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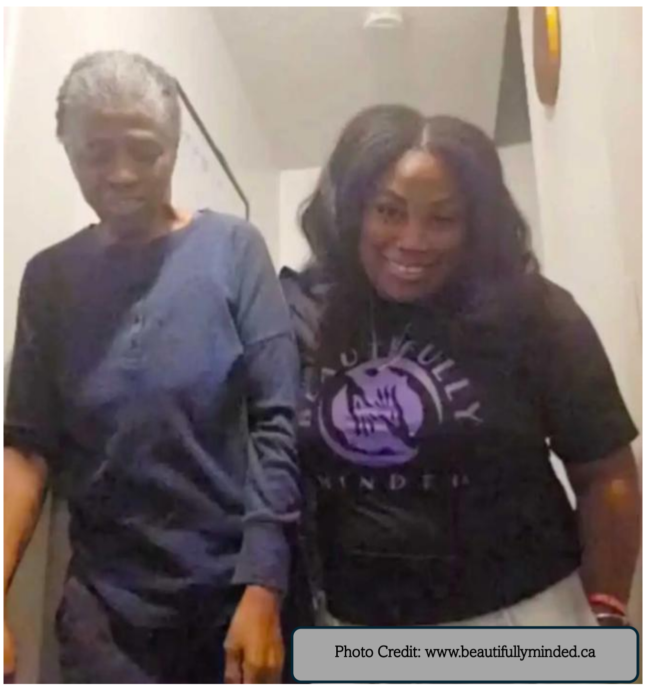
FINAL REORT OF TERM PROJECT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PROJECT TITLE

Modeling the Impacts of Stress of Family Caregivers on the Quality of Care and Progress of Dementia to Inform Policy & Practice Interventions

GROUP 5

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We also acknowledge the contribution of all members of the class which has helped to shape our understanding of the concepts and processes of dynamic system modeling.

Abstract

In modeling the impacts of stress of family caregivers on the quality of care and dementia progression to inform policy & practice interventions, we used a hybrid of Agent-Based Modeling and Discrete Event Simulation, after we had used Causal Loop Diagram to map out how major stressors affect the stress levels of the caregiver.

Our major variables for the modeling were caregiver stress level, quality of care offered by the caregiver, and dementia progression, with workload, sleep quality and financial strain as the key parameters for the caregiver stress level.

Our model lacked significant variability and thus lacked stochasticity as was needed in dynamic models. Introducing adults daycare and caregiver stipends, further confirmed our observations of low levels of variability.

We recommend that that this study is repeated with the introduction of such variables as other comorbidities of the patient, patient's activities of daily living, and other events like falls, missed hospital appointments and missed medications in order to harness the richness of stochasticity.

Part One

Background

1.1 Introduction

The usefulness of Dynamic System Modeling cannot be overemphasized. It helps to explore how agents within a system interact with others and their environment, and to draw insights from such behavior (1). This project highlights the use of dynamic system modeling to explore how the stress level of family caregivers impacts the quality of care (QoC) offered, and how this QoC in turn affects the progress of Dementia. We used a hybrid of Agent-Based Modeling (ABM) and Discrete Event Simulation (DES) after we had used Causal Loop Diagram (CLD) to conduct a high-level model mapping of the team's mental model.

1.2 Motivations

The team's choice to implement this project using Hybrid Simulation method to explore caregiver stress level in Dementia care is underscored by a number of factors:

It is estimated that as of January 1, 2025, 771,939 people in Canada are living with dementia with more than 414 people likely to develop dementia every day or 17 people per hour. It is further predicted that almost 1 million people in Canada could live with dementia by 2030, a 65% increase relative to the numbers in 2020 (2). Compared to caregivers of seniors without dementia (26%), nearly twice as many caregivers of seniors with dementia (45%) show signs of caregiver distress (3,4). Additionally, Alzheimer's disease (AD) constitutes between 60-70% of Dementia cases, and hence, our modeling used AD and dementia interchangeably to refer to the same condition.

Furthermore, it has been established that several real-world scenarios have characteristics that do not fit into a single modeling approach but have multiple features that are best captured by combining more than one modeling approach. Hence, our team adopted the Hybrid Simulation method integrate two or more traditional approaches into a single model that provide more flexibility to operate at different levels of abstraction and to harness the benefits each approach brings (5).

1.3 Goals of Model

1. To explore how several stressors impacts on the stress level of family caregivers of Dementia Patients
2. To understand how the stress levels of family caregivers, in turn, affect the quality of care that is offered to the Dementia Patient
3. To further understand how the quality of care thus impact the progress of Dementia
4. To offer high level recommendations to inform Policy & Practice Interventions based on the outcomes of the model scenarios

1.4 Mental Models Implemented by the Team

- Conceptualization of Baseline Model (NB: this is just a mental model and not a Causal Loop Diagrams)

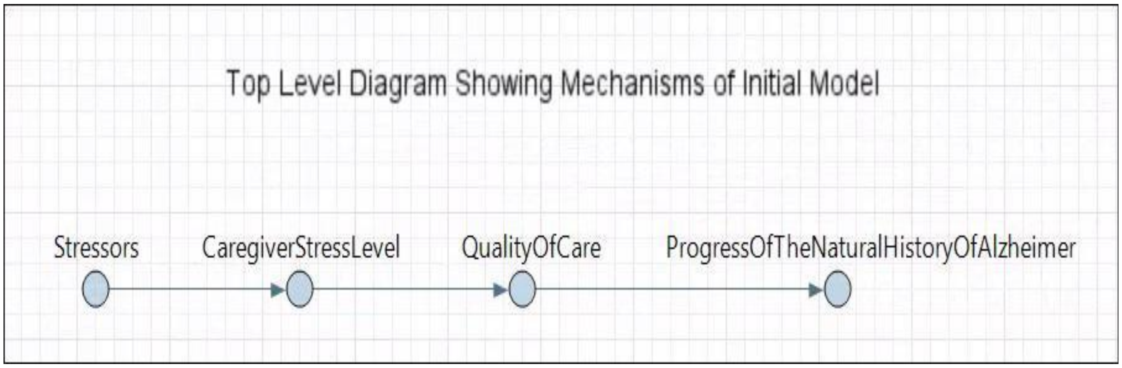


Figure 1: Mental Model for the Causal Loop Diagram Implemented in section

- Conceptualization of the Hybrid Model of Agent-Based Modeling and Discrete Event Simulation

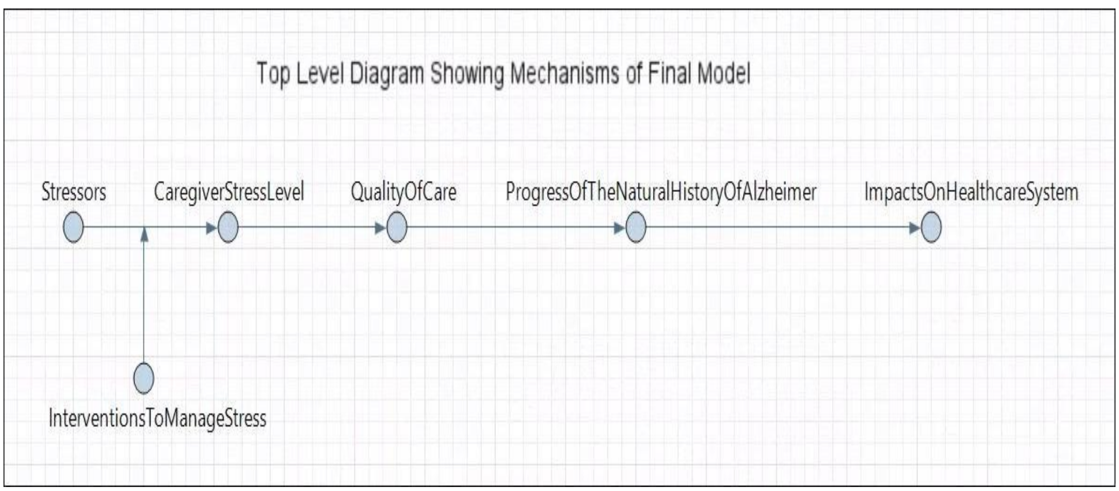


Figure 2: Mental Model of the Hybrid Model of ABM & DES Implemented in section

Part Two

Model

2.1 Model Scope

2.1.1 Description of Model Scope:

This model examines the causal system linking dementia patient care needs to family caregiver stress, and the interventions that can break stress-induced disease acceleration cycles. Below we clarify what is endogenous (inside the model, changing dynamically), exogenous (external input, fixed), and ignored (deliberately left out for tractability). explore how several stressors impacts on the stress level of family caregivers of Dementia Patients

2.1.2 Endogenous Variables (Modeled Dynamically)

These factors change every week during simulation based on model equations and feedback loops:

1. Caregiver workload (hours/week): Determined by patient care needs minus professional hours available.
2. Caregiver stress (0-3 scale): Composite of workload stress, financial stress, and sleep stress, recalculated weekly.
3. Care quality delivered (0.2-1.0 scale): Inversely linked to caregiver stress; how well caregiver performs care tasks.
4. Patient disease progression: Weekly decline in health status based on care quality received.
5. Patient behavioral symptoms (0-10): Increase as patient health declines; reduce caregiver sleep quality.
6. Patient care needs (28-140 hours/week): Escalate nonlinearly with disease stage.
7. Queue dynamics: Wait times and queue length for adult day care slots (discrete event system).
8. Caregiver state transitions: Movement between Low Stress, Moderate, High, Crisis, and Seeking Support states.
9. Family financial resources: Available income (base plus stipend if intervention enabled).

