

# Standardizing Exposure-Response Data for Modeling and Simulation

Using CDISC Principles and {admiral}

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2026-01-27

# Overview

## The Challenge

- ▶ ER modeling critical for drug development
- ▶ Datasets lack standardization
- ▶ CDISC SDTM-PK exists, but no ER equivalent
- ▶ Inconsistent structures hinder reproducibility

## Our Approach

- ▶ Extend CDISC principles to ER data
- ▶ Three key domains:
  - ▶ Exposure-Efficacy (EE)
  - ▶ Exposure-Safety (ES)
  - ▶ Tumor Response
- ▶ Demonstrate with {admiral}

# The ER Modeling Landscape

## What is Exposure-Response Analysis?

- ▶ Quantifies relationship between drug exposure (PK) and outcomes
- ▶ Key questions:
  - ▶ What exposure achieves target efficacy?
  - ▶ What exposure level increases toxicity risk?
  - ▶ How do we optimize dosing for subpopulations?

## Current State

- ▶ Each analysis starts from scratch
- ▶ Variable naming inconsistent
- ▶ Difficult to share methodologies
- ▶ QC challenges

# Why Standards Matter

- ▶ **Consistency:** Same structure across studies and organizations

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  - ▶ **Reproducibility:** Others can verify and extend your work
  - ▶ **Efficiency:** Reusable code and workflows
  - ▶ **Regulatory clarity:** Easier to document and defend analyses
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# SDTM-PK: Our Foundation

## Key Principles from SDTM-PK

- ▶ Relative time variables (*TPT*, *ELTM*)
- ▶ Numeric analysis values (*PCSTRESN*)
- ▶ Analysis flags (*\*FL* variables)
- ▶ Traceability (*\*DTC*, *-SEQ*)
- ▶ Standardized parameter codes

**The Gap:** SDTM-PK focuses on PK measurements, not PK-outcome relationships

## What We Can Leverage

- ▶ Time calculation patterns
- ▶ Covariate structures
- ▶ Metadata approaches
- ▶ Validation frameworks

## Three ER Domains: A Comparison

Aspect	Exposure-Efficacy	Exposure-Safety	Tumor Response
<b>Primary Outcome</b>	Time-to-event (OS, PFS)	Event frequency/rates	Tumor size over time
<b>Data Structure</b>	One record per subject-event	Multiple levels (subject/event)	Longitudinal repeated measures
<b>Key Metrics</b>	Survival time, censoring	AE counts, rates, grades	Percent change, RECIST
<b>Analysis Type</b>	Cox regression, K-M curves	Poisson/negative binomial	Mixed models, waterfall plots
<b>Common Challenges</b>	Censoring handling	Time-varying exposure	Baseline normalization

# Domain 1: Exposure-Efficacy

**Use Case:** Progression-Free Survival by AUC Quartiles

## Key Dataset Features

- ▶ One record per subject-parameter
- ▶ AVAL = time from treatment start (days)
- ▶ CNSR = censoring indicator (1=censored, 0=event)
- ▶ Exposure available as continuous and categorical

```
adee %>%
```

```
  select(USUBJID, AVAL, CNSR, AUCO_24, AUC_TERTILE) %>%  
  head(3)
```

## EE: Code Example

```
1  # Derive time to event
2  adtte <- adtte_source %>%
3    derive_vars_merged(
4      dataset_add = adsl,
5      by_vars = exprs(USUBJID)
6    ) %>%
7    mutate(
8      # Analysis value = days from treatment start
9      AVAL = as.numeric(ADT - TRTSDT),
10     AVALU = "DAYS",
11     # Event indicator (inverse of CNSR for modeling)
12     EVENT = if_else(CNSR == 0, 1, 0)
13   )
14
15 # Create exposure categories
16 exposure_cats <- adsl %>%
17   mutate(
18     AUC_TERTILE = cut(AUC0_24,
```

## EE: Analysis-Ready Output

```
# ADEE structure
```

USUBJID	PARAMCD	AVAL	AVALU	CNSR	EVENT	AUCO_24
001-001	PFS	104	DAYS	1	0	450
001-002	PFS	135	DAYS	0	1	520
001-003	PFS	213	DAYS	0	1	680

**Ready for modeling:**

```
# Cox proportional hazards
```

```
coxph(Surv(AVAL, EVENT) ~ LOGAUC + AGE + SEX, data = adee)
```

```
# By category
```

```
survfit(Surv(AVAL, EVENT) ~ AUC_TERTILE, data = adee)
```

## Domain 2: Exposure-Safety

**Use Case:** Adverse Event Rates by Cmax Categories

### **Unique Challenges**

- ▶ Multiple analysis levels (subject, event, parameter)
- ▶ Time-varying exposure considerations
- ▶ Grade/severity tracking
- ▶ Need both counts and rates

### **Three Dataset Structures**

1. **Subject-level:** Overall AE burden per subject
2. **Event-level:** Individual AE occurrences
3. **Parameter-level:** Specific AE types

