Compliance Thresholds in Intensive Longitudinal Data: Worse than Listwise Deletion: Call for Action

Nicholas C. Jacobson, Ph.D.

Society for Ambulatory Assessment 2020

@NC_Jacobson

nicholasjacobson.com

Common Practices in Ambulatory Assessment

- Ambulatory assessment studies commonly ask people to answer questionnaire prompts repeatedly

- These studies often involves substantial burden to participants and frequently result in moderate-high missingness rates

Types of Missing Data

- Type 1: Data is **missing completely due to chance** (Missing Completely at Random)

- Type 2: Data is **missing due** to a **variable collected within the dataset** (Missing at Random)

- Type 3: **Data is not due to chance**, but the variable influencing the data is not observed by the data (Missing Not at Random)

Missing Practices in Other Contexts

- Most methodologists who encounter missing data in other areas know that appropriately handling strategies are vital

- Complete case analysis (i.e. Listwise deletion): throwing out a record because the data is not complete
  - Systematically lowers statistical power
  - Well-known to bias parameter estimates
  - Also impacts standard errors of parameter estimates

Missing Data Analysis:
Making It Work
in the Real World

John W. Graham

Gold Standard Approaches to Handle Missing Data

- Gold-standard modeling approaches use all observed data and incomplete data

- Examples:

- **Full Information Maximum Likelihood:** Technique which directly incorporates all available to predict each outcome (evolved out of structural equation modeling literature)

- **Multiple Imputation**: Data is estimated based on parameter estimates from observed relationships (note that this accounts for uncertainty in the parameter estimates)

Current Practices in Ambulatory Assessment

Ambulatory Assessment in Psychopathology Research: A Review of Recommended Reporting Guidelines and Current Practices

Timothy J. Trull
University of Missouri—Columbia

Ulrich W. Ebner-Priemer
Karlsruhe Institute of Technology

or EOD reports); (c) report both the mean level of compliance for each type of report and the range of compliance across participants; (d) describe and justify the thresholds for compliance necessary for participants to be included in the analyses (e.g., 75%; although there are no hard-and-fast rules for a specific threshold, it is important to note that as more missing data are included it may be harder to assume data are missing at random and the estimates for lagged effects become less reliable); (e) compare groups of participants for compliance rates; and (f) examine the data for systematic influences on or patterns of compliance rates (e.g., time of day; day of week; day of study). In our review, 65% of articles defined, generally, what constituted compliance (or missing data) and presented descriptive statistics on overall compliance to prompted reports.

Rationale for Compliance Thresholds

- Large proportion of missing data is a problem
- We can "eliminate the problem" if we throw these people out
- Act as if they never enrolled in our study.

Compliance Thresholds:
Worse than Listwise Deletion

- Listwise deletion involves throwing away a single observation (i.e. 1 row in a dataset because the entire row is not present)

- Compliance thresholds can throw out entirely **complete observed data**

- With this established practice we are quite literally **throwing data away**

Going back to theory

- I study depression and anxiety

- I suspect that burdens imposed from collecting ecological momentary assessments will be more difficult for those with high levels of anxiety or depression.

- One would suspect that consequently who struggle the most are probably less likely to be as compliant due

Study 1: Empirical Study

- Empirical study
- Applying machine learning to predict observed levels of missingness in a 50-Day Daily Diary Study
- Using personality and psychopathology characteristics