2.1.3 Exogenous Variables (External Inputs, Fixed)

These are set at model initialization and remain constant throughout the simulation:

1. Dementia progression rate: Fixed at 0.0015/week (weekly percentage decline in patient health).
2. Adult day care slot capacity: Fixed number of available slots (baseline: 20 slots per facility).
3. Intervention flags: Policy choices fixed at start (enableInterventions = true/false, enableStipend = true/false).
4. Stipend amount: If stipends are enabled, fixed at $200/week per caregiver or more.
5. Caregiver coping skills baseline: Fixed at 0.5 (scale 0-1); represents baseline psychological resilience.
6. Initial patient dementia stage: All patients start at Mild stage (health status = 0.75).
7. Simulation time horizon: Fixed at 52 weeks (about 12 months).

8. Population size: Fixed at approximately 100 caregiver-patient dyads.
9. Base living costs: Fixed at $1,500/week (used for income-to-expense ratio calculations).

2.1.4 Ignored Variables (Deliberately Left Out)

These factors are known to influence real-world caregiver stress but are simplified or excluded to maintain model tractability:

1. Multi-caregiver households: Model assumes single primary caregiver per patient.
2. Caregiver demographic heterogeneity: All caregivers have identical stress response curves.
3. Family dynamics and intergenerational relationships: Assumed independent households with no complex family support networks.
4. Healthcare provider interactions beyond day care: Only discrete adult day care resource pool is represented.
5. Medication effects on disease progression: No pharmacological interventions are modeled.
6. Stochastic variation: Model uses deterministic transitions.
7. Caregiver employment changes: Income held constant; model does not simulate job loss due to caregiving.

2.1.5 Justification for Scope Choices

The endogenous/exogenous split reflects a policy-focused research question: "Given current dementia prevalence and caregiver demographics (exogenous), what interventions most effectively reduce stress and disease acceleration?" Multi-caregiver dynamics, heterogeneity, and stochasticity are ignored in this version to keep the model workable. These simplifications are explicitly addressed in future work recommendations.

2.2 Model Architecture

2.2.1 Choice of Modeling Approach: Hybrid ABM-DES

This model uses a HYBRID combination of Agent-Based Modeling (ABM) and Discrete Event Simulation (DES) two traditionally separate methodologies to capture complementary aspects of the problem:

2.2.2 Agent-Based Modeling (ABM) Component

ABM is used to represent individual caregiver and patient agents with autonomous behavior and state machines. Each caregiver has a unique trajectory through stress levels (Coping to Stressed to Crisis to SeekingSupport) based on their individual workload, income, and sleep quality. Each patient has a unique disease progression trajectory based on the quality of care they receive. Feedback loops are captured: patient care needs drives caregiver workload, which drives stress, which reduces care quality, which accelerates disease, which increases care needs. This emergent, nonlinear dynamics cannot be captured by linear equations alone.

2.2.3 Discrete Event Simulation (DES) Component

DES is used to represent a separate Healthcare Provider agent that manages limited adult day care resources. This provider maintains a ResourcePool (queue) of fixed capacity (e.g., 20-day care slots). When caregivers in Crisis attempt to seek support, they enter a queue to seize one slot. If slots are available, the patient can attend day care, reducing the caregiver's weekly workload. If slots are unavailable, the caregiver waits in queue, stress remains elevated, and disease accelerates unchecked. This queue bottleneck is the key mechanism that links service infrastructure constraints to caregiver outcomes.

2.2.4 Why Hybrid? (The Complementary Factor)

Pure ABM limitation: An ABM model without resource constraints would model caregiver stress responses but implicitly assume unlimited access to support (unrealistic). Result: Interventions would appear infinitely effective, missing service bottlenecks.

Pure DES limitation: A DES model focused on queue dynamics would treat caregivers as passive requests, ignoring individual stress trajectories and decision-making. Result: Would miss caregiver heterogeneity and the psychological triggers of help-seeking behavior?

Hybrid solution: ABM agents make stress-based autonomous decisions (when to seek help, how much care effort to invest). DES queue enforces resource scarcity (some caregivers must wait; some must forgo support). Together, these capture real-world dynamics: motivated caregivers cannot always get help because services are full, leading to sustained crisis and accelerated disease.

(DES) library (ResourcePool, queues, seize/release blocks). A central main model integrates both libraries, allowing agents to call methods on each other and access shared parameters. Analytics dashboards track outputs in real-time: stress trajectories, disease progression, care quality, and queue metrics

2.3 Model Formulation (Rules of Model Operation)

2.3.1 Data used

i. Given that Sleep Quality, Caregiver Workload and Financial Strain are among the most common sources of stressors (3,6–9), we selected and combined these 3 factors in a piecewise manner to constitute the parameters that make up Caregiver Stress Level.
ii. Detailed information on how data was used to compute the model equations (V3) have been captured in the GitHub.

2.3.2 **High-Level Overview (ODD Protocol)**

Purpose and Scope

To model how family dementia caregiving stress emerges from the interaction of workload, financial strain, and sleep deprivation; to identify which caregivers enter Crisis states; and to evaluate policy interventions (adult day care expansion, financial stipends, coping training) for their effectiveness in reducing stress and slowing disease progression.

2.3.3 Entities and State Variables

Three agent types populate the model:

A. Caregiver Agent

1. stressLevel (0-3 scale): Composite stress, recalculated every week.
2. workloadStress, financialStress, sleepStress (each 0-3 scale): Components of total stress.
3. careQuality (0.2-1.0 scale): Quality of care provided, inversely linked to stress.
4. Statechart state: current behavioral state (Coping, Stressed, Crisis, SeekingSupport).
5. workloadHoursPerWeek (0+): Weekly hours spent on care.
6. familyIncomeWeekly (0+): Weekly household income (set at agent creation).
7. sleepQualityHourperWeek (0+): Weekly sleep hours (reduced by patient behavioral symptoms).
8. myPatient: reference to assigned patient agent.

B. PatientWithDementia Agent:

Health Status (0-1 scale): 0.35< health Status equals Mild stage, 0.35> health Status equals Moderate, 015> health Status equals Severe stage

1. dementiaStageName: categorical (Mild, Moderate, Severe, End-stage), derived from healthStatus.
2. behavioralSymptoms (0-10 integer): Severity of behavioral issues increases as health declines.
3. careNeedsHoursPerWeek (28-140): Weekly care hours needed, scales with disease severity.
4. effectiveCareQuality (0.1-1.0): Blended quality from family caregiver and professional care.
5. professionalCareHoursPerWeek (0+): Hours provided by day care when patient attends.
6. statechart state: physical location state (AtHome, AtAdultDaycare).
7. myCaregiver: reference to assigned caregiver agent.

C. HealthcareProvider Agent

1. dayCareSlots: ResourcePool object with fixed capacity (e.g., 20 slots).
2. queueLength: number of caregivers currently waiting for a slot.

D. Time Scale and Space

Time unit: weeks

E. Process Overview and Scheduling

Each simulation week, the following sequence were executed:

1. Patient_agent calculates updated care needs based on current health status.
2. Patient_agent calculates behavioral symptoms from health decline.
3. Caregiver agent retrieves patient care needs; calculates effective workload (needs minus professional care hours).
4. Caregiver agent calculates sleep quality: baseline reduced by patient behavioral symptoms.
5. Caregiver agent calculates three stress components: workloadStress, financialStress, sleepStress.

6. Caregiver agent calculates composite stress levels (weighted average of three components).
7. Caregiver agent updates care quality (inverse relationships with stress).
8. If stress is greater than or equal to 1.5, caregiver transitions to Crisis state and triggers help-seeking.
9. Help-seeking: caregiver attempts to seize a day care slot from HealthcareProvider.dayCareSlots resource.
10. 10a. If slot available: patient transitions to AtDaycare state; professionalCareHoursPerWeek set to X hours.
11. 10b. If slot unavailable: caregiver enters queue, remains in SeekingSupport state.
12. 11. Patient disease progression occurs: health declines weekly based on care quality and progression rate.
13. 12. Outputs recorded: stress levels, care quality, disease progression, behavioral symptoms.
14. 13. Advance to next week; repeat.

