MA678 Midterm Project: Modeling Length of Rehabilitation Stay for Spinal Cord Injury Patients

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Abstract

Spinal cord injuries (SCI) are costly lifelong medical conditions. The first weeks and months after an injury are crucial to recovery, but many variables impact the timeline of patient recovery. Both health care professionals and patients can benefit from an accurate prediction of the length of hospitalization. Using fixed effect linear and multi-level linear models, I modeled the number of days patients spent hospitalized in inpatient rehabilitation facilities following a SCI. Although still imperfect, the mixed effect model is more effective at modeling the length of hospitalization in rehabilitation (rehab), since it uses a random slope and intercept based on the neurological level of injury.

Introduction

Spinal cord injury (SCI) is a serious condition where the spinal cord is damaged and has a decreased ability to send and receive nerve signals. Symptoms include paralysis, pain or pressure in the neck or back, weakness and inability to move any part of the body, and difficulty breathing (Mayo Clinic, 2021). Jain et al., 2015 estimates that in the United States, there are approximately 54 cases of SCI per 1 million. Medical professionals divide the spinal cord into neurological segments. For analysis, the cervical and thoracic segments were selected. Each named segment roughly corresponds to muscle groups and functions, and damage at a level closer to the head likely indicates more serious impairment. For example, if there is an injury at the C4 neurological level, the individual will have weak deltoids (in the shoulder region) and reduced strength and sensation everywhere below this region (Young, 2021). Since 1973 the National Spinal Cord Injury Model Systems have been collecting data. The database of unidentifiable patient information is well managed and extensively documented. These data come from twenty-nine facilities across the United States. The database includes information for 32,159 individuals, and collected data include, injury year, age at injury, sex, use of mechanical ventilation, functional independence scores, and American Spinal Cord Injury Association (ASIA) motor index scores, among many others. This report focuses on modeling the number of days a patient spends hospitalized in inpatient rehabilitation (rehab). The rehab process varies for each patient but can include interventions from physicians, physical, occupational, and speech therapists, case managers, social workers, mental health providers, nurses, dietitians, and respiratory therapists. Rehab can include teaching the patient and educating the family on breathing and swallowing strategies, mobility training, safety techniques, and daily living activities (Spinal Cord Injury Rehabilitation—Spaulding Rehab). A model of predicted days spent in rehab is relevant to health care professionals, so they can plan treatment for patients and estimate the number of patients they can accommodate in a given time. This information is also relevant to patients and their families, so they can plan and envision the patient's recovery timeline.

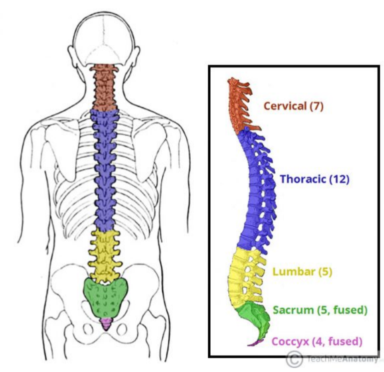

Figure 1: Source: Jones, Olivia. The Vertebral Column, 23 September 2020. https://teachmeanatomy.info/back/bones/vertebral-column/

Table 1: Variable descriptions and notes. More information can be found in the NSCISC Public Data Dictionary that is included in the data download

Variable	Abbreviation	Definition	Notes
Total days inpatient rehab	AHDaSyRb_log	Total length of stay in inpatient rehab unit until discharge	log transformed
Days from injury to rehab admission	AI2RhADa_log	Number of days from injury to the inpatient rehab admission	log transformed
BMI	ABMI_st	Calculated from provided height and weight	centered at 0 and scaled by st.dev
Age at injury	AInjAge	Age of patient (years) on the date the SCI occurred	categorical
Functional independence motor score	AFScorRb	Total score of measures including self care, sphincter control, mobility, locomotion, and eating	valid range = 13-91
Use of mechanical ventilation	AUMVAdm_rcc	Any use of mechanical ventilation used at admission to rehab?	recoded to be binary (1 = yes. 0 = no)
Vertebral injury	AVertInj	Was there a spinal fracture and/or dislocation?	binary (1 = yes. 0 = no)
Spinal surgery	ASpinSrg	Was surgery performed? Includes limited list of relevant surgeries.	binary (1 = yes. 0 = no)
Associated injury	AAsscInj	Was there an additional injury? Includes a limited list	binary (1 = yes. 0 = no)
Neurologic level of injury	ANurLvlR_rcc	The highest point on the spine where normal sensory and motor function can be identified at admission to rehab	Categorical. Selected C01-C08 and T01-T12

Methods

First, I selected relevant variables(Table 1). Although the data set was well organized and documented, I removed missing values and values coded as unknown. In addition, I centered the BMI variable at 0 and scaled it by the standard deviation. I log-transformed the variables that measured days (AHDaSyRb and AI2RhADa). Any additional modifications to the data set can be found in the `clean_data.R` file. I selected only cervical and thoracic injuries for inclusion in the analysis since lumbar and sacral level injuries make up less than 2% of the data. In addition, individuals 0-14y were excluded from the data due to a high rate of missing data. After removing the missing data and the excluded variables, the data set includes 5,168 individuals. Next, I fit a fixed-effect model and random-effect model to predict log(days hospitalized in inpatient rehab). The random effect model includes a random intercept and random slope for the log(days from injury to inpatient rehab admission) based on neurological level of injury.

