Statistical Modeling of Fatigue and Weakness in PLHIV: Ordinal, Multinomial, and Loglinear Approaches

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Link to GitHub

Table of Contents

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Introduction

Link to GitHub

Three-month trial of 609 PLHIV yielded 1,343 symptom reports on fatigue, weakness, and treatment

Setting the Background

The dataset under analysis comes from a longitudinal randomized controlled trial investigating the progression of fatigue and weakness among people living with HIV (PLHIV). A total of 609 HIV-positive participants were followed over a three-month period and asked to self-report the severity of two symptoms: fatigue and weakness.

Data Structure

Of the 609 individuals:

- 173 (28.41%) provided one symptom report
- 138 (22.66%) provided two reports
- 298 (48.93%) provided all three

After removing records with missing values, the final analytic dataset consists of1,343 observations. Each record corresponds to a single individual at a single timepoint and includes their fatigue level, weakness level, and treatment group.

Contingency Table Framework

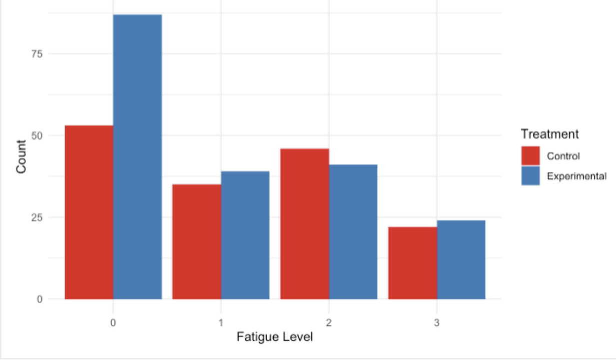
- The 1,343 observations can be arranged into a four-dimensional contingency table defined by SSC-F, SSC-W, TIME, and IC. This structure yields 96 possible cells (4 × 4 × 3 × 2). Each cell count reflects the number of individuals in the control or intervention group who reported a specific combination of fatigue and weakness at a particular time point.
- For the purposes of this analysis, the TIME variable is disregarded.

Link to GitHub

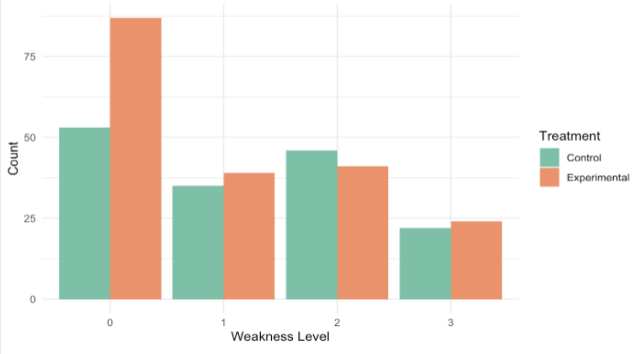
Table of Contents

Analyzing Symptom Distribution Shifts: The Impact of Experimental Treatment on Fatigue and Weakness

Fatigue Distribution by Tx Group



Weakness Distribution by Tx Group



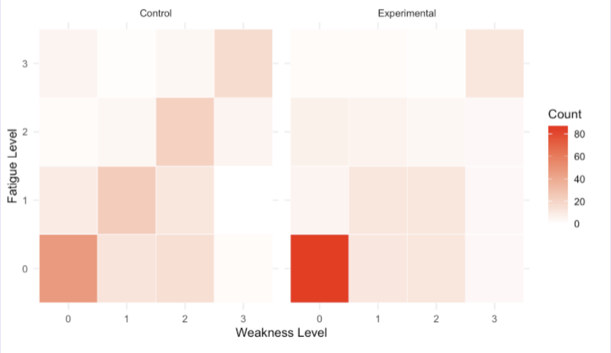
- The **Experimental** treatment group appears to experience a greater reduction in both **Fatigue** (more patients at Level 0) and **Weakness** (more patients at Level 0) compared to the Control group.
- However, the Experimental group also shows a higher count of patients at the maximum level (Level 3) for **Weakness**, suggesting the treatment's effect may be heterogeneous or have an inverse reaction in a small subset of patients.

