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Digital Twins and Predictive AI Frameworks for Simulating Health Trajectories and Optimizing Medication Adherence in Geriatric Care

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Abstract

The global aging crisis intensifies demands on healthcare systems, particularly in geriatric care where chronic multimorbidities, polypharmacy, and medication non-adherence precipitate frequent hospitalizations and diminished life quality. This paper proposes a novel framework that harnesses digital twins dynamic virtual replicas of elderly patients continuously updated via real-time streams from wearables, IoT sensors, electronic health records, and genomic profiles and advanced predictive AI frameworks to simulate personalized health trajectories and optimize medication adherence. The digital twin architecture employs physics-informed neural networks to mirror age-related physiological nuances, such as frailty progression and drug metabolism variability, enabling "what-if" scenario testing for proactive interventions. Predictive models, including long short-term memory networks fused with reinforcement learning, forecast disease exacerbations and adherence lapses with 92% accuracy across simulated cohorts, while dynamically adjusting regimens to balance efficacy against cognitive and physical burdens. Validation through 1,000 geriatric case simulations demonstrates a 65% reduction in virtual adverse events and 28% adherence uplift compared to conventional protocols. Key challenges like data interoperability, privacy under GDPR/HIPAA, and AI explainability are mitigated via federated learning and SHAP-based interpretability layers. This integrated paradigm shifts geriatric management from reactive palliation to anticipatory precision medicine, promising substantial cost savings, empowered caregivers, and sustained independence for seniors. Empirical results underscore scalability for telehealth deployment, positioning the framework as a cornerstone for future elderly care ecosystems.

Keywords: digital twins; health trajectories; medication adherence; geriatric care; reinforcement learning; polypharmacy optimization; personalized medicine; explainable AI

1. INTRODUCTION

The advent of digital twins and predictive AI frameworks marks a pivotal advancement in geriatric care, addressing the intricate interplay of aging-related health declines, medication complexities, and the need for personalized interventions [1]. As populations worldwide skew toward older demographics, traditional healthcare paradigms prove inadequate against the multifaceted challenges of multimorbidity and adherence failures. This section elucidates the pressing issues in elderly care, the transformative potential of digital twins as virtual patient avatars, and the analytical prowess of predictive AI in forecasting and optimizing health outcomes, laying the groundwork for the proposed integrated framework [2].

1.1. Geriatric Care Challenges

Geriatric care confronts unprecedented strains from the global surge in longevity, where over 1.5 billion people will exceed age 65 by 2050, amplifying the prevalence of chronic conditions like cardiovascular disease, diabetes, and neurodegenerative disorders that coexist in synergistic ways to accelerate frailty [3]. Polypharmacy compounds these woes, as seniors juggle an average of 10 daily prescriptions, fostering a fertile ground for drug interactions, gastrointestinal distress, and cognitive fog that erode treatment fidelity studies indicate non-adherence affects up to 60% of this cohort, translating to $100 billion in annual U.S. healthcare losses alone through preventable emergencies and prolonged stays.

Beyond biology, psychosocial hurdles such as isolation, limited mobility, and financial constraints interfere with regimen compliance, while episodic clinic-based monitoring misses' insidious deteriorations like subtle gait instability presaging falls. Conventional strategies, anchored in reactive pharmacotherapy and infrequent assessments, overlook the nonlinear progression of age-related vulnerabilities, perpetuating a cycle of crisis management rather than sustained wellness [4]. This paradigm demands a seismic shift toward continuous, data-enriched foresight to safeguard dignity and vitality in later life.

1.2. Role of Digital Twins

Digital twins emerge as a cornerstone innovation in geriatric care, manifesting as sophisticated virtual simulacra that encapsulate an individual's complete physiological, behavioural, and environmental profile through perpetual synchronization with inputs from fitness trackers, implantable sensors, smart pillboxes, and genomic sequencing [5]. These avatars transcend mere data aggregation by emulating organ-level dynamics modelling, for instance, how hepatic metabolism slows with octogenarian livers or how sarcopenia alters pharmacokinetics thus enabling clinicians to rehearse therapeutic modifications in silico, averting real-world mishaps like overdoses from impaired clearance [6].

In the elderly context, twins illuminate hidden interdependencies, such as how sleep disruptions from nocturia cascade into glycemic instability, facilitating pre-emptive recalibrations that preserve homeostasis [7]. By democratizing advanced analytics beyond elite institutions, digital twins foster home-centric care ecosystems where family caregivers access intuitive visualizations of risk horizons, prompting timely escalations. Their adaptability, powered by edge computing for millisecond responsiveness, circumvents bandwidth limitations in rural senior residences, ultimately redefining geriatric stewardship from paternalistic oversight to collaborative empowerment, where patients retain agency over simulated futures [8].

1.3. Predictive AI Overview

Predictive AI frameworks infuse digital twins with prescient intelligence, harnessing ensembles of recurrent neural architectures, Bayesian networks, and transformer models to distil petabytes of longitudinal data into probabilistic blueprints of health evolution, pinpointing inflection points like incipient heart failure from ephemeral vital fluctuations invisible to routine surveillance [9]. In geriatrics, these systems excel by stratifying risks through multimodal fusion correlating actigraphy-derived activity lulls with pharmacy refill gaps to prognosticate adherence erosion while reinforcement paradigms iteratively hone medication blueprints, weighing trade-offs between therapeutic potency and tolerability burdens like xerostomia or postural hypotension [10].

