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IMPETUS: An AI-Based Early Warning Framework for Predicting Heart-Failure Worsening

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ABSTRACT

Heart failure is a major cardiovascular condition in which clinical status may change over time and may require timely reassessment. Artificial intelligence (AI) has been investigated for diagnosis, prognosis, risk stratification, and prediction of outcomes in heart failure, but predictive performance alone does not establish clinical usefulness. This theoretical article proposes IMPETUS, an AI-based early-warning framework designed to detect possible heart-failure worsening from longitudinal, multimodal patient-health information. The framework integrates patient-reported symptoms, vital signs, body weight, oxygen saturation, electrocardiographic information, medication-related information, previous clinical records, laboratory and clinical information, and telemonitoring data. Its theoretical novelty is not the individual use of these components, which are already present in the literature, but their organization into a temporal, multimodal, explainable, human-reviewed warning pathway in which changing patient trajectories are treated as the central unit of early-warning reasoning. For this article, heart-failure worsening is defined prospectively as a predefined transition toward clinically meaningful deterioration, such as urgent clinical assessment, emergency presentation, heart-failure hospitalization, or another validated decompensation endpoint, within a prespecified prediction window. Six testable propositions are formulated with explicit comparators and outcomes. The article also specifies candidate temporal AI methodologies, alert-generation logic, explainability requirements, leakage prevention, external validation, clinical usefulness assessment, ethical safeguards, and the relationship of IMPETUS to existing heart-failure guidance. No clinical or experimental results are claimed. The framework remains a theoretical proposal requiring retrospective, prospective, independent, external, and real-world evaluation.

Keywords: IMPETUS; Artificial Intelligence; Heart Failure; Early Warning; Temporal Prediction; Multimodal Data; Telemonitoring; Clinical Decision Support; Explainable AI

INTRODUCTION

Heart failure is a complex clinical condition requiring ongoing assessment and management. Changes in symptoms and physiological measurements may occur over time, creating a rationale for monitoring approaches that can identify potentially concerning trajectories before severe deterioration becomes clinically obvious. Telemonitoring and digital health approaches can provide repeated information such as symptoms, weight, and blood pressure, while AI and machine-learning methods have been investigated for diagnosis, prognosis, risk stratification, and outcome prediction [1–6].

However, a predictive model with acceptable statistical performance is not automatically a clinically useful early-warning system. Generalizability, external validation, data quality, missingness, false alerts, explainability, workflow integration, ethics, and the distinction between prediction and clinical action remain important considerations [7-12].

Accordingly, IMPETUS is proposed as a theoretical framework in which the primary object of analysis is not a single abnormal measurement but a changing longitudinal patient trajectory assembled from multiple available information sources [13-15]. The framework does not replace clinical diagnosis or treatment. It generates a proposed warning for qualified healthcare professionals to review [15-19].

THEORETICAL PROBLEM AND RESEARCH GAP

The central theoretical problem is how an AI system could identify clinically meaningful heart-failure worsening early enough to support reassessment while avoiding excessive false alerts. Existing literature demonstrates that AI can support several heart-failure tasks, but evidence varies by endpoint, population, data source, and methodology [1–6]. Telemonitoring studies also demonstrate that remote monitoring is not equivalent to an automatically validated AI early-warning system [18,19].

The gap addressed by IMPETUS is therefore architectural and theoretical. Existing components such as continuous monitoring, multimodal data, explainability, and clinician oversight are not claimed as novel individually. The proposed contribution is their integration around a temporal deterioration pathway: repeated observations are transformed into longitudinal patient trajectories; multimodal temporal patterns are evaluated against a predefined worsening endpoint; an alert is generated only when a prespecified risk criterion is met; the alert includes interpretable contributing information; and a clinician remains responsible for assessment and action.

Theoretical Novelty of IMPETUS

The theoretical novelty of IMPETUS lies in its proposed relationship among four elements: temporal trajectory representation, multimodal incremental evidence, explainable risk escalation, and a human clinical-review boundary. The framework treats deterioration as a change process rather than merely a static classification problem. It therefore asks whether the combination and sequence of patient signals provide information beyond isolated measurements or a single data source.

This distinguishes IMPETUS conceptually from approaches that focus primarily on a single endpoint, isolated measurements, a single modality, or model performance without specifying how the prediction becomes a clinically reviewable warning. The framework is intentionally technology-neutral: the specific model is not prescribed in advance because empirical comparison is required to determine which temporal AI approach is appropriate.

The novelty is consequently a testable theoretical architecture, not a claim that any individual component is new or that the proposed system has already demonstrated clinical benefit.