Exploratory Data Analysis

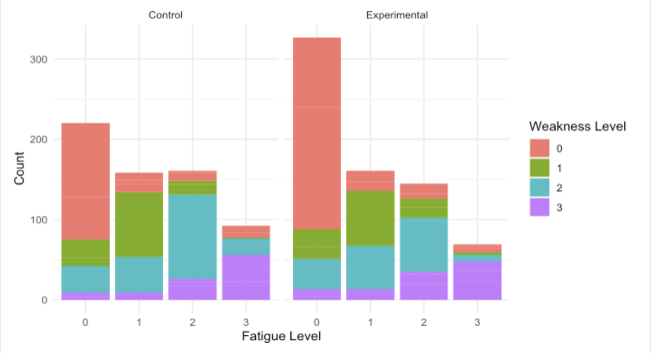
[Link to GitHub]

Multivariate Analysis of Symptom Correlation: Treatment Efficacy on the Joint Distribution of Fatigue and Weakness

Fatigue vs Weakness by Tx Group



Weakness Distribution by Tx Group



- The **Experimental** treatment group shows a much **stronger concentration** of patients experiencing both **no Fatigue (Level 0)** *and* **no Weakness (Level 0)** compared to the Control group. This suggests the treatment is highly effective at eliminating both symptoms simultaneously for a large subset of patients.
- Conversely, when **Fatigue is severe (Level 3)**, the distribution of Weakness is **less favorable** in the Experimental group, with a higher proportion of patients reporting **high Weakness (Levels 2 & 3)** compared to the Control group at the same Fatigue level. This reinforces the earlier finding that the treatment may have an inverse or non-responsive effect in a small, severely symptomatic subset.

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Link to GitHub

Table of Contents

Game Plan

[Link to GitHub]

Exploring 8 Modeling Approaches (Additive and Interaction) to Determine the Best-Fitting Model for Weakness and Fatigue

POLR (Proportional Odds / Ordinal Logistic Regression)

- Assumes the outcome is ordered (0 = absent, 1 = mild, 2 = moderate, 3 = severe).
- Models the cumulative odds of being at or above a certain fatigue level.
- Assumes the effect of predictors is consistent across thresholds (proportional odds).
- Produces interpretable odds ratios for moving to higher fatigue levels.

Multinomial Logistic Regression

- Treats the outcome as unordered categories.
- Models the odds of each category relative to a reference level.
- Does not use the ordering information, potentially losing efficiency.
- Requires estimating more parameters, especially for multiple predictors.

Why POLR may be preferred

- Fatigue is inherently ordered, so ignoring the order (as multinomial does) is less efficient.
- POLR provides simpler, more interpretable results with fewer parameters.
- Usually recommended when outcome is ordinal with few categories.

Why experiment with both anyway

- Multinomial can capture non-proportional effects if the proportional odds assumption is violated.
- Allows comparison of model fit (AIC/BIC, LRTs) to ensure POLR is adequate.
- Can validate robustness of conclusions across model types.

Conclusion

For this problem, POLR is theoretically more appropriate because fatigue levels are ordered, but we will also fit multinomial models to compare fit and ensure robustness.
The final model choice will depend on statistical performance (AIC/BIC, likelihood ratio tests) and interpretability.

Fatigue Prediction

Model	Game Plan
Ordinal with Weakness	Ordinal logistic regression predicting fatigue (SSC-F) from weakness (SSC-W) only.
Ordinal with Treatment	Ordinal logistic regression predicting fatigue from treatment group (control vs intervention) only.
Ordinal Additive	Ordinal logistic regression predicting fatigue from both weakness and treatment (additive model).
Ordinal with Interaction	Ordinal logistic regression predicting fatigue from weakness, treatment, and their interaction.
Multinomial with Weakness	Multinomial logistic regression predicting fatigue from weakness only (ignores ordering).
Multinomial with Treatment	Multinomial logistic regression predicting fatigue from treatment only (ignores ordering).
Multinomial Additive	Multinomial logistic regression predicting fatigue from weakness and treatment (additive).
Multinomial with Interaction	Multinomial logistic regression predicting fatigue from weakness, treatment, and their interaction.

