

March 21, 2018

Common Challenges & Solutions in Analysis & Reporting of PROs in Oncology Clinical Trials

The power of **knowledge.**
The value of **understanding.**



Ari Gnanasakthy, MBA, MSc
Principal Scientist, Patient-
Centered Outcomes
Assessment



Lawrence Rasouliyan, MPH
Director, Biostatistics



Donald Stull, PhD
Head, Data Analytics and
Design Strategy

- Key Learning Objectives:
 - The specific challenges associated with the analysis of data from oncology studies.
 - Why traditional statistical methods for clinical trials can lead to biased results when applied to oncology studies.
 - Possible analytic methods to help account for potential biases and help you better understand your patients.
 - Why safety and patient-reported outcome endpoints may appear contradictory in oncology trials.

Assessment schedule may not be optimal

- Is beginning of cycle the most appropriate time?
- Dose adjustment / interruption may delay treatment cycles.
- How about more assessments during the early cycles while the majority of patients are still in the study?

Imperfect measures may be redundant

- Currently used measures are static.
- Impact of new therapies are missed.
 - Skin rash
 - Vitiligo
 - Photosensitivity
- Summary scores may be misleading.
- Questionable content validity.

Missing Data are just annoying

- Common and rarely random.
- No one cares about exploratory endpoints.
- Suboptimal analytical methods.

PROs are rarely presented in context of efficacy and safety

- Demonstrating Tx-A (PRO) = Tx-B (PRO) is unique to cancer.
- Proving the null hypothesis using imperfect instruments in an underpowered study is nothing to shout about.
- Often this conclusion is not supported by safety data.

Current state of PROs in cancer studies



PRO instruments may not be capturing what is needed



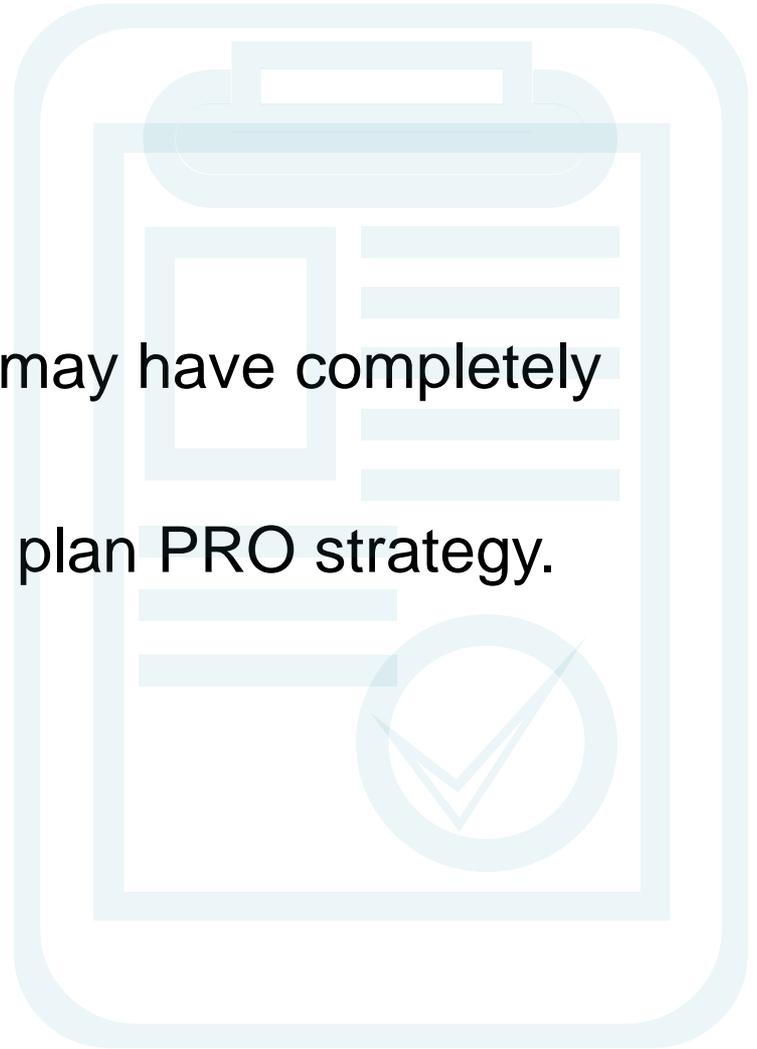
Data capture itself as a process is not ideal

