

Standardizing Exposure-Response Data for Modeling and Simulation

Using CDISC Principles and {admiral}

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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
- ▶ Four key datasets:
 - ▶ ADER: Exposure-Response (foundational)
 - ▶ ADEE: Exposure-Efficacy
 - ▶ ADES: Exposure-Safety
 - ▶ ADTRR: Tumor Response for E-R
- ▶ 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 (AUC, AUC_SS, AUCSS, AUC0_24)
- ▶ Limited exposure metrics (typically 3-5 variables)
- ▶ Difficult to share methodologies
- ▶ QC challenges

Why Standards Matter

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

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- ▶ **Comprehensive:** 20+ exposure metrics vs. 3-5 traditional
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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

What We Can Leverage

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

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

Four ER Datasets: A Comparison

Aspect	ADER	ADEE	ADES	ADTRR
Purpose	Exposure foundation	Time-to-event	Safety events	Tumor response
Structure	Subject-level	BDS (one/subject/param)	BDS + OCCDS hybrid	BDS with visits
Key Variables	20 exposure metrics	AVAL, CNSR, EVENT	TEAE, TEAE-SEV, event details	AVAL, BASE, CHG, PCHG
Unique Features	Comprehensive exposure	Censoring handling	Multiple analysis levels	RECIST 1.1, BOR
Variables	65	74	78	80

ADER: Exposure Foundation

Core Exposure Metrics (20 variables)

Raw Metrics - AUCSS:

Steady-state AUC - CMAXSS:

Steady-state Cmax

- CAVGSS: Steady-state Cavg

Transformed - AUCSLOG:

$\log(\text{AUCSS})$ - CMXSLOG:

$\log(\text{CMAXSS})$ - CAVGLOG:

$\log(\text{CAVGSS})$

Standardized - AUCSSSTD:

Z-score - CMXSSSTD: Z-score

Normalized - AUCSSN:

AUC/mean(AUC) - CMAXSSN:

Cmax/mean(Cmax)

Dose-Normalized - AUCSSDOS:

AUC/Dose - CMXSSDOS:

Cmax/Dose

Categorical - AUCSSCAT:

Tertiles/quartiles - AUCSCATN:

Numeric category

Variable Naming: 8-Character Compliance

CDISC ADaM Requirement: Variable names 8 characters

Our Naming Strategy

Traditional	Updated (8 char)	Rationale
AUCSSLOG	AUCSLOG	Removed one "S"
CMAXSSLOG	CMXSLOG	Abbreviated CMAX
CAVGSSLOG	CAVGLOG	Removed SS
CMAXSSSTD	CMXSSSTD	Abbreviated CMAX
AUCSSDOSE	AUCSSDOS	Removed E
CMAXSSDOSE	CMXSSDOS	Abbreviated + removed E
AUCSSCATN	AUCSCATN	Removed one S

Domain 1: Exposure-Efficacy (ADEE)

Use Case: Progression-Free Survival by AUC Tertiles

Key Dataset Features

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

```
adee %>%
  select(USUBJID, PARAMCD, AVAL, CNSR, EVENT, AUCSS, AUCSSC)
  head(3)
```

ADEE: Code Example

```
1 # Derive time to event
2 adtte <- adtte_source %>%
3   derive_vars_merged(
4     dataset_add = ads1,
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 (in ADER/exposure derivation)
16 exposure_cats <- ads1 %>%
17   mutate(
18     AUCSSCAT = cut(AUCSS,
```

ADEE: Analysis-Ready Output

# ADEE structure (74 variables)								
USUBJID	PARAMCD	AVAL	AVALU	CNSR	EVENT	AUCSS	AUCSSSTD	AGE
001-001	PFS	104	DAYS	1	0	450.2	450.2	61.0
001-002	PFS	135	DAYS	0	1	520.5	520.5	61.0
001-003	PFS	213	DAYS	0	1	680.1	680.1	61.0

Ready for modeling:

```
# Cox proportional hazards (continuous)
coxph(Surv(AVAL, EVENT) ~ AUCSSSTD + AGE + SEX, data = adee)

# By category
survfit(Surv(AVAL, EVENT) ~ AUCSSCAT, data = adee)
```

Domain 2: Exposure-Safety (ADES)

Use Case: Adverse Event Rates by Cmax Categories

Unique Challenges

- ▶ Multiple analysis levels (subject, event, parameter)
- ▶ Time-varying exposure considerations
- ▶ Severity tracking (ASEV vs. AETOXGR)
- ▶ Need both counts and rates

Dataset Structure (78 variables)

1. **Subject-level parameters:** Overall AE burden
2. **Event-level records:** Individual AE occurrences with exposure context

