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A Revised Model for End-Stage Liver Disease Optimizes Prediction of Mortality Among Patients Awaiting Liver Transplantation

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Abstract

Background & Aims—The Model for End Stage Liver Disease (MELD) was originally developed based on data from patients that underwent the transjugular intrahepatic portosystemic shunt procedure. An updated MELD, based on data from patients awaiting liver transplantation (LTx), should improve mortality prediction and allocation efficiency.

Methods—Waitlist data from adult primary LTx candidates from the Organ Procurement and Transplantation Network was divided into a model derivation set (2005–2006: n=14,214) and a validation set (2007–2008: n=13,945). The Cox regression analysis was used to derive and validate an optimized model that updated coefficients and upper and lower bounds for MELD components and included serum levels of sodium. The main outcome measure was the ability to predict 90-day mortality of patients on the LTx waitlist.

Results—The optimized MELD score updated the coefficients and implemented new upper and lower bounds for creatinine (0.8 and 3.0 mg/dl, respectively) and the international normalized ratio (INR, 1 and 3, respectively). Serum sodium concentrations significantly predicted mortality, even after adjusting for the updated MELD model. The final model, based on updated fit of the 4 variables (bilirubin, creatinine, INR, and sodium) had a modest yet statistically significant gain in discrimination (concordance: 0.878 vs 0.865, $P<0.01$) in the validation data set. Utilization of the new score could affect up to 12% of patients (based on changed score for 472 /3981 transplants in the validation set).

Conclusion—Modification of the MELD score to update coefficients, change upper and lower bounds, and incorporate serum sodium levels improved waitlist mortality prediction and should increase efficiency of allocation of donated livers.

Keywords

Liver disease; surgery; prognosis; survival

The Model for End Stage Liver Disease (MELD) was originally developed to predict mortality in patients undergoing Transjugular Intrahepatic Portosystemic Shunts.¹ In 2002,

after validation in multiple types of liver disease patients, the MELD score was adopted as a standard by which liver transplant candidates with end stage liver disease were prioritized for organ allocation in the United States.² This scoring system utilizes three widely available laboratory values - total bilirubin (g/dL), creatinine (g/dL), and international normalized ratio (INR) of the prothrombin time. The MELD system had an immediate impact on the liver transplant landscape leading to a reduction in the number of wait list registrants for the first time ever, and a 15% reduction in mortality among those on the waiting list.^{3, 4}

Since the introduction of MELD as the primary allocation system, there has always been a goal of improving this mathematical prioritization model.⁵ In attempting to achieve this goal, one may alter the coefficients in the existing MELD formula or include new variables that evaluate additional aspects of the patient's health. Both approaches have been attempted, separately. We and others have shown that the addition of serum sodium improves survival prediction of the MELD score.⁶ By updating the MELD coefficients, Sharma et al at the Scientific Registry of Transplant Recipients (SRTR) proposed that a new model (the SRTR MELD, henceforth) improved concordance of model prediction across all subsets of MELD scores.⁷ The SRTR MELD, derived and validated using SRTR data from 2001–2006, re-estimated coefficients of the MELD variables and eliminated upper or low bounds for the variable including the assignment of creatinine of 4mg/dl for patients receiving renal replacement therapy.

Thus, in this study, we had three objectives. First, based on the latest data, we optimized the MELD coefficients, including re-examination of the lower and upper bounds for individual variables. In the current MELD score, serum creatinine has an upper bound of 4.0g/dl, all values above which are set to 4.0g/dl. Second, we examined whether inclusion of serum sodium (Na) concentration still adds value when it is considered in the context of the optimized model. Third, we compared the performance of the final optimized model with that of existing models including the current MELD score, the MELDNa score, and the SRTR MELD score.