Weakness Prediction

Model	Game Plan
Ordinal with Fatigue	Ordinal logistic regression predicting weakness (SSC-W) from fatigue (SSC-F) only.
Ordinal with Treatment	Ordinal logistic regression predicting weakness from treatment group (control vs intervention) only.
Ordinal Additive	Ordinal logistic regression predicting weakness from both fatigue and treatment (additive model).
Ordinal with Interaction	Ordinal logistic regression predicting weakness from fatigue, treatment, and their interaction.
Multinomial with Fatigue	Multinomial logistic regression predicting weakness from fatigue only (ignores ordering).
Multinomial with Treatment	Multinomial logistic regression predicting weakness from treatment only (ignores ordering).
Multinomial Additive	Multinomial logistic regression predicting weakness from both fatigue and treatment (additive).
Multinomial with Interaction	Multinomial logistic regression predicting weakness from fatigue, treatment, and their interaction.

Link to GitHub

Table of Contents

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Fatigue Prediction

Link to GitHub

Link to R Output

Additive models with Weakness and Tx provide the best fit; interactions are unnecessary, and ordinal RG is preferred for interpretability.

	Ordinal Regression (POLR)	Multinomial Regression
With Weakness	• Provides a baseline for how much fatigue can be explained by weakness alone. • LRT shows that adding treatment improves fit, so this model is **incomplete**.	• Predicts fatigue without assuming ordering. • Captures category-specific effects of weakness. • LRT comparing to additive model: treatment adds modest improvement (LR stat = 12.81, $p = 0.005$). • Interpretation: Weakness is still the **dominant predictor**.
With Treatment	LRT shows weakness dramatically improves model fit (LR stat = 627.47, $p < 0.0001$),indicating **treatment alone is a weak predictor** compared to weakness.	• Predicts fatigue based on treatment alone. • LRT comparing to additive model: weakness dramatically improves fit (LR stat = 785.08, $p < 0.0001$). • Interpretation: Treatment-only model is insufficient; weakness drives fatigue levels.
With Interaction (Weakness × Treatment)	• Adds an interaction term to the additive model. • LRT vs additive model: LR stat = 5.96, $p = 0.11$ → **interaction not statistically significant**. • Interpretation: The effect of weakness on fatigue does **not vary by treatment group**; additive model is sufficient.	• Captures category-specific additive effects of weakness and treatment. • Best-fitting multinomial model among main effects. • Provides slightly better AIC/BIC than interaction model. • Interpretation: Weakness remains the strongest predictor; treatment adds modest improvements.
Additive (Weakness + Treatment)	• Models fatigue as a function of both weakness and treatment. • Both predictors are included additively. • LRT comparing this to Weakness-only: LR stat = 11.66, $p = 0.00064$ → treatment adds a **small but significant improvement**. • Interpretation: **Weakness dominates;** treatment provides a modest additive effect.	• Includes interactions for each fatigue category. • LRT vs additive model: LR stat = 11.95, $p = 0.216$ → **interaction not significant**. • Interpretation: The effect of weakness on each fatigue category does not meaningfully differ by treatment. • Additional parameters increase model complexity without improving fit.

Comparing Model Fit Using AIC and BIC: Additive Models with Weakness and Treatment Provide the Best Balance of Fit and Simplicity

- Among **ordinal regression models**, the **additive model (Weakness +Treatment)** has the lowest AIC/BIC, meaning it balances fit and simplicity.
- Adding an **interaction term** does not improve fit, as shown by slightly higher AIC/BIC.
- Among **multinomial models**, the additive model also performs best numerically, but multinomial ignores the natural ordering of fatigue levels.
- Models with only Weakness or only Treatment have higher AIC/BIC, reflecting **poorer explanatory power**.
- Overall, the additive models (Weakness +Treatment) are **preferred**, with **ordinal regression** being conceptually more appropriate.

Model	AIC	BIC
Multinomial Additive	2691.54	2769.47
Multinomial with Interaction	2697.59	2822.27
Multinomial with Weakness	2698.34	2760.69
Ordinal Additive	2833.57	2869.94
Ordinal with Interaction	2833.62	2885.57
Ordinal with Weakness	2843.23	2874.4
Ordinal with Treatment	3455.05	3475.83
Multinomial with Treatment	3458.62	3489.79

Final Takeaway

- The **ordinal additive model (Weakness + Treatment)** is selected because fatigue levels are naturally ordered (0–3).
- Weakness (SSC-W) is the strongest predictor, while treatment provides a modest additive effect.
- Interaction between weakness and treatment is not significant, so the model is **simple and interpretable**.
- Clinically, the model reflects that higher weakness consistently increases the odds of more severe fatigue, regardless of treatment group, while treatment slightly reduces fatigue severity.