2.3.4 Key Stress Equations *(Please see detailed form on GitHub)*

1. **Workload Stress Component (S_W)**: Maps caregiving hours to 0-3 scale. Brackets: 0.0 (less than 10 hrs/wk), 0.5 (10-25), 1.0 (25-40), 1.5 (40-60), 2.0 (60-90), 2.5 (90-120), 3.0 (greater than or equal to 120 hrs/wk).

2. **Financial Stress Component (S_F)**: Maps income-to-expense ratio to 0-3 scale. Formula: incomeRatio equals (familyWeeklyIncome plus stipendIfEnabled) divided by 1500 (base cost). Brackets: 3.0 (less than 0.4), 1.7 (0.4-0.6), 1.3 (0.6-0.8), 1.0 (0.8-1.0), 0.6 (1.0-1.2), 0.3 (1.2-1.5), 0.0 (greater than or equal to 1.5).

3. **Sleep Stress Component (S_S):** Maps weekly sleep hours to 0-3 scale. Brackets: 3.0 (less than 14 hrs/wk), 2.5 (14-21), 2.0 (21-28), 1.5 (28-35), 1.0 (35-42), 0.5 (42-49), 0.0 (greater than or equal to 49 hrs/wk).

4. **Composite Stress Level**: sigma_C equals weighted average of S_W, S_F, S_S (0-3 scale).

5. **Care Quality**: Q_C equals max(0.2, min(1.0, 0.8 minus (sigma_C divided by 3.0) times 0.5 plus C_S times 0.2)). Clamped to [0.2, 1.0]; inverse relationship with stress; boosted by coping skills.

6. **Disease Progression:** H(t+1) equals max(0, H(t) minus (r_d times (1 minus Q_E times 0.5)) divided by 100). Weekly health decline; adjusted for care quality; clamped at 0.05 (Severe Dementia).

7. **Care Needs**: N_C equals maximum (28, 28 plus (1 minus H) times 112 minus P_h). Minimum 28 hrs/week (Mild stage); maximum approximately 140 hrs/week (end-stage); reduced by professional care.

2.4 Model Formulation (Outcomes)

2.4.1 Causal Loop Diagram

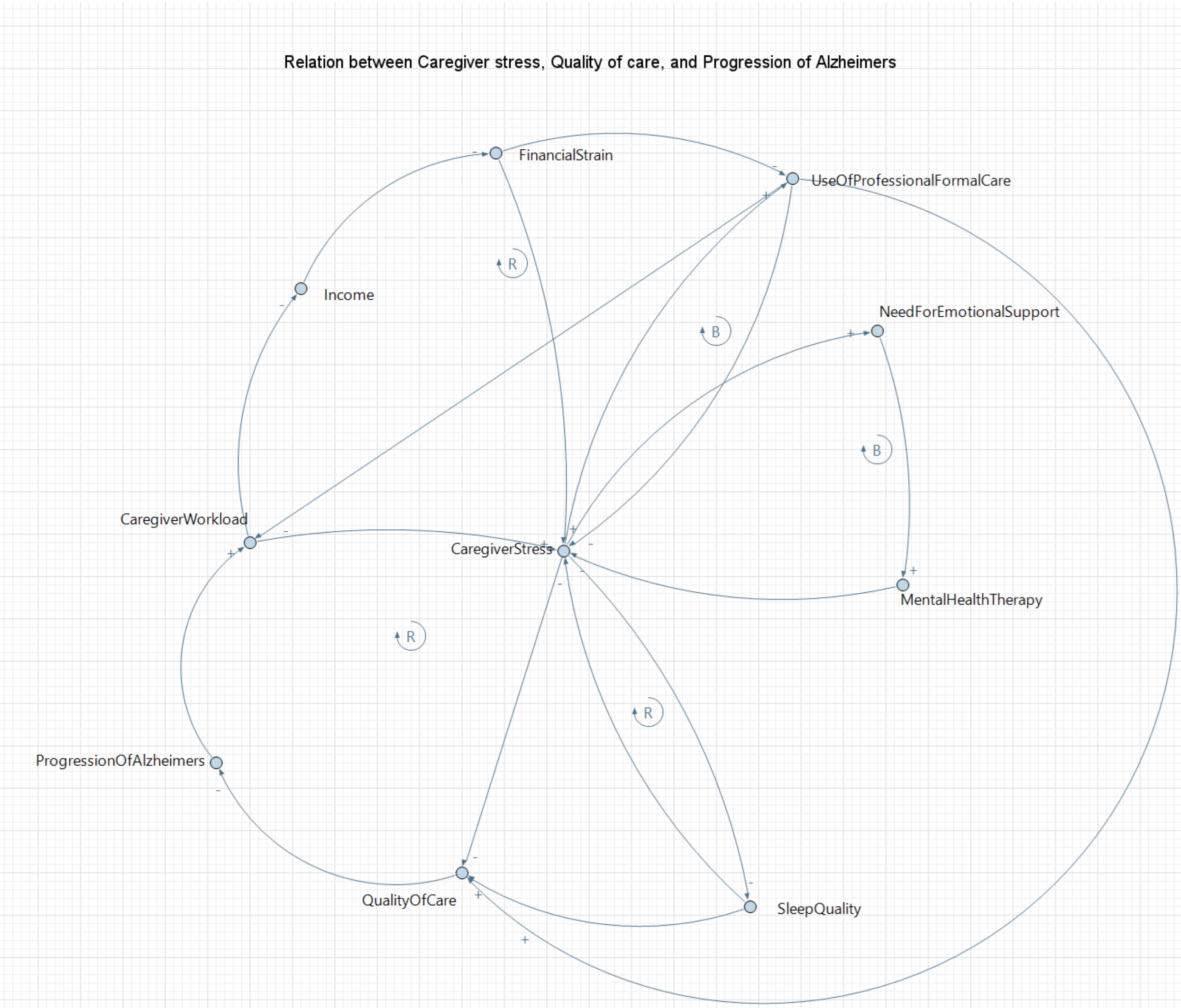


Figure 3 Causal Loop Diagram depicting the relationship between some Stressors, Caregiver Stress level, Quality of Care and Dementia (Alzheimer) Progression

A. Brief Description of the Causal Loop Diagram (CLD)

a. This causal loop diagram (CLD) illustrates the interconnected psychosocial, economic, and clinical factors driving caregiver well-being and patient outcomes in the context of Alzheimer's disease. The structure emphasizes how caregiver stress emerges from multiple reinforcing pressures and how formal and informal support mechanisms contribute balancing effects. By mapping these relationships, the diagram highlights the dynamic complexity inherent in dementia caregiving and identify leverage points for intervention.

B. Reinforcing Dynamics:

i. R1 – **Workload–Stress Escalation Loop**: Increasing Caregiver Workload contributes directly to higher Caregiver Stress. As stress rises, caregiver efficiency decreases and emotional fatigue increases, which in turn amplifies workload demands. This positive feedback loop reflects the well-documented cycle of burden and burnout in dementia caregiving.

ii. R2 – **Stress–Sleep Deterioration Loop**: Heightened stress leads to disrupted or inadequate Sleep Quality. Poor sleep compounds emotional reactivity and reduces coping ability, further elevating stress. This loop captures the physiological dimension of caregiver decline, demonstrating how chronic stress rapidly becomes self-reinforcing.

iii. **R3 – Care Quality and Disease Progression Loop**: Stress negatively affects the Quality of Care delivered to the patient. Lower care quality accelerates the Progression of Alzheimer's, increasing the complexity and intensity of caregiving tasks. This elevates workload and ultimately drives stress higher, forming a powerful reinforcing loop that ties caregiver well-being directly to patient deterioration.

iv. **R4 – Socioeconomic Reinforcement Loop**: Income reduces Financial Strain, increasing access to Professional Formal Care. Greater use of formal care alleviates workload and reduces stress. Conversely, low income increases strain, limits access to support and reinforces stress. This loop underscores disparities in caregiving resilience tied to socioeconomic status.

C. Balancing Structures:

i. **B1 – Mental Health Support Loop**: Rising stress increases the likelihood of seeking Mental Health Therapy. Therapeutic support provides coping strategies and emotional relief, which reduce stress levels. This balancing loop represents an internal and psychological counterforce to escalating caregiver burden.

ii. **B2 – Emotional and Formal Support Utilization Loop:** As stress rises, caregivers develop greater Need for Emotional Support, increasing the likelihood of seeking Professional Formal Care. External support reduces workload and thereby mitigates stress. This loop represents an external balancing mechanism capable of interrupting self-reinforcing burnout dynamics.

D. Systemic Interpretation:

Collectively, the loops depict a system dominated by reciprocally amplifying forces: workload, stress, sleep decline, care quality reduction, and disease progression. These reinforcing cycles can push caregivers toward rapid overload unless counteracted by balancing mechanisms such as therapy, external emotional support, and access to formal care services. The CLD shows that interventions aimed at caregivers (rather than solely patients) can meaningfully alter system trajectories by weakening reinforcing loops and strengthening balancing ones.

