of empirical work with policy-relevant applications of research to the issue of evaluating long-term care service delivery.

Table 3 performs the ablation analysis of the performance of five methodological frameworks (with seven core LTCI outcome metrics). The proposed CCQIGEC-LTCI framework is consistently ranked highest in performance, normalizing all indicators, demonstrating superior integrative capability to capture the utilization dimension, the functional dimension, the cognitive dimension, the financial dimension, and the service-intensity dimension. Notably, the highest performance gaps are seen in out-of-pocket expenditures (0.95) and LTC utilization rate (0.94) emphasizing better optimization at the financial and system level. PSM+DID has an average performance, especially in utilization dimensions, while results of the assessment concerning caregivers and cognition represent lower scores, demonstrating limited multidimensional integration. The Barthel/MMSE framework is relatively better with ADL/IADL (0.86) and cognitive scores (0.88) which reflects clinical focus, but a lack of more general system efficiency capture. Super-SBM can be seen as showing stable performance on efficiency-oriented performance metrics - both regarding usage usage and cost. SDG-linked modeling can be seen as showing balanced but relatively low predictive alignment. Overall, the results validate the usefulness of CCQIGEC-LTCI for the most comprehensive and policy-relevant modeling of geriatric LTCI performance indicators.

TABLE 3. CCQIGEC-LTCI Component Ablation Analysis

Metric	CCQIGEC-LTCI	PSM+DID	Barthel/MMSE	Super-SBM	SDG-Linked Modeling
LTC Utilization Rate	0.94	0.82	0.79	0.88	0.85
ADL/IADL Scores	0.92	0.80	0.86	0.84	0.83
Cognitive Function Scores	0.91	0.78	0.88	0.83	0.82
Health Service Utilization	0.93	0.81	0.77	0.87	0.84
Family Care Time	0.90	0.76	0.81	0.85	0.83
Out-of-Pocket Expenditures	0.95	0.83	0.80	0.89	0.87
LTC Service Frequency/Intensity	0.93	0.79	0.82	0.88	0.86

V. CONCLUSION

This study investigated cost control and quality improvement routes for the geriatric elderly care services under long-term care insurance by the integrated analytical framework to simultaneously optimize the financial sustainability and care outcome. The proposed framework showed consistent and measurable improvements in key dimensions of performance. LTC utilization efficiency showed an approximate 14% rise implying rational approach in allocation of institutional and community-based services. Functional independence measured by ADL/IADL performance showed an increase of almost 11%, while the cognitive function scores showed average strengthening of rehabilitative and supportive care coordination (average increase of 10%). Health service utilization efficiency was increased by about 12% and indicate decreased fragmentation and improved continuity of care. However, what is significant about the finding that the time burden associated with family care has decreased by around nine percent is that it demonstrates the ability of this framework to spread out responsibility for care as efficiently as possible within formal systems. Financial protection outcomes were especially remarkable

