Geospatial Economic Evaluation of Integrated Community-Based Collaborative Care Models for Long-Term Care in Rural Thailand

Scully, P. M. D.,[1] Zheng, L.,[2] Aneksak, W.,[4,5] Meenongwar, C.[4,6] and Nithikathkul, C.[3,4*]
[1]Faculty of Information Communication Technology, Mahidol University, Thailand
[2]Fujian Maternal and Child Health Hospital, Fuzhou, Fujian, China
[3]Faculty of Medicine, Mahasarakham University, Thailand
[4]Tropical Health Innovation Research Unit, Faculty of Medicine, Mahasarakham University, Thailand
[5]Faculty of Nursing, Mahasarakham University, Thailand
[6]Faculty of Science & Technology, Valaya Alongkorn Rajabhat University under Royal Patronage, Pathum Thani, Thailand
E-mail: nithikethkul2016@gmail.com
**Corresponding Author*

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Abstract

Context: *Thailand's public health system is facing rising socioeconomic pressures, especially among its rapidly aging society and the fiscally constrained rural regions of this lower-to-middle income country (LMIC). Identifying cost-efficient Long-Term Care (LTC) public health designs is vital to addressing this challenge across rural geographical regions. Our research set out to find synergies between elderly mental health support and LTC public health protocols, through the design integrated community-based collaborative care (I-CBCC) intervention models.*

Method: *The geospatial decision support tool utilizes discrete event simulation models, measured by 3 quantitative metrics: their operational workload, service delivery quality and cost-efficiency metrics, and compares proposed designs to national protocol baseline designs. Experimental model designs build from the current national public health protocols; the proposed I-CBCC model adds four key interventions, which include home-based case initialization, long-term care giver integration and digital system integration. Ablation analysis studies each (intervention) design component. Parameter sensitivity analyses were conducted to verify robustness of each model. Large geospatial datasets over four rural provinces form the data sources of the evaluations, including epidemiology (106,068 elderly participants; collected 2020-2024) and public health facilities (1,032). A geospatial analysis layer (subdistrict choropleth mapping, spatial cluster statistics, and a multi-criteria priority ranking) localizes the simulated impacts for policy rollout planning.*

Findings: *The proposed I-CBCC model significantly improves performance in the three metrics via the I-CBCC interventions model. Cost efficiency metric found 42% total cost savings per average-patient case, over the baseline. Service delivery quality metric retained and improved upon the level of the national protocol, with positive net effect: .31 Cohen's D. Operational workload metrics reduced in areas of screenings, follow-ups and travel, by up to 44%. Geospatial analysis of the per-patient outputs shows the benefits are region-wide (positive in all 366 analyzed subdistricts), while unmet need is significantly spatially clustered (Moran's I = 0.394, p = 0.001), yielding a district priority ranking for a staggered policy rollout.*

Conclusion: *The intervention synergies of the I-CBCC specialized protocol are preferable to the national protocol in this setting. These findings serve as a scalable framework for improving the national public health protocol, with a geospatial multi-criteria prioritization index identifying the districts for phased policy rollout.*

Keywords: Discrete Event Simulation, Economic Evaluation, Public Healthcare, Health GIS, Spatial Analysis, Multi-Criteria Decision Analysis

1. Introduction

The sustainability of national public health systems, especially in rural geographical regions, are facing many pressures, where the importance of the cost-efficiency of its healthcare protocols are on-par with their delivered care performance. Thailand's public health system is charting its own course with significantly constrained financial resource, as it rapidly transitions from Aged Society (20% of its population now over the age of 60 [1]), and projected to reach

'Super-aged' (>30%) by 2035 [2]. Regionally, Thailand is not alone in this public health challenge, with its public healthcare expenditure at 3.6% of GDP ($6,909 per capita), Singapore's 3.5%, Japan's 9.2% [3] [4]. As a lower-to-middle-income country (LMIC), the stark economic reality is that high efficiency and low-cost resource allocation is required to sustain its growing aged population with public healthcare.

Public health services in rural regions (globally) face particularly unsustainable financial models, where remote and digital care models increase health services available at reduced costs [5] [6]. Rural health services remain under a variety of socioeconomic stressors, such as due to labor migrations (of offspring to the urban centers) and rising *age dependency ratio* [7], which manifests in rural Thai provinces as elderly individuals living with fewer family caregivers [8]. For Thai elderly rural healthcare policy, traditional cultural-norms of *filial piety*, prioritizing *aging-in-place* [9] [10], and devolution of care responsibilities to community-based collaborative care (CBCC) are at the heart of its design towards a culturally imperative and cost-efficient mechanisms [11-14].[1]

The current Long-Term Care (LTC) initiatives (such as the *3Cs* model) operates alongside other health field-specific departments, exposes cost and opportunity for cost-efficiency synergies, via interdepartmental health service delivery; which we explore in this research. Community Health Workers (CHW), nationally referred to as *Caregivers* (CGs) and *Health Volunteers* (HVs), are crucial to supporting the cultural imperatives, and contribute to the LTC via visits to elderly homes to deliver care services [10] [15-19]. In an era of artificial intelligence, integrated departments with digital information flow are the essential missing gap of many performance improvements possibilities that will bridge these LTC community workers with other departments [2] [20] [21], such as the department of mental health (DMH). Transitioning national health policy is complex ([22] [23]), and there is no precedent for this integration. Therefore, we employ an empirical geospatial simulation methodology (with large-scale recent data sources) to evaluate this integration under policymaker intervention design recommendations (in [2] [15] [18] [20] [21], *see suppl. mat.*). Guided by [23], we deliberately structure our evaluation around a refined set of critical metrics, upon which Thailand's health policy interventions predominantly hinge: affordability, cost-effectiveness, and the intervention's effectiveness. The experimental framework focuses a mechanism for *Affordability* and evaluation of *Cost-Efficiency* and *Protocol Effectiveness* (proxied by process adherence to the current standard of care) as a measure of compliance to service delivery quality and its *Operational Workload* (the delivered service efficiency).

In this research, we empirically evaluate policy interventions via detailed geospatial data sources of elderly populations from four rural northeastern Thai provinces. The simulation, spatial analysis and multi-criteria decision analysis testbed measures the metric performance of proposed integrated-CBCC (I-CBCC) model variants, of national DMH and LTC-3C program operations, to prioritize phased-interventions across the geographical region. Specifically, the study addresses the following research questions:

- **RQ1:** To what extent does an I-CBCC model (intervention) reduce **Operational Workloads** (measured by protocol operation frequency) compared to the Standard of care (SoC) baseline?

[1] A detailed review of this field's contexts and motivations can be found within the supplementary materials

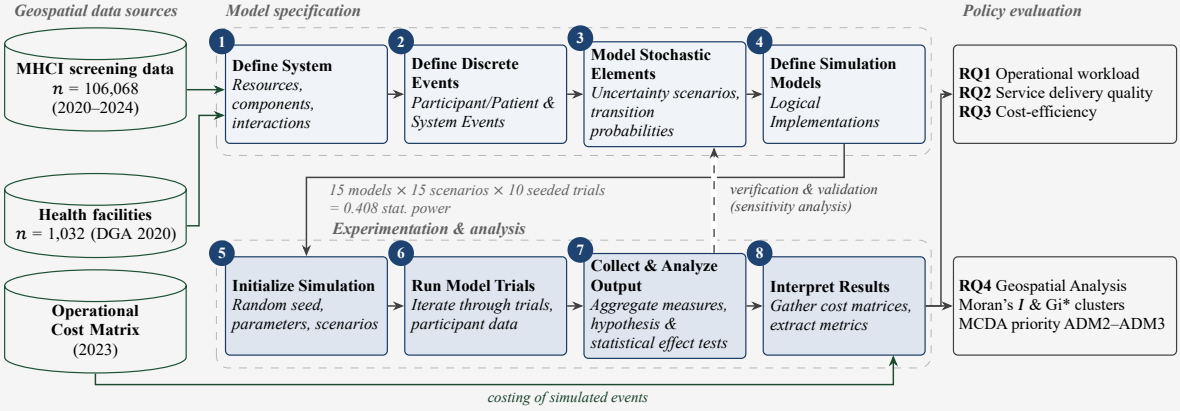


Figure 1: Process workflow diagram of policy simulation modelling procedure within the geospatial system

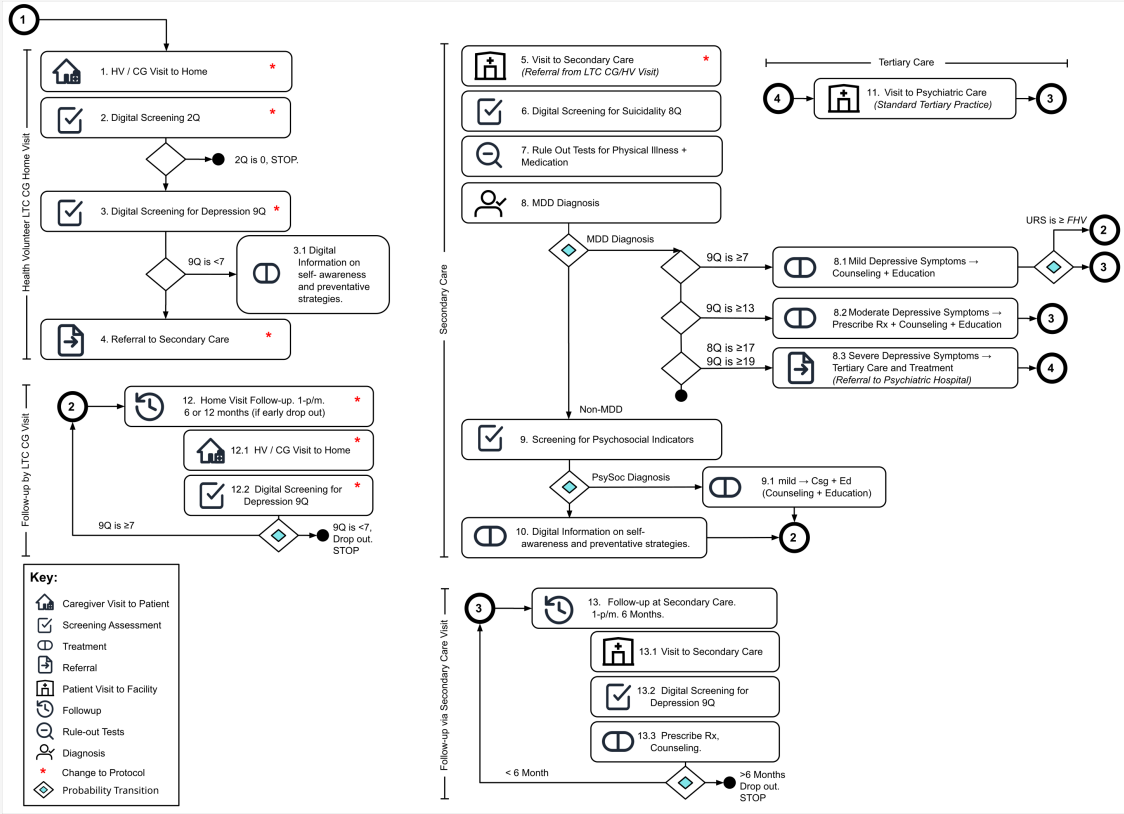


Figure 2: Process diagram of intervention specified by the proposed I-CBCC (HV%) Protocol. Entry-point at Elderly home via LTC Caregiver visit and 2Q digital screening. The HV% Protocol is adapted from the original SDDP 2013 DMH-SDDP [24] and Kongsuk, et al. 2007 variant [16] diagrams, with DMH-SmileConnect Initiative (2020-2023) updates [25] (Suppl. Mat). Changes to the protocols are marked by red asterisks. Probability-state transitions via uniform random sampling (URS) in blue

- **RQ2:** Can an I-CBCC model (intervention) maintain **Service Delivery Quality** (measured by *adherence* to a baseline protocol; as a proxy to *policy effectiveness*) at levels non-inferior to the SoC baseline, and to what extent?
- **RQ3:** Does an I-CBCC model (intervention) demonstrate superior **Cost-Efficiency** relative to the SoC baseline?
- **RQ4:** Where across the rural geography are the I-CBCC model's **operational and cost benefits delivered**, and **which districts should a staggered policy rollout prioritize**?

By answering questions RQ1-3, we study a granular ablation analysis of the policy interventions:

- To understand specific drivers of intervention improvements, including isolation and elimination of individual policy sub-components (i.e. operation de-duplication, home-based initialization, long-term care-caregiver (LTC CG) integration, digital system integration) to measure their contribution to policy performance in terms of the aforementioned three metrics.

2. Methods

2.1 Study Setting

The study focused on rural elderly person in provinces of Northeastern Thailand. The inclusion criteria randomly selected two Health Districts, and subsequently, two provinces, led to four provinces: Buriram and Chaiyaphum (Health District 9), and Sisaket and Ubon Ratchathani (Health District 10).

The eligible target region totaled 1.085 million persons aged 60 and over, comprising 6.7% (73,100) *dependent* individuals with population statistics obtained from Thailand's National Statistical Office (NSO). The eligible target region and inclusion criteria in this study coincide with the second iteration of its sibling (LTC2) study [26], which collected cross-sectional interview data from rural *independent* and *dependent* elderly persons between 2021 and 2023.