Fixed Effect Model: $AHDaSyRb\_log = AI2RhADa\_log + ABMI\_st + AInjAge + AFScorRb + AUMVAdm\_rcc + AVertInj + ASpinSrg + AAsscInj + ANurLvlR\_rcc$

Random Effect Model: $AHDaSyRb\_log = AI2RhADa\_log + ABMI\_st + AInjAge + AFScorRb + AUMVAdm\_rcc + AVertInj + ASpinSrg + AAsscInj + ANurLvlR\_rcc + (1 + AI2RhADa\_log|ANurLvlR\_rcc$

I anticipate that the level of injury will impact the baseline or intercept of the model. The intercept shows the expected average log(days) hospitalized in inpatient rehab if all predictors are set to zero. I anticipate that neurological level of injury would also have a varied impact on the slope of log(days) from injury to rehab admit on the log(days) hospitalized in inpatient rehab. I evaluated the models using Stan's posterior predictive checks and leave-one-out validation (loo).

Results

The mean log(days) hospitalized in inpatient rehab varies based on the neurological level of SCI (Figure 2). I expected high-level injuries (injuries that occur closer to the head) to have longer hospital stays on average. The average stay was 53 $\pm$ 1 days (99.5% confidence interval of the mean(CI)). Nearly 23% of individuals in the data set had a C04 level injury. Individuals with a C04 level injury had an average rehab stay of 62 $\pm$ 4 days (99.5% CI). This was the longest average stay of all injury levels. In addition, the slope of the line that compares log(days) from injury to rehab admission to the log(days) spent in inpatient rehab also varies based on the neurological level of injury (Figure 3). This affirms the use of a multi-level model with a random slope. The various levels of neurological injury have different estimated slopes when predicting log(days) hospitalized in inpatient rehab from the variable log(days)

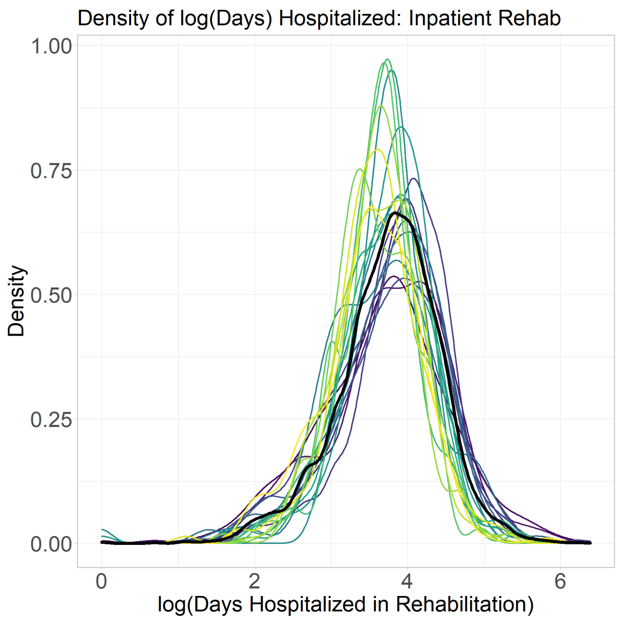

Figure 2: Density of log(days) hospitalized in inpatient acute and subacute rehabilitation unit. The black line is the density of all selected data which excludes individuals who were never admitted either due to recovery or death. Each colored line represents a distribution of log(days) for a given neurologic level of injury.

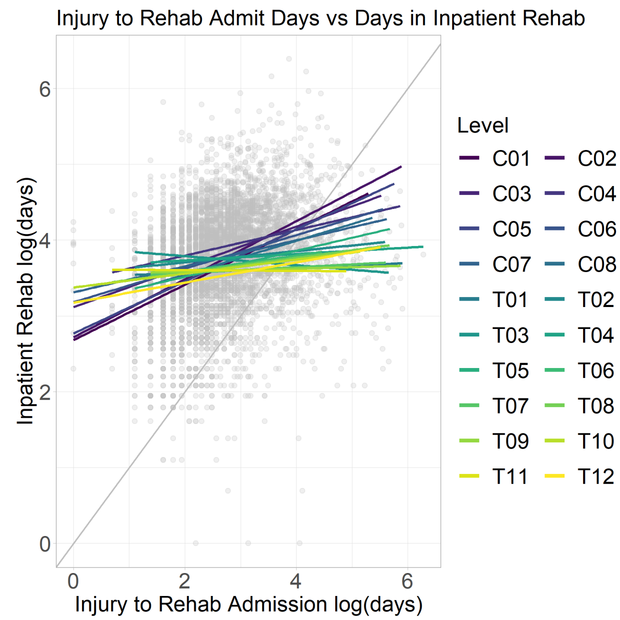

Figure 3: log(Days) from injury to rehab admission compared to log(days) spent in inpatient rehab. The lines are colored by the neurologic level of injury. Darker purple corresponds to higher on the spine, and yellow coresponds to lower on the spine. As the injury level decreases (moves down the spine starting from the head), it appears that the slope also decreases.

