# Benchmarking Waitlist Mortality Prediction Through Time-to-Event Modeling using New UNOS Dataset

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**Background.**
Heart transplantation remains the definitive therapy for end-stage heart failure, a global health crisis impacting about 65 million adults worldwide (1). In the United States, heart allocation decisions are guided primarily by urgency categories defined by the United Network for Organ Sharing (UNOS). However, these static categorizations often fail to adequately capture dynamic changes in patient health status, resulting in suboptimal risk stratification and potentially preventable deaths on the waitlist. Recent UNOS policy revisions in 2018 introduced detailed longitudinal patient data collection, enabling continuous tracking of patient status. Yet, most predictive models still rely only on baseline variables, limiting their utility in dynamically evolving clinical scenarios (2). This study aims to establish a comprehensive benchmark for predictive models using longitudinal UNOS data to improve accuracy in predicting heart transplant waitlist mortality. The motivation lies in providing clinicians with advanced tools capable of updating survival predictions continuously, enabling timely decisions, more efficient allocation, and better patient outcomes.

**Methods.**
We analyzed a large, national dataset comprising 23,807 heart transplant candidate records from the UNOS thoracic registry, collected since October 18, 2018. The dataset contained rich longitudinal clinical data covering 71 dynamic variables, allowing real-time assessment of patient health trajectories. The primary endpoint of our analysis was waitlist mortality, with patient outcomes tracked through December 31, 2023. The dataset was randomly partitioned into training, validation, and test sets with an 80%-10%-10% split. Variables with less than 30% missing data underwent imputation via Markov Chain Monte Carlo techniques. Three distinct modeling approaches were benchmarked against four existing baselines: a time-varying Cox proportional hazards model (3), Random Survival Forest (RSF) (4), and a deep learning-based DeepHit model (5). Model performance was assessed using the concordance index (C-Index) and one-year discrimination measured by AUROC (Area Under the ROC curve), AUPRC (Area Under the Precision-Recall Curve), accuracy, precision, recall and F1 score, and Brier Score at 1 year and Integrated Brier Score (IBS) in 1 year.

**Results.**
As shown in Table 1, the DeepHit model emerged as the best-performing algorithm, achieving a C-Index of 0.94 and a one-year AUC of 0.89, significantly outperforming traditional static models and previously reported benchmarks. The dynamic models consistently demonstrated superior predictive capabilities by integrating longitudinal patient data. The recall rate was lower than precision, due to the class imbalance (with only 8% waitlist mortality). Key predictors included established risk factors like renal dysfunction (BUN, dialysis), serum albumin, ECMO, age, and hospitalization frequency. Notably, underexplored variables such as AST, $SvO_2$, and oral anticoagulant use also emerged as significant, offering promising directions for future clinical validation. These results underscore the value of dynamic modeling for real-time, data-driven transplant decision support.

Table 1. Performance comparison of all models on the latest UNOS dataset. The best-performing model is highlighted in bold, while the second-best model is underlined. '1Y' represents one-year discrimination. 'Dynamic' and 'Static' represent using longitudinally recorded variables and variables recorded only at the time of listing. We re-implement previous baselines (6–9) using our new UNOS dataset, and none of them use longitudinally recorded variables. Lower Brier Score and IBS indicate better performance, while higher values are better for all other metrics.

| Approach | # Features | Accuracy (1Y) | Precision (1Y) | Recall (1Y) | F1 Score (1Y) | Brier Score (1Y) | IBS (in 1 Year) | AUROC (1Y) | AUPRC (1Y) | C-Index |
|---|---|---|---|---|---|---|---|---|---|---|
| Alshawabkeh (2016) | 14 | 0.74±0.01 | 0.64±0.01 | 0.29±0.01 | 0.40±0.00 | 0.18±0.00 | 0.20±0.00 | 0.72±0.00 | 0.55±0.00 | 0.75±0.00 |
| Jasseron (2017) | 5 | 0.70±0.01 | 0.60±0.00 | 0.15±0.01 | 0.24±0.00 | 0.19±0.00 | 0.22±0.00 | 0.70±0.00 | 0.48±0.00 | 0.69±0.00 |
| Hsich (2018) | 21 | 0.75±0.01 | 0.66±0.00 | 0.32±0.01 | 0.43±0.00 | 0.17±0.00 | 0.20±0.00 | 0.75±0.00 | 0.58±0.00 | 0.79±0.00 |
| Bakhtiyar (2020) | 12 | 0.73±0.01 | 0.68±0.01 | 0.17±0.00 | 0.27±0.00 | 0.19±0.00 | 0.23±0.00 | 0.69±0.00 | 0.51±0.00 | 0.69±0.00 |
| Our Dynamic CPH | 77 | 0.87±0.01 | 0.76±0.01 | 0.42±0.00 | 0.54±0.00 | 0.11±0.00 | 0.17±0.00 | 0.87±0.00 | 0.66±0.00 | 0.87±0.00 |
| Our Static CPH | 43 | 0.78±0.01 | 0.72±0.01 | 0.40±0.00 | 0.52±0.00 | 0.16±0.00 | 0.20±0.00 | 0.76±0.00 | 0.63±0.00 | 0.79±0.00 |
| Our Dynamic RSF | 77 | **0.88±0.01** | 0.79±0.01 | 0.44±0.01 | 0.56±0.00 | 0.10±0.00 | 0.16±0.00 | 0.88±0.00 | 0.70±0.00 | 0.91±0.00 |
| Our Static RSF | 43 | 0.79±0.01 | 0.72±0.01 | 0.42±0.00 | 0.52±0.01 | 0.15±0.00 | 0.19±0.00 | 0.78±0.00 | 0.66±0.00 | 0.77±0.01 |
| Our Dynamic DeepHit | 77 | 0.87±0.01 | **0.80±0.01** | **0.45±0.01** | **0.57±0.01** | **0.10±0.00** | **0.16±0.00** | **0.89±0.00** | **0.70±0.00** | **0.94±0.01** |
| Our Static DeepHit | 43 | 0.80±0.01 | 0.73±0.01 | 0.42±0.01 | 0.52±0.00 | 0.15±0.00 | 0.19±0.00 | 0.77±0.00 | 0.65±0.00 | 0.80±0.00 |

