Project Checkpoint 1: Time-to-Recovery Under Traditional versus Telehealth Care

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Github repository: https://github.gatech.edu/yzheng607/chronic-recovery-simulation

1. Abstract. This project simulates recovery trajectories for patients with chronic and sub-acute outpatient conditions with gradual recovery dynamics, modeled here as hypertension, to evaluate how different care modalities influence recovery dynamics. Each simulated patient is represented by a Severity Score $S\epsilon$ [0,1], which reflects overall disease burden and clinical instability. Recovery is modeled as a progressive reduction in S over discrete care cycles corresponding to outpatient visits. Patient transition toward recovery ($S \leq 0.10$) or hospitalization ($S \geq 0.90$) according to probabilistic improvement and complication processes whose parameters vary by severity level and care modality.

The situation framework has evolved through two design iterations up to this point. The initial regression-based model attempted to link dynamic clinical variables including Body Mass Index (BMI), lipid levels, and lifestyle factors to changes in S, but failed to achieve recovery within realistic timeframes due to unbalanced weighting between static and dynamic factors. The current model adopts a simplified single-state formulation using S as the only evolving variable, with category-specific improvement rates and complication probabilities governed by the more complex beta distribution. This allows controlled variability and more plausible recovery trajectories aligned with clinical and literature expectations. Telehealth visits are modeled as 80% as effective per cycle as in-person care, with equal complication risk. This specification is consistent with a two-center non-inferiority randomized trial of home-based telehealth hospitalization for acute COPD exacerbation that prescribed a 20% non-inferiority margin relative to standard in-person care, which maps to our 80% baseline effectiveness assumption [5]

Simulation outputs include time-to-recovery distributions, median and variance in recovery visits, and the proportion of patients reaching hospitalization thresholds under each care policy. Sensitivity analyses explore how parameters influence overall outcomes. Future work will refine these parameters using clinical evidence and extend the simulation to include multiple evolving health variables informed by the full dataset of over 174,000 observations. Unlike traditional health-economic Markov frameworks, this model focuses on continuous recovery dynamics rather than cost-effectiveness, providing mechanistic insight into how simple switching rules and care-modality effectiveness shape recovery timelines at the population level.

2. Description of system being studied. The modeled system represents outpatient management of chronic or sub-acute conditions such as hypertension that exhibit gradual, monitorable progress. It captures the interaction between patient state variables (including health severity, adherence, lifestyle, comorbidities, age, treatment history), care modality (telehealth versus in-person visits), and transition rules governing how health evolves between encounters. Hypertension was chosen for its slow, measurable recovery dynamics and established clinical variability across care types, as described in Drazner et al. [1]. The simulation tracks each patient's Severity Score $S \epsilon [0,1]$, where higher S denotes greater disease burden. S decreases over time according to intervention efficacy and patient-specific modifiers, reflecting disease management and organ-system stabilization.

The system explicitly excludes non-acute, self-limiting infections such as the common cold, as spontaneous resolution dominates treatment. Rapid-onset, high-stakes conditions including sepsis, stroke, and acute MI were also omitted for their minute-to-hour dynamics. Finally, oncologic conditions are multi-pathway diseases with more complex remission dynamics and treatment protocols and were therefore omitted.

3. Conceptual model of system.

3.1. State variables. The core state variable used in this model is the Severity Score S, a continuous index in [0,1]. S may be parameterized from baseline features including blood pressure level, treatment history, comorbidities, adherence risk and lifestyle factors, and age and baseline health. Weights are assigned such that more severe clinical presentations yield a higher S. This is illustrated in Table 1 on the next page.

Table 1

Severity scores and care implications (aligned with model categories)

Category	**S Range**	**Clinical Outlook**	**Proportion of Improvement**	**Complication Probability**	**Typical Recovery (Weeks)**	**Details**
Recovered (Low Acuity)	<0.10	Stable, asymptomatic, or fully recovered; no active management required	N/A	N/A	—	No treatment needed beyond periodic check-ins. May be discharged from active care.
Mild	0.10–0.25	Early or well-controlled symptoms; minimal interference with daily life	0.044	0.02	2–8	Preventative maintenance phase; managed primarily through telehealth or remote monitoring.
Moderate	0.25–0.50	Clear diagnosis with measurable risk factors or daily symptom management	0.137	0.055	6–12	Routine monitoring via hybrid care; may require medication adjustment or follow-up testing.
Moderate-Severe	0.50–0.70	Chronic condition with increased comorbidity burden or worsening trends	0.129	0.115	8–18	Hybrid care preferred; requires coordinated follow-up between care teams.
Advanced	0.70–0.90	Long-standing, unstable disease with multi-system impact	0.109	0.16	12–24	In-person primary care recommended; telehealth only for post-stabilization follow-up.
Critical (Hospitalization Threshold)	>0.90	Unsafe for outpatient management; acute deterioration or life-threatening condition	N/A	N/A	N/A	Requires immediate emergency or inpatient evaluation.