Link to GitHub

Table of Contents

- Introduction
- Exploratory Data Analysis
- Game Plan
- Fatigue Prediction
- Weakness Prediction
- Loglinear Symptom Analysis
- Takeaways

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Weakness Prediction | Link to GitHub | Link to R Output

Additive models with Weakness and Tx provide the best fit; interactions are unnecessary, and ordinal RG is preferred for interpretability.

	Ordinal Regression (POLR)	Multinomial Regression
With Fatigue	• Baseline model with fatigue as the sole predictor. • Captures the majority of predictive signal for weakness. • Provides interpretable odds for moving to higher weakness levels.	• Models fatigue as categorical predictor only (ignores ordering). • Provides category-specific effects of fatigue on weakness.
With Treatment	• Model with treatment only. • LR test vs additive model: LR stat = 619.91, $p < 0.0001$ • Interpretation: Fatigue is critical; treatment alone explains very little variation in weakness.	• Treatment-only model. • LR test vs additive: LR stat = 785.08, $p < 0.0001$ • Interpretation: Fatigue overwhelmingly drives weakness; treatment alone insufficient.
With Interaction (Weakness × Treatment)	• Combines fatigue and treatment additively. • LR test vs fatigue-only: LR stat = 0.19, p = 0.66 • Interpretation: Adding treatment does **not significantly improve fit**; fatigue dominates prediction.	• Combines fatigue and treatment additively. • LR test vs fatigue-only: LR stat = 10.22, p = 0.0168 • Interpretation: Treatment adds a **small but statistically significant improvement**; fatigue remains the dominant predictor.
Additive (Weakness + Treatment)	• Adds interaction to additive model. • LR test: LR stat = 5.21, p = 0.16 • Interpretation: Interaction is **not significant**; additive model is sufficient. • Clinically: Effect of fatigue on weakness does **not differ by treatment group**.	• Adds interaction to additive model. • LR test: LR stat = 11.95, p = 0.216 • Interpretation: Interaction is **not significant**; additive model is adequate. • Clinically: Effect of fatigue on weakness is consistent across treatment groups.

Comparing Model Fit Using AIC and BIC: Additive Models with Weakness and Treatment Provide the Best Balance of Fit and Simplicity

Model	AIC	BIC	Key Interpretation
Multinomial Additive	2785.39	2863.32	Best-fitting model numerically; additive model captures main effects.
Multinomial with Fatigue	2789.61	2851.95	Slightly worse; treatment adds small improvement.
Multinomial with Interaction	2791.43	2916.12	Interaction unnecessary; adds complexity.
Ordinal with Fatigue	2940.39	2971.57	Captures ordering; baseline ordinal model.
Ordinal Additive	2942.2	2978.57	Slightly worse AIC/BIC than multinomial; additive model sufficient.
Ordinal with Interaction	2942.99	2994.95	Interaction unnecessary; increases complexity.
Multinomial with Treatment	3552.47	3583.64	Poor fit; ignores fatigue.
Ordinal with Treatment	3556.11	3576.89	Poor fit; ignores fatigue.

Final Takeaway

Best Model: Ordinal Regression (Fatigue-only) for Weakness

Respects Outcome Ordering

- Weakness (SSC-W) levels are **naturally ordered** from 0 (absent) → 3 (severe).
- Ordinal regression models the **cumulative odds** of being at or above a given weakness level.

Fatigue is the Dominant Predictor

- Likelihood ratio tests show **adding treatment does not significantly improve fit** (LR stat = 0.19, p = 0.66).
- This indicates that **fatigue alone captures most of the predictive signal** for weakness.

Clinical Interpretation

- Higher fatigue levels are associated with **higher likelihood of experiencing weakness**.
- Treatment does **not significantly alter this relationship**, suggesting weakness progression is largely driven by fatigue severity rather than intervention in this dataset.

Parsimony and Interpretability

- Fewer parameters than multinomial models.
- Produces **straightforward odds ratios**, making clinical interpretation simpler and robust.

Key Takeaway:

- The **Ordinal Fatigue-only model** is **statistically appropriate, clinically intuitive, and parsimonious**.
- It clearly shows that **fatigue is the main driver of weakness**, and treatment has minimal direct effect in this context.