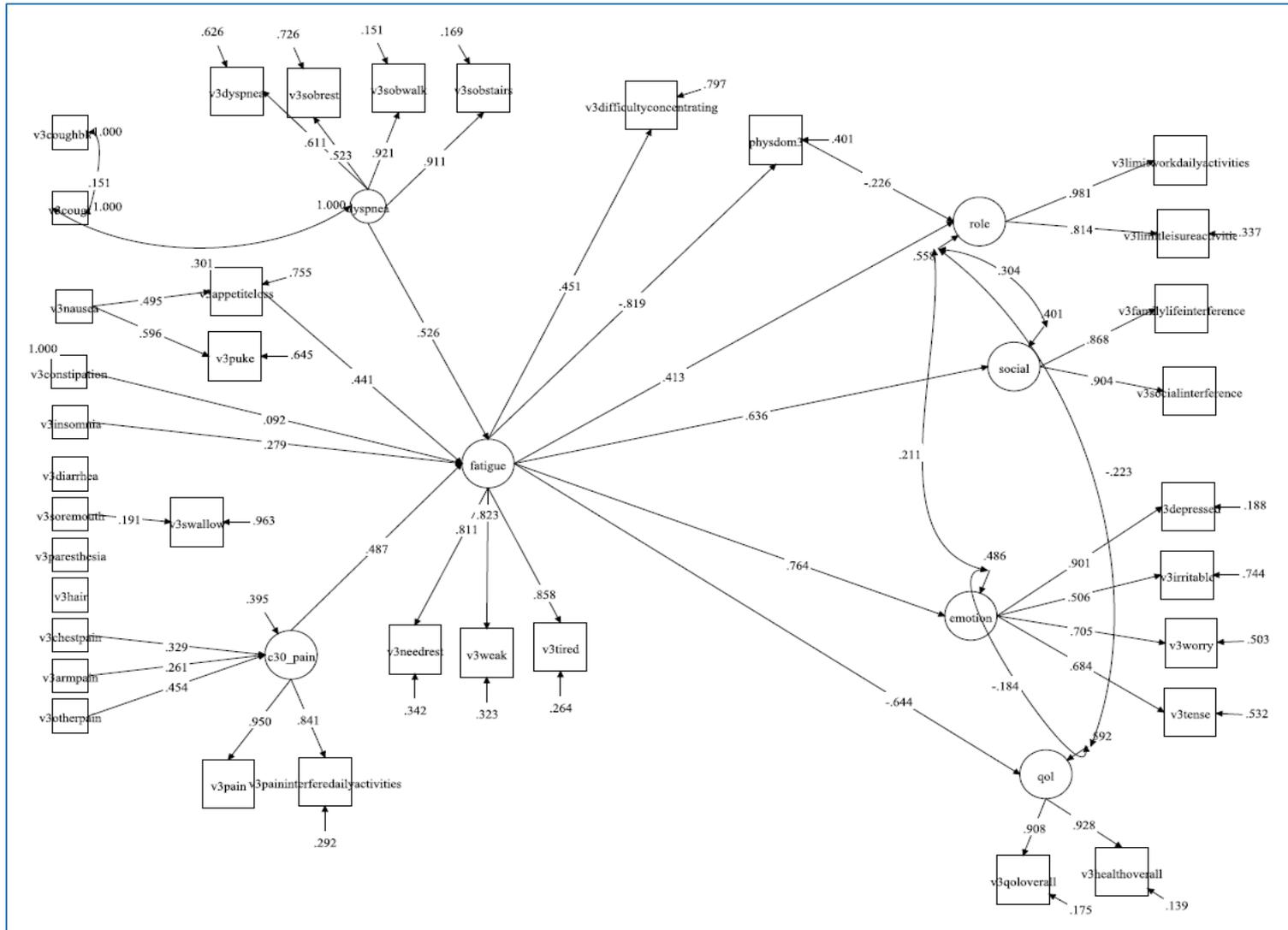


Missing Data

PRO Instruments Are Not Ideal

- PRO instruments should:
 - Measure what is needed
 - Be sensitive enough
- New immuno-oncology therapies may have completely different symptom profile.
- Important to invest time upfront to plan PRO strategy.