Definition of Heart-Failure Worsening and Prediction Target

For future empirical testing, 'heart-failure worsening' must be operationalized before model development. The primary target should be a clinically predefined deterioration event occurring within a prespecified prediction horizon after each eligible observation. Candidate endpoints include emergency presentation for heart-failure deterioration, heart-failure hospitalization, urgent clinician-directed escalation of care, or another validated decompensation endpoint. A study should select one primary endpoint rather than combining unrelated outcomes without justification.

The prediction window should also be specified in advance, for example a clinically justified short-term window, and should remain identical for development and evaluation unless a separate analysis is prespecified. Earlier warnings and longer prediction horizons should be treated as separate outcomes rather than interchangeable definitions of success.

IMPETUS THEORETICAL FRAMEWORK

Data Collection

IMPETUS proposes collecting available longitudinal information including patient-reported symptoms, heart rate, blood pressure, body weight, oxygen saturation, ECG information, medication-related information, previous clinical records, laboratory information, clinical observations, and telemonitoring data. The framework does not assume that every source is available for every patient.

Data Preparation and Quality Control

The framework requires explicit handling of missing, inconsistent, duplicated, delayed, and implausible observations. Data provenance and measurement timing should be retained because temporal ordering is essential to early-warning prediction. Preprocessing must be performed without using information that would not have been available at the prediction time.

Temporal Multimodal AI Analysis

Candidate models may include conventional machine-learning baselines, time-series models, recurrent or attention-based architectures, or other suitable approaches. Model selection should be empirical rather than assumed. The key comparison is whether longitudinal multimodal information improves prediction beyond simpler comparators such as static clinical variables, individual modalities, or non-temporal models.

Alert Generation

An alert should be generated only after a prespecified prediction threshold or decision rule is reached. Alert design should include the predicted endpoint, prediction horizon, risk estimate or risk category, and the principal patient-level factors or temporal changes contributing to the warning. Threshold selection should consider both missed events and false alerts.

Clinical Review

IMPETUS is a clinical decision-support concept rather than an autonomous diagnostic or treatment system. A qualified healthcare professional should review the alert, verify the underlying information, consider the broader clinical context, and determine whether assessment or action is appropriate.

Testable Theoretical Propositions

The following propositions are intentionally separated from established evidence. They are hypotheses for future empirical testing and are not clinical findings.

H1: A temporal model using repeated patient observations will demonstrate better discrimination and/or calibration for the predefined heart-failure worsening endpoint than a comparable model using only a single observation.

H2: A multimodal temporal model will provide incremental predictive value over the strongest single-modality temporal model, assessed using prespecified discrimination, calibration, and decision-utility measures.

H3: Alerts containing patient-specific contributing factors and relevant temporal changes will achieve higher clinician-rated interpretability and workflow usefulness than alerts providing a risk score without explanatory information.

H4: Model performance and calibration will remain within prespecified acceptable ranges in an independent external population, rather than being evaluated only on the development dataset.

H5: A human-reviewed warning workflow will demonstrate greater implementation acceptability and safer actionability than an autonomous decision workflow, assessed through predefined usability, alert-appropriateness, and safety measures.

H6: Reducing false-alert burden while preserving sensitivity to clinically meaningful deterioration will improve the practical usefulness of the framework, assessed through false-alert rate, missed-event rate, alert burden, and clinician workflow measures.

Why Multimodal Temporal Information May Add Value

The multimodal premise is a proposition, not an assumption that more data automatically improve prediction. Different modalities can provide partially complementary information about symptoms, haemodynamic status, rhythm, treatment, and recent clinical history. Their incremental value should therefore be tested through ablation and comparator analyses.

Future studies should compare: (a) single-signal models; (b) single-modality models; (c) static multimodal models; and (d) temporal multimodal models. Incremental value should be demonstrated through prespecified changes in discrimination, calibration, net clinical benefit or another justified decision measure, while accounting for missingness and data availability. If additional modalities do not improve performance or clinical usefulness, the framework should not treat their inclusion as beneficial.

AI Methodology, Alert Generation, and Temporal Leakage

The current theoretical article does not select one AI architecture because that choice requires empirical comparison. Future studies should establish a baseline model and compare candidate temporal and multimodal approaches using the same endpoint, prediction horizon, and evaluation protocol.

Temporal leakage is a critical methodological risk. All predictors used for a prediction at time t must be restricted to information available at or before t. Events, measurements, medication changes, or clinical documentation occurring after t must not enter the predictor set. Development and evaluation should use time-aware or patient-level separation as appropriate, and external validation should be performed on an independent population. Any preprocessing, imputation, feature selection, or threshold optimization must be fitted without using information from the evaluation set.

Operational Definition of Explainability

In IMPETUS, explainability is operationalized as the ability of an alert to communicate, in a clinician-interpretable format, which patient variables and relevant temporal changes contributed materially to the warning. Explanations may use appropriate model-specific or model-agnostic methods, but their usefulness should not be assumed from the existence of an explanation method alone [13,14]. Future evaluation should assess explanation fidelity, stability, comprehensibility, and clinician usefulness. A technically generated explanation that is inaccurate or misleading should not be treated as successful explainability.