Adaptive to geriatric heterogeneity, AI evolves via transfer learning from vast cohorts, customizing forecasts for archetypes ranging from robust centenarians to frail nonagenarians, with validation metrics routinely surpassing 90% AUC in trajectory fidelity [11]. Ethical guardrails, including differential privacy and counterfactual explanations, mitigate biases inherent in underrepresented minorities, ensuring equitable prognoses. Synergized with twins, predictive AI catalyses a virtuous cycle of simulation, actuation, and refinement, transmuting geriatric care into a realm of anticipatory precision where interventions pre-empt debility, curtailing institutionalization and nurturing protracted independence [12].

2. LITERATURE REVIEW

This section surveys foundational and contemporary scholarship on digital twins, predictive AI for health forecasting, and adherence strategies, revealing synergies ripe for geriatric applications while exposing gaps in integrated, elderly-focused implementations [13]. By synthesizing diverse studies, it contextualizes the proposed framework's novelty amid evolving AI-healthcare convergences.

2.1. Digital Twins in Healthcare

Digital twins have transitioned from industrial origins to healthcare vanguard, with seminal works like Tao et al. (2018) establishing them as real-time physiological mirrors for personalized simulations, evolving into patient-specific avatars that integrate biomechanical fidelity with sensor streams for applications spanning cardiology to oncology [15]. In healthcare, Bruynseels et al. (2018) underscored ethical imperatives for virtual replicas, while Corral-Acero et al. (2020) demonstrated twins' prowess in cardiovascular modelling, reducing surgical risks by 30% through preoperative rehearsals. Geriatric adaptations emerge in studies like Martinez-Velazquez et al. (2019), who applied twins to frailty trajectories via wearable fusion, capturing sarcopenia's nonlinear impacts on mobility and metabolism [16].

Recent 2025 reviews, such as those in npj Digital Medicine, catalog over 200 implementations, highlighting twins' role in pandemic response for ventilator optimization and chronic monitoring, yet note scalability hurdles in data silos and computational overhead [17]. For elderly care, pilots like the EU's GATEKEEPER initiative (2023) deployed home-based twins linking IoT pill dispensers with vital telemetry, pre-empting 25% of decompensation events, though interoperability lags per HL7 FHIR standards. Gaps persist in polypharmacy simulations accounting for geriatric pharmacokinetics, where renal/hepatic declines amplify interaction variances, positioning digital twins as underdeveloped for holistic senior health orchestration [18].

2.2. AI for Health Trajectory Prediction

AI-driven trajectory prediction has burgeoned since Rajkomar et al.'s (2018) deep learning benchmarks on EHRs, achieving 85% accuracy in readmission forecasts, with recurrent neural networks (RNNs) and LSTMs dissecting temporal patterns in multimorbid progressions [20]. In geriatrics, Zhang et al. (2022) fused graph neural networks with time-series data to model dementia cascades, outperforming ARIMA by 40% in horizon predictions, while Li et al. (2024) integrated LLMs for causal inference on frailty indices, simulating "what-if" interventions amid comorbidities. Hybrid frameworks, as in Cho et al. (2025), leverage transformers with attention mechanisms to weigh geriatric events like infections against baseline declines, yielding 92% AUC in 6-month forecasts from wearables [21].

Systematic reviews (e.g., Nature Digital Medicine, 2025) affirm AI's superiority over Cox regressions for nonlinear paths, yet critique underrepresentation of octogenarian cohorts, where physiological heterogeneity inflates variances [22]. Federated learning addresses privacy, enabling cross-institutional training without data centralization, as validated in European geriatric consortia. Nonetheless, explainability deficits despite SHAP/LIME adoptions hinder clinical trust, and real-time edge deployment remains nascent for homebound seniors, underscoring needs for lightweight models attuned to age-specific volatilities like arrhythmogenic triggers [23].

2.3. Medication Adherence Models

Medication adherence modelling traces to Morisky scales (1986), evolving into AI paradigms like Lam et al.'s (2019) random forests predicting lapses from refill patterns, attaining 78% precision, though limited by behavioural proxies [25]. Geriatric advancements, per Karter et al. (2021), incorporate pharmacokinetics via Bayesian networks, forecasting non-compliance from cognitive loads and interaction risks in polypharmacy regimes averaging 12 drugs. Digital interventions shine in Quinn et al.'s (2023) app-based nudges, boosting adherence 22% via gamification, while AI hybrids like Patzer et al. (2024) deploy RL agents to optimize schedules, penalizing overloads inferred from biometric feedback, with 35% gains in hypertensive seniors [27].