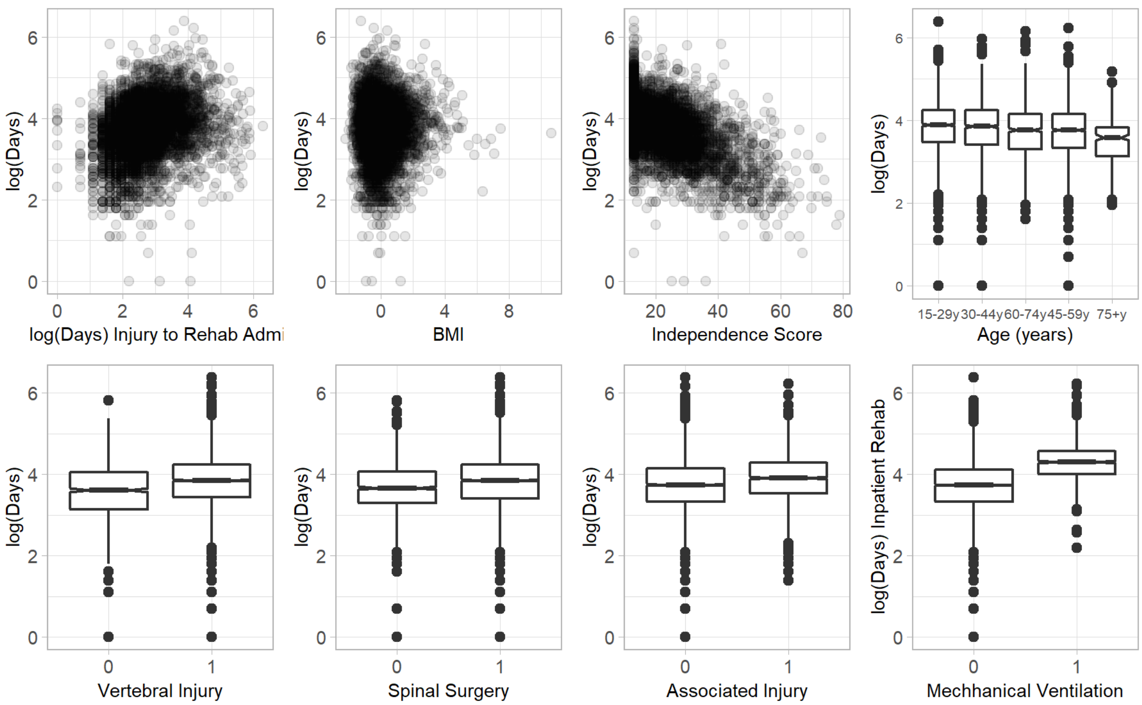

Figure 4: Variables compared to log(days) hospitalized in inpatient rehab. These variables were selected for inclusion in the models. Continuous variables are plotted in a scatterplot. BMI has been centered at zero and scaled to have a standard deviation of 1. Categorical or binary variables are displayed as boxpots.

from injury to rehab admission. Figure 3 suggests that cervical spine level injury categories have a steeper slope when compared to the slope of the thoracic level injuries, which have slopes closer to zero.

Examining the plot of comparisons, patterns, and trends in the data are revealed (Figure 4). As shown in Figure 3, a longer time from injury to rehab admission corresponds to a longer stay in rehab, on average. Individuals who have a more complex health situation or a more traumatic injury will probably take longer to reach a point where they can be admitted to inpatient rehab where they can begin the recovery process, and they will probably spend a longer time recovering. A higher ASIA Independence Score corresponds to a shorter stay in rehab. This makes sense because if an individual starts out being able to feed themselves or go to the bathroom on their own, have less work to do in rehab when compared to someone who is less independent. Based on the notched box plots, individuals who have additional injures (AVertInj, AAsscInj), and surgeries (ASpinSrg) have a longer stay in rehab when compared to those without secondary injuries or traumas. Individuals who need ventilation (AUMVAdm_rcc) also have longer stays compared to those without the need for ventilator assistance. Again these relationships make logical sense when thinking about the impact of additional trauma on the length of recovery.

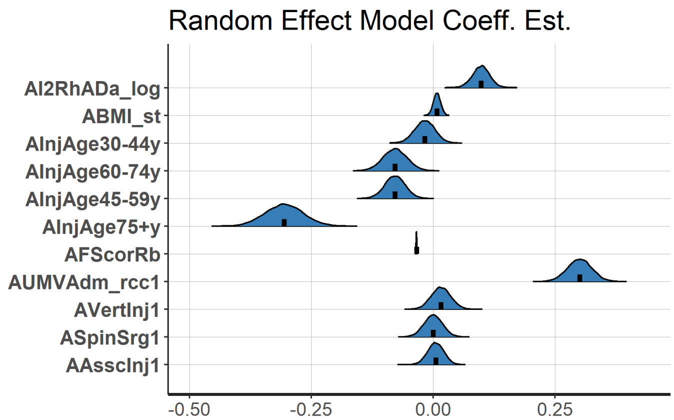

Figure 5: The parameter estimate and predicted density for the nine of the parameters that are fixed in the random effect model. The estimate for those 75 and older is negative, so individuals in this group spend less time in rehabilitation than someone who is 15-29 years old. It also seems that vertebral injuries, spinal surgery, and associated injuries do not play a strong role in the length of time in rehab since their coefficients are close to zero.

As mentioned, I fit two models to examine the differences between the fixed effect model and the random effect model. For both, I used Bayesian methods for the regression. For the random effect model, Figure 5 shows the coefficient estimates for variables that do not have a random component, excluding the intercept. The binary ventilator variable has the largest coefficient suggesting a stronger influence in the model. If someone used a ventilator, their log(days) hospitalized in inpatient rehab is 0.3 log(days) greater than someone with the same characteristics without ventilator use. Please refer to the appendix for detailed outputs of both models and model validation. A leave one out cross-validation that compares the fixed effect model and the random effect model shows that the random effect model is a better fit. The `p_loo` value returned from the validation indicates the number of "effective parameters." In the random effect model, approximately 83% (43/52) of the parameters are effective. In the fixed-effect model, the `p_loo` value indicates a weak predictive power of the model.