Methods

Patient Data

Data from all patients newly registered on the liver transplant waiting list from January 1st, 2005 – December 31st, 2008 were obtained from the Organ Procurement and Transplantation Network (OPTN) through the Standard Transplant Analysis and Research (STAR) file. The target population included all adults with cirrhosis listed for a first liver transplantation. The criteria for exclusion included age younger than 18 years and previous liver transplantation. Patients who were initially listed on inactive status were included as of the date they moved to active status. In addition, patients were excluded if they were listed as status 1 for acute liver failure or with a diagnosis of primary (hepatocellular carcinoma or cholangiocarcinoma) or metastatic hepatic malignancies.

From the STAR file, data necessary for the analysis was extracted. The MELD score components – bilirubin, creatinine, and INR – as well as serum sodium, were the predictor variables. The main outcome variable was death on the waiting list within 90 days of listing.

Patients who died after withdrawal from the list but within 90 days of listing, were considered to have died on the waiting list. Patients who survived 90 days on the waiting list or after withdrawal were censored at 90 days. Patients who received a liver transplant were censored at the time of transplantation. In patients registered on a waiting list at multiple centers, the first date of registration among these centers was used for analysis. Date of registration and activation on the wait list was used as the time zero for survival analysis.

Statistical Analysis

We utilized the 4 consecutive years of OPTN data by dividing them into a model derivation data set (2005–2006) and a validation data set (2007–2008). The first aim of this study was to optimize the coefficients for the MELD score components. We created Cox regression models evaluating mortality within 90 days based on the MELD variables (serum bilirubin, creatinine and INR) obtained at time of registration. A generalized additive model form of the Cox model was used, which allows for a flexible shape for the relationship between a covariate and risk, via a smoothing spline.⁸ The resulting fit can be assessed both visually and with formal tests for linearity and/or significance. These models were executed in a multivariable fashion - namely, in determining the effect of one variable (e.g., bilirubin), the other two variables (e.g., creatinine and INR) were included in the model. In this way, the relationship between the first variable and mortality can be identified independent of effects of the other variables.

We explicitly examined the extent to which the relationship between each variable and the risk of death is linear by we considering lower and upper bounds to each variable, namely limits beyond which linearity of the relationship breaks down. This was accomplished first by visual inspection of the smoothing splines. When it was visually apparent that an upper or lower bound would be necessary, the significance of the cutoffs was evaluated using a backwards elimination strategy: for each variable, a model with proposed bounds was compared to one where the variable in question was added linearly without the bounds and the difference in fit compared to a chi-square with 2 degrees of freedom. The presence/absence of the bounds and the cut-off values for each variable were examined iteratively until the optimal bounds were found. The final determination of the upper or lower bounds was not only based on goodness of fit but also by physiological interpretation (e.g., the upper limit of normals) of the cut-off values.

To achieve the second aim, namely to examine whether serum sodium still provided additional prognostic information when the updated MELD was used, multivariable Cox analysis was carried out in the 2005–2006 data set to determine the relationship between the optimized MELD model, Na, and the 90-day mortality. Again, smoothing splines were used to determine the nature of the relationship between Na and mortality. Interactions between variables were assessed by considering products of individual variables in the multivariable Cox regression model. Finally, the resultant model was adjusted such that the distribution of the new score will be similar to the old one. This is done by matching the scores of the 25th and 75th percentiles of the data.

The final aim of the study was to compare the performance of the optimized model with that of existing models. In order for this comparison to be fair and meaningful, it is important