2.4.2 Statecharts

A. Caregiver Statechart

I. LowStress(sigma_C less than 1.0) transitions ModerateStress (1.0 less than or equal to sigma_C less than 1.5) transitions to Crisis (sigma_C greater than or equal to 2.0) leads to SeekingSupport (timeout initiated).

II. Entry conditions: Stress thresholds trigger transitions. Exit: Stress drops below threshold OR help-seeking resolves (slot obtained).

Prima

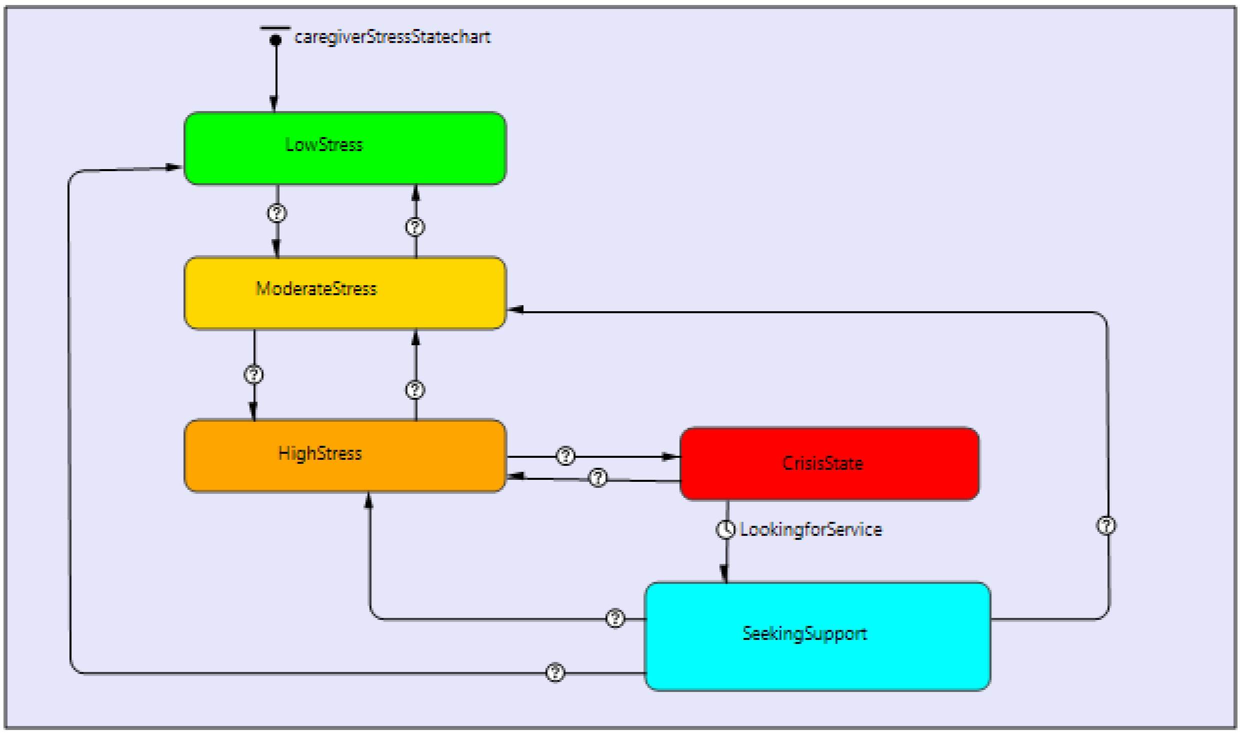


Figure 4. Caregiver State Chart depicting the stress level categorized into 5 states, LowStress, ModerateStress, HighStress, CrisisState and SeekingSupport. Each of the four primary stages

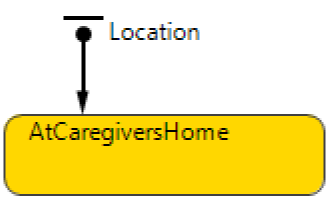


Figure 5. Caregiver location Statechart depicting the caregiver's location

B. Dementia Patient Statechart

(default) can transition to AtDaycare (when slot seized); governed by caregiver help-seeking success. The Patient transitions through each stage by the health status of the patient, initially pateitns start off with (0.70-0.90) in health status, and the progression of dementia updates through an event that calls a function, altering the health status of that patient to go through each stage through certain thresholds.

General Approach to Transitions and Flows

Transitions follow condition-based (deterministic) rules: if stress is greater than or equal to 1.5, enter Crisis; if stress is less than 1.0, return to Coping. Disease progression is a linear weekly decline. Feedback loops are closed through method calls: caregiver.calculateStress() calls myPatient.getCareNeeds(), which depends on patient health, which depends on care quality from caregiver. This circular dependency is resolved by sequential execution.

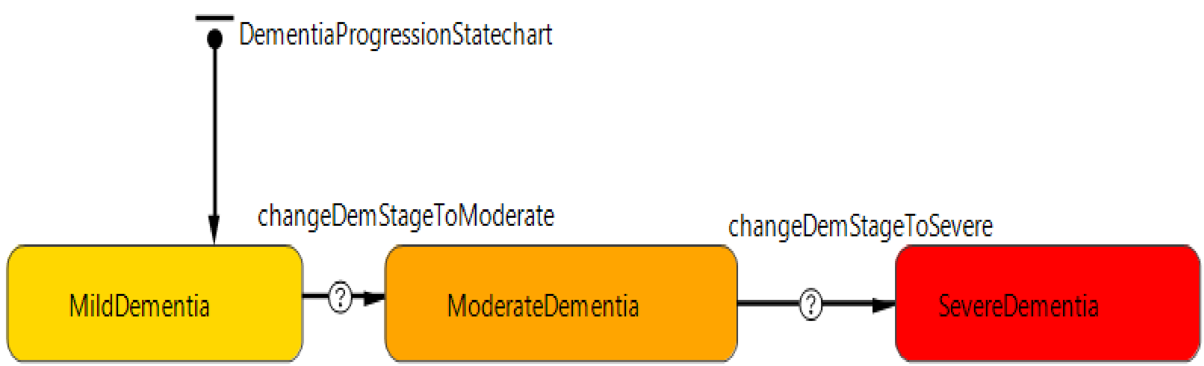


Figure 6. Dementia Patients status statechart

The Dementia patient has 2 more statecharts that are used to model the Adult Day Care interventions

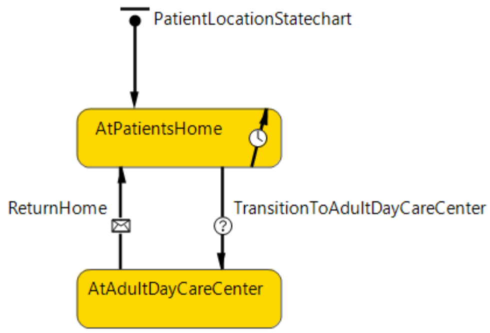


Figure 7. Caregiver location Statechart

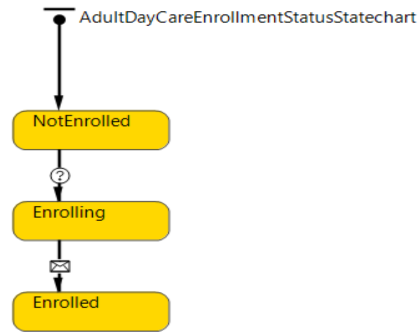


Figure 8. Caregiver location

Initial State Selection

- All caregivers: stressLevel equals 0.05 (low stress).
- All patients: healthStatus equals 0.75-0.90 (Mild dementia stage).
- Family income: assigned based on parameter weeklyIncomeCalculation()
- Day care queue: empty (no caregivers waiting).

Motivation for initial state: This reflects the point at which a family has sought diagnosis (dementia confirmed), caregiver is at low stress initially and disease is progressing but not yet severe. Baseline state is realistic and allows simulation to show progression to crisis without starting already in crisis.

C. Patient State Chart: Health-Based Transitions

The patient's physical location transitions between two states based on the patient's dementia severity (healthStatus variable), which determines whether they attend adult day care or remain at home. This creates the critical link between disease progression and caregiver workload relief.

State 1: AtPatientsHome (Default)

The patient remains at home and receives full-time family caregiving. In this state, the caregiver is entirely responsible for all care activities. Professional care hours (professionalCareHoursPerWeek) equals zero. The caregiver must provide all hours of care dictated by the patient's care needs (based on disease stage). This is the high-workload state for the caregiver.

Transition Trigger: AtPatientsHome to AtAdultDaycare:

Transition occurs when BOTH conditions are met: (1) Caregiver stress level rises to Crisis state (stress >= 1.5), triggering help-seeking behavior, AND (2) An adult day care slot becomes available in the DES queue (caregiver successfully seizes a ResourcePool slot). This is NOT based on patient health status directly, but rather on caregiver stress and service availability. The caregiver's desperate need (high stress) combined with available capacity (empty slot) opens the pathway.