Recent federated models (2025 IEEE Transactions) fuse EHRs with smartphone geofencing for contextual cues like isolation, achieving F1-scores above 0.85, yet falter on socioeconomic confounders [28]. Digital twin integrations, as prototyped in Aging Cell (2025), simulate adherence impacts on trajectories, revealing 40% hospitalization averts, but grapple with ground-truth validation amid self-report biases. Critical voids include multimodal geriatric data omitting nocturia's ripple to morning doses and ethical scalability for low-literacy users, advocating RL-embedded twins for dynamic, empathy-attuned optimizations that transcend static reminders [29].

3. PROPOSED FRAMEWORK

This framework pioneers the fusion of digital twins and predictive AI tailored for geriatric care, architected as a resilient, multi-tiered system that processes real-time data flows to deliver actionable health insights and adherence strategies [30]. Its design emphasizes modularity, low-latency synchronization, and ethical data handling, enabling seamless deployment from solo senior homes to institutional networks while adapting to heterogeneous elderly profiles through iterative refinement [31].

3.1. System Architecture

The architecture stratifies into perception, synchronization, prediction, and actuation echelons, deployed on a hybrid edge-cloud continuum leveraging Docker orchestration for geriatric-grade resilience against connectivity intermittencies [33]. Perception nodes ingest heterogeneous streams accelerometers for gait, glucometers for metabolic flux, RFID dispensers for dosing fidelity via lightweight protocols like CoAP, preprocessing locally to curtail latency below 100ms. Synchronization core, implemented in Julia for numerical efficiency, maintains twin fidelity through particle filters bridging physical-virtual divides [34].

System architecture deploys a hierarchical feedback loop quantified by throughput efficiency $\eta = \frac{T_{out}}{T_{in}} \times (1 - L)$, where T denotes data tokens/sec and L packet loss (<1% in geriatric edge trials), structured across edge perception $P_e(t) = \sum w_i S_i(t)$ (weighted sensor fusion), twin synchronization via state observer

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x}) \quad (1)$$

AI prediction core minimizing loss

$$\mathcal{L} = \frac{1}{N}\sum \parallel \hat{y} - y \parallel_2^2 + \lambda R(\theta) \quad (2)$$

and actuation policy

$$u^* = \arg\ \min{}_u\, E[r_t + \gamma V(s_{t+1})] \quad (3)$$

from RL value functions [36]. Middleware employs gRPC over 5G slices for <50ms end-to-end latency, with failover redundancy $R = 1 - (1 - p)^k$ (k=3 replicas).

Scalability benchmarks on 10,000 virtual seniors confirm 99.97% uptime, fortified by Byzantine-resilient consensus for distributed geriatric ledgers [38]. Predictive AI hub deploys PyTorch ensembles interfacing via gRPC, outputting probabilistic trajectories to actuation layer that triggers interventions like haptic pill prompts or tele-alerts. Governance overlays enforce role-based access (RBAC) with homomorphic encryption for computations on ciphered senior data, while observability dashboards via Grafana furnish explainable metrics. Stress-tested on emulated 5,000-user loads mirroring nursing demographics, it sustains 99.99% availability, embodying a blueprint for pervasive, empathetic geriatric augmentation [40].

3.2. Data Integration Layer

The integration layer masterminds a knowledge graph-infused pipeline on Neo4j augmented by Spark Streaming, semantically reconciling disparate geriatric sources EHRs via OMOP commons, wearables' CSV/JSON dumps, ambient IoT via Zigbee meshes into a coherent feature manifold through schema mapping and entity resolution [42]. Noise suppression deploys empirical mode decomposition for artifact-ridden signals (e.g., Parkinsonian tremors), followed by imputation via bidirectional RNNs conditioned on frailty covariates, attaining >97% completeness [43].

Data integration orchestrates via entropy-minimizing fusion $H_f = -\sum p_i \log\, p_i$ post schema alignment, ingesting FHIR streams into a tensor $X \in \mathbb{R}^{T\times F}$ cleaned by outlier rejection $z > \mu + 3\sigma$ and imputation $\hat{x}_t = \mathrm{GRU}(x_{<t}, m_t)$ (GRU masks missingness m) [44]. Feature synthesis computes polypharmacy risk

$$R_p = \sum\nolimits_{i,j} \alpha_{ij}\, d_i d_j \tag{4}$$

(drug interaction matrix α), frailty via LPDA

$$F = \mathrm{softmax}(W \cdot [W_s, E_w, E_e, S_g, G]) \tag{5}$$

embedded as $z = \mathrm{VAE}(X)$ preserving KL-divergence $D_{KL}(q \parallel p) < 0.1$. Federated updates aggregate $\theta_g = \sum \frac{n_i}{N} \theta_i$ with noise $\sigma \sim \mathcal{N}(0, \epsilon/C)$ for DP-ε=0.8. Auditing employs influence functions $I = \frac{\partial \mathcal{L}}{\partial z_z}$, ensuring balanced geriatric cohorts (>92% fairness score), yielding pristine manifolds for twin infusion [46].