2.2 Discrete-Event Simulation (DES) Method for Policy Assessment

To measure the model policy intervention designs, the Discrete-Event Simulation (DES) stochastic modeling approach [27-34] using Monte Carlo trials over a sequential *Markov* chain process is selected for this work. Stochastic DES models have widely informed mental health policy [35] with *Markov* processes [36] and proven an effective tool to diagnose strategic inefficiencies in healthcare [37] and for capacity planning in mental health [38]. DES modeling followed [39] [40] recommendations, while modeling quality was self-assessed by the Philips Checklist (61-item) [41] at 64.4%, in accordance with the methodology in [36].

2.3 Simulation and Modelling Procedure

The DES model decision-making processes are governed by transition probability distributions, logical decisions (via a flowchart process and processed datasets) and implemented via the procedure in Figure 1. All policy models iterate over model scenarios (uncertainty parameter configurations), each with ten trials, and for all participant records. Each participant begins the model process via a visit from a CG or HV; or at a PC facility (for **-PC models*). Observations are drawn via a large participant dataset with 150 trials (15x10) per model, at a statistical power of 0.408 is calculated for normal-based tests (alpha=0.05; beta=0.2).

2.4 Discrete Event Model Designs

Discrete policy event model designs were defined, according to the intervention requirements, as a set of extensions to evaluate the study objectives, including their variants for an ablation analysis. The evaluated models are (shown in Table 1) two baseline policy models (reported in the literature), seven compliant experimental models, with five subvariants of the HV% model[2]. The baseline models are the current SDDP protocol system (benchmark) event model (referred to as *SDDP2023 (Strict)*) implements the protocol in [24], as updated by [25][3] and the historical *Kongsuk2008* protocol system [16].

The *SDDP2023 (Strict)* model strictly incorporates duplicated patient screening assessments, which are removed in *SDDP 2023* (non-strict) model series. Model *SDDP 2023-HV* introduces initial case finding during elderly home visits, conducted by an LTC care giver (CG) or health volunteer (HV). The I-CBCC model (*HV%)* shown in Figure 2 introduces two further items, (i) the digital system for patient screening (data collection) and referrals, and (ii) a managed parameter (*fhv*; %) of follow-up 9Q screening patient assessments. These follow-ups occur at either the local primary care (PC) facility (100%) or a scheduled elderly home visit (0%) via the LTC CG integration. Equal intervals ([0.0,.25,.50,.75,1.0]) give a broad range from which to evaluate the effect, leading to five discrete model variations of HV%. The *PsySoc* model variants extend the *HV0%* model to address a frequent participant group; those with low 9Q score (<7; non-MDD). Each variant introduces standard psycho-social screening and guidance (such as [42]), at a PC facility or in elderly homes. Model *HV-PsySoc* provides the HV/LTC CG staff to deliver psycho-social assessment and education/referral via a digital support system. Model *SC-PsySoc* refers the participant to SC for psycho-social assessment, adding specific referral/travel for this process.

2.5 System Simulating: Probabilistic Uncertainty Parameters and Geospatial Endpoint Selection

Building upon SDDP protocol to support community-based elderly efficiencies, leads to a basis of a referenced model methodology and model structure; which account for two of four types of simulation model uncertainties [36] [39]. The large participant dataset integrates a range of *heterogeneous uncertainties*; *half-cycle states* (or *patient attrition*) are according to the real participant data. *Parametric uncertainties* are configured as model evaluation scenarios via a set of transition probability ranges and probabilistic thresholds (uncertainty parameters), stated in Table 2. The latter are categorized as *Health Protocol Parameters, Hospital Selection Parameters* and *Data Uncertainty Parameters*; drawn from missing elements or assumptions in the participant data study, SDDP protocols or conditions of the conceptual process.

Of the *Health Protocol Parameters*, MDD prevalence in those with depressive disorders (9Q>=7) was identified in [43] and [44] as 66.1% and 69.4% respectively. Parameters without direct empirical references of transition-probabilities, were explored for stability of model structure [40] (IV-18, IV-13, IV-14), [39] (VI-7,VI-8). In this study, a *conservative* approach to *probabilistic sensitivity analysis* is taken via three normal distributions (at means of 30%, 50% and 70% uncertainties) to measure a range of responses. The *Hospital Selection Parameters* define the travel and spatial dynamics of each protocol in terms of patient and healthcare access. Hospital destinations for patient referrals (to Primary, Secondary, or Tertiary Care) are selected from (*m*) five nearest public health facilities in the local catchment area available for referral. Specific facilities (by type) are assigned per patient via a Bayesian selection framework (Equation 1), using negative $\beta = 1.0$ distance weighting as a cost

Table 1: The discrete event models for rural mental health care in Thailand, according to their health protocol type, experimental role and their intervention (change) description. Each of the SoC baseline models are evaluated with initialization at primary care (-PC) facility and initialization in homes (-HV); giving a total of six variants. Code Implementations at https://github.com/pmdscully/LTC-SDDP_DiscreteEventModels

Discrete Model Name (Protocol)	*Model Type*			*Intervention Type*					*Extended Intervention Contribution*
	Health Protocol Type	Baseline SoC	Experimental	Initialize case at	Operation De-duplication	LTC CG Integration (screening, education)	Digital Information System*	Follow up 9Q in Homes (%)	Description
SDDP 2023 Strict	CBCC	✓		PC					Modern model. [24], as updated by [25]. Contains workload duplication.
Kongsuk2008	CBCC	✓		PC					Historical model. [16]
SDDP 2023-PC	I-CBCC		✓	PC	✓				Removed Duplication.
SDDP 2023-HV	I-CBCC		✓	Home	✓	✓			LTC CG Integration.
HV%: [0, 25,50, 75, 100] %	I-CBCC		✓	Home	✓	✓	✓	0-100%	Follow-up 9Q in Homes. Including 5-subvariant models (via a *FHV* parameter).
SC-PsySoc	I-CBCC		✓	Home	✓	✓	✓	100%	Refer directly to SC for PsySoc screening.
HV-PsySoc	I-CBCC		✓	Home	✓	✓ Added	✓	100%	HV Conducts PsySoc screening in Home.
SC-PsySoc-PC	I-CBCC		✓	PC	✓	✓	✓	100%	Refer directly to SC for PsySoc screening.
HV-PsySoc-PC	I-CBCC		✓	PC	✓	✓ Added	✓	100%	HV Conducts PsySoc screening in Home.

[2] *Specific discrete model implementations are released publicly.*

[3] *Updated with Digital or Online Services integrated via the DMH SmileConnect system table (see suppl. mat.)*

(penalty) function. All travel metrics, are calculated by the Haversine formula (Equation 2), based on orthodromic distance; according to the EPSG:3857 spherical assumption of coordinates, with 0.7 percent error in scale and difference [45].

$$P\left(H_h|d\right) = \frac{\exp\left(-\beta \cdot d_h\right)}{\sum_{i=1}^{m} \exp\left(-\beta \cdot d_i\right)}$$

Equation 1

$$a = \sin^2\left(\frac{\Delta\phi}{2}\right) + \cos\left(\phi_1\right) \cdot \cos\left(\phi_2\right) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right)$$
$$c = 2 \cdot \operatorname{atan2}\left(\sqrt{a}, \sqrt{(1-a)}\right)$$
$$d = R \cdot c$$

Equation 2

The Data Uncertainty Parameters model the uncertainty of accuracy in self-assessed data and/or (HV) volunteer-assessed data compared to medical professionals, as addressed in [46], which found in a survivorship selection study that 18.5% to 33.4% (C.I. 95%) of HV ratings were confirmed by medical professionals. The attrition bias in these results informed two of our (9Q) rating transition probability scenarios; as coarse (uacch) and moderate (uacc) uncertainty of one-step rating transitions (e.g. mild to low, mild to moderate, etc.).

2.5.1 Model verification

Our model verification was guided by the Phillips Checklist [36] [41]. Data based unit testing confirmed consistent *diagnoses* and *treatments* outcomes, across models for individual participant (row-wise) simulations; and *per-configuration* aggregate sums of all event, travel and cost metrics were confirmed across trial batches. Simulation software was unit and subsystem tested. Four experts reviewed the model logic code to assess implementations matched each protocol's flowchart intentions. Model parameter decisions were reviewed by three subject matter experts. This review improved the parsimonious binary decision models at 50% (±20%) bounds for process parameters conditions in the absence of direct data of transition probabilities. Agreement was reached by maintaining equivalent conditions across all models, by citing estimates from nearby but non-identical study conditions (specified in Table 2 including [47-50]) and by concurring with the *conservative* approach of DES modeling task force recommendations in [39] (VI-8) and [40].

2.5.2 Model validation

A *sensitivity analysis* was conducted to incorporate the noise effects of unobserved confounding variables on each model under plausible stochastic scenario variations, according to the *parametric uncertainties*. Especially relevant for variables which are not available in the study dataset(s); such as MDD diagnosis, drop-out

Table 2: Uncertainty parameters to estimate patient chronologies via stochastic uncertainty scenarios. Decision sources based on current LTC/SDDP procedures, from empirical study values via reference decisions (as cited) or estimates from imprecise references (**). Uniform pseudorandom generated (PRG) sampling (URS), with comparable PRG seeds per trial

Parameter Name	Reference	Baseline Value [Range]	Decision	Method
Health Protocol Uncertainty Parameters				
`mdd`	[43] [44]	69.4% [±5%]	Major depressive disorder (MDD) diagnosis.	69.4% (threshold) of 9Q score is >=7. URS. MDD 3.87% prevalence and 69.4% (0.0387/0.0558) of depressive disorders (9Q>=7)[44]. Equivalently, 66.1% [43].
`psy`	**[49] [51] [42]	50% [±20%]	Social or Psychological (Soc-Psy) problem diagnosis; e.g. Anxiety or Stress-related.	Requires TEST_RO_PSYCHOSOCIAL event. 50% of non-MDD patients; URS. *Non-identical conditions rates were: 34-43%* [51]*, 23.7%* [42]*, 8.7-27.8%* [49].
`rpsc`	**[47] [48]	50% [±20%]	Decision to refer P to PC or SC facility.	50% of patients are referred to PC and 50% to SC facilities for existing SDDP models. (Proposed models refer 100% to SC under this condition). *Non-identical conditions indicate majority at PC, compared to SC* [47] [48].
`fpc`	**[50]	50% [±20%]	Drop-out rate for Primary Care Follow-up (every month for 12 months). Drop-out if 9Q<7.	50% of patients drop-out after 6 months; URS. 50% complete 12 months follow-up. *Non-identical conditions indicate 53.3% after 1 month, 78.2% after 6 months* [50].
`fsc`	**[50]	0% [10%, 20%]	Drop-out Rate for Secondary Care Follow-up (every month for 6 months). Drop-out if 9Q<7 and Rx no longer necessary.	0% of patients drop-out after 3 months; URS. Otherwise, complete 6 months follow-up. *Non-identical conditions as fpc in* [23] [50].
Data Uncertainty Parameters				
`uacch`	[46] [52]	0% [66.6%, 81.5%]	Coarse uncertainty in rating classifications conducted by HV / Self-assessment reporting.	Informed by [46] [53], 18.5% to 33.4% of HV ratings were confirmed by Medical Professionals. Parameter defines the probability of 9Q rating with a one-step transition (e.g. mild to moderate or mild to low). Coarse binary increase/decrease probability is set at URS 50%.
`uacc`	[22] [46]	0% [66.6%, 81.5%]	Moderate uncertainty in rating classifications conducted by HV / Self-assessment reporting.	Informed by [46] [54]. Defines the probability of 9Q rating one-step *Fuzzy membership* transitions (i.e. low-mild transitions to low; mild-moderate transitions to moderate).

conditions, patient hospital preferences. Table 2 states the default, upper and lower bound ranges of each uncertainty assumption. A total of 15 parameter variants (executed in a grid search manner) at 10 trials, giving 150 trials for each of the 15 models.

2.6 Data Sources

2.6.1 Elderly participants

A dataset of elderly participant (patient) records are the basis for the simulated geospatial analysis of each policy model (per trial).

The secondary public domain data was retrieved from the health data center (HDC), Department of Mental Health, Ministry of Public Health (MOPH) [55]. Notably, the participant records consisted of self-assessed characteristics, of mental health screening under the SDDP protocol framework [24] [25] [56]. 106,609 records were within the eligible target scope during a data retrieval period of May 2020 to 2024 (46 months), filtered by age and province name. 106,068 records contained complete geolocations. No personally identifiable information is included, and geolocations are truncated to 1.11 km approximations to protect privacy. Screening characteristics data included the 2Q-scale and the 9Q-scale depression assessment instruments developed from DSM-IV-TR, 2000 [refer to [56] for these instruments]. The eligible participant geolocations are shown in Figure 3, with Table 3 states descriptive statistics of their characteristics and instrument responses. Overall, 56.9% of participants were female (*Mean 0.431, Std. 0.495, grouped by province*). 41% were aged between 60 and 65 years (*Mean 69.1,*

Table 3: Dataset of eligible patients: Summary of screening data [55]

	All Ages	(Eligible) 60 or older	2Q Test Score >0	9Q Test Score >0	9Q Score 13<19	9Q Score >=19
Buriram	79,029	18,780	250	2,683	17	6
Chaiyaphum	26,967	4,916	504	1,527	52	18
Sisaket	171,462	43,255	1,053	1,012	55	12
Ubon Ratchathani	162,403	39,117	694	669	48	11
Totals	*439,861*	*106,068*	*2,501*	*5,891*	*172*	*47*
% of Eligible	--	*100%*	*2.36%*	*5.55%*	*0.16%*	*0.04%*

Std. 7.63). Participants' province ranged from 4.6% to 40.8% across the four provinces. 2.36% gave a positive (>0) response to 2Q (*Mean 0.033, Std. 0.227*). While, 5.55% gave a positive response to 9Q (*Mean 0.347, Std. 1.576*), with 0.16% rated as *moderate* (13<19) and 0.04% rated as *severe* (>=19).