that an independent data set is used, which was not included in the derivation of the models being compared. This was achieved by utilizing the 2007–2008 data set, which was not used for derivation of any of the models considered. The main gauge of comparison was each model's ability for discrimination, which can be defined as the ability of a model to accurately differentiate two classes of outcomes such as survival and death.^{2, 9} These characteristics were measured by the concordance statistic (c statistic).^{10, 11} The jackknife method was used to calculate the p values for comparison of c statistics.¹² For calculation of the current MELD, the following formula was used: $11.2 \times \log_e(\text{INR}) + 9.57 \times \log_e(\text{creatinine, mg/dl}) + 3.78 \times \log_e(\text{bilirubin, mg/dl}) + 6.43$, with a lower bound of 1 for all three variables and an upper bound of 4 for serum creatinine. The MELDNa score was calculated by: $\text{MELD} - \text{Na} - [0.025 \times \text{MELD} \times (140 - \text{Na})] + 140$ where Na was bounded at 125 and 140. The SRTR MELD score was obtained by: $1.266 \log_e(1 + \text{creatinine}) + 0.939 \log_e(1 + \text{bilirubin}) + 1.658 \log_e(1 + \text{INR})$.

Results

Patient Characteristics

A total of 28,131 registrants on the waiting list for liver transplantation met the inclusion criteria and had completed data for this study, including 14,190 in the model development set (2005–2006) and 13,941 in the model validation set (2007–2008). Patients' baseline information is presented in Table 1. In the total population, the median age was 54 and majority of patients were white males. Underlying liver disease was most commonly due to hepatitis C (43%) with a median MELD score at presentation of 15 (range 6 – 40). There were no clinically important differences in baseline characteristics between the derivation and validation cohorts.

In the model derivation data set (n=14,190), 7% died and 30% received a transplant within 90 days, whereas 64% remained on the waiting list 90 days after listing. A small fraction (0.14%, n=20) withdrew from the list for reasons other than transplantation or being too ill. In the model validation data set (n=13,941), 29% underwent liver transplantation and 7% died within 90 days after being placed on the waiting list. Most of the remaining patients (64%) stayed on the list, whereas 38 (0.27%) withdrew from the list within 90 days.

Optimizing the MELD Score

Smoothing splines (Figure 1) were used to determine the functional relationship between bilirubin, creatinine, and INR and the risk of death in the Cox model. The serum bilirubin (Figure 1a) displayed a linear relationship in the Cox model with risk of death for a wide range of bilirubin values. The significance of bilirubin below the level of 1mg/dl is questionable in part because of the few events as suggested by the rapidly widening confidence interval. Based on this observation and in keeping with the original MELD score, the coefficient for bilirubin was fit while a lower bound of 1.0mg/dl was retained (Figure 1b).

The serum creatinine (Figure 1c) demonstrated a triphasic pattern with risk of death, which was linear between 0.8mg/dl and 3.0mg/dl, whereas the effect of creatinine above and below

the range changed direction with rapidly widening confidence interval. Based on this pattern, we adopted a lower and upper bound of 0.8mg/dl and 3.0mg/dl with a linear fit in between (Figure 1d). This change would affect 2.2% of patients, who had serum creatinine > 3.0mg/dl but less than the previous bound of 4.0mg/dl.

Figure 1e demonstrates that INR has a yet different pattern from the other two variables. It has a parabolic shape in which the rise in the risk of death became less steep as INR increased beyond 3.0. Based on this observation, we propose a new upper bound of 3.0 for INR, while keeping the existing lower bound of 1.0 (Figure 1f). This change on INR would affect 3.6% of patients on the wait-list.

Based on these considerations, the formula for the ReFit MELD score with optimized coefficients and updated upper and lower bounds are as follows:

$$\text{ReFitMELD} = 4.082 * \text{Log}_e(\text{bilirubin}_C) + 8.485 * \text{Log}_e(\text{creatinine}_C) + 10.671 * \text{Log}_e(\text{INR}_C) + 7.432$$

where the modified terms bilirubin_C = bilirubin bounded below by 1mg/dl; creatinine_C = creatinine capped by 0.8mg/dl below and 3mg/dl above; and INR_C = INR bounded by 1 below and 3 above. Patients receiving renal replacement therapy were automatically assigned the upper bound for creatinine (3mg/dl).