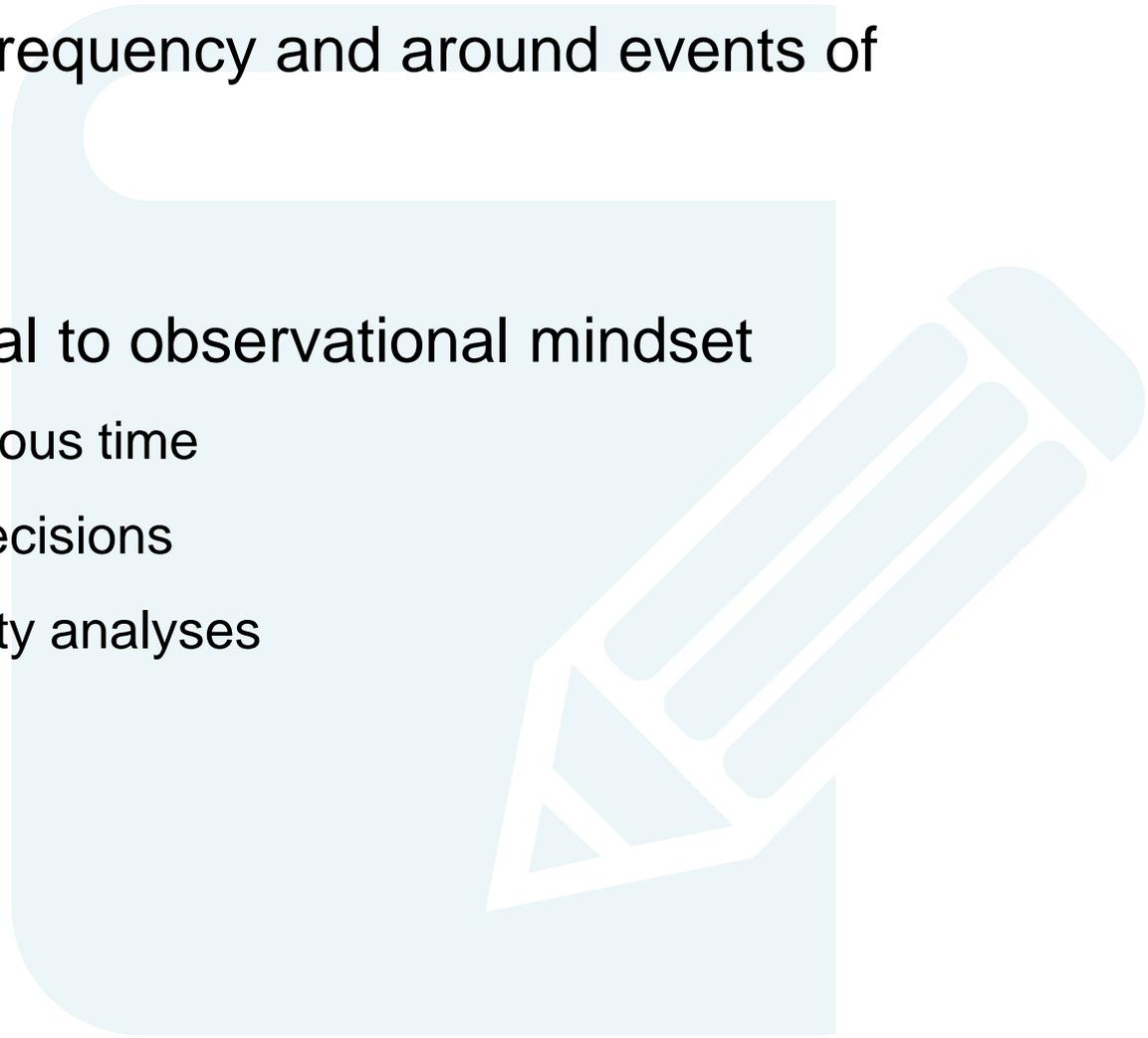




Dependent variable	Explanatory variable	Total effects	Direct effects	Total indirect effects
GLBLQOL	Dyspnea	-0.345***	NS	-0.345***
GLBLQOL	Nausea	-0.141***	NS	-0.141***
GLBLQOL	Pain	-0.319***	NS	-0.319***
GLBLQOL	Appetite Loss	-0.284***	NS	-0.284***
GLBLQOL	Insomnia	-0.180***	NS	-0.180***
GLBLQOL	Constipation	-0.059*	NS	-0.059*
PHYSICAL	Dyspnea	-0.431***	NS	-0.431***
PHYSICAL	Nausea	-0.179***	NS	-0.179***
PHYSICAL	Pain	-0.399***	NS	-0.399***
PHYSICAL	Appetite Loss	-0.361***	NS	-0.361***
PHYSICAL	Insomnia	-0.229***	NS	-0.229***
PHYSICAL	Constipation	-0.075*	NS	-0.075*