ADES: Subject-Level Parameters

```
1 # Subject-level AE summary parameters
2 ades_subj <- adsl %>%
3   left_join(ae_summary, by = "USUBJID") %>%
4   mutate(
5     PARAMCD = "TEAE",
6     PARAM = "Treatment-Emergent Adverse Events",
7     AVAL = n_aes, # Count of AEs
8     AVALC = as.character(n_aes)
9   ) %>%
10  bind_rows(
11    # Additional parameters: TEAESEV, TESAE, etc.
12    create_param("TEAESEV", "Treatment-Emergent Severe AEs"),
13    create_param("TESAE", "Treatment-Emergent Serious AEs")
14  )
```

ADES: Severity Variables

Important: ADES uses ASEV/ASEVN (not AETOXGR/AETOXGRN)

Variable	Values	Description
ASEV	MILD, MODERATE, SEVERE	Severity (character)
ASEVN	1, 2, 3	Severity (numeric)
AESER	Y, N	Serious flag
AEREL	NOT RELATED, UNLIKELY, POSSIBLE, PROBABLE, RELATED	Relationship
AERELN	0, 1, 2, 3, 4	Relationship (numeric)

Key Parameters

ADES: Event-Level Records

```
# Event-level dataset structure
```

USUBJID	AESEQ	AEDECOD	ASEV	ASEVN	AEREL
001-001	1	NAUSEA	MILD	1	POSSIBLE
001-001	2	FATIGUE	MODERATE	2	PROBABLE
001-002	1	NEUTROPENIA	SEVERE	3	RELATED

Enables analyses like:

- ▶ Time to first Severe AE (ASEVN = 3)
- ▶ Recurring event models
- ▶ Exposure-toxicity relationships by AE type
- ▶ Relationship analysis (AERELN as continuous)

Domain 3: Tumor Response (ADTRR)

Use Case: Longitudinal Tumor Measurements with RECIST 1.1

Key Features (80 variables)

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

Analysis Approaches

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

ADTRR: Longitudinal Structure

```
1 adtr <- tr_raw %>%
2   mutate(
3     PARAMCD = "TSIZE",
4     PARAM = "Target Lesion Size",
5     PARAMN = 1,
6     AVAL = TRORRES, # Raw measurement (mm)
7     AVALU = "mm",
8     ADY = as.numeric(ADT - TRTSDT) + 1
9   ) %>%
10  # Identify baseline
11  group_by(USUBJID, PARAMCD) %>%
12  mutate(
13    ABLFL = if_else(AVISITN == 1, "Y", ""),
14    BASE = first(AVAL[ABLFL == "Y"])
15  ) %>%
16  # Calculate changes
17  mutate(
18    CHG = if_else(ABLFL != "Y", AVAL - BASE, NA_real_),
19    PCMG = if_else(AVISITN > 1, ((AVAL - BASE) / BASE), NA_real_)
```

ADTRR: Additional Parameters

Beyond Target Lesion Size

```
# Best Overall Response (BOR)
adtrr_bor <- adtrr %>%
  group_by(USUBJID) %>%
  summarise(
    PARAMCD = "BOR",
    PARAM = "Best Overall Response",
    PARAMN = 2,
    AVALC = derive_best_response(AVALC),
    BORN = case_when(
      AVALC == "CR" ~ 4,
      AVALC == "PR" ~ 3,
      AVALC == "SD" ~ 2,
      AVALC == "PD" ~ 1
    )
  )
# Nadir (minimum tumor size)
```

RECIST Criteria Implementation

```
1 adtrr <- adtrr %>%
2   mutate(
3     # RECIST 1.1 response at each visit
4     AVALC = case_when(
5       ABLFL == "Y" ~ "BASELINE",
6       AVAL == 0 ~ "CR", # Complete Response
7       PCHG <= -30 ~ "PR", # Partial Response ( 30% decrease)
8       PCHG >= 20 & CHG >= 5 ~ "PD", # Progressive Disease
9       TRUE ~ "SD" # Stable Disease
10    )
11  )
12
13 # Best Overall Response across all visits
14 bor <- adtrr %>%
15   filter(ABLFL != "Y") %>%
16   group_by(USUBJID) %>%
17   summarise(
18     BOR = case_when(
19       (AVALC == "CR") | (AVALC == "SD") ~ "CR",
```

ADTRR: Output Structure

# Longitudinal measurements (80 variables)							
USUBJID	PARAMCD	AVISITN	AVISIT	BASE	AVAL	CHG	
001-002	TSIZE	1	BASE	65.0	65.0	NA	
001-002	TSIZE	2	WEEK 6	65.0	55.0	-10	
001-002	TSIZE	3	WEEK 12	65.0	35.0	-30	
001-002	BOR	99	OVERALL	NA	NA	NA	
001-002	NADIR	99	OVERALL	65.0	35.0	-30	