Looking at the caterpillar plots, we can see the random slope and intercept estimates for the fitted random effect model (Figure 6). In general, injuries closer to each other, for example (T06, T07, and T08) have similar coefficient estimates. As the injury level moves down the spine (head to neck to lower back), the coefficient estimate for that neurologic level of injury does not also decrease. In contrast, if a neurological level has an above average intercept, it also often has a below average slope. The most prominent example of this pattern is for injuries at the T03 level since this level has the largest intercept estimate and the smallest slope estimate.

I selected the median value for numeric inputs and the most common input for categorical variables and used posterior prediction with 15,000 draws to estimate the predicted log(days) spent hospitalized in inpatient rehabilitation. I also included each of the neurological levels of injury. With this simple prediction, individuals with levels T04, T11, and T03 have the longest expected stay in rehab. In contrast, individuals with C01, C02, and C05 level injuries have the shortest estimated stay.

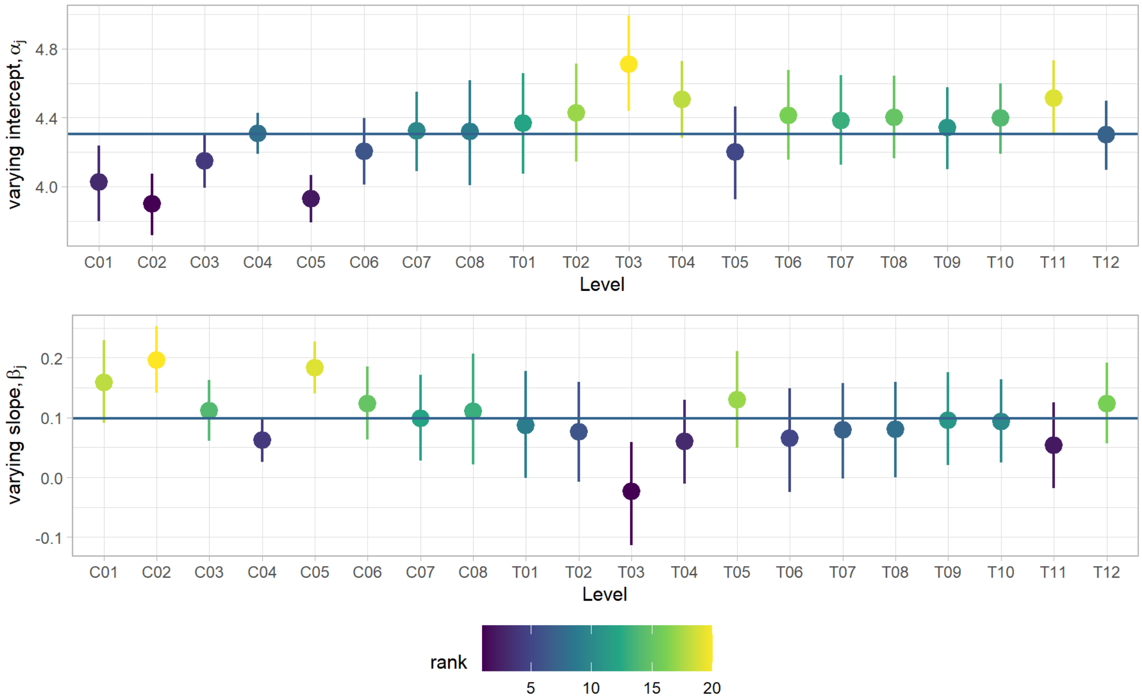

Figure 6: The caterpillar plots show the point estimate of the random intercepts at top and slopes at bottom and the 95 credible interval. The x-axis lists the level of neurologic injury from highest level to lowest when read left to right. The color represents the "rank" (1 = largest coefficient estimate. 20 = smallest coefficient estimate) of the intercept or slope. The dark horizontal line shows the average of the coefficients.

Table 2: Predicted log(days) hospitalized in inpatient rehab. All input variables have been held constant and only neurological level of injury changes

	Injury Level	Mean log(days)	99.5% CI of Mean	Std.Dev. log(days)
Largest Predicted log(days)				
1	T04	4.00	0.01	0.53
2	T11	3.99	0.01	0.53
3	T03	3.98	0.01	0.53
Smallest Predicted log(days)				
18	C01	3.77	0.01	0.53
19	C02	3.75	0.01	0.53
20	C05	3.74	0.01	0.53

Discussion

In the random effect model, several elements were unexpected and should be investigated further. It was surprising that when all else is equal, patients with lower levels of injury (further from the head and less of their body impacted) were predicted to have longer stays. This is the opposite of what I was expecting. This could be because they have more body functions, so there are more areas where they can improve and progress. In contrast, individuals with high levels of injuries are more limited since more of their body is impacted by the injury. Perhaps healthcare institutions more quickly discharge those with little hope of recovery to focus their resources on individuals who have potential to recover independence. In addition, with real patients, variables are not held constant. Perhaps most individuals with a certain neurological level of injury have some characteristic that has not been included in the model. Additionally, I was not expecting that individuals in the 75+ age group would have a shorter duration of rehab hospitalization. Perhaps this is due to a similar phenomenon as the injury level. Individuals who are older and already lack some functions are more quickly discharged since there is less room to improve. The result could also be due to a lack of data for this population. SCIs are most common in young people, and in the data set used for the model, less than 5% of patients were in the 75+ age group. The results of the prediction also deserve further investigation. I was surprised that when all else is equal, individuals with C01 level injuries have one of the shortest expected stays in rehab. Before this analysis, I thought that individuals whose injuries were closer to the head would have the longest stay in rehab, since most of their body would be impacted by the injury.