2.6.2 Public health facilities

To conduct the geospatial simulation, a dataset of public health facilities serves as destinations of elderly health care within the simulation of policy models. Elderly participant care *level* types are implicit within the participant data records, in accordance to the SDDP protocol framework. Specific facilities visited are not specified. Therefore, a Bayesian model of distance (stated above) simulates the patient selection of visited facilities. Public health facility geolocations were recorded in 2020 by the national health facilities dataset, published by Digital Government development Agency (DGA) (Public Organization) [57] [58]. Facility names, addresses and geolocations of 1,032 public health facilities are within the target scope, with 1,021 (98.93%) primary care facilities, ten (0.97%) secondary facilities and one tertiary (specialist) care facility. Figure 4 illustrates the geospatial positions of public health facilities within the study provinces.

Care-Level service labels (i.e. primary, secondary, tertiary) and *Facility-Category* labels (i.e. a budgetary mapping to care-level) are added to the dataset, which determine the regional facilities available to patients under the policy procedures. [59] [60] specify secondary care (A, S, M1 categories) and tertiary (psychiatry) hospital categories. Subdistrict Health Promotion Hospitals (SHPH) specify primary care facilities (and local administration) which coordinate community health volunteers (HV) and have no onsite DMH sub-specialist. Community hospitals that fall into the M2, F1, F2, or F3 categories are specified as primary care, i.e. without a depressive disorders department. Table 4 summarizes the mappings of *Care-Level* to *Facility-Category*.

2.7 Metric: Operational Workloads

Measuring Number of Service Operations (by Categories): The SDDP Protocol process flow ([24]) utilizes 25 patient *events* categories, aligned to public health care operations. We categorized each event as: *referral, visit, travel event, travel distance, screening test type, treatment type* or *follow-up* type. These occur at primary (PC), secondary (SC) and tertiary care (TC) facilities and via health volunteers (during outbound visits) which are quantified as their number of occurrences or distance traveled in kilometers, respectively.

2.8 Metric: Service Delivery Quality

This metric is an estimator of healthcare service delivery outcomes and therefore a proxy of policy *effectiveness*. It measures *process adherence* to the current standard of care (baseline) protocol of the policy models. Intuitively, a model's *process-adherence* is significantly similar or has significantly fewer activities (under distinct cases), as the baseline. As such, it either (i) adheres to (*consistent*), (ii) improves upon (*positive effect*), or (iii) degrades from (*negative effect*) the baseline. Accumulating these items establishes a (iv) *net effect*.

Measuring Process Adherence Scoring Logic and Weighting: The *process-adherence* metric is based on the 25 operational measurements with use of "inequality constraints", shown in Table 5. The metric evaluates 19 event types as key performance indicators (KPIs), each assigned an equal binary weighting (1).

Six event types were excluded to ensure a fair comparison: newly introduced Health Volunteer (HV) operations (which lack a baseline equivalent), notifications, and 8Q suicide assessments (deemed out-of-scope). For each KPI, an "effective" change is defined by a mathematical operator (<, ≤, =) reflecting the clinical or operational goal:

- **Improvement (<, ≤):** Generally, captures reductions in patient responsibility (e.g., fewer hospital trips, less travel distance) or systematic operation (e.g., screening de-duplication).

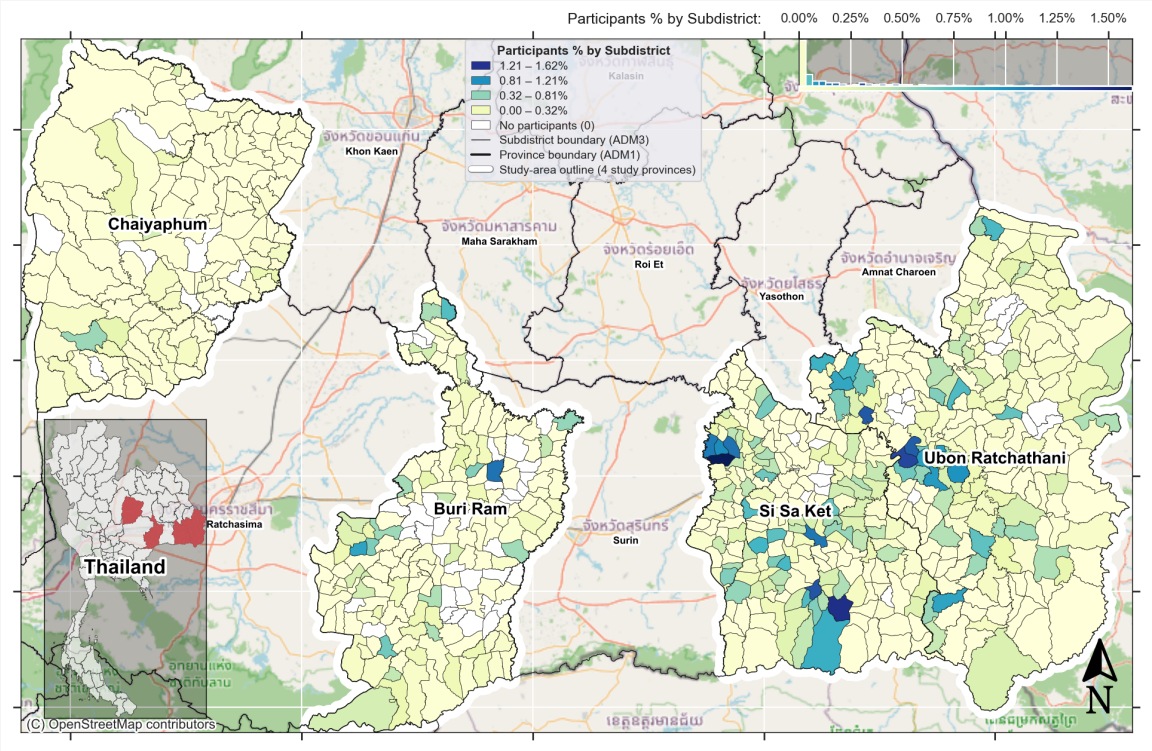


Figure 3: Participant geolocations (n=106,068) by subdistricts, shown as a choropleth plot via % (in range 0.0-1.6%). Colour-scale histogram shows the frequency distribution of subdistrict values; darker-scaled colors indicate higher percentages, white indicates no data from source [55]. Showing data in Chaiyaphum, Buriram, Sisaket and Ubon Ratchathani study provinces. Projected into the WGS 84/Pseudo-Mercator coordinate reference system (EPSG:3857)

Table 4: Dataset of Health facilities [57] and [58], categorized using [59] and [60]

	Tertiary (TC) Psychiatric	Secondary (SC) A	S	S or M1	M1	Secondary (w/o DMH) (PC) M2,F1,F2 or F3	Primary (PC) SHPH	*Total*
Buriram	-	1	1	-	-	22	220	244
Chaiyaphum	-	-	1	-	1	13	164	179
Sisaket	-	-	1	-	1	20	243	265
Ubon Ratchathani	1	1	1	1	1	21	318	344
Total								*1,032*

- **Consistency (=):** Ensures that clinical outcomes (such as the number of Major Depressive Disorder (MDD) diagnoses or prescriptions) remain stable and are not compromised by new policy protocols.

Each *effective* event type measure contributes to the fraction (and therefore percentage) of the method's *Process-Adherence*, as well as a worsening effect ("*ineffective*"). The "*net effect*"[4] is the summed net difference, that summarizes the *process-adherence* metric's performance. Results are drawn from the simulation trials per model. Significance is determined via the Kolmogorov-Smirnov test for goodness of fit (null hypothesis of equality) and two-sample independent T-tests (<) at critical alpha scales (.01, .05, .10), with Bonferroni family-wise error corrections. The magnitude of *process adherence* or degradation is quantified using Cohen's D, providing a *net effect* score that summarizes the model's overall performance impact.

[4]The mean (and standard deviation) Cohen's D effect sizes of all (19) weighted criteria (including significant and insignificant metrics; which differs from the effective and ineffective measures).
[5]The cost-matrix table can be found within supplementary materials

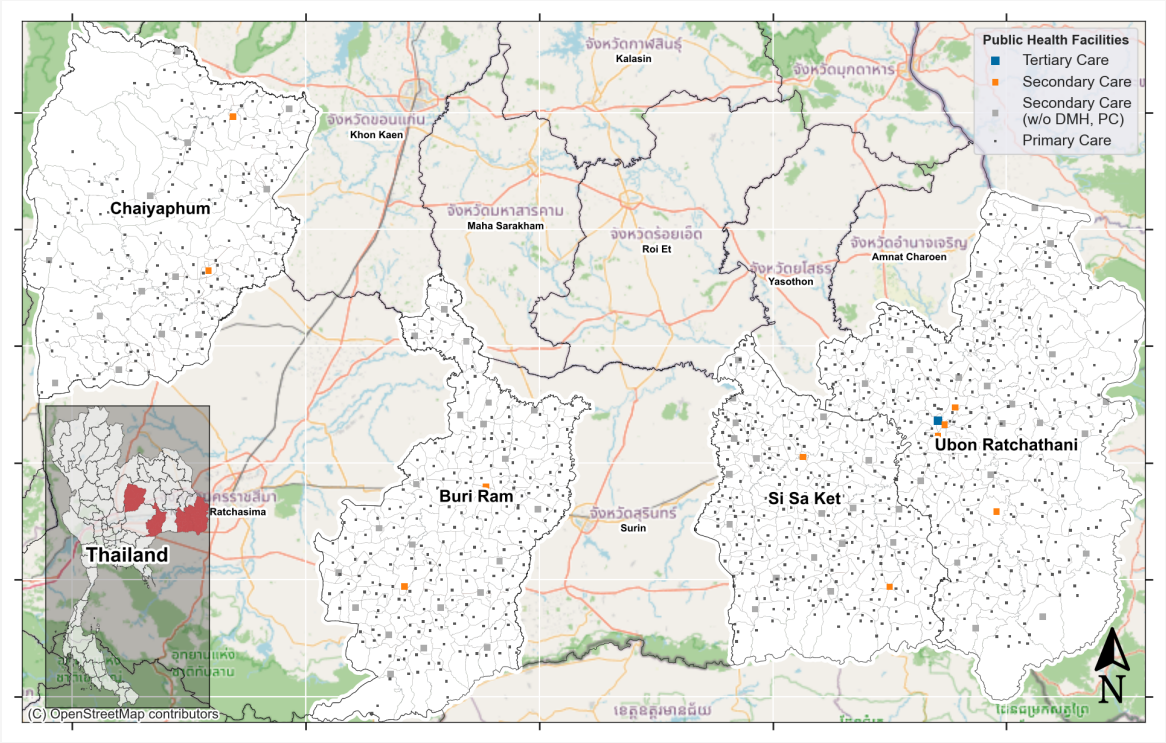


Figure 4: Public health facility geolocations (n=1,032). Care-level shown by color. Adapted from DGA Dataset [57]. Showing data in Chaiyaphum, Buriram, Sisaket and Ubon Ratchathani study provinces. Projected into the WGS 84 / Pseudo-Mercator coordinate reference system (EPSG:3857)

2.9 Metric: Cost-Efficiency

Policy model *cost-efficiency* (direct and indirect synergy) is calculated as the Events (RQ1) results multiplied by a *cost-matrix* of public healthcare costs within the target scope region[5]. Cost are separated as, to the public healthcare service ("*to protocol*") and to the participant ("*to patient*").

Measuring Operational Cost: Hospital operations costs were collected from a publicly available price list within the target area for the fiscal year of 2023. Intuitively, costs for newly introduced operations are mapped to existing hospital operations costs; such as the follow-up 9Q screening test (HV to P) is assumed an equal cost as its corresponding hospital operation. Other costs types have an alternative source. Travel costs are 4 THB per kilometer, an expense claim rate from a regional government institution. Prescription (Rx) item unit costs were collected from the Department Internal Trade web service for national public hospitals. Each Rx item's producer is the Government Pharmaceutical Organization (GPO), with a price given by the average nationwide hospital cost. Prescription quantities are specified as first-time-only prescriptions under SDDP process [see [61] guidelines].

Items with multiple occurrences and prices are taken at their harmonic mean average (AVG). Costs shown in US dollars[6].

2.10 Ablation Procedure per Policy Intervention

To assess the importance of each policy intervention component, we adopt the single unit ablations (subtraction) of performance concept [62] (Table 6). This observes the I-CBCC (HV%) model policy's performance, in absence of an invention, according to *Service Delivery Quality* and *Cost-Efficiency* metrics. The trialed policy interventions are:

i. Remove duplicated operations (de-duplication),
ii. LTC CG integration (as home-case finding),
iii. introduce digital system for information flow (inc. screening and information delivery),
iv. relocate follow-up visits into the LTC CG home-visits for elderly patient (*FHV* parameter).