Incorporation of serum sodium: ReFit MELDNa

Figure 2 demonstrates that after adjusting for bilirubin, INR, and creatinine, 90-day waitlist mortality increased as the serum sodium decreased between 140mEq/L and 125 mEq/L. This relationship including a lower and upper bound at 125mEq/L and 140mEq/L, respectively, was statistically significant ($p < 0.01$). We then examined a possible interaction between serum sodium and the other components of the ReFit MELD score. There is a significant interaction between sodium and bilirubin in that the impact of serum sodium on mortality became smaller as the serum bilirubin increased ($p < 0.01$). This interaction was most pronounced when serum bilirubin was between 1 and 20mg/dl.

Based on these data, the following equation represents the updated MELDNa:

$$\begin{aligned} \text{ReFitMELN}a = & 4.258 * \text{Log}_e(\text{bilirubin}_C) + 6.792 * \text{Log}_e(\text{creatinine}_C) + \\ & 8.290 * \text{Log}_e(\text{INR}_C) + 0.652 * (140 - \text{Na}_C) - 0.194 * (140 - \text{Na}_C) * \text{Bili}_{CC} + 6.327, \end{aligned}$$

where the bilirubin_C , creatinine_C , and INR_C are defined as above and Na_C = Na bounded by 125mEq/l below and 140mEq/l above; and bili_{CC} is bilirubin bounded below by 1mg/dl and above by 20 mg/dl. Here again, patients on renal replacement therapy were assigned a creatinine of 3mg/dl.

Validation of ReFit MELD and ReFit MELDNa in comparison with existing models

Figure 3(a–c) displays the relationship of individual MELD variables with 90 day mortality in the 2007–2008 validation data set. Similar to Figure 1, the relative risk of 90 day mortality is shown for each variable (while adjusting for other components of the score) as a

black curve accompanied by the 95% confidence interval. This is superimposed by lines that represent the coefficients of ReFit MELD, SRTR MELD, and the original MELD models. For all three variables, the ReFit MELD fit more closely the 2007–2008 data than other models.

Table 2 formally compares these models by the model chi-squares and concordance (c-) statistics. The model chi-squares for the original and ReFit MELDNa increased by 107 and 111 respectively, relative to the existing MELD, whereas that for SRTR MELD decreased by 208. The ReFit MELDNa model provides a modest yet significant increase in the c-statistic in the prediction of death when compared to MELD, SRTR MELD (both $p = 0.0001$), and MELDNa, ($p=0.040$). The ReFit MELD, without the serum sodium variable, also demonstrates improved discrimination compared to the existing MELD ($p=0.020$) and SRTR MELD ($p=0.0001$). When considering discrimination among patients that are more realistic LTx candidates (MELD ≤ 15), the c-statistic for ReFit MELDNa of 0.8408 was larger than that for the other models; SRTR MELD: 0.8117 ($p=0.0001$); MELDNa: 0.8357 ($p=0.0044$); MELD: 0.8239 ($p=0.0001$). Likewise, for patients with MELD >15 the ReFit MELD without serum sodium yields an increased c-statistic of 0.8369 which represented a statistically significant improvement over the existing MELD ($p=0.0005$) and SRTR MELD ($p=0.0001$). Supplementary Figure 1 illustrates the relationship between the 90-day mortality and each of the four models considered. Overall the whole range of scores, the ReFit MELD and ReFit MELDNa as well as the original MELD had the most linear configuration, indicating a better performance than the SRTR model, which tended to overestimate the risk of mortality at high scores.

