ForeSight-HF: AI for Heart Failure Detection in Skilled Nursing Facilities

INTRODUCTION

Heart failure (HF) represents one of the most significant public health challenges of the 21st century, with more than 64 million people affected worldwide and prevalence rate expected to increase by 25% in the US by 2030.[1] Hospital readmission rates remain persistently high, with approximately 25% of patients readmitted within 30 days of discharge.[2]

One in five Medicare beneficiaries discharged from the hospital receives post-acute care in a skilled nursing facility (SNF), at a cost exceeding $28 billion annually.[3] However, SNFs face unique challenges: variable documentation quality, limited specialty physician availability, insufficient monitoring, and a geriatric population with multiple comorbidities.[4]

ForeSight-HF—named for its foundation in Forrester hemodynamic classification and its goal of proactive clinical guidance—is specifically designed for SNF HF management[5]. As an agentic AI system, it is capable of autonomous multi-step reasoning. The system was developed as a component of ProviderLoop, a platform designed to manage SNF cardiac care through real-time data sharing and remote cardiologist oversight. ForeSight-HF functions as a decision support tool; all final clinical decisions remain with the treating clinician. In this study, we evaluate the accuracy of ForeSight-HF's HF detection capabilities. Assessment of its management recommendations and care plan generation will be the subject of future investigation.

THE FORESIGHT-HF SYSTEM

Using OpenAI's GPT-5 mini model (accessed October–December 2025) via HIPAA-compliant infrastructure, the system continuously evaluates patients through a structured multi-step process analyzing both structured and unstructured clinical information to generate real-time risk assessments and hemodynamic classification using a continuous Forrester scoring system. While the underlying GPT-5 model was not specifically trained or fine-tuned on SNF patient populations or the ProviderLoop dataset, its clinical specificity is achieved through extensive prompt engineering that layers disease-specific instructions onto the model's foundational medical knowledge.

Unlike general-purpose AI applications that allow unconstrained generative outputs, ForeSight-HF follows a structured analytical pathway with predefined branchpoints, ensuring consistent outputs rather than allowing the AI to determine its own reasoning approach. The model's 400,000-token context window enables processing of extensive clinical documentation without truncation, while explicit guardrails protect against hallucination and context rot (loss of instruction adherence over lengthy inputs). This architecture supports HF triage even when clinical documentation is sparse or incomplete, a common reality in SNF settings.

ForeSight-HF employs a two-stage agentic architecture. In the first stage, a Note Processing bot ingests unstructured clinical documentation and extracts, summarizes, and structures relevant clinical information, processing the complete historical record at admission and updating weekly to create a dynamic long-term memory of the patient's clinical trajectory. In the second stage, a Decision-Making module synthesizes this data to generate real-time clinical assessments.

METHODS

The system analyzes clinical notes, labs, and imaging to generate HF presence (yes/no), classification, and confidence score (0–1.0). We evaluated 81 consecutive SNF admissions (Oct–Dec 2025) at a single facility. AI determinations were compared with blinded internist review, using cardiologist adjudication as reference.

RESULTS/CASE DISCUSSION

AI identified HF in 34/81 patients (42%) with 82.7% overall agreement (67/81) between AI and internist determinations. All 14 discordant cases were AI-positive but internist-negative. AI detected all

internist-identified HF cases (20/20) with no false negatives. Among 47 cases where both the AI and internist agreed HF was absent, no cardiologist-confirmed HF cases were identified to date.

Preliminary cardiologist adjudication showed AI-identified cases had objective evidence, including echocardiographic abnormalities, elevated natriuretic peptides, and HF-directed therapy. AI sensitivity and specificity were 100% (34/34 and 47/47), versus internist sensitivity of 59% (20/34). High-confidence AI detections (≥0.8) aligned with objective findings.

CONCLUSION

ForeSight-HF identified HF cases missed by internists while capturing all internist-identified cases, suggesting high sensitivity for HF detection from SNF documentation. These findings address a critical unmet need in post-acute care, where specialist access is limited and accurate HF identification is the necessary foundation for appropriate management. Ongoing cardiologist adjudication and prospective validation are needed to confirm detection performance. Future studies will evaluate the system's management recommendations and care plan generation capabilities.

REFERENCES

1. Savarese G, Becher PM, Lund LH, et al. Global burden of heart failure: A comprehensive and updated review of epidemiology. Cardiovasc Res. 2023;118(17):3272-3287.

2. Dharmarajan K, Hsieh AF, Lin Z, et al. Diagnoses and timing of 30-day readmissions after hospitalization for heart failure, acute myocardial infarction, or pneumonia. JAMA. 2013;309(4):355-363.

3. Burke RE, Xu Y, Rose L. Skilled Nursing Facility Performance and Readmission Rates Under Value-Based Purchasing. JAMA Netw Open. 2022;5(2):e220721

4. Dolansky MA, Capone L, Engelman K, et al. Skilled Nursing Facility Care for Patients With Heart Failure: Can We Make It "Heart Failure Ready?" J Card Fail. 2020;26(6):522-534.

5. Forrester JS, Diamond G, Chatterjee K, Swan HJC. Medical therapy of acute myocardial infarction by application of hemodynamic subsets. N Engl J Med. 1976;295(24):1356-1362.

KEYWORDS

Artificial Intelligence, Heart Failure, Skilled Nursing Facilities, Large Language Models

Conflict of Interest Statement

Jeffrey Bander, MD is the founder of ProviderLoop and holds a financial interest in the company. No other authors have financial relationships with or are employed by ProviderLoop. All other authors declare no conflicts of interest relevant to this work.