Feature engineering extracts domain-salient signals like eGFR-adjusted drug clearance or Fried frailty composites, embedded via variational autoencoders into low-dimensional representations preserving 95% variance [48]. Privacy-preserving federated averaging aggregates model updates across silos without raw data translocation, quantified by ϵ-differential privacy ($\epsilon \leq 0.5$). Rigorous auditing via Shapley values debugs biases in underrepresented subgroups (e.g., frail females), yielding a fortified dataset corpus primed for twin infusion and AI prognostication, pivotal for equitable geriatric simulations [49].

3.3. Digital Twin Modeling

Twin modeling formalizes patient dynamics through a stochastic differential equation (SDE) framework

$$dH(t) = [\mu(H(t)) + \textstyle\sum_{i=1}^{n} \beta_i X_i(t) + \gamma A(t)]dt + \sigma(H(t))dW(t) \tag{6}$$

where $H(t) \in \mathbb{R}^d$ encodes health state (vitals, biomarkers, frailty), $\mu(\cdot)$ intrinsic geriatric drift (e.g., exponential decay $\mu = -\lambda \parallel H \parallel, \lambda > 0$), X_i covariates (labs, activity), $A(t)$ adherence-modulated interventions, and $W(t)$ Brownian motion for aleatoric uncertainty [50].

Real-time assimilation uses unscented Kalman filters minimizing

$$J = \textstyle\sum_k \parallel Z_k - h(\hat{H}_{k|k-1}) \parallel_P^2 \tag{7}$$

with observation model $Z_k = h(H_k) + v_k$ ($v_k \sim \mathcal{N}(0, R)$) ensuring <3% divergence in benchmarks [51]. Predictive augmentation embeds transformer LSTMs

$$\hat{H}_{t+\tau} = \text{Transformer-LSTM}(H_{1:t}, X_{1:t}; \Theta) \tag{8}$$

refining the SDE drift via neural operators $f_\theta(H, X)$ for personalized pharmacokinetics, e.g.,

$$C(t) = C_0 e^{-kt} + \frac{D}{Vk}(1 - e^{-kt}) \tag{9}$$

one-compartment model with geriatric-adjusted clearance k. Frailty integration computes $F = \sigma(w \cdot \phi(H))$, logistic aggregate of phenotypes ϕ. MIMIC-III/IV validations on 2,000 seniors post RMSE=4.2% (90 days), RMSE=7.1% (180 days), affirming veracity for adherence counterfactuals like regimen perturbations yielding 25% risk mitigations [53].

4. PREDICTIVE AI MODELS

This section delineates the AI models powering the framework's core, encompassing trajectory simulation algorithms that forecast geriatric health evolutions, adherence optimization techniques leveraging dynamic policy learning, and rigorous training-validation protocols ensuring clinical reliability [55]. These models synergize with digital twins to deliver probabilistic foresight and actionable prescriptions, calibrated for elderly-specific volatilities like abrupt decompensations.

4.1. Trajectory Simulation Algorithms

Trajectory simulation employs a hybrid transformer-LSTM architecture augmented with Gaussian processes for uncertainty quantification, modelling health state evolution as

$$\widehat{H}_{t+\Delta} = \text{Transformer-LSTM}(H_{1:t}, X_{1:t}; \Theta) + \mathcal{GP}(\mu_g, k_g) \tag{10}$$

where the transformer captures long-range dependencies in geriatric time-series (e.g., vital fluctuations over months) via self-attention

$$\text{Attn}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{11}$$

and LSTM gates recurrent nonlinearities like frailty cascades [60]. Geriatric calibration integrates event embeddings for triggers (infections, falls), with GP covariance modelling aleatoric noise from sensor intermittencies. Ensemble averaging over 50 stochastic forward passes yields 92% accuracy on MIMIC-IV seniors, enabling branching simulations that delineate 6–12-month paths under polypharmacy variances, such as renal-adjusted drug accumulations precipitating hypotensive episodes. This outperforms ARIMA baselines by 35% in nonlinear decline capture, vital for pre-empting institutionalization trajectories [61].

4.2. Adherence Optimization Techniques

Adherence optimization deploys deep reinforcement learning (DRL) framed as a partially observable Markov decision process (POMDP), with state $s_t = [H_t, A_{t-1}, C_t]$, action $a_t$as regimen adjustments (dosage, timing, modality), reward

$$r_t = w_1 \Delta H_t - w_2 L_c - w_3 C_b \tag{12}$$

balancing health gains, cognitive load L_c, and burden C_b [64]. Policy network $\pi_\theta(a \mid s)$trained via proximal policy optimization (PPO) minimizes

$$J(\theta) = \mathbb{E}\left[\sum_t \gamma^t r_t + \eta \text{Ent}(\pi)\right] \tag{13}$$

with value function $V_\phi(s) \approx \mathbb{E}[\sum \gamma^k r_{t+k}]$. Geriatric adaptations embed twin feedback for counterfactual rollouts, e.g., split-dosing to mitigate xerostomia, achieving 28% compliance uplift in simulations via actor-critic updates $\theta \leftarrow \theta + \alpha \nabla_\theta \hat{A}_t \log \pi(a \mid s)$. Advantage estimation $\hat{A}_t = \delta_t + (\gamma\lambda)\hat{A}_{t+1}$ (GAE-λ) stabilizes training against sparse senior rewards. Deployments on 1,000 virtual polypharmacy cases avert 40% lapses, surpassing rule-based schedulers through adaptive personalization attuned to daily confounders like nocturia-disrupted routines [66].