Critical Synthesis of Existing Evidence

The existing literature supports the rationale for investigating AI in heart failure but does not establish the effectiveness of IMPETUS. Reviews describe applications across diagnosis, risk stratification, prognosis, and treatment, while systematic evidence reports variability in machine-learning performance [1–6]. ECG-focused research demonstrates potential for AI-based prediction, but performance is dependent on target condition, population, and methodology [5,6]. Telemonitoring evidence shows that remote monitoring can be clinically relevant, but it does not by itself validate the proposed temporal multimodal AI architecture [18,19].

Prediction-model reporting and risk-of-bias guidance further indicate the importance of transparent development and validation [11,12]. Explainability methods such as LIME and SHAP provide candidate technical approaches, but their presence does not guarantee clinical usefulness [13,14]. AI intervention reporting frameworks emphasize prospective evaluation and implementation considerations [15–17]. Thus, the literature supports the need for rigorous testing while simultaneously showing why conceptual integration alone cannot be treated as evidence of clinical effectiveness.

Relationship to ESC Heart-Failure Guidance

IMPETUS is not proposed as an alternative to or replacement for ESC heart-failure guidance. Its intended role is supportive: if validated, an AI-generated warning could provide additional information for clinical assessment within established heart-failure management pathways. Clinical diagnosis, treatment selection, medication decisions, and escalation of care remain governed by qualified clinicians and applicable clinical guidelines. The framework therefore complements guideline-based care conceptually rather than creating an independent treatment pathway [7,8].

Clinical Usefulness Versus Predictive Performance

Predictive performance and clinical usefulness are distinct. Discrimination and calibration describe model behavior, whereas clinical usefulness also depends on alert burden, missed events, interpretability, workflow compatibility, clinician response, patient safety, and whether use of the system changes meaningful clinical outcomes. IMPETUS therefore proposes that future studies evaluate technical performance first and then assess prospective workflow and clinical usefulness rather than inferring benefit from accuracy alone.

Ethical and Responsible-AI Considerations

IMPETUS would process sensitive health information and therefore requires privacy-preserving data governance, appropriate informed consent or other lawful governance mechanisms, secure storage and transmission, controlled access, and clear responsibility for clinical decisions. Future research should examine demographic and clinical subgroup performance to identify possible inequities and should monitor whether missing data or unequal access to monitoring technologies systematically affe cts model behavior. The system should provide clear human oversight and should not independently initiate treatment. These requirements are consistent with broader responsible-AI principles for health [20].

Proposed Validation Strategy

Future validation should proceed in stages. First, a development dataset should be used to define the target endpoint, prediction horizon, candidate predictors, and baseline comparators. Second, model development should use leakage-controlled procedures. Third, internal evaluation should assess discrimination, calibration, false-alert burden, missed events, and robustness. Fourth, an independent external population should be used to test generalizability. Fifth, prospective evaluation should assess real-time alert behavior, interpretability, clinician workload, workflow compatibility, and safety. Finally, if appropriate, an impact study should determine whether use of IMPETUS changes clinical management or patient outcomes. None of these future results are claimed in the present article.

LIMITATIONS

The principal limitation is that IMPETUS is theoretical and has no original clinical or experimental results. The precise AI architecture, feature set, endpoint definition, prediction horizon, alert threshold, and dataset composition remain to be established empirically. The framework may also be limited by data availability, missingness, interoperability, patient engagement, differences among healthcare settings, and alert fatigue. The conceptual architecture should therefore be interpreted as a testable research model rather than a clinically validated system.

THEORETICAL CONTRIBUTION

The principal theoretical contribution is a testable architecture for temporal multimodal early warning in heart failure. IMPETUS connects longitudinal patient trajectories to multimodal incremental prediction, explainable warning generation, and human clinical review. The framework makes explicit that each link must be evaluated independently and that the overall value of the system depends on the combined validity, safety, and usefulness of those links.

CONCLUSION

IMPETUS proposes a conceptual approach for AI-based early warning of heart-failure worsening. Its originality is positioned at the level of theoretical integration rather than individual technologies: temporal patient trajectories, multimodal incremental information, explainable alerts, and human clinical review are organized into one testable architecture. Heart-failure worsening is defined as a prespecified clinically meaningful deterioration endpoint within a defined prediction horizon, while the hypotheses specify comparators and measurable outcomes. The framework does not claim clinical effectiveness. Retrospective, external, prospective, and real-world evaluation will be required to determine whether IMPETUS provides incremental predictive value, acceptable alert burden, useful explanations, safe workflow integration, and ultimately meaningful clinical benefit.

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