Data Capture Is Not Ideal

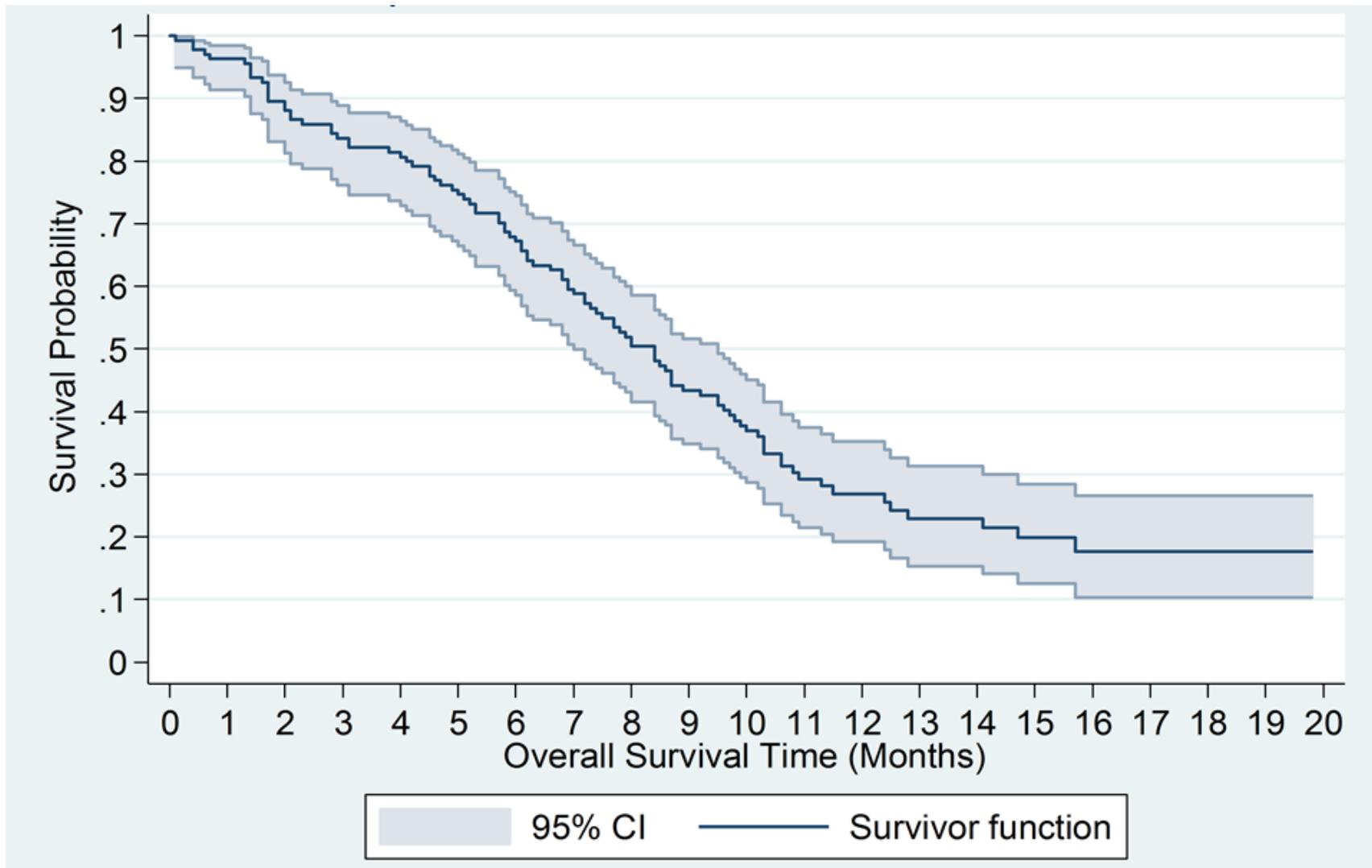
- PRO data collection frequency and around events of interest.
- Patient burden
- Analysis: Experimental to observational mindset
 - Fixed visits vs. continuous time
 - Data-driven analytic decisions
 - Importance of sensitivity analyses