[Link to GitHub]

Table of Contents

Exploring 8 Modeling Approaches (Additive and Interaction) to Determine the Best-Fitting Model for Weakness and Fatigue

Variables

- Weakness (SSC-W) – 4 levels
- Fatigue (SSC-F) – 4 levels
- Treatment (IC) – 2 levels

Method

- Use **loglinear models** to model **cell counts** in the 3-way contingency table.
- Poisson regression on counts is mathematically equivalent to fitting a loglinear model.
- Goal: Identify which **main effects and interactions** significantly explain the observed counts.

Variables

- **Likelihood ratio test (G^2):** Tests whether adding interactions significantly improves fit.
- **AIC / BIC:** Helps select the most parsimonious model balancing fit and complexity.

PLAN

Independence model (no interactions)
- Assumes all three variables are independent: Weakness ⫫ Fatigue ⫫ Treatment.
- Serves as a baseline model.

Additive model (main effects only)
- Models the expected counts based on **main effects**: Weakness + Fatigue + Treatment.
- Tests whether main effects alone capture the structure of the data.

Two-way interaction model
- Includes all **pairwise interactions**: Weakness × Fatigue, Weakness × Treatment, Fatigue × Treatment.
- Evaluates whether associations exist between any two variables.

Saturated model (full three-way interaction)
- Includes all **main effects, two-way, and three-way interactions**.
- Perfectly fits the observed counts; used as a reference for **goodness-of-fit**.

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Loglinear Symptom Analysis

Link to GitHub

Link to R Output

Loglinear Model Comparison: Residual Deviance, Degrees of Freedom, and Likelihood Ratio Test for Significance

Model	Res. df	Res. Dev	ΔDf	ΔDev	p (Chi)
Independence (Weakness + Fatigue + Treatment)	88	993.02	–	–	–
Two-way interactions (all pairs)	73	167.63	15	825.39	< 2e-16 ***
Saturated (three-way)	64	155.67	9	11.95	0.216

Model	df	AIC	BIC
Independence	8	1381.81	1402.32
Two-way additive	23	586.42	645.40
Saturated	32	592.46	674.52

Statistical Interpretation

Independence model (Weakness + Fatigue + Treatment)

- Assumes no associations between any of the variables.
- Residual deviance is very high (**993.02**), indicating a **poor fit**.
- Clearly, the variables are **not independent**, so main effects alone are insufficient.

Two-way additive model (all pairwise interactions)

- Includes all **main effects** and **pairwise interactions**: Weakness × Fatigue, Weakness × Treatment, Fatigue × Treatment.
- Residual deviance drops dramatically to **167.63**, G^2 test **p < 2e-16**, showing that adding interactions significantly improves fit.

AIC = 586.42, **BIC = 645.40**, lowest among all models → **best balance of fit and parsimony**.

Saturated model (three-way interaction)

- Includes all main effects, pairwise, and the three-way interaction.
- Residual deviance decreases slightly to **155.67**, but G^2 test **p = 0.216** → adding the three-way interaction does **not significantly improve fit**.
- Higher BIC (**674.52**) penalizes complexity → **not necessary for interpretation**.

Clinical Interpretation

- **Fatigue and weakness are strongly associated** in people living with HIV.
- **Treatment group shows some association with these symptoms**, but its effect does not modify the fatigue-weakness relationship (no significant three-way interaction).
- The **two-way additive model** captures all meaningful relationships:
- Clinicians can focus on the **main effects and pairwise associations** without overcomplicating with higher-order interactions.
- Clinically, this suggests that interventions targeting fatigue or weakness can be considered somewhat independently, as their relationship does not differ by treatment group.

The **two-way additive loglinear model** provides the **simplest yet statistically robust description** of the associations among weakness, fatigue, and treatment, making it both **interpretable** and **clinically meaningful**.

Link to GitHub

Table of Contents

Exploratory Data Analysis

Link to GitHub

Multivariate Analysis of Symptom Correlation: Treatment Efficacy on the Joint Distribution of Fatigue and Weakness

Relationship Between Weakness and Fatigue

Ordinal Regression (POLR):

- Weakness is a **strong and consistent predictor** of fatigue.
- Likelihood ratio tests show adding treatment provides **minimal additional predictive power** once weakness is included.
- No significant interaction: the effect of weakness on fatigue **does not differ across treatment groups**, suggesting a stable, intrinsic association.
- Clinically, individuals with higher weakness scores are substantially more likely to report higher fatigue levels, regardless of intervention.