## ES: Subject-Level Structure

```
# Subject-level AE summary
ades_subj <- exposure_cats %>%
  left_join(ae_summary, by = "USUBJID") %>%
  mutate(
    # Total events
    N_AES = n(),
    N_SAE = sum(AESER == "Y"),
    N_GRADE3 = sum(AETOXGR >= "3"),

    # Rates per 100 patient-days
    RATE_AES = (N_AES / TRTDURD) * 100,
    RATE_SAE = (N_SAE / TRTDURD) * 100,

    # Binary indicators
    ANY_SAE = if_else(N_SAE > 0, "Y", "N"),
    ANY_GRADE3 = if_else(N_GRADE3 > 0, "Y", "N")
  )
```

## ES: Event-Level for Detailed Analysis

# Event-level dataset

USUBJID	AEDECOD	AETOXGR	ASTDY	CMAX	CMAX_TERTII
001-001	Nausea	1	15	125	Low
001-001	Fatigue	2	32	125	Low
001-002	Neutropenia	3	56	145	Medium

**Enables analyses like:**

- ▶ Time to first Grade 3+ AE
- ▶ Recurring event models
- ▶ Exposure-toxicity relationships by AE type



## Domain 3: Tumor Response

**Use Case:** Longitudinal Tumor Measurements with RECIST 1.1

### **Key Features**

- ▶ Repeated measures over time
- ▶ Baseline normalization critical
- ▶ Categorical response criteria (CR, PR, SD, PD)
- ▶ Best overall response (BOR) derivation

### **Analysis Approaches**

- ▶ Waterfall plots (best percent change)
- ▶ Spider plots (individual trajectories)
- ▶ Response rate by exposure
- ▶ Time to response

## Tumor Response: Longitudinal Structure

```
adtr <- tr_raw %>%
  mutate(
    PARAM = "Sum of Target Lesion Diameters",
    PARAMCD = "STDIAM",
    AVAL = TRORRES, # Raw measurement
    ADY = as.numeric(ADT - TRTSDT) + 1
  ) %>%
  # Identify baseline
  group_by(USUBJID, PARAMCD) %>%
  mutate(
    ABLFL = if_else(VISITNUM == 0, "Y", NA_character_),
    BASE = AVAL[ABLFL == "Y"]
  ) %>%
  # Calculate changes
  mutate(
    CHG = if_else(ABLFL != "Y", AVAL - BASE, NA_real_),
    PCHG = if_else(ABLFL != "Y", (AVAL - BASE) / BASE * 100
  )
```

# RECIST Criteria Implementation

```
adtr <- adtr %>%
  mutate(
    AVALC = case_when(
      ABLFL == "Y" ~ "BASELINE",
      AVAL == 0 ~ "CR", # Complete Response
      PCHG <= -30 ~ "PR", # Partial Response (30% decrease
      PCHG >= 20 ~ "PD", # Progressive Disease (20% increase
      TRUE ~ "SD" # Stable Disease
    )
  )

# Best Overall Response (BOR)
bor <- adtr %>%
  filter(ABLFL != "Y") %>%
  group_by(USUBJID) %>%
  summarise(
    BOR = case_when(
      any(AVALC == "CR") ~ "CR",
```

# Tumor Response: Output Structure

# Longitudinal measurements

USUBJID	VISIT	ADY	BASE	AVAL	CHG	PCHG	AVA
001-002	BASE	1	65	65	NA	NA	BAS
001-002	WEEK 6	43	65	55	-10	-15.4	SD
001-002	WEEK 12	85	65	35	-30	-46.2	PR
001-002	WEEK 18	127	65	32	-33	-50.8	PR

**Each subject has:**

- ▶ Longitudinal trajectory (for spider plots)
- ▶ Best overall response (for response rate)
- ▶ Exposure metrics (for ER modeling)

# Common Patterns Across Domains

## Time Variables

- ▶ ADT: Analysis date
- ▶ ADY: Study day (relative to TRTSDT)
- ▶ AVAL: Numeric outcome
- ▶ Consistent calculation methods

## Exposure Metrics

- ▶ Raw values (AUC, Cmax, Cavg)
- ▶ Transformed (log, standardized)
- ▶ Categorized (tertiles, quartiles)
- ▶ Available at subject level

## Analysis Flags

- ▶ ANL01FL: Primary analysis population
- ▶ ANL02FL: Sensitivity analyses
- ▶ Domain-specific (GRADE3FL, RESPFL, etc.)