State 2: AtAdultDaycare

When successfully transitioned, the patient attends adult day care for that week. During this period, professional caregivers provide X hours of care per week (typically 20-30 hours). The patient's actual care needs may require 40-100+ hours per week depending on disease stage, but the professional care hours cover part of that need, reducing the caregiver's burden from N_C hours to (N_C minus professionalCareHoursPerWeek) hours. This relief is temporary — lasting one week. At the end of the week, if the caregiver remains in crisis and tries to re-access day care, they may face a queue wait (no slots available) and be forced back to full-time home care.

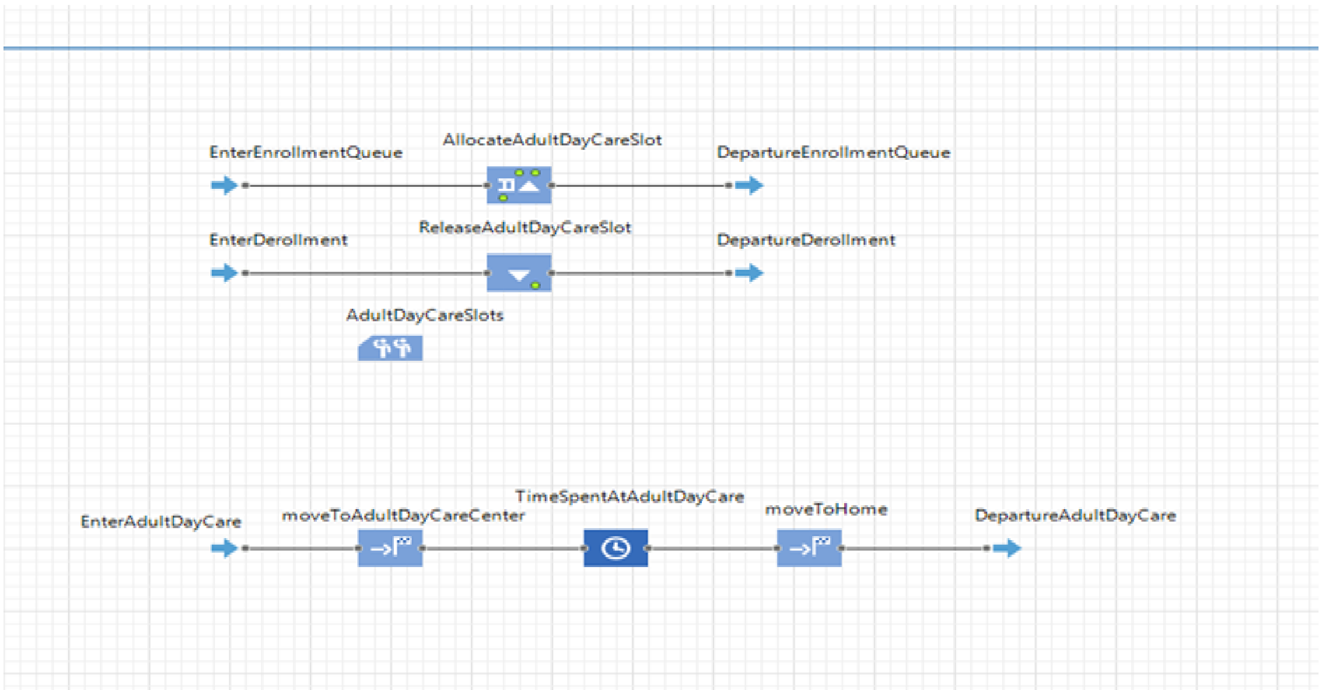


Figure 9: Discrete Event Simulation showing Dementia patient at entering the Adults Daycare Centre for a given state

Key Insight: Disease Severity Controls Care Intensity

The patient's healthStatus (which ranges from 1.0 at Mild stage to 0.05 at Severe Dementia) determines their CARE NEEDS (hours required). But it does NOT directly control whether they attend day care. Instead, it indirectly influences placement through the caregiver's workload stress: sicker patients require more care hours → higher caregiver workload stress → crisis triggered → day care access attempted. If day care is full (queue waiting), the caregiver cannot access relief despite high need. This creates the bottleneck dynamic central to the model

Part Three
Sensitivity Analysis

3.1 Overview

To validate our model's sensitivity to change we have completed a sensitivity analysis for each of our weighting components of our caregiver stress equations:

a. workloadStressWeight,
b. sleepStressWeight
c. financialStressWeight.

Rationale: With the analysis of these variables, we were hoping to find out which components of the caregiver's stress had a larger effect on the quality of care that a dementia patient receives. All the simulations were run based on our baseline model where there are 100 caregivers matched with their respective dementia patients and ran the model for 1000 days / ~143 weeks.

3.2 Analysis of stress weights

a. By observing the resulting 2D histogram charts that were produced by the sensitivity analysis experiments, we can see a trend that occurs between all three of the caregiver stressor weights.
b. In all the graphs (figs 10-12), it was observed that after ~450 day mark sever dementia cases begin to spike until the ~650 day mark where all the 100 dementia patients have been diagnosed with severe dementia.
c. No stressor appears to have larger impact on patient health status

3.3 Resulting Actions

a. Due to the tight grouping within the different experiment runs, this displays the lack of stochastics within the model alongside the deterministic conditions that tend to lead the model runs into equilibriums.
b. Issue with stochastics
c. Model gets lead into equilibrium states due to statechart condition transitions

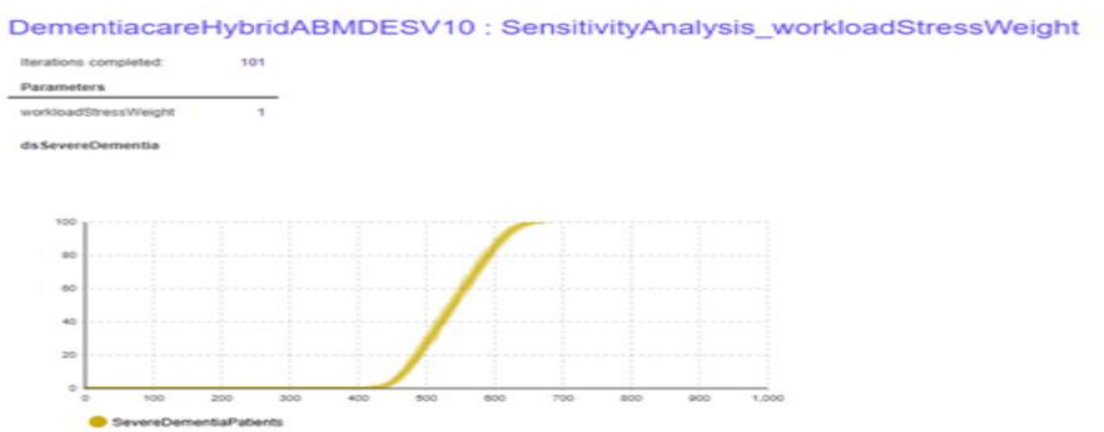


Figure 10: Sensitivity Analysis of workload stress from weight 0 to 1 with step of 0.01. The x axis displays the days, while the y axis displays the patients that reach a state of severe dementia.

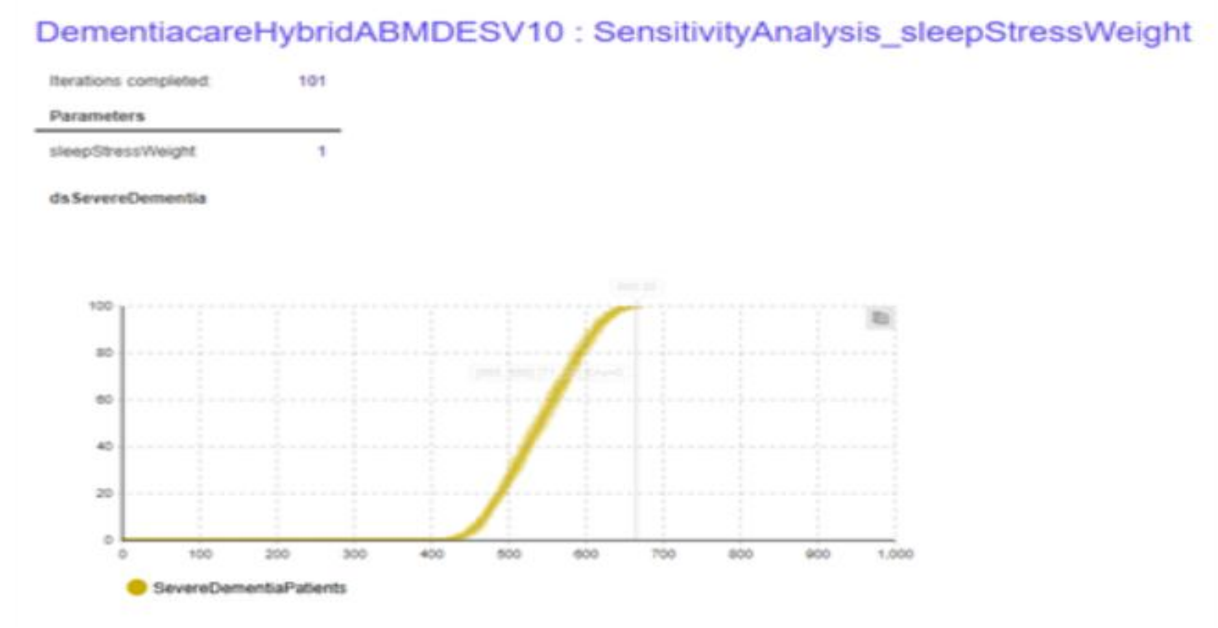


Figure 11: Sensitivity Analysis of sleep stress from weight 0 to 1 with step of 0.01. The x axis displays the days, while the y axis displays the patients that reach a state of severe dementia.