Works Cited

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Appendix:

Summary of fixed effect model

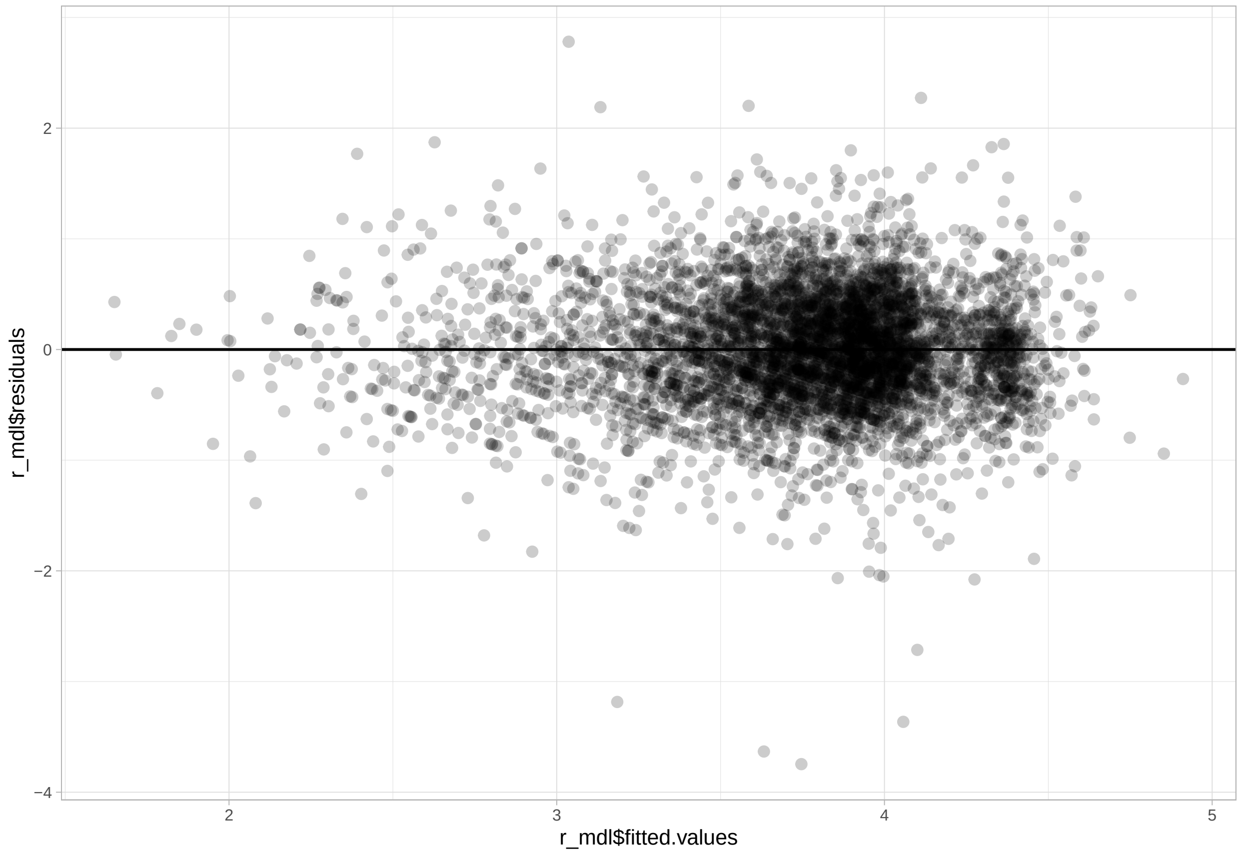
	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	4.15	0.00	0.06	4.08	4.15	4.23	2201	1
AI2RhADa_log	0.11	0.00	0.01	0.10	0.11	0.12	14841	1
ABMI_st	0.01	0.00	0.01	0.00	0.01	0.02	13648	1
AInjAge30-44y	-0.02	0.00	0.02	-0.05	-0.02	0.01	10208	1
AInjAge60-74y	-0.07	0.00	0.02	-0.10	-0.07	-0.04	8579	1
AInjAge45-59y	-0.07	0.00	0.02	-0.10	-0.07	-0.05	8408	1
AInjAge75+y	-0.30	0.00	0.04	-0.35	-0.30	-0.25	12297	1
AFScorRb	-0.03	0.00	0.00	-0.04	-0.03	-0.03	13442	1
AUMVAdm_rcc1	0.32	0.00	0.02	0.28	0.32	0.35	12387	1
AVertInj1	0.02	0.00	0.02	-0.01	0.02	0.04	13249	1
ASpinSrg1	0.00	0.00	0.02	-0.02	0.00	0.03	15823	1
AAsscInj1	0.00	0.00	0.02	-0.02	0.00	0.02	14346	1
ANurLvlR_rccC02	-0.02	0.00	0.05	-0.08	-0.02	0.05	1490	1
ANurLvlR_rccC03	0.00	0.00	0.05	-0.06	0.00	0.06	1472	1
ANurLvlR_rccC04	0.03	0.00	0.04	-0.03	0.03	0.08	1321	1
ANurLvlR_rccC05	-0.02	0.00	0.04	-0.07	-0.02	0.04	1358	1
ANurLvlR_rccC06	0.10	0.00	0.05	0.04	0.10	0.17	1749	1
ANurLvlR_rccC07	0.16	0.00	0.06	0.09	0.16	0.24	2467	1
ANurLvlR_rccC08	0.22	0.00	0.07	0.13	0.22	0.32	3242	1
ANurLvlR_rccT01	0.19	0.00	0.08	0.09	0.19	0.29	3341	1
ANurLvlR_rccT02	0.22	0.00	0.07	0.13	0.22	0.30	2675	1
ANurLvlR_rccT03	0.19	0.00	0.06	0.11	0.19	0.26	2031	1
ANurLvlR_rccT04	0.25	0.00	0.06	0.18	0.25	0.32	1985	1
ANurLvlR_rccT05	0.13	0.00	0.06	0.05	0.13	0.21	2363	1
ANurLvlR_rccT06	0.16	0.00	0.06	0.08	0.16	0.24	2245	1
ANurLvlR_rccT07	0.17	0.00	0.07	0.09	0.17	0.26	2837	1
ANurLvlR_rccT08	0.20	0.00	0.06	0.13	0.20	0.28	2353	1
ANurLvlR_rccT09	0.18	0.00	0.06	0.10	0.18	0.26	2271	1
ANurLvlR_rccT10	0.24	0.00	0.05	0.17	0.24	0.30	1737	1
ANurLvlR_rccT11	0.26	0.00	0.06	0.18	0.25	0.33	1974	1
ANurLvlR_rccT12	0.23	0.00	0.06	0.15	0.22	0.30	2048	1
sigma	0.53	0.00	0.01	0.52	0.53	0.53	15122	1
mean_PPD	3.75	0.00	0.01	3.74	3.75	3.77	13292	1
log-posterior	-4038.79	0.06	4.01	-4044.05	-4038.44	-4033.93	4220	1