Each subject has:

- ▶ Longitudinal trajectory (TSIZE records)
- ▶ Best overall response (BOR parameter)
- ▶ Nadir tumor size (NADIR parameter)
- ▶ Exposure metrics on all records

Common Patterns Across Datasets

Time Variables

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

Exposure Metrics (20 variables)

- ▶ Raw: AUCSS, CMAXSS, CAVGSS
- ▶ Transformed: AUCSLOG, CMXSLOG
- ▶ Standardized: AUCSSSTD, CMXSSSTD
- ▶ Categorical: AUCSSCAT, AUCSCATN

Traceability

Baseline Covariates (13 variables)

- ▶ Demographics: AGE, SEX, RACE
- ▶ Vitals: WTBL, HTBL, BMIBL, BSA
- ▶ Renal: CREATBL, CRCLBL, EGFRBL
- ▶ Hepatic: ALTBL, ASTBL, TBILBL

Analysis Flags

- ▶ ANL01FL: Primary analysis
- ▶ ANL02FL: Sensitivity analyses
- ▶ Domain-specific flags

8-Character Compliance Summary

All Variable Names 8 Characters

Category	Examples	Count
Exposure (raw)	AUCSS, CMAXSS, CAVGSS	3
Exposure (log)	AUCSLOG, CMXSLOG, CAVGLOG	3
Exposure (std)	AUCSSSTD, CMXSSSTD	2
Exposure (norm)	AUCSSN, CMAXSSN	2
Exposure (dose)	AUCSSDOS, CMXSSDOS	2
Exposure (cat)	AUCSSCAT, AUCSCATN	2
Covariates	CRCLBL, EGFRBL, BMIBL	13
Response	NADPCHG, NADVST	2

Total: 20 exposure metrics + 13 covariates across all datasets

Why {admiral}?

Advantages for ER Data

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

Example Extension

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

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- ▶ **8-character compliance:** Follows naming conventions

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  method = c("tertile", "quartile", "continuous")
) { ... }
```

Benefits: Reproducibility

Before Standardization

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

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

After Standardization

```
# All studies use consistent approach and naming
adee <- derive_er_tte_data(
  ads1 = ads1,
  adrs = adrs,
  exposure_vars = c("AUCSS", "AUCSLOG", "AUCSSSTD", "AUCSSC"),
  param = "PFS")
```

Benefits: Comprehensive Exposure Metrics

Traditional Approach: 3-5 exposure variables

```
# Typical traditional dataset  
c("AUC", "CMAX", "CAVG")
```

New Framework: 20 standardized exposure variables

```
# All transformations pre-computed  
exposure_vars <- c(  
  # Raw (3)  
  "AUCSS", "CMAXSS", "CAVGSS",  
  # Log-transformed (3)  
  "AUCSLOG", "CMXSLOG", "CAVGLOG",  
  # Standardized (3)  
  "AUCSSSTD", "CMXSSSTD", "CAVGSTD",  
  # Normalized (3)  
  "AUCSSN", "CMAXSSN", "CAVGSSN",  
  # Dose-normalized (3)  
  "AUCSSDOS", "CMXSSDOS", "CAVGDOS",  
  # Categorical (2)
```

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
- ▶ Analysis: No data prep needed

Quality Improvements

- ▶ Fewer manual errors (automated derivations)
- ▶ Consistent validation approach
- ▶ Peer review easier (standard structure)
- ▶ Regulatory submissions smoother
- ▶ 8-character compliance built-in

Real Impact

"Standardized E-R datasets reduced programming time from 3 weeks to 1 week per study while improving quality"

Path Forward: Community Adoption

What We Need

- 1. Feedback on proposed structures**
 - ▶ Variable naming conventions (especially 8-char compliance)
 - ▶ 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 with code
 - ▶ 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 (simulated data)
- ▶ Complete derivation scripts (ADER, ADEE, ADES, ADTRR)
- ▶ ADaM specifications (P21 format + Excel)
- ▶ Metacore objects for metadata
- ▶ Presentation materials

Try It Yourself

```
# Clone repository
git clone https://github.com/jeffreyad/er-standards.git
cd er-standards