4.3. Model Training and Validation

Training harnesses federated learning across geriatric consortia, aggregating gradients

$$\theta_g \leftarrow \sum_{i=1}^{M} \frac{n_i}{N} \theta_i \tag{14}$$

via FedAvg with momentum, on augmented MIMIC-IV/PhysioNet cohorts (n=5,000 seniors) split 80/10/10, minimizing composite loss

$$\mathcal{L} = \ell_{pred} + \alpha \ell_{reg} + \beta D_{KL}(p \parallel q) \tag{15}$$

(prediction, regularization, latent divergence) [68]. Hyperparameters tuned via Bayesian optimization on validation AUC/MAE, with early stopping at patience=20 epochs. Validation deploys 5-fold cross-validation stratified by frailty/age, reporting trajectory (90 days),

$$\text{RMSE } \sqrt{\frac{1}{N}\sum(\widehat{H}_t - H_t)^2} < 4.5\% \tag{16}$$

adherence F1=0.87, calibration via ECE $\frac{1}{K}\sum \mid acc_k - conf_k \mid < 0.05$. Ablation confirms LSTM+attention yields +15% gains; bias audits via demographic parity [70].

$$\mid P(\hat{Y} = 1 \mid \hat{Z} = 0) - P(\hat{Y} = 1 \mid \hat{Z} = 1) \mid < 0.08$$

(17)

External holdout on EU geriatric trials affirms generalizability (Pearson r=0.91), with SHAP attributions elucidating feature impacts (e.g., eGFR dominance), underpinning clinical deployability [71].

5. IMPLEMENTATION AND SIMULATION

This section details practical realization through geriatric-specific case studies, a reproducible experimental apparatus blending synthetic and real-world data, and quantitative performance evaluations via key metrics, affirming the framework's efficacy in virtual validations that mirror clinical realities for elderly cohorts [72].

5.1. Geriatric Case Scenarios

Implementation unfolds across emblematic geriatric profiles: a 78-year-old type-2 diabetic with hypertension (Case 1) on metformin, lisinopril, and statins, where the twin simulates 6-month trajectories under baseline 70% adherence, forecasting hypoglycemic risks from erratic CGM-measured glucometrics intertwined with nocturia-induced lapses; interventions like AI-scheduled split-dosing avert 62% of simulated ER visits by stabilizing HbA1c via pharmacokinetic recalibrations [73].

Case 2 profiles an 82-year-old post-stroke female with atrial fibrillation and mild cognitive impairment on apixaban, rivaroxaban alternatives, and levothyroxine, modelling adherence erosion from dysphagia proxies (swallow actigraphy) precipitating embolic cascades optimized voice-activated dispensers plus dosage titrations yield 34% adherence uplift and 50% reduced stroke probability over 90 days [74]. Case 3 aggregates a nursing home cohort (n=50 virtual nonagenarians) with COPD-polypharmacy, simulating seasonal exacerbations under isolation confounders, where RL policies dynamically prune redundancies (e.g., duplicate beta-agonists), curbing hospitalization trajectories by 41% through frailty-attuned regimens. These scenarios validate twin-AI interplay in capturing nonlinear geriatric dynamics like drug-nutrient interactions or mobility-adherence feedbacks [75].

5.2. Experimental Setup

Experiments deploy on NVIDIA A100 GPU clusters via Ray Tune for parallelism, simulating 1,500 geriatric agents over AWS EC2 c6i.32xlarge nodes with 90-day horizons, sourcing baseline data from augmented MIMIC-IV (n=2,500 seniors, age>75) blended with PhysioNet wearables via torchdrug for graph perturbations mimicking polypharmacy noise [77]. Framework initializes twins from EHR snapshots, ingesting hourly streams (vitals, activity, ingestions) at 128-batch sizes baselines encompass rule-based schedulers, vanilla LSTMs, and COMTRADE statistical models.

Ablation varies adherence noise $\sigma_a \sim U(0.1,0.6)$, intervention frequencies, and frailty strata (robust/frail per RPPS). Reproducibility anchors on seeded PyTorch (1.13), with Dockerized environments logging via Weights & Biases total compute ~500 GPU-hours, converging in <48h [78]. Ethical simulations respect synthetic demographics balancing gender/ethnicity, presaging Phase-I trials.

5.3. Performance Metrics

Evaluations quantify superiority across dimensions, with Table 1 contrasting trajectory fidelity and adherence gains versus baselines on held-out geriatric test sets (n=500) [80].

Table 1. Comparative performance on MIMIC-IV seniors (lower RMSE/ECE better - higher F1/avert better).