Summary of mixed effect model

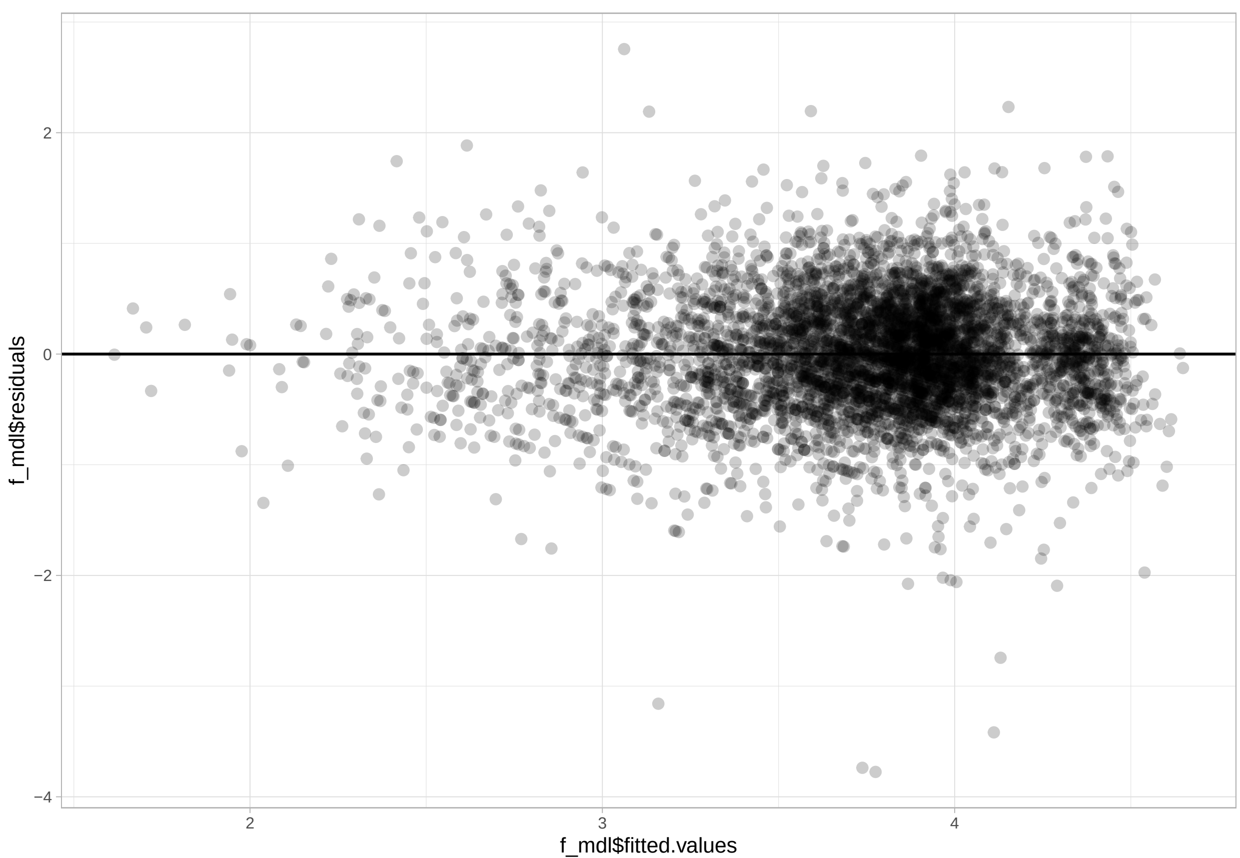
	mean	mcse	sd	10%	50%	90%	n_eff	Rhat
(Intercept)	4.31	0.00	0.07	4.22	4.31	4.39	5049	1
AI2RhADa_log	0.10	0.00	0.02	0.08	0.10	0.12	5020	1
ABMI_st	0.01	0.00	0.01	0.00	0.01	0.02	17446	1
AInjAge30-44y	-0.02	0.00	0.02	-0.04	-0.02	0.01	13153	1
AInjAge60-74y	-0.08	0.00	0.02	-0.11	-0.08	-0.05	12516	1
AInjAge45-59y	-0.08	0.00	0.02	-0.11	-0.08	-0.05	11959	1
AInjAge75+y	-0.31	0.00	0.04	-0.36	-0.31	-0.26	15742	1
AFScorRb	-0.03	0.00	0.00	-0.04	-0.03	-0.03	18763	1
AUMVAdm_rcc1	0.30	0.00	0.03	0.27	0.30	0.33	19122	1