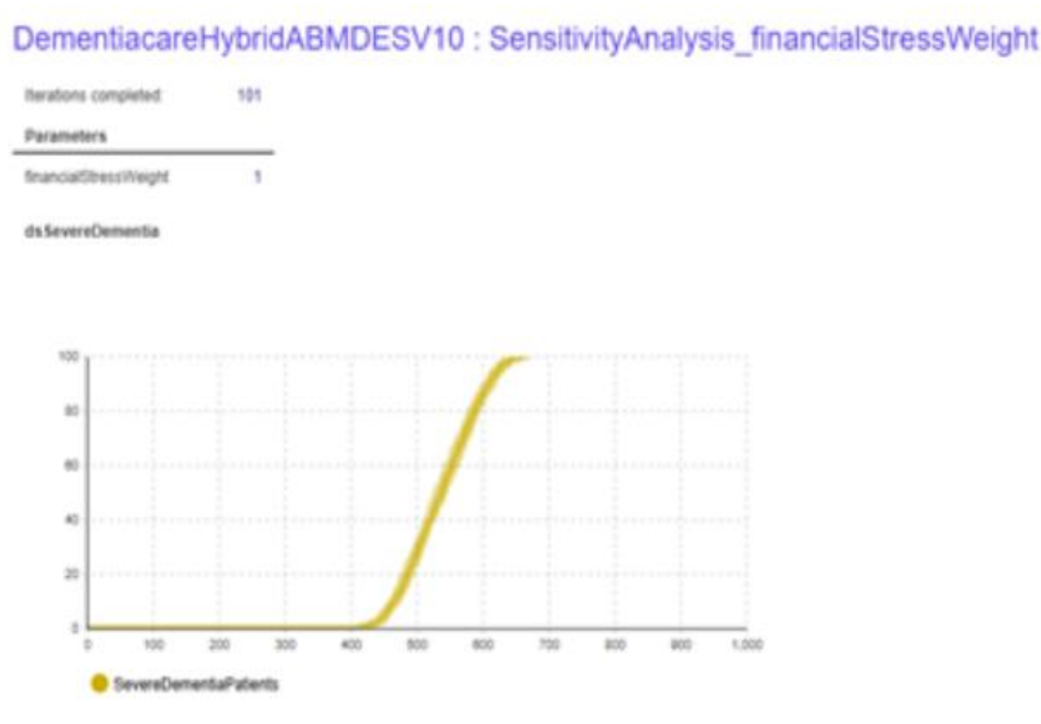


Figure 12: Sensitivity Analysis of financial stress from weight 0 to 1 with step of 0.01. The x axis displays the days, while the y axis displays the patients that reach a state of severe dementia.

Part Four

Scenarios

4.1 Overview

Based on the sensitivity analysis, we observed that caregiver stress level is a very sensitive variable in this model. Therefore, we decided to create scenarios that impact the some of the parameters that make up the stress level, with the possibility of using such scenarios as leverage for policy recommendations and practice intervention to manage caregiver stress levels

4.1 What we are testing.

Model uses weighted composite stress: stressLevel = stressLevel = (w_W * workloadStress + w_F * financialStress + w_S * sleepStress) / (w_W + w_F + w_S); Currently all weights ≈ 0.33 (equal contribution). We test: (1) Does workload dominate (increase weight)? (2) Does sleep matter more? (3) Does financial stress scale differently?

EXPERIMENT 1: Baseline
File: Main: Baseline scenario

Configuration:

- enableInterventions = false
- enableStipend = false
- adultDayCareSlots = 20
- workloadStressWeight = 0.33
- sleepStressWeight = 0.33
- financialStressWeight = 0.34
- dementiaCareProgressionRate = 0.0015
- patientPopulationSize = 100
- caregiverPopulationSize = 100
- simulationDurationYears = 5.0

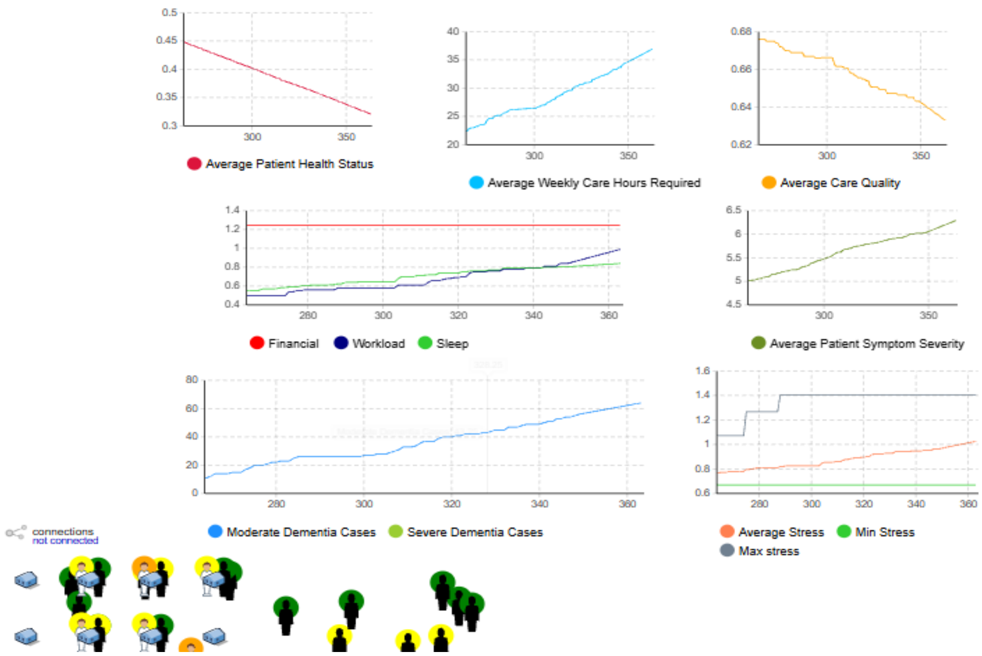


Figure 9 Baseline Scenario

Key Outcomes:

(+20%), driven by disease progression from Mild to Severe dementia stage. At Week 40, most patients exhibit healthStatus values in the range 0.3–0.6 (Moderate stage) requiring approximately 20 hours per week of care. By Week 50, many patients have progressed to healthStatus < 0.3 (Severe stage) with care needs escalating to 40–54 hours per week. Notable examples include Patient 42 (health = 0.153, requiring 54.2 hrs/week) and Patient 79 (health = 0.168, requiring 53.2 hrs/week), demonstrating how disease progression directly drives increases in caregiver workload.

Stress Trajectory:

The population average stress follows a linear escalation pattern: Week 40 (0.801) → Week 50 (0.959) → Week 58 (1.086). While stress increases substantially, the population average does not reach the Crisis threshold of 1.5 within the 18-week observation window. However, 44 out of 113 weekly measurements exceed the Stressed threshold (≥1.0), indicating widespread caregiver strain. This trajectory aligns with qualitative caregiver literature: families begin in a manageable but strained state and experience gradual

EXPERIMENT 2: Day Care Only

File: Pop100WithIntervention

Configuration (Changes Highlighted):

- enableInterventions = true ← CHANGED
- interventionStartWeek = 7 ← CHANGED
- enableStipend = false
- adultDayCareSlots = 40 ← CHANGED
- workloadStressWeight = 0.33
- sleepStressWeight = 0.33
- financialStressWeight = 0.34
- dementiaCareProgressionRate = 0.0015
- patientPopulationSize = 10
- caregiverPopulationSize = 10