Projected Impact of Utilizing ReFit MELDNa for Liver Allocation

Figure 4 shows the correlation between the current MELD and refit MELDNa scores. As expected, there is overall agreement between the two scores. The horizontal and vertical lines of the figure consider hypothetical scenarios where the 13,945 patients represented in the validation data set are given the 3,816 livers that were available within the first 90 days of listing in the order determined by the respective score. Thus, patients in the right upper quadrant would have received an organ under both systems ($n=3357$) and those in the left lower quadrant ($n=10,125$) would not have been given an organ under either system. Those in the right lower quadrant ($n=459$) would have received a liver based on the current MELD score but not on the refit MELDNa, whereas those in the left upper ($n=459$) would have assigned a liver only under the refit MELDNa and not under the current MELD score. Thus, implementation of the new score will affect 3.3% ($459/13941$) of all waitlist registrants and 12.0% ($459/3816$) of all transplants.

Finally, we considered the potential impact of implementing the ReFit MELD score for liver allocation. While the best estimate may be obtained via a formal simulation program conducted by the Scientific Registry of Transplant Recipients, a useful insight may be gained by comparing survival of patients with discordant waitlist outcomes projected in Figure 4, namely those in the left upper and right lower quadrants. The 90-day Kaplan-Meier probability of mortality in the group that would be missed by the existing MELD but picked up by the refit MELDNa (left upper quadrant) was 15.6% compared to 7.2% in those

who would have been favored by the existing MELD (log rank test $p < 0.01$). In terms of the total number of deaths, there would have been 324 deaths under the existing MELD compared to 295 under refit MELDNa within 90 days, the difference being 29 fewer deaths ($p < 0.01$).

Discussion

The Model for End Stage Liver Disease successfully predicts 90 day mortality in patients with cirrhosis, and results in improved liver transplant wait list survival.^{1, 2} Methods to improve its predictive capabilities have entailed adding clinical variables or optimizing coefficients for the existing variables. Herein, we have described an improved model fit and waitlist mortality prediction through further refinement of the MELD coefficients, introduction of new upper and lower bounds, and inclusion of serum sodium.

The original MELD variable coefficients were derived from patients undergoing Transjugular Intrahepatic Portosystemic Shunt (TIPS) procedures, and subsequently validated in ambulatory, hospitalized, and historical cohorts of patients with mostly severe liver disease.¹³ In this study, we have re-estimated the coefficients for the original MELD variables – bilirubin, creatinine, INR – in patients who were *actually* placed on the liver transplant waiting list in the US from 2005–2006 and validated these coefficients in 2007–2008 wait list patients.

The upper and lower bounds were re-evaluated for bilirubin, creatinine, and INR. In the existing MELD model, there is a lower bound for bilirubin, INR, and creatinine (all set to 1), and an upper bound for creatinine (4mg/dl). Since these bounds were set entirely based on clinical intuition of the policy making body when the MELD score was implemented, our work represents the first formal examination of these bounds. Whereas bilirubin showed a continuously linear pattern, all other variables had a linear element restricted by lower and upper bounds. The results of this analysis suggest an upper bound for INR provides a better fit to the data. This novel proposition addresses in part previous concerns that the INR may not be an ideal marker to gauge coagulopathy associated with liver dysfunction by limiting the impact of outliers.^{14,15} Our work suggests updated bounds for creatinine will provide a better fit for the data. Based on visual inspection of Figure 1(c), statistical examination of other potential cut-off values and clinical considerations, we decided on a lower bound of 0.8 mg/dl and an upper bound of 3.0 mg/dl. It is well known that serum creatinine is influenced by the muscle mass, which is frequently decreased in patients with end stage liver disease.^{16–24} The new lower bound of 0.8 makes intuitive sense for the clinician who is aware that in patients with ESLD, normal creatinine does not necessarily mean normal renal function.⁶ Lowering the upper bound from 4.0 to 3.0 should gain support from transplant physicians who have felt that there is too much emphasis on renal function in the MELD score and that patients with a component of intrinsic renal function are disproportionately advantaged under the current scheme.