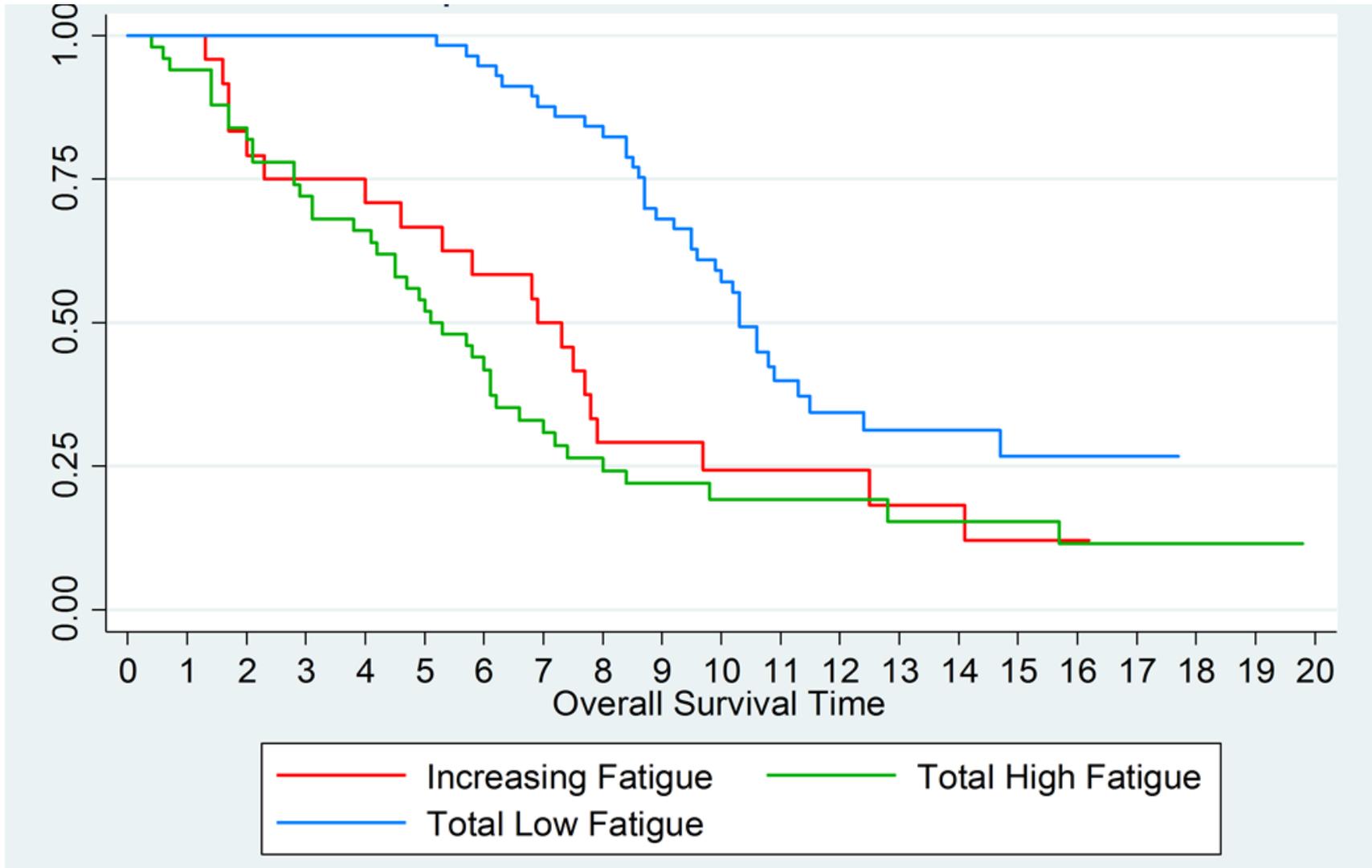
Missing Data

- Very common and usually not at random.
- Traditional mixed effects models and imputation methods do not work well.
- Need to account for the informative nature of missing data.
 - Selection Models / Shared Parameter Models
 - Pattern Mixture Models
 - Extended Pattern Mixture Models

Kaplan-Meier Overall Survival Estimate



Kaplan-Meier Survival Estimates





Q&A

GO

Generating knowledge and providing greater understanding so that you—and those who regulate, pay for, prescribe, and use your products—can make better decisions.

rtihs.org

RTI-HS Contact Information

Ari Gnanasakthy, MBA, MSc

Principal Scientist, Patient-Centered
Outcomes Assessment

+1.919.597.5165

gnanasakthy@rti.org

Lawrence Rasouliyan, MPH

Director, Biostatistics

+34 933 624 297

lrasouliyan@rti.org

Donald Stull, PhD

Head, Data Analytics and
Design Strategy

+1.919.597.5158

dstull@rti.org