## Traceability

- ▶ Clear link to SDTM (via -SEQ, -DTC)
- ▶ Derivation rules documented
- ▶ Metadata specifications

# Why {admiral}?

## Advantages for ER Data

- ▶ **Modular functions:** `derive_vars_*`, `derive_param_*`

## Example Extension

```
# Hypothetical future function
derive_param_er_response <- function(
  dataset, exposure_var, outcome_var,
  method = c("tertile", "quartile", "continuous")
) { ... }
```

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- ▶ **CDISC-aligned:** Built with standards in mind

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# Benefits: Reproducibility

## Before Standardization

```
# Study A
data$time_days <- difftime(data$event_dt, data$trt_start, u
data$AUC_cat <- cut(data$AUC, breaks=c(0,500,1000,Inf))

# Study B
df$tte <- as.numeric(df$EventDate - df$TreatmentDate) + 1
df$exposure_grp <- ifelse(df$auc < median(df$auc), "Low", "
```

## After Standardization

```
# All studies use consistent approach
adee <- derive_er_tte_data(
  adsl = adsl,
  adrs = adrs,
  exposure_var = "AUC0_24",
  param = "PFS"
)
```

# Benefits: Efficiency

## Time Savings

- ▶ Dataset creation: 50% reduction with templates
- ▶ QC: Automated checks via {admiral} assertions
- ▶ Documentation: Metadata-driven specs
- ▶ Onboarding: New analysts can follow patterns

## Quality Improvements

- ▶ Fewer manual errors
  - ▶ Consistent validation approach
  - ▶ Peer review easier
  - ▶ Regulatory submissions smoother
- "We reduced our ER dataset programming time from 3 weeks to 1 week per study" - [Example quote]*

# Path Forward: Community Adoption

## What We Need

### 1. **Feedback on proposed structures**

- ▶ Variable naming conventions
- ▶ Mandatory vs. optional elements
- ▶ Domain-specific needs

### 2. **Real-world testing**

- ▶ Pilot studies across organizations
- ▶ Edge cases and exceptions
- ▶ Tooling gaps

### 3. **Documentation**

- ▶ Implementation guides
- ▶ Worked examples
- ▶ Best practices

### 4. **Potential formalization**

- ▶ Could inform future CDISC guidance
- ▶ Pharmaverse ER working group?

# Getting Started Today

## Resources Available

- ▶ GitHub repository: [<https://github.com/jeffreyad/er-standards>]
- ▶ Example datasets and scripts
- ▶ ADaM specifications templates
- ▶ Presentation materials

## Try It Yourself

```
# Install development version
remotes::install_github("your-username/er-standards-project")

# Run examples
library(erstds)
run_ee_example()
run_es_example()
run_tumor_response_example()
```

## Connect

- ▶ Questions: [[jeff.dickinson@navitaslifesciences.com](mailto:jeff.dickinson@navitaslifesciences.com)]

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  - ▶ Exposure-Efficacy: time-to-event

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5. **Benefits are real** - efficiency, reproducibility, quality
6. **Community input needed** - pilot, refine, formalize



# Questions?

## Contact Information

- ▶ Email: [jeff.dickinson@navitaslifesciences.com](mailto:jeff.dickinson@navitaslifesciences.com)
- ▶ GitHub: [jeffreyad]
- ▶ LinkedIn: [<https://www.linkedin.com/in/jeffreyad/>]

## Resources

- ▶ Repository: [<https://github.com/jeffreyad/er-standards>]
- ▶ Documentation:  
[<https://github.com/jeffreyad/er-standards/specifications>]
- ▶ Pharmaverse: <https://pharmaverse.org>
- ▶ Examples: <https://pharmaverse.github.io/examples/>

Thank you!

## Backup Slides

## Backup: SDTM-PK Variables Reference

### Key Variables from SDTM-PK

Variable	Description	ER Relevance
PCTPT	Time Point Name	Timing of outcome assessment
PCTPTNUM	Numeric Time Point	Analysis visit sequencing
PCELT	Planned Elapsed Time	Relative timing calculations
PCSTRESN	Numeric Result	Maps to AVAL
PCSTRESU	Units	Maps to AVALU

## Backup: Detailed Variable Specifications

### Proposed Core Variables for ADEE

Variable	Type	Description	Required
PARAMCD	Char	Parameter Code (e.g., "PFS", "OS")	Yes
AVAL	Num	Analysis Value (days)	Yes
CNSR	Num	Censoring (1=censored, 0=event)	Yes
ADT	Date	Analysis Date	Yes
EXPOSURE_VAR	Num	Exposure metric	Yes
EXPOSURE_CAT	Char	Categorized exposure	No
ANL01FL	Char	Primary analysis flag	Yes

# Backup: Handling Edge Cases

## Common Challenges

### 1. **Missing Exposure Data**

- ▶ Imputation strategies
- ▶ Sensitivity analyses
- ▶ Flagging for exclusion

### 2. **Competing Risks (EE)**

- ▶ Death vs. progression
- ▶ Multiple event types

### 3. **Time-Varying Exposure (ES)**

- ▶ Dose changes
- ▶ Cumulative exposure

### 4. **Unscheduled Assessments (Tumor)**

- ▶ Off-schedule scans
- ▶ Response confirmation

# Acknowledgments

Synthetic data and code examples were developed with assistance from Claude (Anthropic, 2024), an AI assistant. All code was reviewed, tested, and validated by the author. Any errors or omissions are the responsibility of the author.