- **Hypothesis 1:** Data is **<u>not</u> missing due to chance**. Rather rates of **missing data can be significantly predicted** based on individual difference measures.
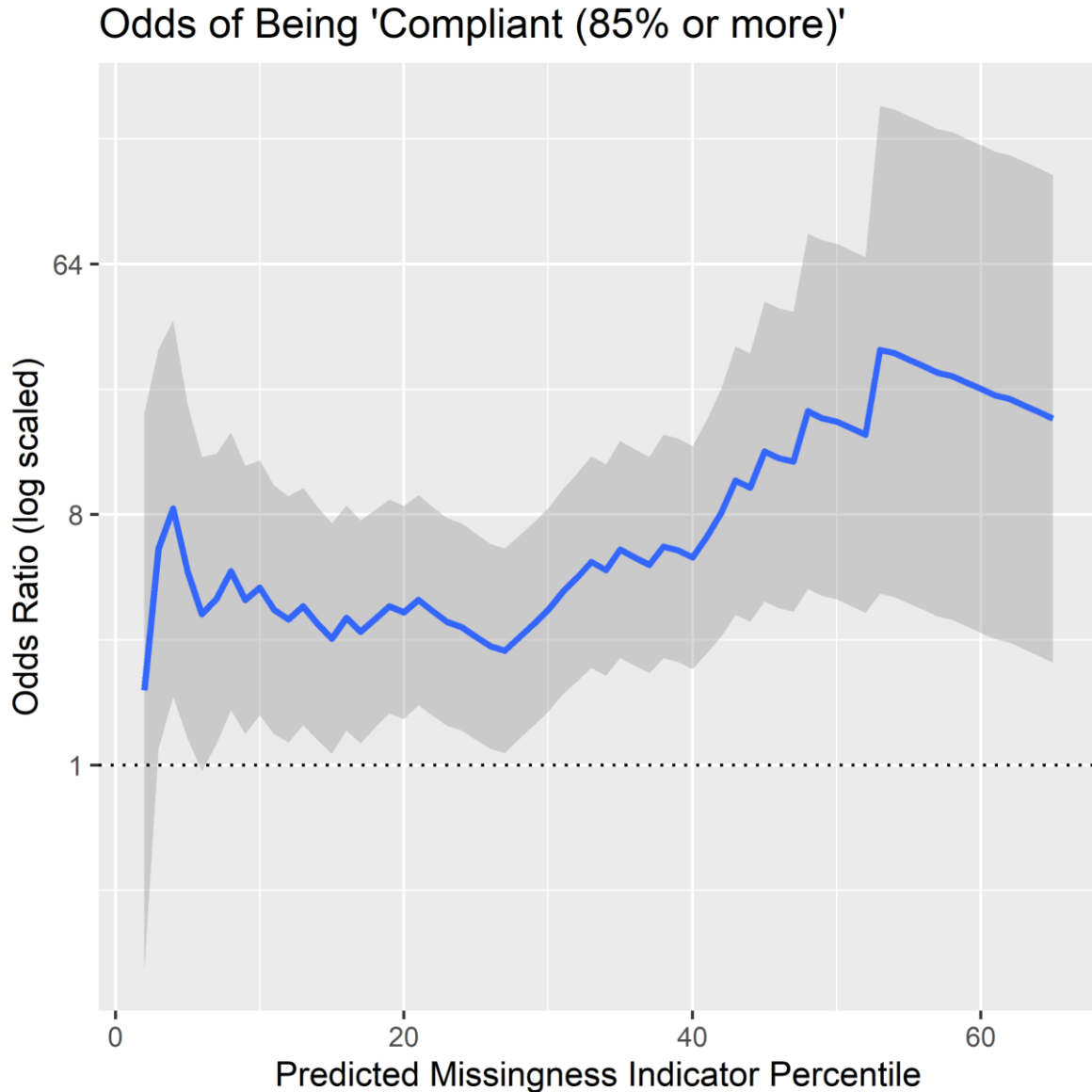
Method

- 176 undergraduates enrolled in a 50-day daily diary study

- Measures personality and psychopathology characteristics

- **Ensemble** of machine learning models:
  - Random forests, generalized linear modeling via penalized maximum likelihood, support vector machines, k-nearest neighbors, classification and regression trees, deep-neural networks, and extreme gradient boosting

- All predictions are based on out-of-sample predictions

Results

Predicting Likelihood of Being 'Compliant' (85% or more)

AUC: 0.781
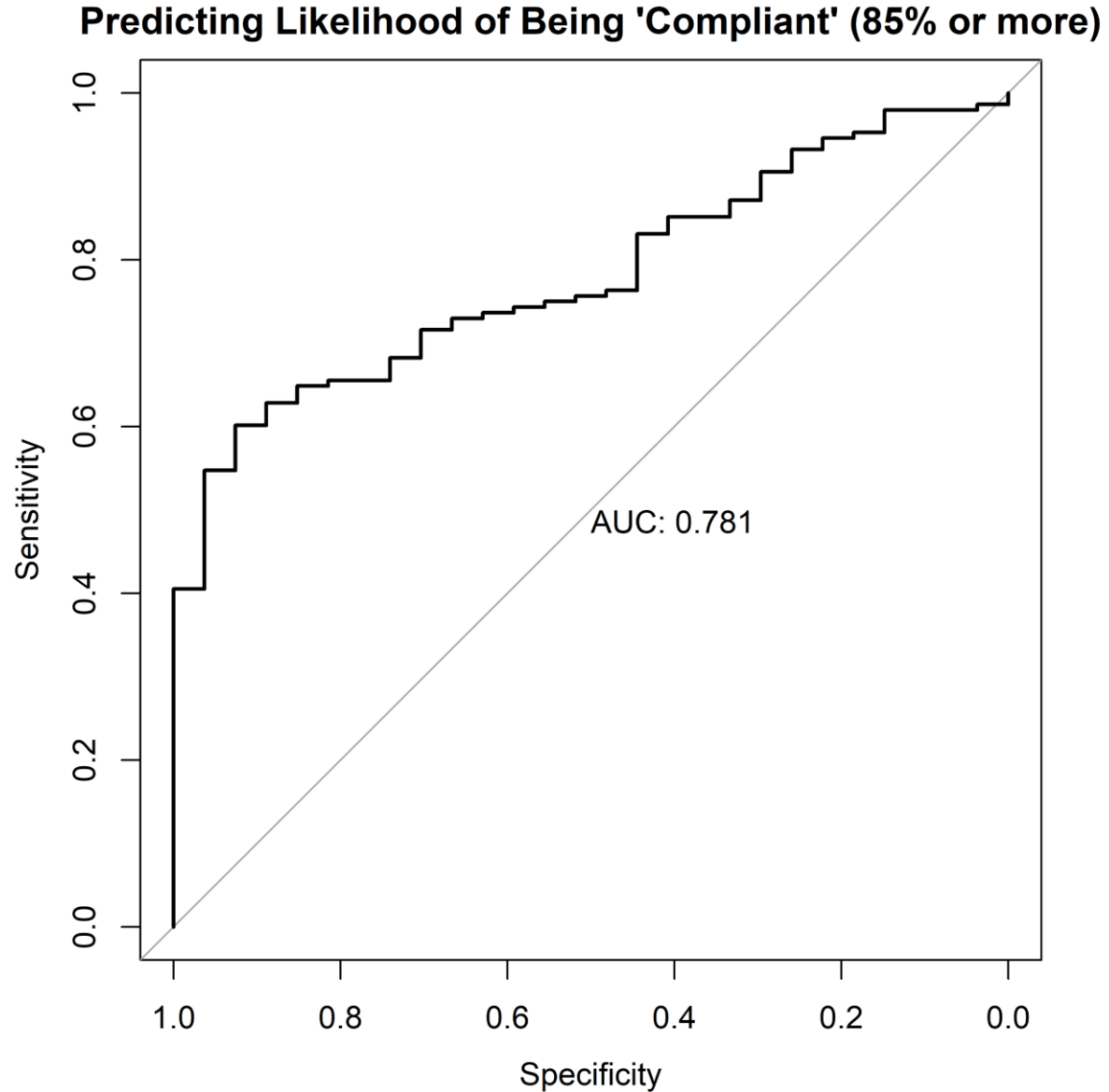
- Sensitivity = 60.1%;
- Specificity = 92.6%