With regard to the effect of serum sodium on mortality, this work is confirmatory to previous results by us and others that serum sodium remains an important indicator of mortality in patients with ESLD.⁶ In our previous work, we demonstrated that the

importance of sodium became less as the MELD score increased. This current analysis verified this interaction, which is further attributed to the bilirubin component of the MELD score – the impact of hyponatremia is greatest if bilirubin is low, whereas in patients who are already ill with bilirubin higher than 20mg/dl, hyponatremia did not confer any higher risks. Further, we demonstrate that even when the MELD score was optimized, serum sodium continues to play an important role.

However, the liver transplant community has been slow to incorporate serum sodium in organ allocation with lingering skepticism about its potential for being subject to manipulation. We are reminded that, when the MELD score was first proposed, similar concerns were raised about INR and creatinine. Of the variables being considered, INR is by far the easiest to manipulate. One could simply take coumadin for a few days to raise INR and then discontinue. A similar gaming may be possible by acutely dehydrating a patient to induce prerenal azotemia and elevated creatinine. In the past eight years while MELD has been used, there has not been a serious accusation that these manipulations have been practiced for willful manipulation of the system. We believe that all involved in the care of transplant patients, having the patient's best interest in our hearts, subscribe to the principle of 'primum non nocere'. Another point is that data are scarce about the extent to which serum sodium can be lowered by increasing free water intake in patients with liver cirrhosis. This concern chiefly applies to patients with low MELD and normal sodium, as the impact of sodium becomes progressively smaller in patients with high MELD. Impaired free water clearance is thought to be initiated by arginine vasopressin secretion as a result of the cascade of hemodynamic changes that occur in patients with hepatic decompensation. Obviously, massive amounts of water drinking such as seen in individuals with primary polydipsia can cause hyponatremia, but it is not certain whether it is possible to manipulate serum sodium in our patients to the degree that will substantially alter probability of organ allocation. Nonetheless, we present in this paper both ReFit MELD and ReFit MELDNa and demonstrate that if the sodium data are missing or not used, the ReFit MELD still represents an improvement over existing models. We submit that the nation's liver allocation system will be better served by the updated MELD, with or without the inclusion of the serum sodium data.

Finally, the comparison of the various models, as presented in Table 4, is instructive. The concordance statistic has been used widely as an indicator of model discrimination. As we have pointed out previously, the limitation of c-statistics is that it compares the proportion of subjects whose rank order changes but it is insensitive in the magnitude of the change. In other words, a small change in ranking in a large number of patients will yield a big improvement in the c-statistic, whereas the importance of a big change in ranks that affect a small number of patients will be underestimated. With this caveat, the comparison of the models shows that the latest update using best bounds and coefficients only resulted in a modest gain. This suggests that it is unlikely that further adjustment of existing models will produce a large improvement in the model prediction. We suspect that given the frequency of random events that occur in the natural course in a given individual subject, models with c-statistics above 0.9 are difficult and likely impossible to develop.

In conclusion, we presented in this work optimized versions of the MELD and MELDNa scores based on the most recent waitlist patients with end stage liver disease. These models, for the first time, incorporate coefficients as well as lower and upper bounds to individual variables that have been optimized in the very population of patients in whom the MELD score is being applied. There were demonstrable improvements in the model performance with the optimized models compared to existing ones. We propose that adoption of the ReFit MELD and/or ReFit MELDNa score will provide more accurate means to assess waitlist mortality and thus allow most efficient allocation of donated organs.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations

MELD	Model for End Stage Liver Disease
LTx	liver transplantation
INR	international normalized ratio
SRTR	Scientific Registry of Transplant Recipients
MELDNa	Model for End Stage Liver Disease - Sodium
Na	serum sodium
OPTN	Organ Procurement and Transplantation Network
STAR	Standard Transplant Analysis and Research
c-	concordance
g	gram
dl	deciliter
mg	milligram

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(a)

(b)

(c)

(d)

(e)

(f)

Figure 1.

The relation between risk of 90 day mortality and individual MELD variables.