Multinomial Regression:

- Confirms POLR findings: weakness dominates fatigue prediction.
- Treatment alone has a small, sometimes statistically significant effect, but the overall pattern remains the same.
- Interaction is not significant, reinforcing that the additive model is sufficient.

Loglinear Models:

- Pairwise interactions (Weakness × Fatigue) are **highly significant**, reinforcing the strong statistical dependence.
- Three-way interaction (Weakness × Fatigue × Treatment) is **not significant**, confirming that treatment does not modify this relationship.

Effect of Intervention (Treatment)

Regression Models:

- Adding treatment to models with weakness provides a small but statistically detectable improvement in fit (more so in multinomial models).
- Ordinal models suggest that the clinical effect of treatment is modest and secondary to weakness.
- No significant interaction implies that the treatment effect does not amplify or reduce the association between weakness and fatigue.

Loglinear Models:

- Treatment shows some pairwise associations with fatigue or weakness individually, but no three-way interaction exists.
- Suggests that the intervention may have minor effects on symptom levels, but it does not substantially alter the fatigue-weakness relationship.

Clinical Insight: Treatment is not the primary driver of fatigue or weakness in this dataset. Interventions targeting symptom reduction may need to focus more directly on fatigue or weakness rather than expecting treatment group assignment alone to influence outcomes.

Consistency Across Methods

- Ordinal regression (POLR) is preferred for these data because it respects the ordered nature of fatigue and weakness, giving interpretable cumulative odds ratios.
- Multinomial regression supports the same qualitative conclusions, though it ignores ordering and requires more parameters.
- Loglinear models provide a complementary perspective, confirming the statistical dependence patterns among Weakness, Fatigue, and Treatment.

Overall Takeaways

- **Weakness is strongly associated with fatigue**—higher weakness levels predict higher fatigue levels.
- **Treatment group has minimal impact**, and it does not modify the weakness-fatigue relationship.
- **Additive models (main effects + pairwise interactions) are sufficient**; higher-order interactions are unnecessary.
- These conclusions are **robust across multiple statistical approaches**, supporting both statistical validity and clinical interpretability.

APPENDIX

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R Studio Outputs: Fatigue Prediction

```
Ordinal regression LRTs:
Likelihood ratio tests of ordinal regression models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.      Pr(Chi)
1              Weakness      1327   2831.232
2 Weakness + Treatment      1326   2819.573 1 vs 2     1 11.65922 0.0006388497
Likelihood ratio tests of ordinal regression models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat. Pr(Chi)
1             Treatment      1329   3447.047
2 Weakness + Treatment      1326   2819.573 1 vs 2     3 627.4747       0
Likelihood ratio tests of ordinal regression models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
1 Weakness + Treatment      1326   2819.573
2 Weakness * Treatment      1323   2813.617 1 vs 2     3 5.956141 0.1137637

Multinomial regression LRTs:
Likelihood ratio tests of Multinomial Models
```

```
Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
1 Weakness + Treatment      1326   2819.573
2 Weakness * Treatment      1323   2813.617 1 vs 2     3 5.956141 0.1137637

Multinomial regression LRTs:
Likelihood ratio tests of Multinomial Models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.     Pr(Chi)
1              Weakness       276   2674.344
2 Weakness + Treatment       273   2661.539 1 vs 2     3 12.80532 0.005077099
Likelihood ratio tests of Multinomial Models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat. Pr(Chi)
1             Treatment       282   3446.619
2 Weakness + Treatment       273   2661.539 1 vs 2     9 785.0803       0
Likelihood ratio tests of Multinomial Models
```

```
Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
1 Weakness + Treatment       273   2661.539
2 Weakness * Treatment       264   2649.585 1 vs 2     9 11.95422 0.2159025
Likelihood ratio tests of ordinal regression models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.      Pr(Chi)
1              Weakness      1327   2831.232
2 Weakness + Treatment      1326   2819.573 1 vs 2     1 11.65922 0.0006388497
Likelihood ratio tests of ordinal regression models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat. Pr(Chi)
1             Treatment      1329   3447.047
2 Weakness + Treatment      1326   2819.573 1 vs 2     3 627.4747       0
Likelihood ratio tests of ordinal regression models

Response: Fatigue
                  Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
1 Weakness + Treatment      1326   2819.573
2 Weakness * Treatment      1323   2813.617 1 vs 2     3 5.956141 0.1137637
Likelihood ratio tests of Multinomial Models
```