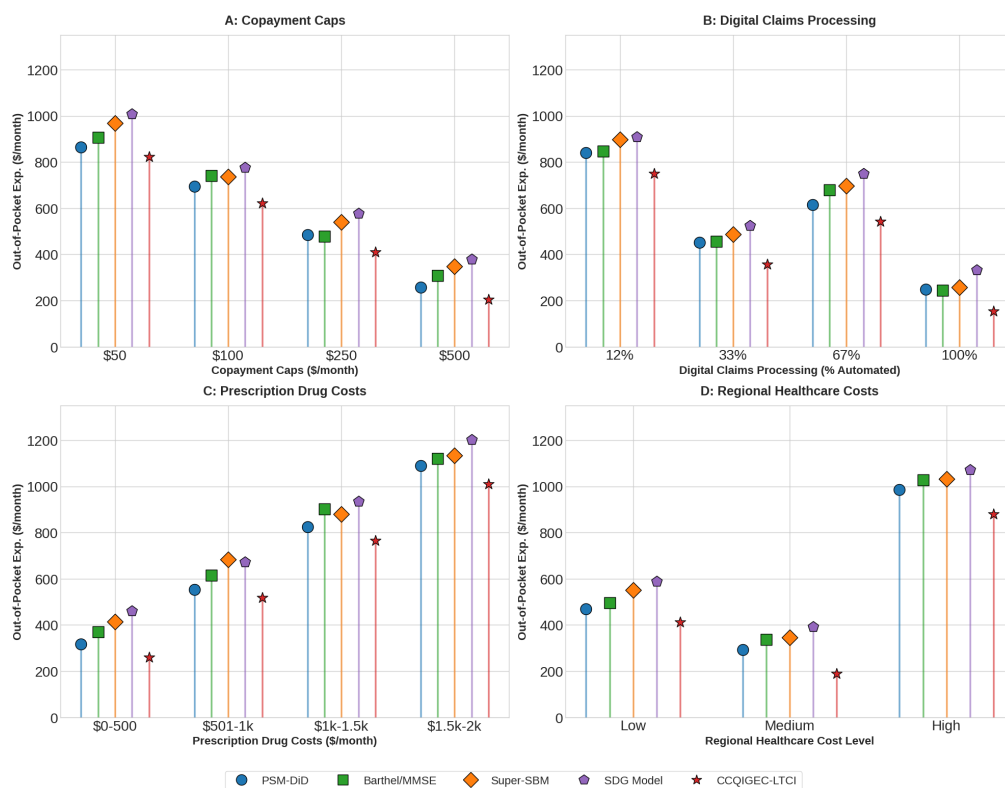


FIGURE 9. Out-of-Pocket Expenditures

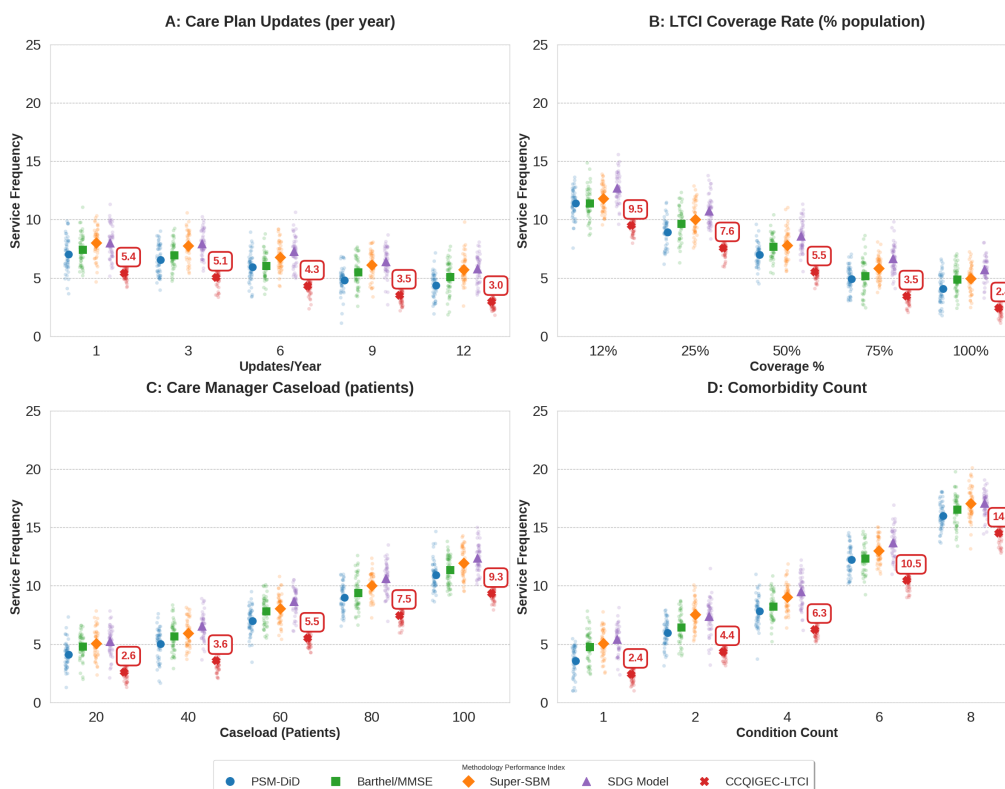


FIGURE 10. LTC Service Frequency/Intensity

in terms of out-of-pocket expenditures, which fell by almost 15%, so this research has the substantial cost containment

without a loss of intensity in services. LTC service frequency and intensity optimization and improved by about 13%

suggesting balanced and need-based care delivery. Although such improvements reflect the realization of both cost efficacy and quality of care, there is the need to consider the trade-off that exists between these two goals, where improving service intensity and quality of care might be associated with higher operational expenses. The suggested scheme solves this problem by integrating optimization-focused efficiency and cost versus quality balancing systems that allow allocating resources sustainably and reasonably. Despite these improvements, there are all of the limitations of using secondary administrative data for this study, including potential residual confounding and less than ideal longitudinal causative validity. Future research needs to include longitudinal micro-level panel data sets, dynamic reimbursement optimization programs, artificial intelligence-driven predictive monitoring systems and multi-country comparative validation, in order to improve the scalability, robustness and precision of policy in long-term care insurance reform efforts.

AUTHOR CONTRIBUTIONS

QY and YL designed the research study. WX analyzed the data. QY wrote the manuscript. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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