AVertInj1	0.02	0.00	0.02	-0.01	0.02	0.04	16746	1
ASpinSrg1	0.00	0.00	0.02	-0.02	0.00	0.02	19187	1
AAsscInj1	0.01	0.00	0.02	-0.02	0.01	0.03	18315	1
b[(Intercept) ANurLvlR_rcc:C01]	-0.28	0.00	0.12	-0.43	-0.28	-0.13	9888	1
b[AI2RhADa_log ANurLvlR_rcc:C01]	0.06	0.00	0.04	0.01	0.06	0.11	11084	1
b[(Intercept) ANurLvlR_rcc:C02]	-0.41	0.00	0.10	-0.54	-0.41	-0.28	8798	1
b[AI2RhADa_log ANurLvlR_rcc:C02]	0.10	0.00	0.03	0.06	0.10	0.14	10745	1
b[(Intercept) ANurLvlR_rcc:C03]	-0.16	0.00	0.09	-0.27	-0.16	-0.04	6658	1
b[AI2RhADa_log ANurLvlR_rcc:C03]	0.01	0.00	0.03	-0.02	0.01	0.05	7916	1
b[(Intercept) ANurLvlR_rcc:C04]	0.00	0.00	0.08	-0.10	0.00	0.10	5867	1
b[AI2RhADa_log ANurLvlR_rcc:C04]	-0.04	0.00	0.02	-0.07	-0.04	-0.01	7080	1
b[(Intercept) ANurLvlR_rcc:C05]	-0.38	0.00	0.08	-0.48	-0.38	-0.27	6822	1
b[AI2RhADa_log ANurLvlR_rcc:C05]	0.09	0.00	0.03	0.05	0.08	0.12	8872	1
b[(Intercept) ANurLvlR_rcc:C06]	-0.10	0.00	0.10	-0.23	-0.10	0.03	8493	1
b[AI2RhADa_log ANurLvlR_rcc:C06]	0.02	0.00	0.03	-0.02	0.02	0.07	9418	1
b[(Intercept) ANurLvlR_rcc:C07]	0.02	0.00	0.12	-0.14	0.02	0.17	11023	1
b[AI2RhADa_log ANurLvlR_rcc:C07]	0.00	0.00	0.04	-0.05	0.00	0.05	11528	1
b[(Intercept) ANurLvlR_rcc:C08]	0.01	0.00	0.15	-0.18	0.02	0.20	13996	1
b[AI2RhADa_log ANurLvlR_rcc:C08]	0.01	0.00	0.05	-0.04	0.01	0.07	13592	1
b[(Intercept) ANurLvlR_rcc:T01]	0.06	0.00	0.15	-0.13	0.06	0.25	13940	1
b[AI2RhADa_log ANurLvlR_rcc:T01]	-0.01	0.00	0.05	-0.07	-0.01	0.05	14001	1
b[(Intercept) ANurLvlR_rcc:T02]	0.12	0.00	0.14	-0.06	0.12	0.30	12778	1
b[AI2RhADa_log ANurLvlR_rcc:T02]	-0.02	0.00	0.04	-0.08	-0.02	0.03	12687	1
b[(Intercept) ANurLvlR_rcc:T03]	0.40	0.00	0.14	0.23	0.40	0.59	9492	1
b[AI2RhADa_log ANurLvlR_rcc:T03]	-0.12	0.00	0.04	-0.18	-0.12	-0.07	9596	1
b[(Intercept) ANurLvlR_rcc:T04]	0.20	0.00	0.12	0.05	0.20	0.35	10558	1
b[AI2RhADa_log ANurLvlR_rcc:T04]	-0.04	0.00	0.04	-0.09	-0.04	0.01	11452	1
b[(Intercept) ANurLvlR_rcc:T05]	-0.11	0.00	0.14	-0.28	-0.10	0.07	12433	1
b[AI2RhADa_log ANurLvlR_rcc:T05]	0.03	0.00	0.04	-0.02	0.03	0.08	12549	1
b[(Intercept) ANurLvlR_rcc:T06]	0.11	0.00	0.13	-0.06	0.10	0.28	10381	1
b[AI2RhADa_log ANurLvlR_rcc:T06]	-0.03	0.00	0.04	-0.09	-0.03	0.02	10788	1
b[(Intercept) ANurLvlR_rcc:T07]	0.08	0.00	0.13	-0.09	0.08	0.25	12319	1
b[AI2RhADa_log ANurLvlR_rcc:T07]	-0.02	0.00	0.04	-0.07	-0.02	0.03	12389	1
b[(Intercept) ANurLvlR_rcc:T08]	0.09	0.00	0.12	-0.06	0.09	0.25	10493	1
b[AI2RhADa_log ANurLvlR_rcc:T08]	-0.02	0.00	0.04	-0.07	-0.02	0.03	11029	1
b[(Intercept) ANurLvlR_rcc:T09]	0.03	0.00	0.12	-0.12	0.03	0.19	10804	1
b[AI2RhADa_log ANurLvlR_rcc:T09]	0.00	0.00	0.04	-0.05	0.00	0.05	11280	1
b[(Intercept) ANurLvlR_rcc:T10]	0.09	0.00	0.11	-0.05	0.09	0.23	8272	1
b[AI2RhADa_log ANurLvlR_rcc:T10]	-0.01	0.00	0.04	-0.05	-0.01	0.04	9675	1
b[(Intercept) ANurLvlR_rcc:T11]	0.21	0.00	0.11	0.06	0.21	0.35	9035	1
b[AI2RhADa_log ANurLvlR_rcc:T11]	-0.04	0.00	0.04	-0.09	-0.04	0.00	10136	1
b[(Intercept) ANurLvlR_rcc:T12]	-0.01	0.00	0.11	-0.14	0.00	0.13	9080	1
b[AI2RhADa_log ANurLvlR_rcc:T12]	0.03	0.00	0.04	-0.02	0.02	0.07	10046	1
sigma	0.52	0.00	0.01	0.52	0.52	0.53	17748	1
Sigma[ANurLvlR_rcc:(Intercept),(Intercept)]	0.05	0.00	0.02	0.03	0.05	0.08	4717	1
Sigma[ANurLvlR_rcc:AI2RhADa_log,(Intercept)]	-0.01	0.00	0.01	-0.02	-0.01	-0.01	4924	1
Sigma[ANurLvlR_rcc:AI2RhADa_log,AI2RhADa_log]	0.00	0.00	0.00	0.00	0.00	0.01	5344	1
mean_PPD	3.75	0.00	0.01	3.74	3.75	3.77	14556	1
log-posterior	-4064.10	0.11	6.85	-4073.05	-4063.79	-4055.55	4007	1