Our conjecture is that the combined I-CBCC components (*HV%* model) provide a simplified data flow from homes-to-public institution to support data collection, decision making and referral recommendations to reduce costs by patient event de-duplication and improving economic choices. This ablation analy-

Table 5: Criteria explanations for each event measurement to evaluate the relative Process-Adherence of each model

Category	SDDP Events	Conditions Operator	Importance Weighting	Operational Goal Criteria Explanation
Number of Travel Events	Patient	≤	1	Patients travel less.
	HV	N/A	0	Increased HV duties increases visits.
Number of Hospital Visits (or Home Visits)	P visits PC	≤	1	Screening decreased at PC, increased at Home.
	P visits SC	≤	1	Treated patients remain unchanged (9Q≥7) while Fewer non-treatment patients sent to SC (9Q<7)
	P visits TC	=	1	Treated patients remain unchanged.
	HV visits P	N/A	0	Increased HV duties increases visits.
Number of Hospital Referrals	P to PC	≤	1	Fewer patients referred
	P to SC	≤	1	Treated patients remain unchanged (9Q≥7) while Fewer non-treatment patients sent to SC (9Q<7)
	P to TC	=	1	Treated patients remain unchanged.
Number of Screening Tests	2Q	=	1	Quantity of screening unchanged
	9Q	≤	1	Information flow decreases quantity of screening tests
	8Q	N/A	0	Not measured.
Rule-Out Tests	Physical	=	1	Treated patients remain unchanged.
	Medicine	=	1	Treated patients remain unchanged.
	Psycho-Social	=	1	Treated patients remain unchanged.
Diagnoses	MDD	=	1	Treated patients remain unchanged.
Number of Treatments	Education (Ed)	≤	1	Information flow decreases educational duplication.
	Counselling (Csg)	=	1	Treated patients remain unchanged.
	Prescription (Rx)	=	1	Treated patients remain unchanged.
Number of Follow-ups	HV to P 9Q	N/A	0	Increased HV duties. Screening increased at Home.
	P to PC 9Q	≤	1	Screening decreased at PC, increased at Home.
	P to SC 9Q+Rx	=	1	Treated patients remain unchanged.
Kilometers Travelled	P	≤	1	Patients travel less.
	HV	N/A	0	Increased HV duties increases travel.

Table 6: Ablation of Policy intervention components of the I-CBCC (HV%) model, and its corresponding model name

Intervention Components					Model
Baseline	**Operation De-duplication**	**Home case finding. LTC CG Integration**	**Digital System**	**Move Follow-up 9Q to 100% in Homes**	
✓	✓	✓	✓	✓	**HV0%**
✓	✓	✓	✓		**HV100%**
✓	✓	✓			**SDDP 2023-HV**
✓	✓				**SDDP 2023-PC**
✓					**SDDP 2023 (Strict)**

sis measures performance differences per intervention to inform future studies.

2.11 Geospatial Analysis of Simulated Policy Impact

The geospatial policy impact of I-CBCC HV-50% (*fhv = 0.5*) model versus SoC baseline SDDP2023-PC (Strict) is the subject of RQ4. The 3-step analysis at the subdistrict-level (ADM3) reports (i) spatial findings, (ii) neighborhood-clustering of *need* and *benefit*, and (iii) per-district prioritized policy rollout by multi-criteria decision analysis.

2.11.1 Per-Patient instrumentation and subdistrict spatial join

The DES engine was instrumented to emit per-patient outcome records (geolocations, operational events, kilometers travelled, and costs; means over the seeded trials). Records were aggregated to subdistrict (ADM3) polygons via point-in-polygon spatial join [63], with a nearest-polygon fallback for boundary coordinates (106,068 joined). Cartography uses EPSG:3857 with quantile classification; the focal

comparison is I-CBCC HV-50% (*fhv = 0.5*) versus the SoC baseline SDDP2023-PC (Strict).

2.11.2 Spatial cluster statistics of local and global need

To evaluate whether *unmet need* clustered hotspots exists, global clustering is quantified by Moran's $I = \left(\frac{n}{S_0}\right) * \sum_{ij} \frac{w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_i (x_i-\bar{x})^2}$, with binary queen neighbor-contiguity weights w_{ij} ($S_0 = \Sigma_i \Sigma_j w_{ij}$; n = 366 subdistricts, x = the mapped metric) for the *need* rate, with islands attached to their nearest neighbor ([64-68]). The 9Q-positive *need* rate is determined by the 9Q-positive (>7) prevalence per 1,000 population (MHCI screenings dataset). Local clusters are identified with Getis-Ord Gi* measure ([69-72]) with 999 seeded permutations and Benjamini-Hochberg false-discovery-rate correction at *alpha=0.05* ([73] [74]). To mitigate small-sample denominator noise, the Assuncao-Reis empirical Bayes-adjusted (EB) variant is applied to the Moran's I rate values, and the Marshall EB smoothing [75] to local Gi* *need* rate values. All local statistics and rankings are restricted to the 366 subdistricts with n >= 30 patients.

2.11.3 Multi-Criteria priority index and weight sensitivity

A multi-criteria decision analysis (MCDA) weighted sum ([76]), see [22] in Thai health policy) combines three criteria blocks (as below) into a MCDA prioritization index:

Need is determined by the 9Q-positive (>7) prevalence per 1,000 screened. Data is from the eligible screened individuals (60+ population) of the MHCI dataset only; mild and above, and 8Q-positive counts. The subdistrict population counts are from DOPA's house-registration population aged 60+ (December 2022, stat.bora.dopa.go.th; districts pop. = sum of subdistricts pop.). The 9Q-positive prevalence is computed from the routine screening dataset: patients entered through service-delivery screening, not through an RCT or random population sampling, so rates describe the screened elderly population.

- *Benefit* is per patient saved (i) travel km, (ii) visits and (iii) cost USD saved vs SoC; by the I-CBCC HV 50% simulation.
- *Access* is the subdistrict-level mean haversine distance in km of patient geolocations to their (simulation) assigned health facilities (aggregated to district means for Table 17; larger values indicate worse access).

Each unit's composite is $Score_i = \Sigma_k \, w_k \cdot \tilde{x}_{ik}$, where $\tilde{x}_{ik} = (x_{ik} - min_k)/(max_k - min_k)$ is the min–max-normalized indicator for block $k \in \{Need, Benefit, Access\}$ and $w_k = 1/3$ (equal weights). Each district-level (ADM2) is classified into quantile tiers (Tier 1 ($\geq 90^{th}$ percentile), T2 (p75–p90) and T3 (<p75)) where subdistrict aggregation resolves small samples (82 of 86 districts n >= 30). Weight sensitivity is assessed by Spearman rank correlation with p-values across all pairwise weighting schemes (equal (⅓ each) plus need-/benefit-/access-weighted schemes as emphasized block 0.50 with remainder split equally; see supplementary table). All spatial statistics use PySAL (libpysal/esda) and GeoPandas libraries with seeded permutations for exact reproducibility.

3. Results

3.1 Results of Operational Workloads

3.1.1 Proposed models: Impact on operational efficiency and event reduction

The result of the *operational workload* metric of integrated community-based care models (HV%) found significant reduced patient and healthcare system load compared to SoC baseline model (*SDDP2023-PC (Strict)*). The I-CBCC (HV%) model's relative difference is caused by its combination of intervention parts, shifting *stationary* health facility events into *mobile* and synergized digital interdepartmental community-based events. The most significant variations occurred in patient-side metrics (e.g., Visits to PC and KM Traveled by P), which remained consistently lower than the baseline across all HV% variants. Table 8 illustrates these reductions of the I-CBCC models (HV%) over SoC baseline by category, while Table 7 and Figure 5 (as point-estimate mean averages[7]) illustrate broad systemic efficiency gains.

While the raw data (in *suppl. mat.*) indicates a substantial increase in Health Volunteer (HV) travel totaling approximately 577,000 km (in 46 months over the four provinces) in the HV=50% variant this does not represent a new operational cost, as these trips already occur under the LTC CG visits without DMH integration. The net kilometer distance traveled by both patients and providers is 18% lower in the I-CBCC model than the SoC baseline total, showing that mobile care model is spatially more efficient than facility-centric care. This HV travel distance is already accounted for within existing Long-Term Care (LTC) 3C CG visitation schedules, under the LTC-DMH integration assumption. Thus, the I-CBCC model's operations for mental health protocol synergizes with

[6]Prices in US dollars were calculated at USD $0.02760 = 1THB (avg. July 2024 exchange rate)

Table 7: Operational Workload: Comparative Performance, as summary metrics of six categories, between I-CBCC models to the baseline (SDDP2023.PC (Strict)): Shown are means and 95% confidence intervals (bootstrapped) as relative percentage ratios. Per policy, operational values are compared to the SoC baseline model's mean (SDDP2023 PC (Strict)=1.0). 150 trials per model. See raw values table in suppl. mat. for details

	Proposed I-CBCC Model Variants (HV%)					Baseline and Historical Models		
Service Category (Totals)	**HV-0%**	**HV-25%**	**HV-50%**	**HV-75%**	**HV-100%**	**SDDP2023 PC (Strict)**	***SDDP 2023 PC**	**Kongsuk 2008 PC**
Travel Events	**0.77 (0.69-0.86)**	**0.77 (0.68-0.87)**	**0.77 (0.67-0.88)**	**0.77 (0.68-0.88)**	**0.77 (0.68-0.88)**	1.00 (0.83-1.17)	1.00 (0.85-1.16)	0.91 (0.84-0.99)
Referral Events	**1.00 (0.73-1.28)**	**1.00 (0.68-1.34)**	**1.00 (0.74-1.32)**	**1.00 (0.70-1.34)**	**1.00 (0.65-1.27)**	**1.00 (0.70-1.34)**	**1.00 (0.72-1.32)**	1.02 (0.73-1.37)
Screening Tests	**0.56 (0.47-0.65)**	**0.56 (0.49-0.65)**	**0.56 (0.48-0.64)**	**0.56 (0.48-0.66)**	**0.56 (0.47-0.63)**	1.00 (0.89-1.14)	0.99 (0.86-1.15)	0.91 (0.84-0.98)
Follow-up Appoints.	**0.54 (0.40-0.72)**	**0.54 (0.38-0.73)**	**0.54 (0.39-0.72)**	**0.54 (0.36-0.72)**	**0.54 (0.38-0.71)**	1.00 (0.74-1.39)	1.00 (0.74-1.31)	0.81 (0.67-0.95)
Treatment Events	**0.76 (0.59-0.93)**	**0.76 (0.62-0.95)**	**0.76 (0.60-0.92)**	**0.76 (0.61-0.92)**	**0.76 (0.60-0.95)**	1.00 (0.78-1.24)	1.00 (0.77-1.25)	5.59 (5.34-5.87)
Total Distance (KM)	**0.82 (0.69-0.94)**	**0.82 (0.71-0.96)**	**0.82 (0.69-0.94)**	**0.82 (0.69-0.97)**	**0.82 (0.70-0.96)**	1.00 (0.81-1.20)	1.00 (0.83-1.19)	0.97 (0.86-1.07)

Table 8: Best performing operational workload improvements of I-CBCC (mid-way) model (HV50%) compared to baseline. Showing "Totals" per category. Percentage reductions shown as means and bootstrapped confidence intervals at 95%-confidence, (n=150). HV50% is given as the middle-ground option, between public service and patient operational workload expense

Service Category (Totals)	**Reduction vs. SoC Baseline** HV-50% vs *SDDP2023-PC (Strict)*	**Relative T-test** *(a=0.05;df=149) (T, Pv)*	**Cohen's d** (w/ Effect Sizes: *S,M,L*)	**Primary Driver of Efficiency**
Screening Assessments	44% (0.36–0.52)	16.24; 0.0	0.64; M	Synergized digital system to eliminate redundant testing (inc. 8Q/9Q)
Follow-up Appointments	44% (0.28–0.61)	6.11; 0.0	0.28; S	Shift to digital and home-based 9Q screenings
Treatment Events	24% (0.08–0.40)	6.23; 0.0	0.19; S	Streamlined education protocols via digital system in home visits.
Travel Events	23% (0.12–0.33)	6.12; 0.0	0.27; S	Reduced patient-initiated facility trips
Total Distance (KM)	18% (0.06–0.31)	6.34; 0.0	0.17; S	Net spatial optimization of the care network (inc. service and patients)

these pre-scheduled visits, effectively achieving these reductions with zero additional logistics expenditure.

3.2 Results of Service Delivery Quality

The *service delivery quality* results are reported by measuring the *quantitative process-adherence* per model, in comparison to the SoC baseline; if the model's process adheres to the SoC baseline for every included metric, it reaches 100%. The proposed (HV%) models are reported first (19 metrics) with their negatively impacted (6) metrics reported separately; then followed by the historical benchmark and alternative models.

3.2.1 Proposed models: Impact on process adherence metrics

The findings show that every version of the new I-CBCC home-visit policy (HV%) significantly met or outperformed the current SoC baseline (SDDP) in terms of service quality, in accordance with the characterized *process-adherence* criteria. Figure 6 and Table 9 illustrate a net positive Cohen's D effect of *quantitative process-adherence* of the five HV% (0-100%) policy models, as compared to the current policy (SDDP2023.PC (Strict) benchmark). HV=0.00

[7]Extensive interval-estimate results in supplementary materials, as relative terms (to the mean average value of the SDDP 2023 (Strict) benchmark policy (1.0)) and in absolute terms (raw) for trials over the eligible participants of the MHCI dataset. Inferential significance and effect size (to the benchmark model) are reported, as calculated by Relative T-test (critical alpha=0.05; df=149) and Cohen's D (df=149) statistics.