- a. The pattern for serum bilirubin in the 2005–6 data (adjusted for creatinine and INR).
- b. ReFit bilirubin coefficient (lower bound=1.0mg/dl) superimposed on Figure 1a
- c. The pattern for serum creatinine in the 2005–6 data (adjusted for bilirubin and INR)
- d. ReFit creatinine coefficient (lower bound = 0.8mg/dl, upper bound = 3.0mg/dl) superimposed on Figure 1c.
- e. The pattern for serum INR in the 2005–6 data (adjusted for bilirubin and creatinine)

f. ReFit INR coefficient (lower bound = 1.0, upper bound = 3.0) superimposed on Figure 1e.

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Na and Relative Risk of Death at 90 Days Adjusted for bilirubin, creatinine and INR

Figure 2.
The relation between serum sodium concentration and the relative risk of death after adjustment for the ReFit MELD Score

(a)

(b)

(c)

Figure 3.

Comparison of model fit in the validation data (2007–8): The refit coefficient (blue) fits the 2007–8 data better than the current MELD (green) and SRTR MELD (red) for all variables.

- a. Bilirubin
- b. Creatinine
- c. INR

Figure 4.

Correlation between the existing MELD and refit MELDNa scores in the validation data set (2007–8). The horizontal and vertical lines represent 3,816 livers that were available within the first 90 days of listing.

Table 1

Characteristics of Liver Transplant Waitlist Registrants

Variable	2005–2006 (N=14190)	2007–2008 (N=13941)	Total (N=28131)
Age at listing	53 (48, 59)	54 (48, 59)	54 (48, 59)
Male (n,%)	9090 (65%)	8694 (64%)	17784 (64%)
Race/Ethnicity (n,%)			
. African American	1073 (8%)	1113 (8%)	2186 (8%)
. Asian	425 (3%)	472 (3%)	897 (3%)
. Hispanic	1993 (14%)	2038 (15%)	4031 (14%)
. Other	339 (2%)	412 (3%)	751 (3%)
. White	10360 (73%)	9906 (71%)	20266 (72%)
Diagnosis (n,%)			
. Alcoholic	2564 (18%)	2439 (17%)	5003 (18%)
. Cholestatic	1268 (9%)	1152 (8%)	2420 (9%)
. Hepatitis C	6263 (44%)	5959 (43%)	12222 (43%)
. Other	4095 (29%)	4391 (31%)	8486 (30%)
MELD Score	15 (12, 21)	16 (12, 21)	15 (12, 21)
Bilirubin (mg/dl)	2.5 (1.4, 4.8)	2.5 (1.4, 5.0)	2.5 (1.4, 4.9)
Creatinine (mg/dl)	1.0 (0.8, 1.4)	1.0 (0.8, 1.4)	1.0 (0.8, 1.4)
INR	1.4 (1.2, 1.7)	1.4 (1.2, 1.7)	1.4 (1.2, 1.7)
Sodium (mEq/l)	137 (133, 139)	137 (133, 139)	137 (133, 139)
Status at 90 days after registration on waiting list			
. Alive	9012 (64%)	8974 (64%)	17986 (64%)
. Died	964 (7%)	948 (7%)	1912 (7%)
. OLT	4194 (30%)	3981 (29%)	8175 (29%)
. Withdrawn	20 (0%)	38 (0%)	58 (0%)

Data presented are median and interquartile range except where proportions (%) are shown.

Table 2

Model discrimination in the validation data set (2007–8)

Model	Model Chi-Square	Concordance (SE)
Existing MELD	2263	0.8653(0.0062)
SRTR MELD	2055 (–208)	0.8581(0.0063)
ReFit MELD	2294(+31)	0.8675(0.0062)
MELDNa	2370 (+107)	0.8758(0.0059)
ReFit MELDNa	2374 (+111)	0.8778(0.0058)

MELD, Model For End Stage Liver

Disease; Na, Sodium; SRTR, Scientific Registry of Transplant Recipients; SE, Standard Error