# Generate example data
source("data-raw/S0_Generate_Example_Data.R")

# Run ADaM derivations
source("programs/run_all_adams.R")
```

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Questions?

Contact Information

- ▶ Email: jeff.dickinson@navitaslifesciences.com
- ▶ GitHub: [jeffreyad](https://github.com/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: Complete Variable List (ADER)

ADER: 65 Variables

Exposure Metrics (20) -

AUCSS, CMAXSS, CAVGSS -
AUCSLOG, CMXSLOG,
CAVGLOG - AUCSSSTD,
CMXSSSTD, CAVGSTD -
AUCSSN, CMAXSSN, CAVGSSN
- AUCSSDOS, CMXSSDOS,
CAVGDOS - AUCSSCAT,
AUCSCATN - CMXSSCAT,
CMXSCATN

Baseline Covariates (13) -

WTBL, HTBL, BMIBL, BSA -
CREATBL, CRCLBL, EGFRBL -
ALTBL, ASTBL, TBILBL -
ALBBL - ECOGBL, SMOKEBL

Demographics (8) -

AGE, AGEGR1, AGEGR1N - SEX,
SEXN - RACE, RACEN -
ETHNIC, ETHNICN

Treatment (8) -

ARM, ARMN,
ARMCD - TRT01P, TRT01PN -
TRT01A, TRT01AN - DOSE

Other (16) -

Identifiers:
STUDYID, USUBJID, SUBJID,
etc. - Dates: TRTSDT,
TRTEDT, TRTDURD - Flags:
SAFFL, ITTFL, EFFFBL

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
PCELM	Planned Elapsed Time	Relative timing calculations
PCSTRESN	Numeric Result	Maps to AVAL
PCSTRESU	Units	Maps to AVALU

Our Extensions

- ▶ Added comprehensive exposure transformations
- ▶ Categorical exposure variables
- ▶ Baseline covariate integration
- ▶ Domain-specific parameters

Backup: Detailed Variable Specifications

Proposed Core Variables for ADEE (74 total)

Variable	Type	Description	Re- quired?	Notes
PARAMCD	Char	Parameter Code (PFS, OS, TTP, TTNT)	Yes	Stan- dard codes
AVAL	Num	Analysis Value (days)	Yes	Con- tin- uous out- come
CNSR	Num	Censoring (1=censored, 0=event)	Yes	Stan- dard TTE
EVENT	Num	Event (1=event, 0=censored)	Yes	For mod- eling

Backup: Handling Edge Cases

Common Challenges

1. Missing Exposure Data

- ▶ Imputation strategies
- ▶ Sensitivity analyses
- ▶ Flagging for exclusion (ANL01FL = "N")

2. Competing Risks (ADEE)

- ▶ Death vs. progression
- ▶ Multiple event types as separate parameters

3. Time-Varying Exposure (ADES)

- ▶ Dose changes over time
- ▶ Cumulative exposure metrics
- ▶ Landmarking approaches

4. Unscheduled Assessments (ADTRR)

- ▶ Off-schedule scans
- ▶ Response confirmation windows
- ▶ Handling missing visits

5. 8-Character Limit Conflicts

- ▶ Systematic abbreviation rules
- ▶ Document in specifications
- ▶ Hard-coded suffixes

Backup: Variable Name Abbreviation Rules

Systematic Approach to 8-Character Compliance

1. Remove vowels from middle (if >8 char)
 - ▶ BASELINE → BASELN (not used, but example)
2. Abbreviate common terms
 - ▶ MAXIMUM → MAX → MAX
 - ▶ AVERAGE → AVG → AVG
 - ▶ CATEGORY → CAT
3. Remove repeated letters
 - ▶ AU**C**S**S**LOG → AU**C**SLOG (one S removed)
 - ▶ AU**C**SS**C**ATN → AU**C**SCATN (one S removed)
4. Abbreviate exposure terms
 - ▶ CMAX → CMX (when combined with other suffixes)
 - ▶ STEADY STATE → SS
5. Remove last vowel from suffix
 - ▶ DOSE → DOS (when combined: AUCSSDOS)

Documentation: All abbreviations documented in define.xml and specifications

Backup: Comparison with Traditional

Traditional Single-File Approach

```
# All data in one wide row per subject  
C | PTNM | TRT | AUC | CMAX | OS | PFS | NADIR | BOR | TEAI
```

Issues: - Non-standard variable names - Limited exposure metrics (3-5 variables) - Hard to extend with new parameters - No transformation variants - Mixed parameter types

New Framework (4 Datasets)

```
# ADER: 20 exposure metrics  
# ADEE: Time-to-event + exposure (74 vars)  
# ADES: Safety + exposure (78 vars)  
# ADTRR: Tumor + exposure (80 vars)
```

Benefits: - CDISC-compliant (8-char limit) - Comprehensive exposure (20 metrics) - Flexible parameter addition - Pre-computed transformations - Domain-optimized structures

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