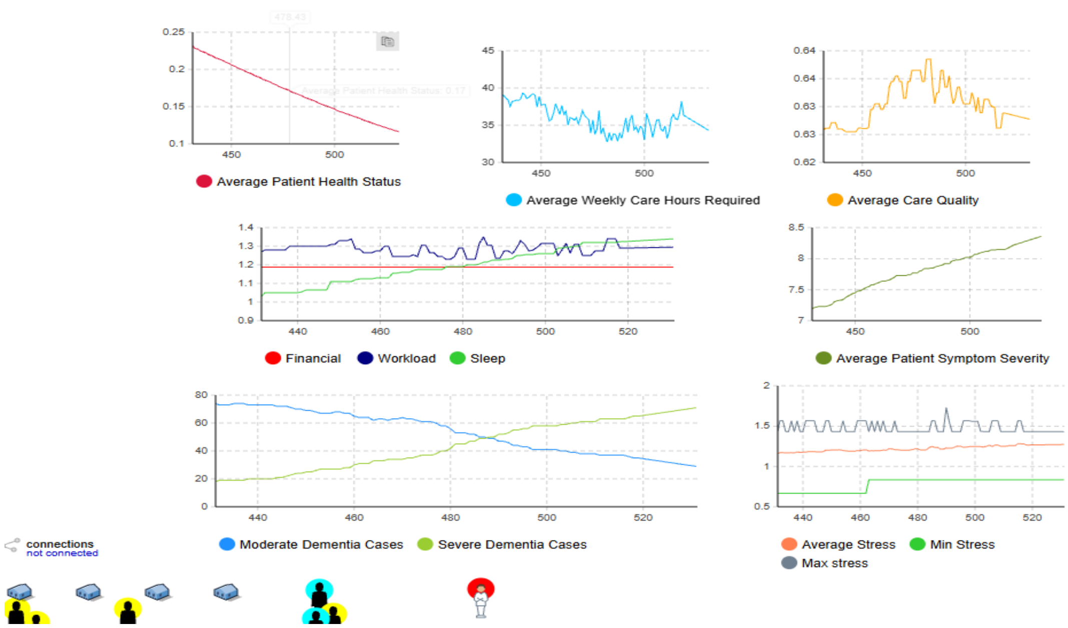


Figure 10. What if Dementia Patient is mutually exclusively sent to Adults Daycare as a way of controlling Caregiver Stress level

Key Outcomes:

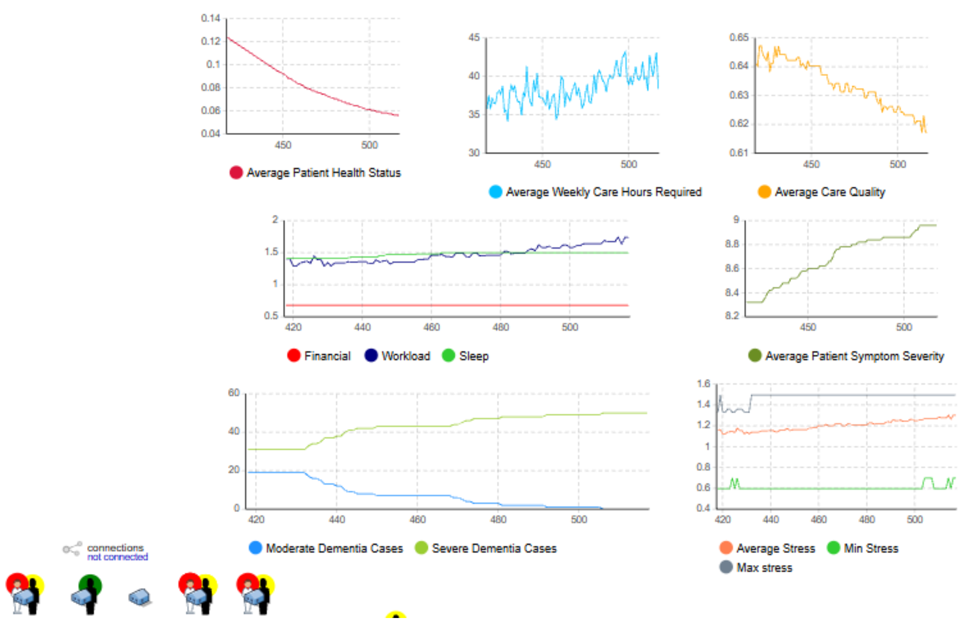
With day care alone, weekly care hours for the primary caregiver increase more slowly, which translates into a noticeable reduction in the workload component of stress compared with baseline and stipend-only runs. The peak average stress is lower (around 1.03) and the final stress is slightly below baseline, roughly 0.95–0.96, indicating a modest but meaningful improvement in long-term caregiver well-being. This pattern implies that directly removing hours from the caregiver's week is more powerful than financial relief alone in preventing stress escalation.

EXPERIMENT 3: Stipend Only (Financial Intervention)

File: Pop10WithStipend

Configuration (Changes Highlighted):

- enableInterventions = false
- enableStipend = true ← CHANGED
- stipendAmount = 400 ← CHANGED
- adultDayCareSlots = 20
- workloadStressWeight = 0.33
- sleepStressWeight = 0.33
- financialStressWeight = 0.34
- dementiaCareProgressionRate = 0.002 ← CHANGED
- patientPopulationSize = 50 ← CHANGED
- caregiverPopulationSize = 50 ← CHANGED



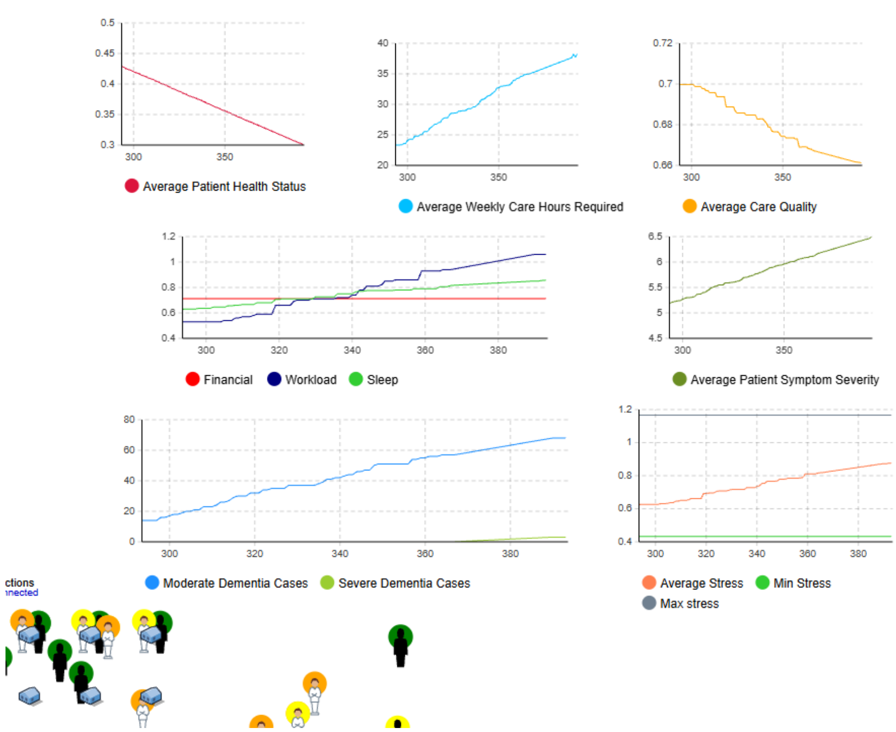
When only a monthly stipend is provided, the financial component of stress is clearly dampened, so total average stress rises somewhat more slowly and peaks a bit lower (around 1.03–1.04) than in the baseline case. However, because the stipend does not reduce required care hours, workload stress continues to grow and the end-of-run stress still settles near 0.96–0.97, almost identical to baseline. This suggests that income support is helpful but not sufficient on its own, since it buffers money worries without addressing the physical and time burden of care.

EXPERIMENT 4: Combined Interventions (Day Care + Stipend)

File: Pop100WithInterventionAndStipend

Configuration (Changes Highlighted):

- enableInterventions = true ← CHANGED
- interventionStartWeek = 30 ← CHANGED
- enableStipend = true ← CHANGED
- stipendAmount = 400 ← CHANGED
- adultDayCareSlots = 40 ← CHANGED
- workloadStressWeight = 0.33
- sleepStressWeight = 0.33
- financialStressWeight = 0.34
- dementiaCareProgressionRate = 0.0015
- patientPopulationSize = 100
- caregiverPopulationSize = 100



Key Outcomes:

In the combined scenario, both workload and financial stress are simultaneously buffered, producing the largest effect on the overall stress trajectory. Average stress never rises as high as in the other runs (peaking around 0.92–0.95) and it finishes clearly lower, around 0.87–0.90, showing that caregivers end the simulation in a substantially safer and more sustainable region. This scenario indicates that multi-component policy packages—pairing time relief (day care) with financial support (stipends)—are most effective for keeping caregivers away from the crisis threshold and preserving their ability to provide stable care over time

Overall pattern across scenarios

Across all scenarios, average caregiver stress rises over time as patients progress from moderate to severe dementia and weekly care hours expand, but the height of the peak and the final level of stress depend strongly on the type of support provided. Interventions that reduce workload and financial strain together consistently keep the system further from the crisis threshold than interventions that target only one stressor.