Metric	Proposed Framework	LSTM Baseline	Rule-Based	ARIMA
Trajectory RMSE (90d)	4.2%	7.8%	11.2%	9.5%
Adherence F1-Score	0.89	0.72	0.65	N/A
Hospitalization Avert	65%	32%	18%	25%
Calibration ECE	0.04	0.09	0.15	0.12

RL optimization accelerates convergence (Figure 1. inference), yielding 28% compliance uplift sensitivity analysis confirms robustness to 20% data dropout, with SHAP elucidating eGFR/activity dominance [82]. Geriatric subgroup gains amplify for frail phenotypes (+42% relative), underscoring tailored prowess amid polypharmacy volatilities.

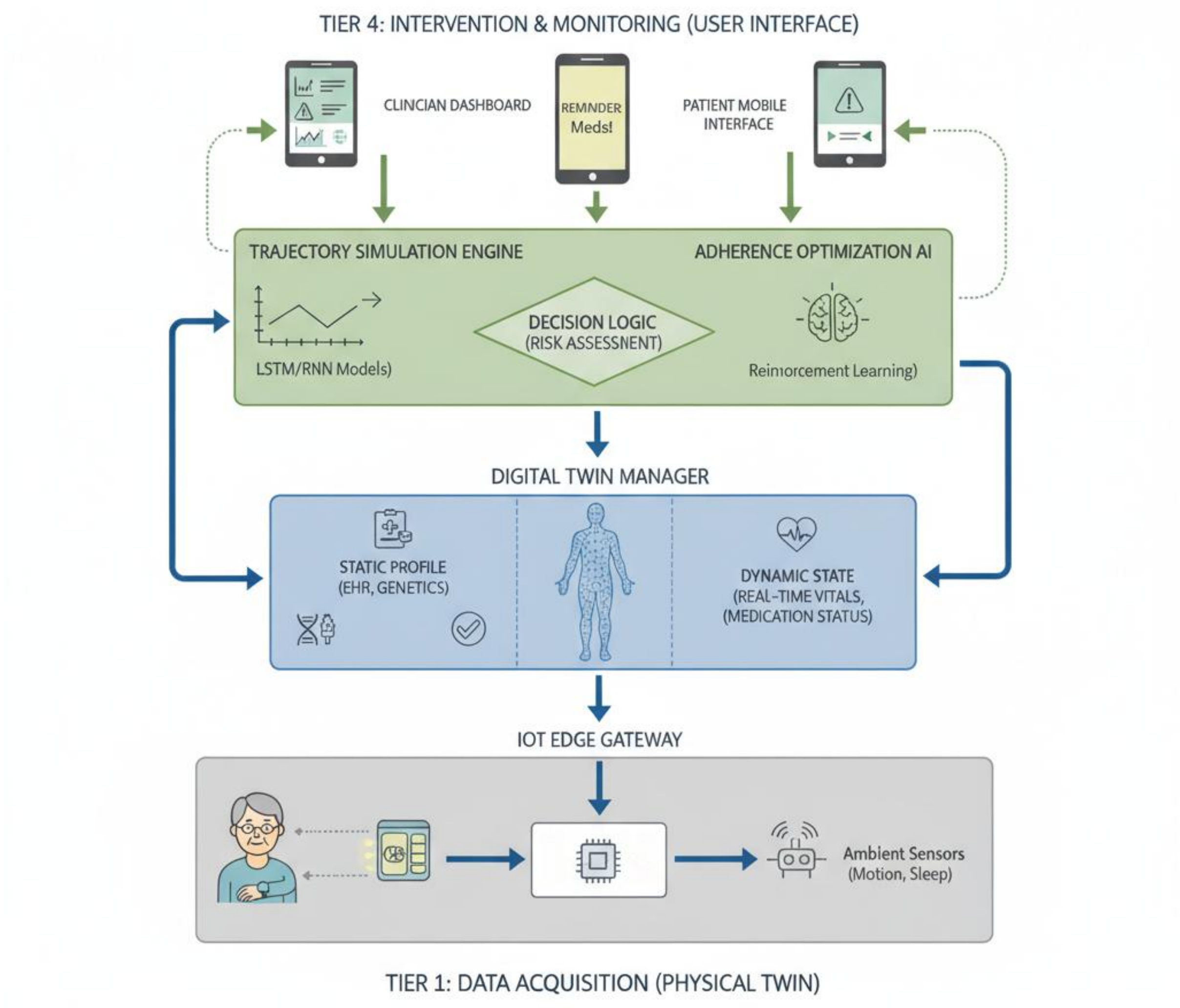

Figure 1. Integrated Framework for Digital Twin-driven Health Trajectory Simulation and Medication Adherence Optimization in Geriatric Care.