3.2. Transition logic. Each simulation step represents a discrete care cycle corresponding to the time between outpatient encounters. At each cycle, the model updates the patient's Severity Score S according to a regression-based mapping that reflects current health, adherence, and care modality. The eventual model will evolve to include more complex state transitions. The ideal update rule will take the form $S_{t+1} = f(S_t, X_t, M_t)$, where S_t is the previous severity level, X_t represents the patient's state variables, M_t denotes the modality of the most recent visit. State transitions can trigger rule-based modality switches (e.g. progress thresholds or complication fallback). The outpatient simulation terminates when a patient enters the critical (inpatient threshold) ($S \geq 0.90$) or when recovery is achieved at a defined cutoff ($S \leq 0.10$).

3.3. Simulation outputs. Results of the simulation will include detailed time-to-recovery distributions for all simulated patients under each care policy. Each patient trajectory is simulated until recovery ($S \leq 0.10$) or hospitalization ($S \geq 0.90$), generating a per-patient outcome including number of visits to recovery, final severity score, and outcome status. Aggregate simulation outputs will be summarized through median, mean, and variance of recovery visits across patients for each modality, empirical distributions visualized through histograms, proportion of hospitalizations, and sensitivity analyses.

4. Platforms of development. This project is developed in Python 3.12.3 using Jupyter Notebooks(`.ipynb`) for interactive development, visualization, and testing. The notebooks allow modular function definitions, iterative simulation runs, and inline documentation of results. Eventually, the finalized functions will be migrated into standalone `.py` scripts, making all processes fully executable from the command line.

The main packages used include:

- NumPy – for mathematical operations, random number generation, and Beta distribution sampling in the recovery simulations.
- Pandas – for dataset manipulation, DataFrame creation, and formatted output tables.
- Matplotlib – for visualizing simulated outcomes such as recovery time distributions.

All simulations and analyses currently run locally within Jupyter for transparency and reproducibility. Upon project completion, the entire environment (including dependencies, data, and scripts) will be containerized and exported as a `.tar.gz` archive to ensure portability and standardized execution across systems.

5. Literature Review.

5.1. Introduction. Simulation modeling is a powerful tool for evaluating how different care modalities affect chronic disease management. While most studies have used Markov or system-dynamics frameworks to assess the economic impact of telehealth, few have examined how care modality itself influences recovery patterns. Our project addresses this gap by studying how in-person versus telehealth visits affect the speed and variability of patient recovery in simulated populations.

5.2. Main results. Liu et. al [7] developed a Markov state-transition model to assess the clinical and economic impacts of telehealth programs for patients with congestive heart failure. The model simulated transitions among five health states plus death in monthly cycles over a five-year horizon, incorporating hospitalization and morbidity probabilities. Costs were estimated from a U.S. payer perspective, including inpatient/outpatient care, telehealth setup and monitoring, and clinical personnel costs. Sensitivity analyses evaluated how telehealth effectiveness, hospitalization costs, and reduced length of stay influenced overall outcomes. The study found that telehealth was cost-saving for intermediate- and high-risk congestive heart failure patients (those with prior hospitalizations) but cost-increasing for low-risk patients, meaning telehealth becomes economically viable only when readmission risk and inpatient costs are high. This framework informs our work by providing a structured, state-based approach to modeling disease progression, while our model diverges by focusing on recovery dynamics and variability in health outcomes rather than cost-effectiveness.

Grustam et al. [2] similarly developed a Markov cohort model to evaluate three care modalities (home telemonitoring, nurse telephone support, and usual care) over a 20-year time horizon for congestive heart failure patients. The model simulated monthly transitions among four health states (no, one, two, or three or more prior hospitalizations) plus death, using transition probabilities and mortality rates derived from clinical trial meta-analyses. Each modality was assigned distinct relative-risk reductions for hospitalizations and mortality, allowing estimation of cost and Quality-Adjusted Life Year (QALY) outcomes from a European healthcare payer perspective. The study concluded telehealth can be economically advantageous to moderate- to high-risk congestive heart failure patients, though benefits depend strongly on baseline risk. This model similarly provides a structural blueprint for simulating disease progression.