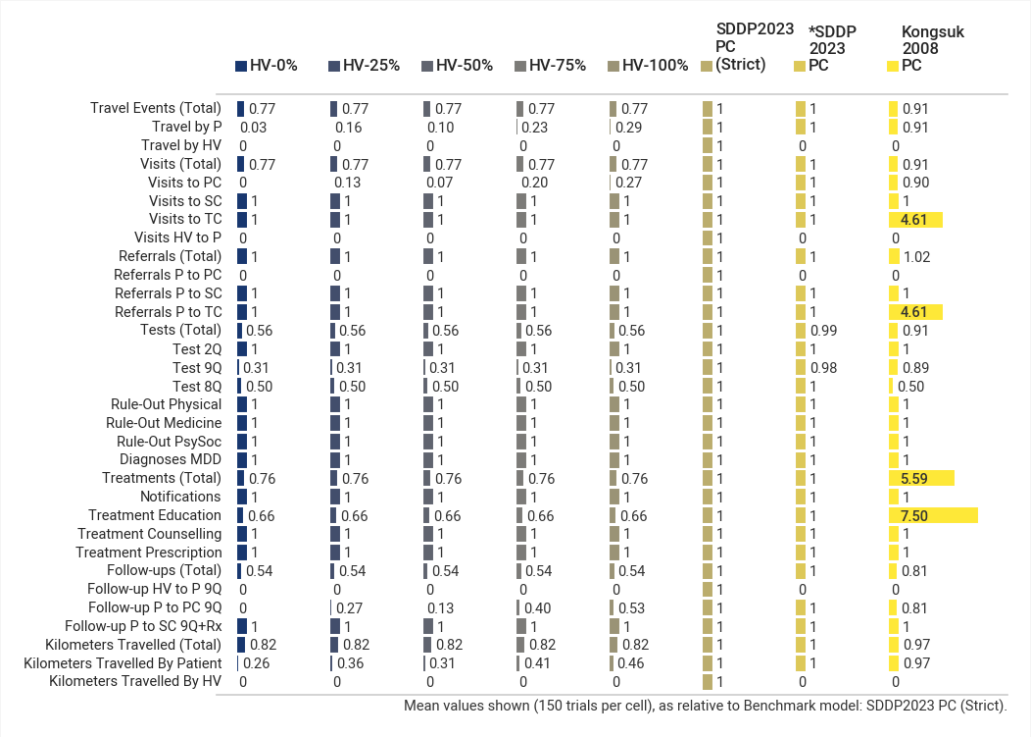


Figure 5: Illustration of mean relative percentage ratios per policy (106,068 patient records) compared to SoC baseline mean (SDDP2023 PC (Strict)=1.0). 150 trials per cell. All process event measures. New HV event metrics are incomparable to SoC, shown as zeroes; see Raw values table in suppl. mat

(100% of 9Q screening follow-ups conducted by HV at the elderly person's home) reported the greatest overall positive effect size (Cohen's D=0.31±0.5 at 0.01 *alpha*) at "small" to "medium" effect, over the current policy. With 19/19 "*effective*" metrics and zero "*ineffective*" metrics (negative) effect sizes. The five incomparable metrics are excluded (analyzed in 3.2.2), which add HV operations to the current policy.

3.2.2 Proposed Models: Impact on Travel Requirements and Diagnostic Utility

The additional workload operations of HVs are included in Table 10, to illustrate a per-patient (relative) comparison under the new policy models compared to the SDDP2023.PC (Strict) protocol. The findings show that shifting care from the facilities (SoC) to the home (CBCC models) significantly increases travel requirements, however it improves operational efficiency by reducing redundant mental health testing. As a result, 8Q testing is reduced by half (at 0.06 test per patient). The *fhv* parameter (in Table 10 as two result blocks) show that I-CBCC model (HV%) at *fhv*=1.0 gives the most streamlined workloads (1.0 visit / 3.84 km traveled), with initial case-finding and follow-ups[8] consolidated at the home (per average patient case). The I-CBCC model (HV%) at *fhv*=0.0 gives the highest workload at (1.54 visits / 5.98 km), with the added 0.54 visits (and 2.14 km) corresponding to the number of 9Q test follow-ups conducted (only) at a primary or second care facility. HV% models (25,50,75%) follow at a linear rate between 0% and 100% models for these measures.

3.2.3 Baseline & alternative models: impact on process adherence metrics

The *Process-Adherence* assessment was repeated with SDDP2023.PC (Strict) benchmark and alternative model variants (of historical protocols and minor adjustment model variants). While the historical and alternative protocols can improve certain parts of the care process, they often cause significant "*worsening*" in others, making them less stable than the current policy, which is illustrated in Table 11 and Figure 7. The maximum net effect is "small" given by protocol HV-PsySoc-HV (Cohen's D=0.21 (±0.6)) at each *alpha* level with 3/19 metrics of significantly worsened performance than the current policy amounting to "medium" effect (-0.49 (±0.5) at each *alpha* level). The maximum positive effect (*process-adherence*) is of

[8]Travel and visit categories: (i) the proportion of 9Q follow-ups by HV (parameter fhv %) at the patient home and (ii) the initial case finding at the elderly person's home

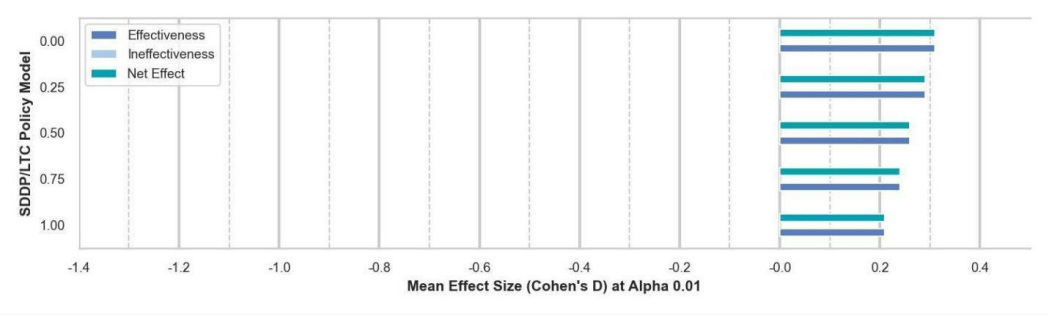


Figure 6: Effectiveness metric performance. Showing proposed I-CBCC models (HV% 0.00, 0.25, 0.50, 0.75, 1.00) as their mean positive Cohen's D effect size differences at Critical Alpha 0.01, compared to the baseline SDDP2023.PC (Strict) model. Reports effect sizes of only significant (P<0.01, with familywise adjustments) hypothesis test results. Small-to-medium positive net effect improvements

Table 9: Process-Adherence Effectiveness per proposed HV model compared to the SDDP2023.PC (Strict) benchmark policy model. Percentages and fractions show statistically significant (equal or improved) criteria over 19 metrics. Cohen's D effect sizes (mean and standard deviation) are shown for positive effect (summed effective metric sizes), negative (summed ineffectiveness metric effect sizes) and net effect size (summed effect difference) per model

	Alpha=0.01				
HV Model Variable: *(FHV)*	**HV = 0.00**	**HV = 0.25**	**HV = 0.50**	**HV = 0.75**	**HV = 1.00**
%	**100**	**100**	**100**	**100**	**100**
Fraction	**19/19**	**19/19**	**19/19**	**19/19**	**19/19**
Effect Size	**0.31 (±0.5)**	0.29 (±0.5)	0.26 (±0.4)	0.24 (±0.4)	0.21 (±0.3)
Ineffectiveness Effect	-	-	-	-	-
Net Effect Size	**0.31 (±0.5)**	0.29 (±0.5)	0.26 (±0.4)	0.24 (±0.4)	0.21 (±0.3)

"medium" size by protocol SC-PsySoc-HV (Cohen's D=0.49 (±0.5) at each *alpha* level), with 7/19 metrics worsened, amounting to "medium" effect (-0.42 (±0.3) at each *alpha* level). Interestingly, by introducing only initial case finding via Health Volunteers into the current SDDP protocol (*SDDP 2023-HV) gives a negligible (yet improved) net effect size (Cohen's D=0.05 (±0.4) at each *alpha* level); however, three metrics significantly worsen compared to the current policy, amounting to "medium" effect (-0.51 (±0.6) at each *alpha* level). Removing duplications (*SDDP 2023-PC) shows no notable effect size differences.

3.3 Results of Cost-Efficiency Analysis

3.3.1 Cost comparisons of models

The key findings the proposed integrated home-visit HV% models achieve a 39% reduction in total costs compared to the current SoC baseline (SDDP), which is achieved by process workload efficiency and the cost-rebalancing via the *fhv%* parameter. Figure 8 illustrates the distinct differences in total model costs per (average) patient for the MHCI participant dataset, especially costs to the public health service (protocol). Table 12 tabulates the cost per patient and the calculated *all-in* cost for the MHCI participants dataset during 2020-2024 in the target scope. We note a USD$1.3 M. dollar saving (39%) between the baseline (*SDDP2023-PC (Strict)*) model ($3,348,510) and proposed equivalent HV% model variants ($2,026,078) under this target scope (46 months, approximately 3.8 years). This primary saving is driven by the *protocol* (public health service) costs, which drop from $31.57 per patient in the baseline to a significantly lower rate in the integrated models. The baseline *SDDP2023-PC (Strict)* model cost is $31.57 (to protocol) and $1.17 (to patient). Each of the HV% model variants carry equal costs, at a total of $19.10 per patient. The *cost-rebalancing* from patient to the public health service expenditure, is managed by the *fhv* (%) parameter, which governs the percentage of costs associated patient travel for follow-ups at a PC facility.

3.3.2 Cost Convergence and trade-off analysis

Under the design constraint of single-point changes of LTC integrated care into the DMH SDDP and the review of the digital system design, the *fhv* parameter (bounded between 0.0 and 1.0) emerged as the primary mechanism for cost optimization. Linear regression analysis confirmed a statistically significant, linear correlation (R^2>0.999, p<0.001) between the *fhv* parameter and system-wide economic distributions. The

Table 10: Per average-patient case performance of the five excluded metrics from the Process-Adherence assessment of the proposed I-CBCC HV models (at two extremes: FHV=0.00 and FHV=1.00). Each trial metric value has been normalized to a per average-patient basis

Metric	Proposed Model(s) Mean	Conf. Int. 95%	N	Benchmark Model: SDDP2023.PC (Strict) Mean	Conf. Int. 95%	N	Differences Mean Difference	Relative Difference	Cohen's D Effect Size
Proposed Model: HV = 0.00									
TRAVEL_HV	1.54	(1.4, 1.75)	150	0	(0.0, 0.0)	150	-1.54	-	-1.96
VISIT_HV	1.54	(1.39, 1.74)	150	0	(0.0, 0.0)	150	-1.54	-	-1.96
TEST_8Q	0.06	(0.04, 0.08)	150	0.12	(0.09, 0.16)	150	0.06	0.5	0.32
FOLLOWUP HV 9Q	0.06	(0.04, 0.08)	150	0	(0.0, 0.0)	150	-0.06	-	-0.69
KM TRAVEL HV	5.98	(5.37, 6.74)	150	0	(0.0, 0.0)	150	-5.98	-	-1.99
Proposed Model: HV = 1.00									
TRAVEL_HV	1	(1.0, 1.0)	150	0	(0.0, 0.0)	150	-1	-	-
VISIT_HV	1	(1.0, 1.0)	150	0	(0.0, 0.0)	150	-1	-	-
TEST_8Q	0.06	(0.04, 0.08)	150	0.12	(0.09, 0.17)	150	0.06	0.5	0.32
FOLLOWUP HV 9Q	0	(0.0, 0.0)	150	0	(0.0, 0.0)	150	0	-	-
KM TRAVEL HV	3.84	(3.84, 3.84)	150	0	(0.0, 0.0)	150	-3.84	-	-9.87E+15

Table 11: Process-Adherence per alternative model compared to the baseline. Percentages and fractions show statistically significant (equal or improved) criteria over 19 metrics. Cohen's D effect sizes (mean and standard deviation) are shown for positive effect (summed effective metric sizes), negative (summed ineffectiveness metric effect sizes) and net effect size (summed effect difference) per model

Alpha = 0.01									
Model	**SDDP2023-PC (Strict)**	***SDDP2023-PC**	**SC-PsySoc-HV**	**HV-PsySoc-PC**	**SC-PsySoc-PC**	**Kongsuk 2008-PC**	**Kongsuk 2008-HV**	**HV-PsySoc-HV**	***SDDP2023-HV**
%	**100**	**100**	63.16	84.21	63.16	84.21	47.37	84.21	84.21
Fraction	**19/19**	**19/19**	12/19	16/19	12/19	16/19	9/19	16/19	16/19
Effect Size	0.0 (±0.0)	0.0 (±0.0)	**0.49 (±0.5)**	0.16 (±0.2)	0.22 (±0.2)	0.04 (±0.1)	0.35 (±0.3)	0.36 (±0.5)	0.16 (±0.3)
Ineffectiveness Effect	**-**	**-**	-0.42 (±0.3)	-0.24 (±0.3)	-0.21 (±0.2)	-3.58 (±0.6)	-0.91 (±1.3)	-0.49 (±0.5)	-0.51 (±0.6)
Net Effect Size	0.0 (±0.0)	0.0 (±0.0)	0.12 (±0.6)	0.09 (±0.3)	0.04 (±0.3)	-0.6 (±1.4)	-0.35 (±1.1)	**0.21 (±0.6)**	0.05 (±0.4)