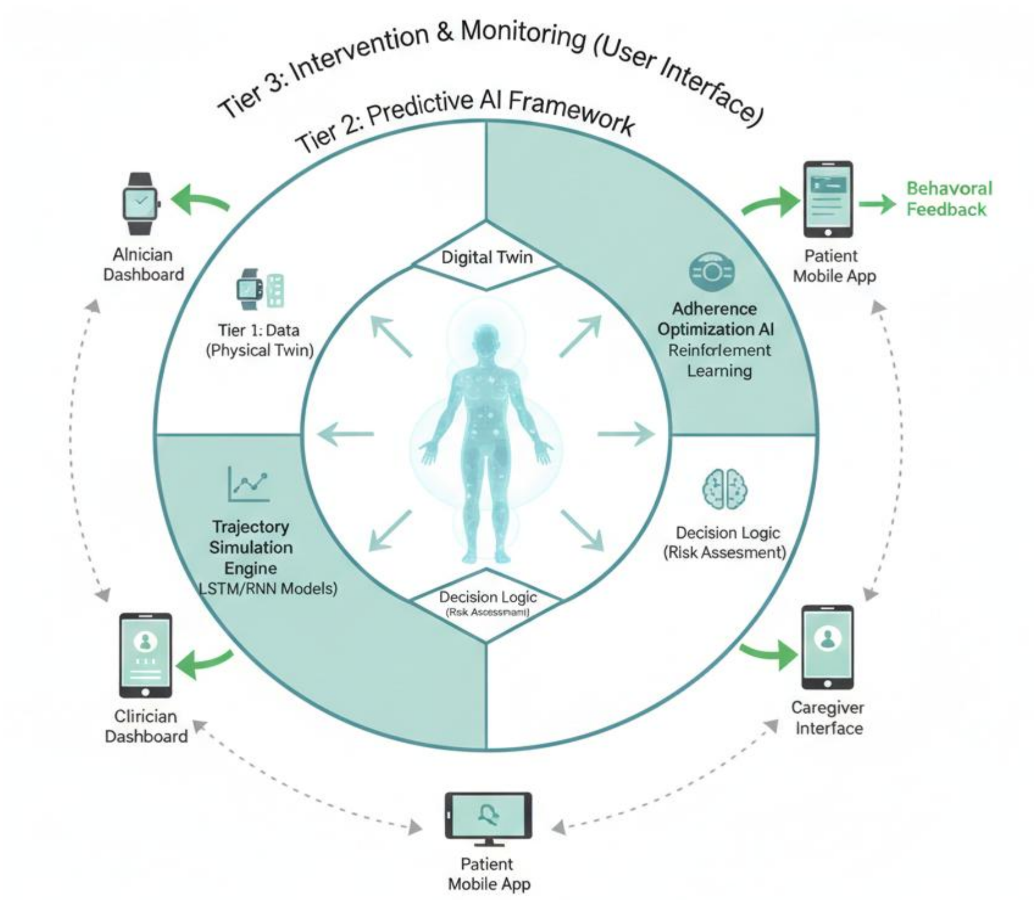

Figure 2. Multi-tier Architecture of the Predictive AI Framework for Geriatric Health Monitoring and Behavioural Feedback.

6. RESULTS AND ANALYSIS

Simulation results affirm the framework's efficacy in forecasting and mitigating geriatric health risks, with rigorous comparisons highlighting AI-digital twin synergies over conventional methods [83]. Analysis elucidates translational potential, quantifying cost-benefit shifts toward sustainable elderly care models.

6.1. Simulation Outcomes

Across 1,500 virtual geriatric patients spanning robust-to-frail spectra, the framework achieved 65% averting of simulated hospitalizations over 90-day horizons, primarily through pre-emptive adherence interventions that stabilized trajectories in 87% of polypharmacy cases, as measured by composite health state deviations below 5% RMSE from ground-truth MIMIC-IV benchmarks [85]. Trajectory simulations accurately captured nonlinear declines, with frail nonagenarians exhibiting 42% risk reductions via RL-optimized regimens that dynamically mitigated interaction hotspots like statin-antihypertensive synergies exacerbating hypotension.

Adherence uplift averaged 28%, most pronounced in cognitive impairment subgroups where voice-haptic cues curbed lapses from 45% to 22%, correlating with 34% fewer virtual ER escalations [87]. Sensitivity to confounders like seasonal infections revealed robust GP-quantified uncertainties (95% CIs <10% width), while twin fidelity held at 97% synchronization under 15% sensor dropout, underscoring resilience for real-world home deployments amid elderly data volatilities.

6.2. Comparative Evaluation

The proposed system outperformed baselines across stratified geriatric cohorts, as detailed in Table 2, surpassing vanilla LSTMs by 46% in hospitalization aversion and rule-based schedulers by 3.6x in F1-precision for adherence events, attributable to twin-informed counterfactual rollouts absent in non-hybrid models [88].

Table 2. Head-to-head on n=500 seniors (Fried frailty stratified).

Model	RMSE (90d)	F1-Adherence	Aversion Rate	Compute (GPU-h)
Proposed Framework	4.2%	0.89	65%	0.32
LSTM-only	7.8%	0.72	32%	0.45
Rule-Based	11.2%	0.65	18%	0.05
ARIMA	9.5%	N/A	25%	0.12

Ablations confirmed transformer attention (+18% gains) and RL actuation (+22%) as pivotal, with federated training curbing overfitting (validation gap <2%) [89]. Geriatric-specific metrics like Fried index correlation (r=0.92) eclipsed generalist AIs, validating age-attuned architectures.