Ionov et al. [4] also developed a Markov cohort model to evaluate long-term clinical and economic impact of blood pressure telemonitoring for patients with uncontrolled hypertension, simulating 2,000 patients over a 10-year horizon with annual cycles. Each patient began in a non-complicated state and transitioned to various disease complication states or death based on clinical trial data and costs were modeled from the Russian payer perspective, with outcomes expressed in QALYs. The model predicted blood pressure telemonitoring produced greater clinical benefit and lower cost than usual care based on deaths, QALYs, and life expectancy. This informs our model with a recovery-trajectory framework using a Markov model.

Hofer et al. [3] combines a Markov model and decision tree to evaluate cost-effectiveness of telemonitoring as a supplement to standard care for German patients with moderate-to-severe COPD. The Markov component simulated disease progression through four severity stages plus death over a 20-year horizon with one year cycles. Within each cycle, a decision tree modeled frequency and treatment of disease progression, and QALYs and costs were calculated at each stage. Sensitivity analyses were also included to test robustness of the model. The model concluded that telemonitoring increased costs relative to standard care, indicating that telemonitoring equipment costs were the strongest drivers of model outcomes. The Markov decision framework will inform the structure of our project. Parameterization of telemonitoring impact and the combined Markov + decision tree design provides a practical way to track long-term disease progression; however, we intend to focus on health outcomes rather than costs.

Decision tree and Markov models are the most frequently used methods in health economic evaluations. However, discrete-event simulation (DES), a patient-level, event-driven model that works in continuous time, has recently gained attention because it can overcome some of the limitations of traditional approaches. Quang A et al.[6] used a DES model to assess the cost-effectiveness of current treatment guidelines for women with postmenopausal osteoporosis (PMO). The results showed that Denosumab (drug) was the most cost-effective treatment option at common willingness-to-pay thresholds. Further analysis considering patient heterogeneity, which was classified as low, medium, high, and very high fracture risk, led to a similar conclusion.

Standfield et al.[8] compared Markov modeling and DES in published studies and found several key differences. The main advantages of DES include its ability to model queues for limited resources, track individual patient histories, handle greater complexity and uncertainty, represent time more flexibly, account for competing risks, and manage multiple events happening at the same time. However, DES also has some disadvantages compared to Markov modeling, such as the risk of model overspecification, higher data requirements, the need for specialized and costly software, and longer time needed for model development, validation, and computation.

5.3. Conclusions. Prior work predominantly employs (i) Markov state-transition models to compare fixed telehealth programs in coarse health states and (ii) DES/Agent Based Modeling frameworks to optimize access and capacity. While informative, these approaches rarely analyze time-to-recovery emerging from a continuous recovery process, nor do they examine how variations in care effectiveness and simple switching thresholds shape the full distribution of outcomes. This project addresses that gap. We simulate recovery as a continuous state and systematically vary the effectiveness of in-person versus telehealth care, alongside user-defined switching thresholds, to quantify their impact on median time-to-recovery, distributional tails, and between-patient variability. We report contrasts across tele-first, in-person-first, and hybrid scenarios, complemented by sensitivity analyses to identify the most influential parameters. The result is a quantitative basis for understanding when telehealth accelerates recovery, when in-person care is critical, and how simple switching rules shape population-level recovery timelines.

6. Update on current state, initial results. In the first iteration (`visit_sim.ipynb`), our team defined a target variable S to represent hypertension acuity, derived from a simple regression in *initial_s.ipynb*. All available features were included and split into static variables (gender, education level) and dynamic variables (BMI, LDL, HDL, alcohol use). We assigned plausible change ranges to the dynamic variables, recalculated S for each perturbed state, and used $S < 0.1$ as the recovery threshold. Two issues emerged. Given the current regression, individuals with severe static profiles could not practically reach $S < 0.1$. In addition, Gaussian sampling of dynamic changes produced no meaningful movement toward recovery, even after 1000 simulations.

In the second iteration (`in_state_only.ipynb`), the state was simplified to S alone, still initialized using the same regression, which remains a known limitation. We introduced severity bands with fixed improvement proportions and complication probabilities, then drew improvements from a beta distribution with $\kappa = 20$ to better control the mean and spread of change. The recovery threshold remained $S < 0.1$ and a provisional complication multiplier of 0.1 was used. For care modality, telehealth effectiveness was set to 80% of in-person visits, and complication rates were held equal. All parameter values are placeholders that require validation against the literature.

Next steps include validating all parameters and ranges with published sources and updating the parameter table accordingly. We will add a simple cost model (e.g., \$100 per in-person visit and \$20 per telehealth visit, subject to validation) and then simulate visit mixes to assess cost effectiveness. Two extensions are planned: first, reintroduce selected dynamic variables alongside S to capture more realistic variability and to better leverage the dataset; second, explore an agent-based approach that tracks individual patient trajectories, calibrated on the full dataset of more than 174,000 observations.

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