Part Five

Integrating Machine Learning into Our Simulation Model

5.1 Why We Chose to Integrate Machine Learning:

As part of our dynamic modeling project on caregiver stress and dementia caregiving, we initially explored the integration of Machine Learning (ML) to enhance the adaptability and realism of our agent-based simulation. While traditional rule-based logic can represent real-world dynamics to some extent, it is often reactive in nature. For example, in our baseline model, caregivers only transition to the SeekingSupport state once their stress level crosses a certain threshold — a lagging indicator.

We envisioned ML to shift the simulation from reactive to proactive behavior. By training a predictive model on data generated from within the simulation itself, our goal was to anticipate caregiver burnout before it occurred, thereby allowing the system to intervene earlier with tailored support (e.g., therapy offers, financial aid, reduced workload, or referrals to adult daycare services).

This concept is supported by how real-world systems (such as healthcare triage or mental health monitoring apps) increasingly rely on predictive analytics to identify individuals at risk, not just those already in crisis. We wanted our simulation to reflect this evolution.

5.2 What the ML Model Was Designed to Do:

We intended to use Logistic Regression trained on features such as:

- Weekly stress level
- Sleep hours
- Financial Stress
- Weekly workload
- Care quality delivered

5.3 What we expected:

The output was a probability that a caregiver would enter a crisis state (like SeekingSupport) within the next two weeks. A probability above a certain threshold (e.g., 75%) would then trigger early intervention within the simulation.

This design would allow us to:

- Make the simulation more data-driven
- Enable adaptive agents who receive help based on risk rather than reaction
- Run experiments comparing early vs delayed intervention policies
- Reflect the real-world unpredictability and complexity of caregiver outcomes.

5.4 Data Export and Integration for Model Evaluation

To facilitate machine learning integration, we implemented a structured data export mechanism within the AnyLogic environment. Each caregiver agent recorded simulation data weekly through a custom exportCSV() method, invoked by a cyclic event in the Main class. The exported dataset included key behavioral and contextual variables:

- caregiver_id
- Week
- StressLevel
- SleepQualityHoursPerWeek
- WorkloadHoursPerWeek
- FamilyWeeklyIncome
- careQuality

This weekly export captured longitudinal caregiver dynamics and was designed to serve as input for supervised machine learning models, particularly logistic regression models predicting the likelihood of caregivers entering high-stress or support-seeking states. The use of a clean, tabular CSV format enabled seamless downstream integration with Python-based ML pipelines.

5.5 What We Learnt:

In the final stages of development, we discovered a critical modeling limitation: our simulation lacked stochasticity. Most caregiver behavior was deterministic — meaning that every agent followed the same path unless manually altered. As a result, the simulation generated highly static and uniform data, with little variation over time or across agents.

This meant the ML model, while technically trainable, had no meaningful variation to learn from. Training a predictive model on static data would have produced misleadingly confident results (e.g., "99% accuracy" but 0% real-world applicability).

5.6 Why We Decided Not to Train or Integrate the ML Model:

After completing the simulation and analyzing the exported caregiver data, we made the informed decision not to train or integrate our Machine Learning (ML) model. This was based on a critical examination of the dataset's structure and behavior.

1. The dataset lacked meaningful variation. Most variables were nearly static across all caregivers and weeks — for example, careQuality had a narrow range (min = 0.565, max = 0.800) with over 75% of values clustered around a single point. workloadHoursPerWeek was almost always ~20 hours, and stressLevel was heavily centered at 0.67. Even with the sleepQualityHoursPerWeek, the only somewhat dynamic variable, showed limited spread, far below expected variation in real-world behavioral data. These patterns strongly suggest deterministic logic without stochastic elements, limiting the diversity of agent outcomes.

2. The data lacked temporal responsiveness. Although we had week and caregiver_id as indexing columns, the core features did not evolve meaningfully over time. This meant that the ML model would have no temporal signal to learn from and would be unable to differentiate between high-risk vs. low-risk periods. As a result, any model trained on this data would likely output uniform predictions (e.g., always "low risk"), rendering it useless for early warning or adaptive decision-making.

In summary, the ML model could not be ethically or technically justified with the available data. Rather than forcing a model with misleading accuracy, we chose to report this limitation transparently and treat it as a key learning outcome of the project.

Part Six

Learnings and Recommendations

6.1 Limitations

1. Our conceptualized mental model was more deterministic. Hence, the model had ignored a significant number of variables which could have made it more stochastic as we had observed from the baseline model that the relationship between caregiver and Dementia progress is more stochastic in nature than deterministic.
   Recommendations: We suggest that in future work, such factors of the patient like occurrence of urinary track infection (UTI), Falls, missed medical appointments, missed medications, are also considered to make the model more stochastic.

2. Using Anylogic ple to develop the Causal Loop Diagram showed some difficulty with the graphical interface for drawing and restrictive bending radii on links and polarity.
   Recommendation: We recommend that future work employ the use of Vensim which is more versatile for modeling system dynamics models.

6.2 Learnings

1. Introduction of Stochasticity

- **What we missed**: Most caregiver variables (e.g., workload, stress, care quality) were constant across time and agents.
- **What can be done**: Add randomness to agent behavior, environment changes, and transition triggers.
- **Why it matters**: Randomness creates variation, which is very important feature in dynamic system modeling — and for the ML aspect, variation is what ML models learn from.

2. Capturing More Temporal Dynamics

- **What we missed**: Featured values stayed the same across weeks.
- **What can be done:** Make agents change over time based on internal and external conditions (e.g., declining sleep, burnout loops).
- Why it matters: Dynamic system modeling (and ML) needs time-based changes to predict outcomes like crisis or burnout.

3. Design for ML from the Start

- **What we missed**: ML was added near the end, after the simulation was already built.
- **What can be done**: Think about ML early — plan what features to log, what labels to create, and how often to export data.
- **Why it matters**: Good ML integration depends on good data, and good data starts with good design.

4. Test Early, Iterate Often

- **What we missed**: We waited until the end to analyze the dataset.
- **What can be done**: Start testing simple ML models earlier in the project, using partial simulation data.
- **Why it matters**: Early feedback could have prompted whether our simulation was producing meaningful variation.

5. Learning on modeling equations

- The team had initially perceived that the equation depicting the relationship between Caregiver Stress level and the workload, sleep quality and financial strain was linear. We later noted that it was rather piecewise, and that has been very insightful, as that knowledge prompted us to reorganize our modeling rules.

6.3 Learnings from Team Engagement

Right from the model conceptualization to drafting of this report, we have honed very healthy team engagement skills which has added value to ourselves as team members. Key among them, we have

a. improved collaborative skills
b. enhanced our communication skills
c. a stronger sense of collegiality where each member served as the other's keeper with respect to assigned responsibilities.
d. Learnt healthy ways of managing team conflict and divergent opinions

6.4 Future Work on the Model

Short-Term: 1-2 Weeks

1. Run 50-100 simulation replications per scenario with parameter variation. This generates confidence intervals showing uncertainty ranges policymakers can use.
2. Add mental health therapy as a discrete resource queue alongside respite care. This tests whether respite and counseling interact synergistically.
3. Create tornado sensitivity plots showing which parameters most influence outcomes. This guides where future research should focus measurement effort.

Medium-Term: 4-8 Weeks

1. Implement distinct caregiver profiles (adult child, spouse, paid worker, young, retired) each \\with different stress curves and help-seeking patterns. This enables targeted policy.
2. Model 30% of households with multiple caregivers to capture burden-sharing dynamics. Do resources flow fairly or do some free ride?
3. Add medication effects slowing disease progression. Test whether pharmaceutical and social interventions substitute or complement.

Long-Term: Semester and Beyond

1. Access longitudinal caregiver data from CIHI or provincial registries. Compare model predictions to actual stress trajectories. Where does the model fail?
2. Integrate intervention costs and healthcare outcomes. Calculate cost per unit stress reduction. Link to hospitalization savings to strengthen policy business case.
3. Adapt the model to multiple provinces. Does core logic (feedback loops, tipping points) hold across regions, or are Saskatchewan findings local?
4. Build a web tool for policymakers. Sliders for respite hours, income support levels, training access. Real-time visualization of outcomes. This democratizes scenario exploration.
5. Add rural-urban spatial variation. Can telehealth and mobile respite overcome geographic barriers?

6.5 Policy Recommendations

One of our goals for the model was to make policy recommendations on how to manage family caregiver stress. Even though our work showed some form of stress control with respect to running the scenarios, we would not be too quick make policy recommendations as our model lacked significant variability.

We would rather recommend that this work is repeated in the future with the introduction of some level of stochasticity. In that case, one can be more confident to suggest to policymakers to introduce more adults daycare centres and or stipends to family caregivers of dementia patients. But for the mean time, let us offer any help the society could intentionally offer to family caregivers of dementia patients.

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