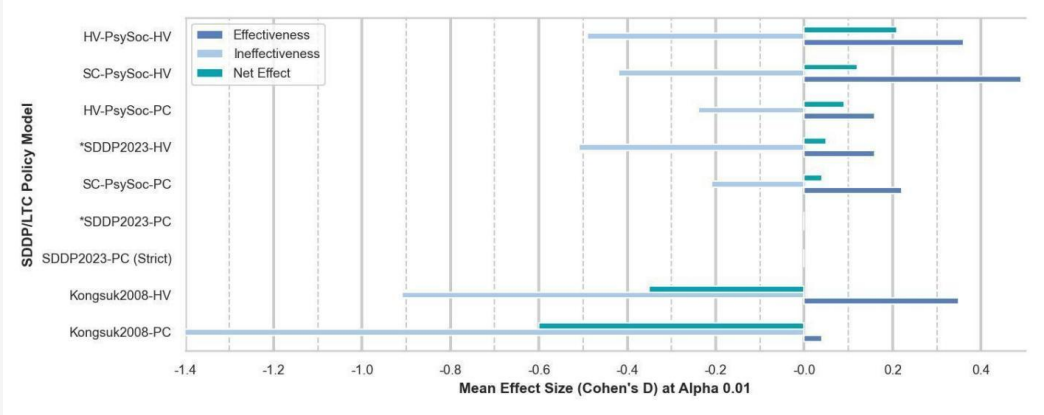


Figure 7: Effectiveness metric performance of alternative (experimental) policy models, shown as their mean Cohen's d effect sizes, at Critical Alpha 0.01. Comparisons to baseline SDDP2023.PC. Reports effect sizes of only significant (P<0.01, with familywise adjustments) hypothesis test results. A variety of improving and declining net effect sizes.

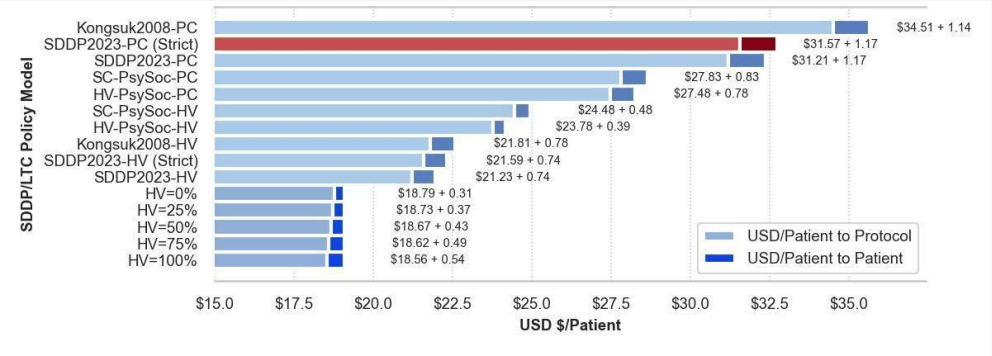


Figure 8: Cost per model policy (shown as means; n=150 trials per patient) in USD ($) on a per average-patient case basis. Current baseline (SDDP2023.PC (Strict)) policy highlighted in red and proposed I-CBCC (HV%) models (darker blue rows). Attributed costs are: to health protocol (lighter colors), to the patient (darker colors); summed as cost per policy model

analysis reveals a strict zero-sum economic trade-off (r =−1.00) between public health service expenditures (”protocol costs”) and out-of-pocket expenses for the elderly (”patient costs”). The HV% models (Figure 8 and Table 12) illustrate this dynamic: protocol costs are minimized at an *fhv* of 1.0, while patient costs are minimized at 0.0. The cost-shifting mechanism is demonstrated by exactly $6,228 USD transferred between the patient and the LTC caregiver (CG) process for every 25% adjustment in the *fhv* parameter. This represents the exact transfer of the follow-up 9Q assessment travel and operational burdens.

The expected linearity of the *fhv* effect was confirmed at patient level from the per-patient event records of the *fhv* = 0.0, 0.5 and 1.0 runs (106,068 paired patients × 10 seeded trials; common random numbers). Protocol and patient travel costs shift dollar-for-dollar (per-patient r = −1.000; total cost fhv-invariant) and exactly linearly (midpoint deviation ≈ 0; $R^2 = 0.999998$), in all 17 parameter configurations; only the 1.0% of patients with 9Q follow-ups are affected (see supplementary figures). While the *fhv* parameter isolates this precise cost-shifting behavior, the digital system factors provide additional possibilities for absolute cost-optimization information flow, scheduled reminders, facility scheduling, clinical recommendations, and speed of referrals not yet fully assessed.

3.3.3 nationwide cost projection estimate

To assess the fiscal implications of national-scale implementation, we projected the observed per-patient cost savings of the SDDP2023-HV (32.9%) and HV% (41.66%) policies onto a nationwide scope. Using the MHCI dataset [55] as a validated surrogate for healthcare demand [24] [25] [56], we normalized the 106,068 participant records to an annual provincial demand of n=6,918 cases. Under these parameters, the normalized annual savings, per province, are estimated at USD $74.5k and $94.4k, respectively, or USD $204 and $258 per day.

Extrapolated across 76 provinces (excluding the Bangkok metropolitan area), this represents a nationwide economic recovery potential of USD $5,661,000 to $7,171,000 per year. To ensure the robustness of this estimate against regional variances (e.g. infrastructure, labor), a sensitivity analysis suggests an 80% implementation. In this case, the I-CBCC model yields an annual public health saving of USD $5.74 million (Table 13). This projection indicates the extent of cost mitigation of the model at scale.

3.4 Ablation Analysis

3.4.1 Service delivery quality

The findings of the *service delivery quality* ablation study illustrate that the digital system integration and home-based follow-ups are the key drivers of service quality (as *process adherence*) improvements; whereas community integration alone (without digital support) actually destabilizes the SoC and referral process. This ablation analysis determines this via *Net Effect* Sizes of policy models at the critical alpha level 0.01[9] (shown in Table 14) and demonstrates this hierarchical service delivery quality of the sub-component models:

- The current SoC baseline model (SDDP2023.PC (Strict)) is defined at 100% *process adherence effectiveness* with 0.0 (±0.0) *net effect* via Cohen’s D formula.
- Removal of explicit duplication in the protocol (SDDP 2023-PC) has no effect (100%, 0.0 (±0.0) *net effect*).

[9]Critical alpha at 0.01 reported; findings are similar at 0.05 and 0.1 alpha levels.

Table 12: Cost per model policy (shown as means; n=150). Current SoC baseline (SDDP) policy highlighted in grey. Patients n=106,068 from MHCI Dataset 2020-2024, for the target scope (four provinces) ages 60 and above

		USD/Patient (2020-2024)			USD All Patients (2020-2024)		
		of Protocol	to Patient	Sum Total	of Protocol	to Patients	All
Proposed CBCC Policy Variants	**HV=100%**	**18.56**	0.54	**19.10**	**1,968,356**	57,722	**2,026,078**
	HV=75%	18.62	0.49	**19.10**	1,974,576	51,502	**2,026,078**
	HV=50%	18.67	0.43	**19.10**	1,980,802	45,276	**2,026,078**
	HV=25%	18.73	0.37	**19.10**	1,987,009	39,069	**2,026,078**
	HV=0%	18.79	**0.31**	**19.10**	1,993,279	**32,799**	**2,026,078**
Modified SoC Policies	**SDDP2023-HV**	21.23	0.74	21.97	2,252,343	78,379	2,330,722
	SDDP2023-HV (Strict)	21.59	0.74	22.33	2,290,012	78,379	2,368,391
	Kongsuk 2008-HV	21.81	0.78	22.59	2,312,993	82,682	2,395,676
Alternative Proposed Policies	**HV -PsySoc**	23.78	0.39	24.17	2,522,121	41,766	2,563,887
	SC -PsySoc	24.48	0.48	24.96	2,596,381	50,683	2,647,064
	HV -PsySoc-PC	27.48	0.78	28.26	2,914,853	83,107	2,997,960
	SC -PsySoc-PC	27.83	0.83	28.66	2,952,295	87,546	3,039,841
SoC Policy & Historical Policies	**SDDP2023-PC**	31.21	1.17	32.39	3,310,841	124,382	3,435,224
	SDDP2023-PC (Strict)	31.57	1.17	32.74	3,348,510	124,382	3,472,893
	Kongsuk 2008-PC	34.51	1.14	35.65	3,660,774	120,699	3,781,472

- Integrating SDDP with LTC CGs for case finding at elderly homes (SDDP 2023-HV) establishes 84.21% *process adherence* with 0.05 (±0.4) *net effect*; a negligible positive improvement, with significant worsening change in three metric types. These are small effect sizes in visits and referrals to SC facilities (-0.16 and -0.17 Cohen's D), and increased referrals to PC facilities (-1.21 Cohen's D) for 5% of patients (mean).

The cause of this 84.21% *process adherence* to SoC reduction are 3/19 operational workload types that (significantly) failed to meet the conditions. Due to increased (i) visits to secondary care (SC), and increased (ii) referrals to primary care and (iii) to SC[10]; while 16/19 maintained or improved upon SoC. Those visits and referrals are explained by travel to screening locations; instead of via LTC community worker screenings via digital tools.

- The integration of the digital system (HV100%) (which retains follow-up 9Q assessments at PC facilities) retains 100% *process adherence* at 0.21 (±0.3) *net effect*. Visits and referrals to SC and referrals to PC facilities are realigned to the baseline; however, LTC CGs (HV) absorb this operational workload. One LTC-CG visit is conducted at 3.84 km traveled on a per average-patient case basis (see Table 5).

HV0% (four added components to baseline) moves follow-up 9Q assessments from PC facilities into elderly homes (adding to LTC CG workload) leads to 100% *process adherence* at 0.31 (±0.5) *net effect*. However, 1.54 LTC-CG visits are conducted, traveling 5.98 km, including 0.06 follow-up 9Q assessments on a per average-patient case basis (Table 10).

3.4.2 Cost analysis

The *cost-efficiency* ablation findings show that integrated community-based case finding is the primary driver of cost savings, while the digital system and home visits optimize who benefits from those savings. We conducted the elimination analysis upon the following summed total cost savings (refer to Table 12) in comparison to the current SoC baseline model (at $32.74 USD per average patient). On an average per patient-case basis, the results (Table 15) demonstrate:

- Removing duplicated events (SDDP 2023-PC) led to a summed total cost saving of 1.07% (-$0.35). Integrating SDDP with LTC CGs for case finding at elderly homes (SDDP 2023-HV) establishes 32.9% cost saving (-$10.77).
- The integration of the digital system (HV100%) gives a further 13.1% cost saving (-$2.87) which retains follow-up 9Q assessments at PC facilities; a 41.66% savings in summed total cost ($19.10) from baseline ($32.74). Reductions are 41.2% to health protocol (-$13.01) and 53.9% to patient (-$0.63).
- HV0% (four added components to baseline) moves follow-ups 9Q assessments from PC facilities into elderly homes leads to no further (summed) cost saving ($19.10), as it shifts cost ($0.23 per patient on average) from patient to protocol. Savings in summed total cost remain at 41.66%, with 40.5% saving to health protocol (-$12.78) and 73.5% saving to patient (-$0.86).

Table 13: Estimates of Nationwide Economic Recovery Potential of Proposed Integrated Policies. Results compare per-patient savings (to All) and annual provincial/national (76 province) scaling, including a 20% sensitivity reduction for conservative estimation

Policy	Savings/Patient (USD)	Provincial Annual Savings (USD)	Nationwide Annual Savings (USD)	Conservative Implementation Savings (at 80%) (USD)
SDDP2023-PC (Strict)	[Baseline] 32.74	-	-	-
SDDP2023-PC	0.35	2,456.67	186,707.22	149,365.77
SDDP2023-HV	10.77	74,489.41	5,661,195.39	4,528,956.31
HV% (All)	13.64	94,357.50	7,171,170.00	5,736,936.00

Table 14: Ablation Analysis of Service Delivery Quality, via process adherence effectiveness percentage and net effect (Cohen's d as mean, std. dev.) performance (at alpha=0.01) of the policy intervention in the CBCC (HV%) model

Model	SDDP2023 (Strict)	SDDP2023-PC	SDDP2023-HV	HV100%	HV0%
Intervention	**Baseline**	**Removed Duplication**	**Home case finding. LTC CG Integration**	**Digital System**	**Move Follow-up 9Q to 100% in Homes**
Process Adherence %	100%	100%	84.21%	100%	100%
Net Effect	0.0 (±0.0)	0.0 (±0.0)	0.05 (±0.4)	0.21 (±0.3)	0.31 (±0.5)

3.5 Geospatial Distribution of Policy Impact

This section evaluates where across the four rural provinces the benefits of the proposed Integrated Community-Based Collaborative Care model with 50% health-volunteer follow-up (I-CBCC HV-50%, *fhv* = 0.5) are delivered, relative to the Standard-of-Care (SoC) baseline SDDP2023-PC (Strict). Per-patient Discrete-Event Simulation outputs (n = 106,068; default parameter set; mean of 10 trials) were aggregated to subdistrict (ADM3) polygons via spatial join. In aggregate, HV-50% saves 460,404 km in patient-borne travel (−81.7%) and 118,174 facility visits (−95.1%) versus SoC, adding 110,144 health-volunteer home visits.