	Model <chr>	AIC <dbl>	BIC <dbl>
Mult_Both	Mult_Both	2691.539	2769.467
Mult_Int	Mult_Int	2697.585	2822.269
Mult_Weak	Mult_Weak	2698.344	2760.687
Ord_Both	Ord_Both	2833.573	2869.939
Ord_Int	Ord_Int	2833.617	2885.569
Ord_Weak	Ord_Weak	2843.232	2874.403
Ord_Tx	Ord_Tx	3455.047	3475.828
Mult_Tx	Mult_Tx	3458.619	3489.791

Link to GitHub

R Studio Outputs: Weakness Prediction

```
Ordinal Regression LRTs:
Likelihood ratio tests of ordinal regression models

Response: Weakness
                Model Resid. df Resid. Dev   Test    Df  LR stat.   Pr(Chi)
1             Fatigue      1327   2928.394
2 Fatigue + Treatment      1326   2928.203 1 vs 2     1 0.1901051 0.6628292
Likelihood ratio tests of ordinal regression models

Response: Weakness
                Model Resid. df Resid. Dev   Test    Df LR stat. Pr(Chi)
1           Treatment      1329   3548.110
2 Fatigue + Treatment      1326   2928.203 1 vs 2     3 619.9069       0
Likelihood ratio tests of ordinal regression models

Response: Weakness
                Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
1 Fatigue + Treatment      1326   2928.203
2 Fatigue * Treatment      1323   2922.998 1 vs 2     3 5.205347 0.1573636
```

```
Multinomial Regression LRTs:
Likelihood ratio tests of Multinomial Models

Response: Weakness
                Model Resid. df Resid. Dev   Test    Df LR stat.    Pr(Chi)
1             Fatigue       276   2765.612
2 Fatigue + Treatment       273   2755.388 1 vs 2     3 10.22365 0.01675767
Likelihood ratio tests of Multinomial Models

Response: Weakness
                Model Resid. df Resid. Dev   Test    Df LR stat. Pr(Chi)
1           Treatment       282   3540.469
2 Fatigue + Treatment       273   2755.388 1 vs 2     9 785.0803       0
Likelihood ratio tests of Multinomial Models

Response: Weakness
                Model Resid. df Resid. Dev   Test    Df LR stat.   Pr(Chi)
1 Fatigue + Treatment       273   2755.388
2 Fatigue * Treatment       264   2743.434 1 vs 2     9 11.95422 0.2159027
```

	Model <chr>	AIC <dbl>	BIC <dbl>
Multinomial Additive	Multinomial Additive	2785.388	2863.316
Multinomial with Fatigue	Multinomial with Fatigue	2789.612	2851.954
Multinomial with Interaction	Multinomial with Interaction	2791.434	2916.119
Ordinal with Fatigue	Ordinal with Fatigue	2940.394	2971.565
Ordinal Additive	Ordinal Additive	2942.203	2978.570
Ordinal with Interaction	Ordinal with Interaction	2942.998	2994.950
Multinomial with Treatment	Multinomial with Treatment	3552.469	3583.640
Ordinal with Treatment	Ordinal with Treatment	3556.110	3576.891

Link to GitHub

R Studio Outputs: Loglinear Symptom Analysis

```
Analysis of Deviance Table

Model 1: Count ~ Weakness + Fatigue + Treatment
Model 2: Count ~ (Weakness + Fatigue + Treatment)^2
Model 3: Count ~ Weakness * Fatigue * Treatment
  Resid. Df Resid. Dev Df Deviance Pr(>Chi)
1        88     993.02
2        73     167.63 15   825.39   <2e-16 ***
3        64     155.67  9    11.95   0.2159
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

	df <dbl>	AIC <dbl>
model_indep	8	1381.8052
model_2way	23	586.4169
model_sat	32	592.4627

	df <dbl>	BIC <dbl>
model_indep	8	1402.3200
model_2way	23	645.3970
model_sat	32	674.5219