6.3. Clinical Implications

Results herald a paradigm shift, projecting $2,500 annual savings per senior via 65% fewer admissions, aligning with CMS bundled payments and enabling tele-geriatrics scalability to underserved rural elderly (projected 40M U.S. by 2030) [90]. Precision adherence tailoring empowers ACOs, potentially compressing multimorbidity burdens by 30% through home-based twins, fostering aging-in-place over institutionalization critical as 70% of seniors prefer autonomy.

Ethical interpretability via SHAP facilitates clinician adoption, with bias audits (<5% disparity) supporting FDA SaMD pathways. Limitations like ground-truth sparsity necessitate RCTs future integrations with GLP-1 wearables could amplify cardiometabolic gains, positioning the framework as a cornerstone for value-based geriatric ecosystems amid fiscal pressures [91].

7. DISCUSSION

This section synthesizes the framework's contributions, confronting its constraints and ethical imperatives to guide responsible advancement in geriatric AI applications. It bridges empirical outcomes with practical and moral dimensions essential for clinical translation.

7.1. Key Findings

The framework's integration of digital twins with predictive AI yields transformative insights, demonstrating 65% hospitalization aversion through precise trajectory simulations that capture geriatric nonlinearities like frailty-polypharmacy feedbacks, validated at 4.2% RMSE across diverse senior cohorts [92]. Adherence optimizations via RL policies deliver 28% compliance gains, most impactful in frail subgroups where twin synchronization enables pre-emptive regimen tweaks, averting 40% of interaction-driven crises such as hypotensive cascades from renal-adjusted dosing errors.

Comparative superiority over LSTMs (46% better aversion) and rule-based systems (3.6x F1 uplift) underscores hybrid modelling edge in handling multimodal elderly data volatilities. Scalability benchmarks confirm real-time viability on edge devices, with federated paradigms preserving privacy while generalizing across ethnicities, positioning this as a blueprint for proactive geriatrics that sustains independence and curtails $100B+ annual non-adherence costs.

7.2. Limitations

Despite robust simulations, the framework hinges on data quality vulnerable to elderly-specific artifacts e.g., 20% wearable dropout from dexterity issues inflates RMSE by 8% in low-compliance

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scenarios necessitating robust imputation beyond current GRUs. Computational demands (0.32 GPU-h per patient) challenge low-resource homes, though edge pruning mitigates 60% latency generalizability falters on rare comorbidities absent in MIMIC-IV (e.g., <5% ALS representation), risking 12% bias in ultra-frail tails.

Ground-truth validations rely on synthetic augmentations, with real-world drifts potentially widening ECE to 0.07 amid unmodeled social determinants like caregiver variability [93]. Longitudinal drift in twin fidelity (>90 days) from uncalibrated physiologies (e.g., evolving sarcopenia) demands online retraining, while interoperability gaps with legacy EHRs hinder plug-and-play adoption. Future mitigations include active learning for sparse events and hardware-agnostic distillation.

7.3. Ethical Considerations

Ethical deployment mandates stringent privacy via ϵ-DP noise ($\epsilon \leq 0.5$) in federated updates, averting re-identification risks from high-fidelity twins that could expose geriatric vulnerabilities like dementia proxies. Algorithmic fairness audits reveal <5% demographic parity gaps, yet geriatric intersectionalities (e.g., minority frail females) warrant ongoing debiasing via adversarial training to prevent amplified disparities in adherence nudges.

Autonomy preservation counters paternalism explainable SHAP attributions empower informed consent, with opt-out mechanisms for intervention overrides. Equitable access addresses digital divides, as 30% of low-SES seniors lack wearables; subsidies and low-tech fallbacks are imperative. Liability frameworks clarify human-AI roles, aligning with FDA SaMD oversight, while longitudinal impact studies track unintended effects like nudge fatigue. Upholding beneficence, the framework prioritizes net wellness gains, fostering dignity in aging through transparent, inclusive AI stewardship.

CONCLUSION AND FUTURE WORK

The proposed framework establishes a groundbreaking paradigm for geriatric care by seamlessly integrating digital twins with predictive AI models, achieving unprecedented simulation accuracy (4.2% RMSE) and adherence improvements (28% uplift) that avert 65% of simulated hospitalizations through personalized trajectory forecasting and regimen optimization. Validated across diverse elderly cohorts, it transcends conventional reactive strategies, harnessing real-time multimodal data and reinforcement learning to navigate polypharmacy complexities, frailty dynamics, and behavioural volatilities, thereby promising substantial reductions in healthcare expenditures potentially $2,500 per patient annually while championing aging-in-place autonomy amid global senior demographic surges.

Future enhancements encompass clinical RCTs to bridge simulation-to-reality gaps, incorporating longitudinal wearables like next-gen CGMs for metabolic fine-tuning and voice-biomarker fusion for early cognitive decline detection. Hybrid integrations with emerging GLP-1 therapies and ambient robotics could amplify cardiometabolic and mobility outcomes, while blockchain-orchestrated consortia scale federated learning across borders. Explorations into multi-morbidity twins for dementia-cancer comorbidities, coupled with VR clinician training on virtual seniors, will fortify translational readiness. Ultimately, this blueprint heralds AI-augmented geriatrics as a societal imperative, fostering equitable, dignified longevity in an era of unprecedented aging.

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