3.5.1 Spatial distribution of savings and costs

Figure 9 maps the per-patient savings. Both travel and visit relief are positive in every participating subdistrict, with the largest per-patient values concentrated in western Chaiyaphum and along provincial peripheries distant from secondary care. Figure 10 holds the two monetary maps together: net protocol cost saved (mean 8.49 USD/patient; a net increase in only 21 of 672 subdistricts, 19 of which have n < 30) and patient travel cost saved (km saved × the 4 THB/km ≈ 0.11 USD/km expense-claim rate; is positive everywhere, a universal patient-side monetary benefit).

3.5.2 Spatial clustering of unmet need and intervention benefit

Figure 11 and Table 16 test whether these patterns are statistically clustered with neighboring subdistricts. Global clustering is quantified with Moran's I = 0.394, p = 0.001. 7 Gi* FDR-robust subdistrict hotspots of *unmet need* (9Q-positive prevalence) are significantly locally clustered, shown in red in southern Chaiyaphum. These 7 subdistricts delineate an area of significant geospatial clustering of unmet need. Patient-travel savings are region-wide (globally positive in all 366 analyzed subdistricts) without local concentration of hot or cold spot clusters (not significant). The local cluster mapping of benefit in patient travel km shows this as no FDR-robust local clusters. However, benefit clustering is metric-dependent: the visit- and cost-saving metrics do form FDR-robust clusters (see Table 16). Rollout targeting should therefore prioritize *need* and *access* criteria.

3.5.3 Rollout prioritization: multi-criteria priority tiers

Figure 12 and Table 17 present the resulting rollout prioritization calculated by the multi-criteria decision analysis (MCDA) prioritization index (0.0-1.0) of *Need*, *Benefit* and *Access*; computed at the district (ADM2) level to resolve small samples (82 of 86 districts n ≥ 30). Top 9 (within 90th-percentile) scoring districts are annotated within the figure, with top 20 districts reported in the table. Quantile classes are Tier 1 (≥ 90th percentile), T2 (p75–p90) and T3 (<p75), with respective number of districts in each tier: 9/12/61. The ranking is shown as robust to the choice of weights[11]; the equal-weighting choice introduces minimal bias into the prioritization.

[10] See raw operational workload (DES Events) in supplementary table

[11] Weight-sensitivity analysis in supplementary Table S3: Spearman ρ = 0.930–0.980 (all p < 0.001, n = 82), across all pairwise weighting-

Table 15: Ablation for cost reduction performance (as a percentage of the baseline cost) in terms of summed total cost to Health Protocol expenditure and Patient expenditure of the policy intervention components in the HV% model

Model	SDDP2023 (Strict)	SDDP2023-PC	SDDP2023-HV	HV100%	HV0%
Intervention	**Baseline**	**Removed Duplication**	**Home case finding. LTC CG Integration**	**Digital System**	**Move Follow-up 9Q to 100% in Homes**
Cost Saving % (Total Cost)	0%	1.07%	32.9% ($10.77)	41.66% ($13.64)	41.66% ($13.64)
Cost Saving % (to Protocol)	0%	1.07%	32.9% ($10.34)	41.66% ($13.01)	40.5% ($12.78)
Cost Saving % (to Patient)	0%	0%	36.75% ($0.43)	53.85% ($0.63)	73.5% ($0.86)

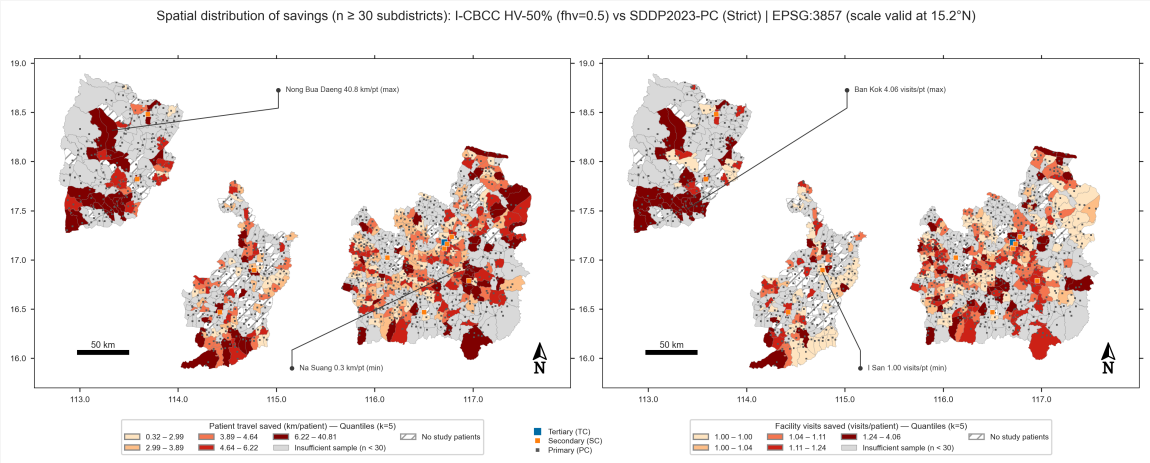


Figure 9: Per-patient savings of I-CBCC HV-50% vs the SoC baseline, by subdistrict — values mapped for the 366 subdistricts with n ≥ 30; grey shows insufficient sample size, hatched = no study patients. Left panel shows patient travel saved, right shows facility visits saved; each as Quantile classification [77]; public health facilities overlaid. Maximum and minimum subdistricts are annotated. EPSG:3857; scale bar valid at 15.2°N

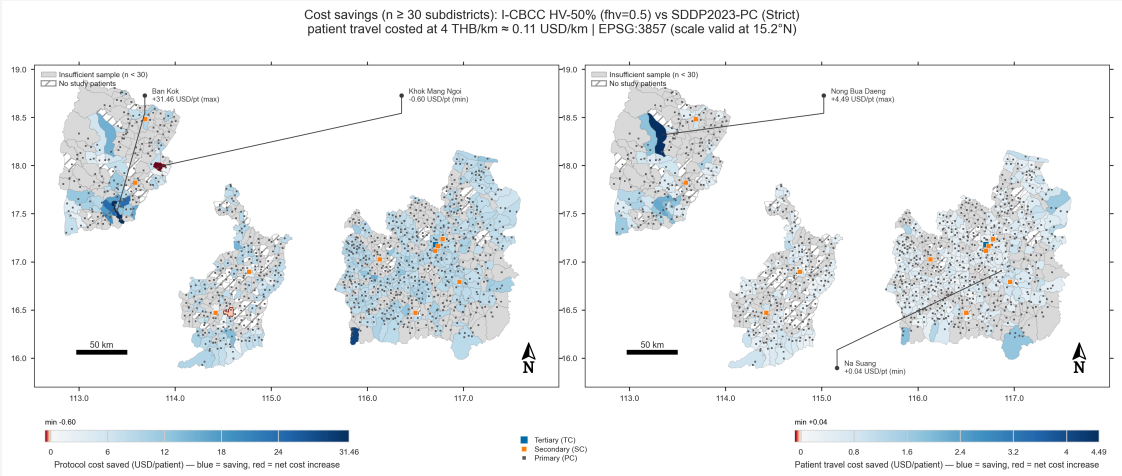


Figure 10: Cost savings by subdistrict (n ≥ 30 mapped; grey shows insufficient sample size). Left panel shows net protocol cost saved and right shows patient travel cost saved (USD/patient). Two subdistricts show a net protocol increase (red). All 21 increases including n < 30 are listed in supplementary table. Colors span the mapped range, with the data minimum at the red end (−0.60 USD protocol; +0.04 patient). Maximum and minimum subdistricts are annotated. EPSG:3857

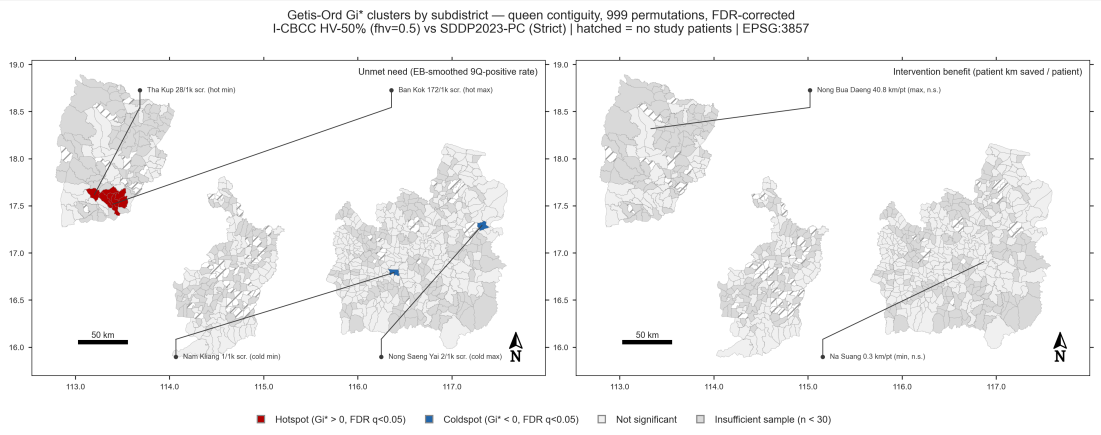


Figure 11: Local Getis-Ord Gi* clusters: unmet need (left) and intervention benefit (right; patient km saved per patient). Benjamini-Hochberg FDR α = 0.05 (999 seeded permutations), n ≥ 30 analysis set (insufficient samples shown as darker grey). Annotations of extreme cluster values of hot/cold maxima and minima for need (per 1,000 screened) and for benefit. Benefit has no FDR-robust clusters (not significant). EPSG:3857

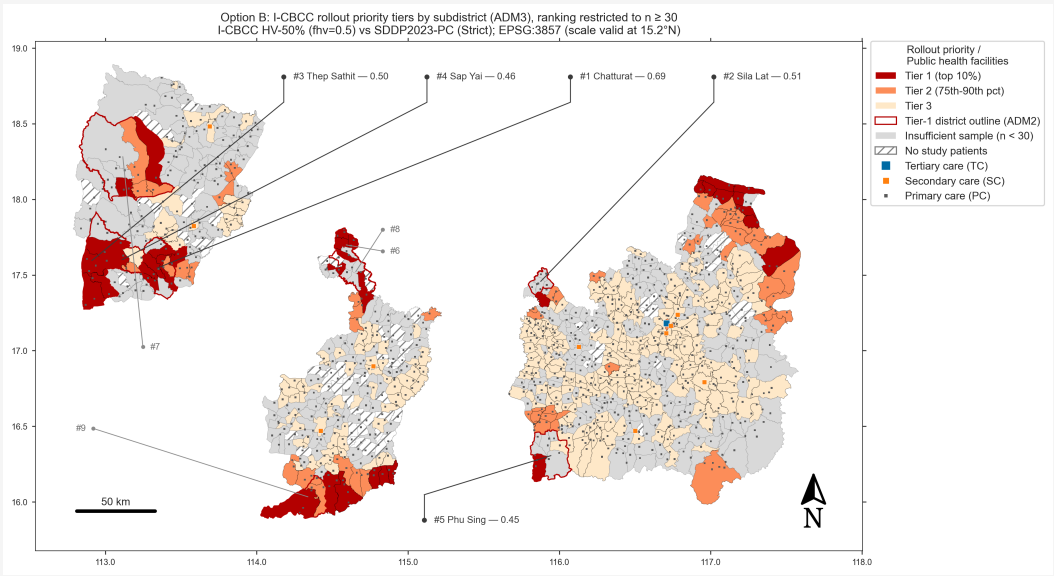


Figure 12: I-CBCC rollout priority tiers by subdistrict (ADM3; ranking restricted to n ≥ 30), MCDA weighted-sum composite [22] [76] of Need, Benefit and Access; public health facilities overlaid. Quantile tiers (Tier 1 = top decile). Tier-1 districts (ADM2) are outlined in the tier color and annotated. EPSG:3857

Table 16: Global and local spatial statistics for the need variant and 3 benefit metrics; separating region-wide benefit from local clustering. % of Positive Subdistricts is the share of the 366 analysed subdistricts with a strictly positive per-patient saving; Mean (min–max) gives the mean and full range of the metric across them. Gi* hot and coldspots columns identify number of subdistricts in locally clustered high/low priority areas

Variable	Summary Spatial Statistics		Spatial Clustering of Hot/Cold spots			
	% of Positive Subdistricts	Mean [unit] (min–max)	Moran's I	Pseudo-p (**Sig.<0.05)	Gi* hot (FDR)	Gi* cold (FDR)
Unmet need (9Q+ prevalence, EB)	—	—	0.394	0.001 **	7	2
Benefit: travel km saved/pt	100	5.01 (0.32-40.81)	0.311	0.001 **	0	0
Benefit: visits saved/pt	100	1.18 (1.00-4.06)	0.396	0.001 **	9	31
Benefit: USD saved/pt	99	8.49 (−0.60-31.46)	0.389	0.001 **	7	8