Table 3. Summary of time-varying Cox model for heart transplant waitlist mortality. Significant variables with a p value less than 0.01 are listed: orange indicates increased risk; blue indicates decreased risk.

| Variable | Coef. | H.R. | Std. Err. | p value |
|---|---|---|---|---|
| Number of Hospital Admissions in 12 Months | 0.119 | 1.127 | 0.023 | 0 |
| On Anti-Arrhythmics: Yes | 0.161 | 1.175 | 0.046 | 0 |
| On Continuous Invasive Mechanical Ventilation: Yes | 0.815 | 2.258 | 0.112 | 0 |
| On Dialysis: Yes | 0.409 | 1.505 | 0.106 | 0 |
| Patient number of previous TXPs | -0.15 | 0.86 | 0.037 | 0 |
| Patient age in years | 0.314 | 1.369 | 0.029 | 0 |
| On Vasoactive Support: Yes | 0.472 | 1.603 | 0.065 | 0 |
| On Oral Anticoagulant when INR was Obtained: Yes | -0.323 | 0.724 | 0.058 | 0 |
| Serum Sodium (mEq/L) | -0.208 | 0.812 | 0.022 | 0 |
| Patient initial waitlist status: New Status 1 | 0.791 | 2.206 | 0.17 | 0 |
| BUN (mg/dL) | 0.108 | 1.114 | 0.019 | 0 |
| AST (U/L) | 0.026 | 1.027 | 0.007 | 0 |
| Serum Albumin (g/dL) | -0.343 | 0.71 | 0.022 | 0 |
| Serum Bilirubin (mg/dL) | 0.063 | 1.065 | 0.009 | 0 |
| Patient initial waitlist status: New Status 2 | 0.418 | 1.519 | 0.091 | 0 |
| Patient initial waitlist status: Old Status 2 | -0.614 | 0.541 | 0.107 | 0 |
| Central Venous Pressure (in mmHg) | 0.156 | 1.169 | 0.025 | 0 |
| Resting Heart Rate (in bpm) | 0.104 | 1.109 | 0.024 | 0 |
| Mixed Venous Oxygen Saturation (SvO2) (in %) | -0.087 | 0.916 | 0.026 | 0.001 |
| Patient functional status at WL | -0.093 | 0.911 | 0.027 | 0.001 |
| BNP (pg/mL) | 0.056 | 1.058 | 0.018 | 0.002 |
| INR | 0.072 | 1.074 | 0.023 | 0.002 |
| Patient initial waitlist status: Old Status 1A | -0.485 | 0.616 | 0.164 | 0.003 |
| On Pulmonary Vasodilators: Yes | 0.189 | 1.208 | 0.066 | 0.004 |
| Patient On ECMO at REG: Yes | 0.462 | 1.587 | 0.163 | 0.005 |
| Diastolic Blood Pressure (in mmHg) | -0.077 | 0.926 | 0.028 | 0.006 |
| Patient initial waitlist status: Old Status 1B | -0.259 | 0.772 | 0.095 | 0.007 |
| Patient eGFR | -0.076 | 0.927 | 0.031 | 0.013 |
| Patient initial waitlist status: New Status 3 | 0.248 | 1.281 | 0.1 | 0.014 |
| Patient initial waitlist status: New Status 6 | -0.191 | 0.826 | 0.085 | 0.026 |
| On a Diuretic: Yes | -0.117 | 0.89 | 0.054 | 0.032 |
| Pulmonary Artery Diastolic Pressure (in mmHg) | 0.08 | 1.083 | 0.039 | 0.041 |
| History of Stroke: Yes | 0.126 | 1.134 | 0.063 | 0.047 |

**Conclusion.**

This study presents the first comprehensive benchmark for dynamic modeling of heart transplant waitlist mortality using longitudinal UNOS data. Dynamic models significantly improve predictive accuracy, supporting real-time urgency assessment and allocation decisions. These advances may reduce preventable deaths and optimize resource use. Future work should focus on external validation, integration of broader clinical data, and translation into actionable decision support tools.

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