Results

Odds of Being 'Compliant (85% or more)'

- Those who where at or 50th percentile or above in the prediction score were greater than 15 times more likely to be "compliant" compared to those below the 49th percentile and below

What does this mean?

- This mean that the data is **<u>not</u>** missing due to chance
- Rather, the data as least partially missing due to individual differences in personality characteristics

- So what?
- Throwing people out based on their missing data would lead to **biases** regarding **who is included**

So, what's the alternative?
Study 2:
Simulation Study with Intensive Longitudinal Data

- Our prior simulation studies using intensive longitudinal data have shown that:

- Gold-standard missing data rates can result in parameter estimates with **low biases** and **good standard errors**

Routledge
Taylor & Francis Group

Check for updates

Handling Missing Data in the Modeling of Intensive Longitudinal Data

Linying Ji,[1] Sy-Miin Chow,[1] Alice C. Schermerhorn,[2] Nicholas C. Jacobson,[1] and E. Mark Cummings[3]

[1]The Pennsylvania State University
[2]The University of Vermont
[3]The University of Notre Dame

But, some of these people have a lot of missingness! Study 3: Simulation Study with Intensive Longitudinal Data and Higher-Order Lags

- Even then! Simulation studies show appropriate data strategies can lead to unbiased parameter estimates with good standard errors, with

- Greater than **70% Missing data for the <u>average person</u>**

- This included **higher-order lagged structure** – which makes it even more difficult

CrossMark

The Differential Time-Varying Effect Model (DTVEM): A tool for diagnosing and modeling time lags in intensive longitudinal data

Nicholas C. Jacobson[1] · Sy-Miin Chow[1] · Michelle G. Newman[1]

Call for Action: Researchers

- All persons who complete any assessments should be included in the analyses
- Otherwise, likely ***biasing our inferences*** and neglect important individual differences

- Use appropriate model-based missing data strategies

- Increasingly utilize passive sensing techniques as these can give us data about variables of interest during missing periods.

Using Digital Phenotyping to Accurately Detect Depression Severity

Nicholas C. Jacobson, MS, Hilary Weingarden, PhD, and Sabine Wilhelm, PhD

Objective digital phenotypes of worry severity, pain severity and pain chronicity in persons living with HIV

Nicholas C. Jacobson and Conall O'Cleirigh

Digital biomarkers of mood disorders and symptom change

Nicholas C. Jacobson [1,2,3], Hilary Weingarden[1,2] and Sabine Wilhelm[1,2]

Call for Action: Reviewers and Editors

- Do **<u>not</u>** penalize or downgrade studies that find higher missing data rates

- This could be a **<u>naturally occurring phenomenon</u>** based on the population being studied

- In critiquing or recommending a study for rejection based on this literature:
  - Suggesting that the literature be biased in favor of those highly functioning enough to nearly fully comply with the study

- When you see a study that uses compliance thresholds: ask authors to include those with lower compliance thresholds in the analyses.

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- Colin Goodbred
- Brandon Feng
- Alexandra Limb
- Iain Sheerin
- Mia Seiner
- MK Song
- Rapael Huang
- Vernoica Abreu
- William Chen

Postbac Research Assistant
- Natalie Thomas

Software Engineer
- William Hasslet, Ph.D.