Table 17: Top 20 priority districts sorted by MCDA Composite Score (0.0–1.0), with equal-weighted sum of the min–max-normalized Need/Benefit/Access criteria blocks. Tier = quantile class: T1 (≥ 90th percentile), T2 (p75–p90) and T3 (<p75). Est. 60+ Pop. from DOPA subdistrict-level house-registration population aged 60+ (December 2022, stat.bora.dopa.go.th; districts pop. = sum of subdistricts pop.). From the screening dataset: n = study patients; 9Q+/1k scr. = prevalence per 1,000 screened (not RCT population samples). Simulation outcome findings: for savings per-patient vs SoC; Access km = the mean haversine distance in km of patient geolocations to their assigned facilities (district mean)

				Screening Data Source			Results: I-CBCC HV 50% vs SoC				MCDA Scoring	
#	Province	District	Est. 60+ Pop.	n	9Q+/1k scr.	9Q Severe	km saved/pt	Visits saved/pt	USD saved/pt	Access km	MCDA Composite Score (0.0–1.0)	Tier
1	Chaiyaphum	Chatturat	17,185	420	173.8	11	15.64	2.94	+21.845	44.8	0.689	T1
2	Si Sa Ket	Sila Lat	4,116	44	136.4	0	7.18	2.42	+19.942	76.1	0.509	T1
3	Chaiyaphum	Thep Sathit	11,588	323	55.7	0	9.41	1.61	+6.257	112.5	0.504	T1
4	Chaiyaphum	Sap Yai	2,517	991	45.4	0	10.44	1.51	+9.418	76.6	0.460	T1
5	Si Sa Ket	Phu Sing	7,774	178	112.4	1	10.58	2.24	+16.925	59.0	0.452	T1
6	Buri Ram	Na Pho	6,866	1,500	3.3	1	4.36	1.04	+8.089	109.5	0.388	T1
7	Chaiyaphum	Nong Bua Daeng	17,766	692	31.8	1	12.36	1.37	+6.378	67.9	0.381	T1
8	Buri Ram	Phutthaisong	9,788	356	8.4	1	5.43	1.09	+7.936	98.1	0.372	T1
9	Buri Ram	Non Din Daeng	4,318	1,012	14.8	0	5.57	1.17	+8.746	93.7	0.358	T1
10	Ubon Ratchathani	Khemarat	13,014	2,286	5.7	0	3.51	1.06	+8.329	97.0	0.357	T2
11	Ubon Ratchathani	Na Tan	6,270	486	6.2	0	3.75	1.08	+8.399	97.6	0.347	T2
12	Buri Ram	Ban Mai Chaiyaphot	5,332	356	0.0	0	3.14	1.00	+7.935	102.9	0.347	T2
13	Ubon Ratchathani	Nam Yuen	9,381	479	18.8	0	12.40	1.23	+8.679	66.2	0.342	T2
14	Chaiyaphum	Kaeng Khro	17,137	173	52.0	0	7.10	1.60	+7.364	63.7	0.339	T2
15	Ubon Ratchathani	Pho Sai	7,060	588	11.9	1	4.84	1.12	+7.770	89.2	0.333	T2
16	Ubon Ratchathani	Kut Khaopun	6,933	94	10.6	0	6.20	1.19	+8.563	78.2	0.316	T2
17	Buri Ram	Khaen Dong	5,045	46	43.5	0	6.67	1.56	+12.156	54.8	0.299	T2
18	Ubon Ratchathani	Sirindhorn	7,369	102	9.8	0	6.47	1.11	+8.391	68.7	0.283	T2
19	Buri Ram	Satuek	19,216	1,079	4.6	0	4.44	1.05	+8.122	67.3	0.280	T2
20	Ubon Ratchathani	Khong Chiam	5,221	1,462	0.7	0	6.31	1.01	+7.631	73.6	0.278	T2

4. Discussion

Our study evaluated the integration of the established Long-Term Care (LTC) infrastructure into the national mental health protocols (DMH) as a strategy for inter-departmental synergy and collaboration via a geospatial simulation methodology. The integrated collaborative care model (I-CBCC) is the primary mechanism to augment existing community care-based roles (caregivers and health volunteers of the WHO pyramid model [17] [78]) in elderly rural homes. The experimental models encoded five policy interventions mechanisms including those derived from established MOPH and policymaker guidelines ([2] [15] [18] [20] [21]) and the ablation analysis isolated the impacts of each intervention.

4.1 Statement of Principal Findings

The principal finding is that the integrated community-based care (I-CBCC) model achieved significant operational workload efficiencies across all top-level categories, which led to significant improvements in all three policy evaluation metrics: *workload, effectiveness* and *cost-efficiency*, with large projected public health expenditure savings. Notable reductions included a 44% decrease in screenings (95% CI: 0.36–0.52) and follow-ups (0.28–0.61), alongside an 18% reduction in total distance traveled (0.06–0.31). Furthermore, the HV0% variant demonstrated a 40.5% reduction in protocol costs ($12.78 USD savings per capita) while maintaining 100% service delivery quality (net effect size: 0.31 ± 0.5). These simulation-based gains substantiate that shifting facility-based tasks to Digital-LTC community-based operations optimizes rural health logistics without increasing facility burdens or compromising the standard of care (SoC).

4.2 Strengths and Limitations

Following key criteria identified by Thai health policymakers for effectiveness and cost-efficiency [22] [23] [53] [54], a major strength of this study was the utilization of DES ([32] [35] [36] [38]) to measure operational workload, process adherence, and cost-efficiency at scale. This evaluation leveraged granular geospatial datasets comprising 106,068 elderly patient records across 1,032 facilities over 46 months, to provide a robust cross-sectional comparison with the

scheme comparisons; Tier-1 overlap vs the equal-weight ranking 7–8 of 9

current standard of care (SoC) protocol. The geospatial analysis adds further strengths: prioritized district-level rollout recommendations, ranked by a robust multi-criteria prioritization index. This index is calculated from official DOPA house-registration denominators independent of the screening data and is supported by FDR-controlled permutation-based local spatial statistics. Its prioritized ranking is shown to be robust to its (equal) weighting choice (Spearman ρ = 0.881–0.974; see supplementary table).

While the simulation framework provides a strong evaluation of interdepartmental synergies, several limitations inherent to secondary data and parametric modeling warrant consideration.

- First, due to missing data, four binary decisions within the process model lacked empirical evidence to guide transition probabilities. In these cases, parsimonious models following conservative recommendations [39] [40] are reported for their structural decision stability to confirm the decision effect is equal across policy models.
- Second, a notable limitation relates to the granularity of the secondary data regarding elderly dependency groups. The available national health protocol data for elderly mental health in the region did not record independent versus dependent status. Consequently, our assessment of policy interventions was conducted without distinguishing the specific Activities of Daily Living (ADL) dependency classifications utilized by the LTC 3C program [9] [51] [79-84]. Because care-level dependency significantly impacts mental health conditions [82], future data gathering that integrates ADL status with mental health metrics will be vital for refining how specific LTC 3C cohorts respond to these integrated policy interventions.
- Finally, the DES assumes fixed-time system dynamics for the geospatial network of health facilities and patients. Generalizability of the model to other regions of Thailand or other LMICs may be limited.

Further, the geospatial analysis and its district-level policy rollout prioritization index carries four limitations:

- The composite score index's depression prevalence (9Q-positive) rates carry coverage-selection bias (nonrandomized sampling) from the MHCI screening dataset.
- The MCDA index's denominator utilizes elderly population counts from the national (DOPA) house registration counts; these carry 0.6-1.2% error from provincial totals (*unknown-age*), which cannot be attributed to single subdistricts.
- 306 of 672 subdistricts are excluded from the geospatial analysis due to small sample sizes ($n<30$); which motivates the district-level primary ranking at 82 of 86 districts included.
- All spatial analyses are cross-sectional over the study window; spatiotemporal extension of the clustering and prioritization remains future work.

4.3 Interpretation in the Context of Previous Studies

Digital tools and Community Workers in Rural Settings:

- Systematic reviews by [85] identified digital tools for community health workers (CHW), as enhancing impact of care delivered, and by [86] corroborates this within mainly higher-income (HIC) studies by ~9.2%. [87] [88] found evidence of neutral-to-general-improvements by their inclusion. Our ablation analysis extends findings specifically in rural LMIC as integrating LTC personnel (CHW) without a digital support system creates a specific critical screening interdependency, that (paradoxically) degrades service delivery. While service delivery (protocol effectiveness) synergized as digital integration and home-based follow-ups were combined; improving the net effect size from 0.21 to 0.31 (Cohen's d). We deemed this a specific process-improvement of mutually reinforcing "*constellation effect*" of enhancing care delivery impact.

Interdepartmental Integration of MH in LMICs:

- Our findings demonstrate that integrating DMH protocols into LTC infrastructure creates a measurable synergy. Specifically, the simulated findings corroborate those of [89] as resource-efficiency of CHW task-shifting via a RCT in China, and serve as an empirical data-point responding to recommendations for age-specific integrated-care LTC-DMH restructuring of health-care provisioning, via information systems with CHW among LMICs in [90]. While geriatric-specific adapted protocols for MH are favored in LMIC settings and in Thailand [84] [91-93], however simulation model comparisons are lacking. [94] [95] identified DES as a tool to analyze constrained cohorts, this work establishes a partial-empirical baseline of shifting from age-generic (SoC) to a geriatric-specific LTC-DMH protocol in LMIC rural settings. In their systematic review of meta-analyses [36] identified a scarcity of economic evaluation models for MH in LMIC contexts despite a

rising DALY burden; to which this empirical work responds directly.

Economic Sustainability of LTC-DMH Screening:

- The economic sustainability findings of LTC and DMH integration is important to reduce hesitation to policy change, that are supported by empirical findings. Similarly, [92] [93] CHW integrated LTC model in northern Thailand demonstrated effectiveness (as reduced caregiver burden, functional decline and depression) without cost-utility analysis. [33] studied the optimization of tertiary hospital efficiencies of elderly health care resources via DES, while this research complements via structural (process-based) workload reductions via community-based (decentralized) rural referrals, within the MOPH's LTC and DMH programs. While [19] engaged stakeholders on fund management in a rural province with economic findings informing further integration between LTC and DMH.

4.4 Policy and Clinical Implications

Our projections demonstrate that Digital-LTC integration effectively reduces the economic stress of rural geriatric mental health care. The I-CBCC (HV0%) model reduces the per-capita public health expenditure by 5.13% for the affected elderly cohort from 3.6% ($248.72 [3]) to 3.4% ($235.94) of relative GDP. In protocol-specific cost terms (from $31.57 SoC to $18.79 for HV0%, and down to $18.56 for HV100% per avg. patient) the model reclaims important fiscal capacity, providing the necessary space to offset the initial costs of digital infrastructure and community health volunteer training, while financing other age-related health agendas. At the provincial level, the I-CBCC (HV0%) model generates USD $94,000 in annual savings; extrapolated nationwide (76 rural provinces), this represents a yearly recovery potential of USD $7.17 million. The primary policy lever identified for scalability is the Follow-up Health Volunteer (FHV%) parameter. The FHV% rate allows policymakers to transfer intensive follow-ups for vulnerable elderly cohorts between LTC caregiver home visits and in-facility trips. This serves as a vital mechanism for managed affordability and the prioritization of care (and patient cost) via LTC integration. Consequently, we recommend a risk-stratified, staggered rollout where the FHV% is prioritized for the most vulnerable elderly cohorts.

The geospatial analysis translates the aggregate economic findings into a prioritized implementation strategy. The MCDA priority index tiers (Figure 12 and Table 17) identify the districts where clustered *unmet need*, high simulated *per-patient savings*, and distant facility *access* coincide. Therefore, a staggered rollout of the I-CBCC protocol yields the greatest early return at these Tier-1 districts (Table 17). The *FHV%* lever parameter can then be tuned per district; i.e. higher home-based *follow-up* shares in remote, *access*-poor subdistricts (largest patient-side relief), facility-based follow-up where facilities are denser. Because local clustering is metric-dependent (Table 16); the composite index combines all three blocks and is robust to the weighting choice between these criteria (supplementary table).

4.5 Future Research Directions

To refine our predictive precision, future research may prioritize gathering geospatial data on psychosocial attrition and recovery curves with managed selection biases. Ultimately for the proposed I-CBCC protocol, future research should map the FHV% thresholds to specific LTC-focused *elderly vulnerability* groupings to support managed system-wide *affordability* [23] with staggered pilot implementations across the geographical rural regions.

5. Conclusion

Our findings in this study support that the integration of specialized national mental health (DMH) protocols into existing rural Long-Term Care (LTC) community-based infrastructure facilitated by digital task-shifting offers improvements over the current facility-based standards of care (SoC). This evaluation shows the digital I-CBCC model significantly reduces high-level operations and costs without compromising adherence to SoC. Importantly, the findings reveal that the success of such policy change is driven by a mutually reinforcing constellation effect between digital tools and community health workers, and interdepartmental synergies. A geospatial-driven multi-criteria prioritization index guided the choice towards 9 rural districts (the top decile) that can gain most from rolling-out this policy intervention within the study region. The Follow-up Health Volunteer (FHV%) parameter of the I-CBCC model is the primary lever to manage risk-stratification of policy rollout for rural interdepartmental geriatric care in this region and nationwide.

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