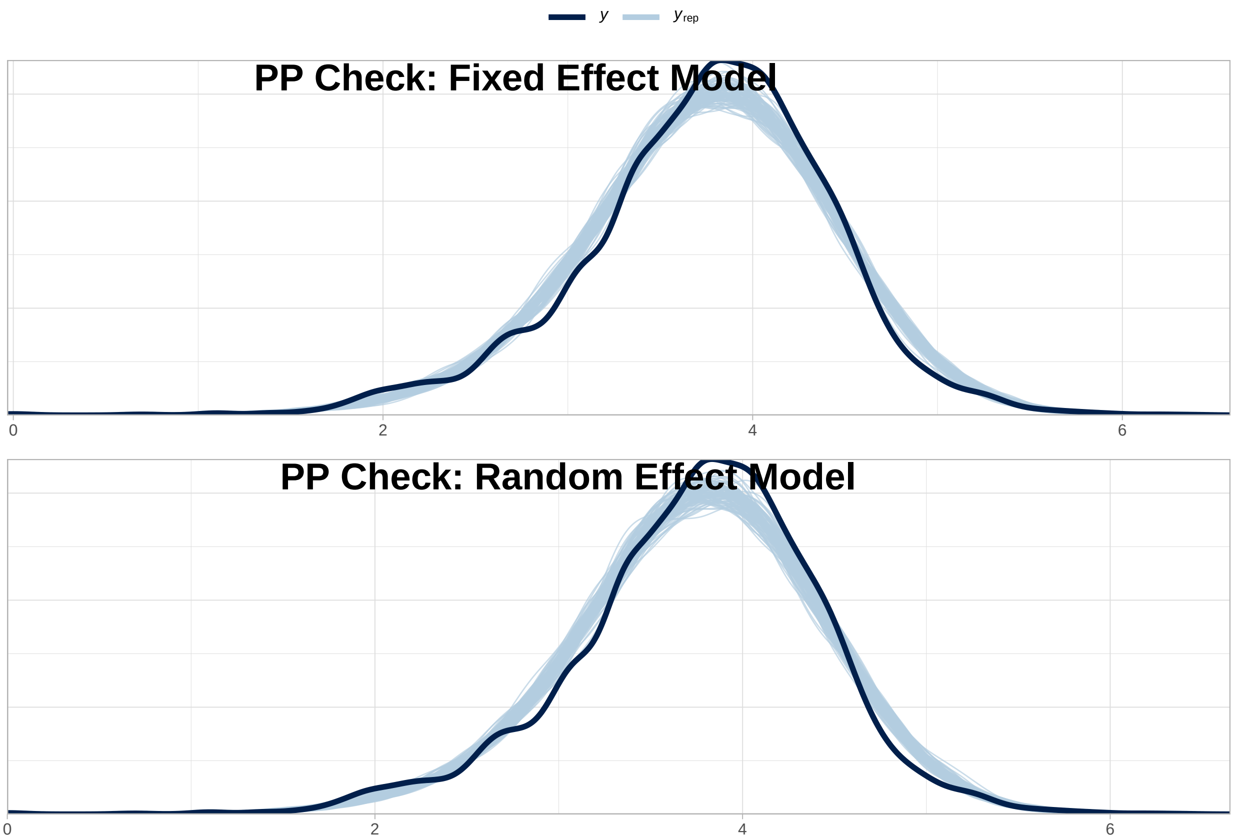
Random Effect Residual Plot



Fixed Effect Residual Plot



PP Checks



Results/Output of LOO

```
##
## Computed from 15000 by 5168 log-likelihood matrix
##
##          Estimate    SE
## elpd_loo  -4005.4  75.6
## p_loo        43.7   2.0
## looic      8010.7 151.2
## ------
## Monte Carlo SE of elpd_loo is 0.1.
##
## All Pareto k estimates are good (k < 0.5).
## See help('pareto-k-diagnostic') for details.
```

```
##
## Computed from 12000 by 5168 log-likelihood matrix
##
##          Estimate    SE
## elpd_loo  -4025.9  75.8
## p_loo        34.1   1.5
## looic      8051.8 151.5
## ------
## Monte Carlo SE of elpd_loo is 0.1.
##
## All Pareto k estimates are good (k < 0.5).
## See help('pareto-k-diagnostic') for details.
```

```
##       elpd_diff se_diff
## r_mdl   0.0       0.0
## f_mdl -20.5       7.2
```