



The Clinical Data
Science Conference

US 2025

16–19 March
Renaissance Orlando at SeaWorld Florida

Gen-AI for Statistical Reporting and Clinical Study Report Writing Leveraging CDISC ARS Model

Paper & Presentation # ML26

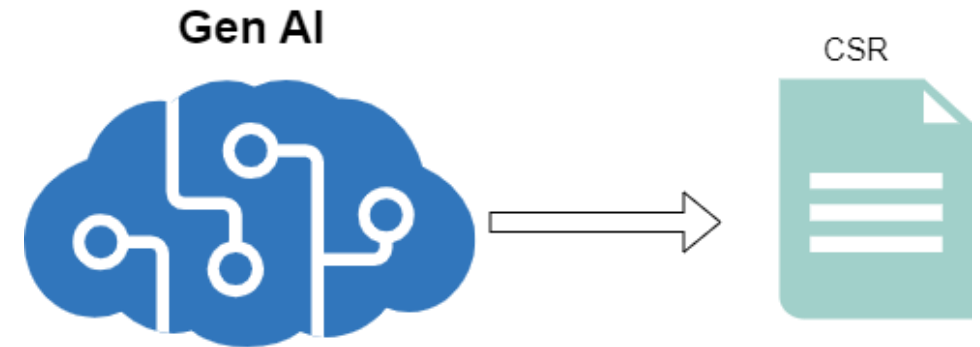
March 19, 2025

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Gen AI for Clinical Study Report (Content) Generation

- CSR Writing: a critical yet time-consuming process
- Interpreting complex statistical outputs from TFLs demands precision
- Gen-AI accelerates CSR authoring, improving both speed and accuracy
- Our Proof of Concept (POC), powered by CDISC ARS & ARD, redefines how CSRs are written.



Gen-AI Models used by Clymb

1st POC

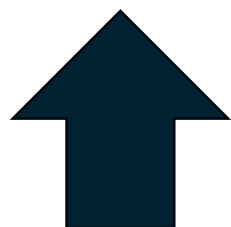
Prompt-Based
Models

2nd POC

Embedding
Models

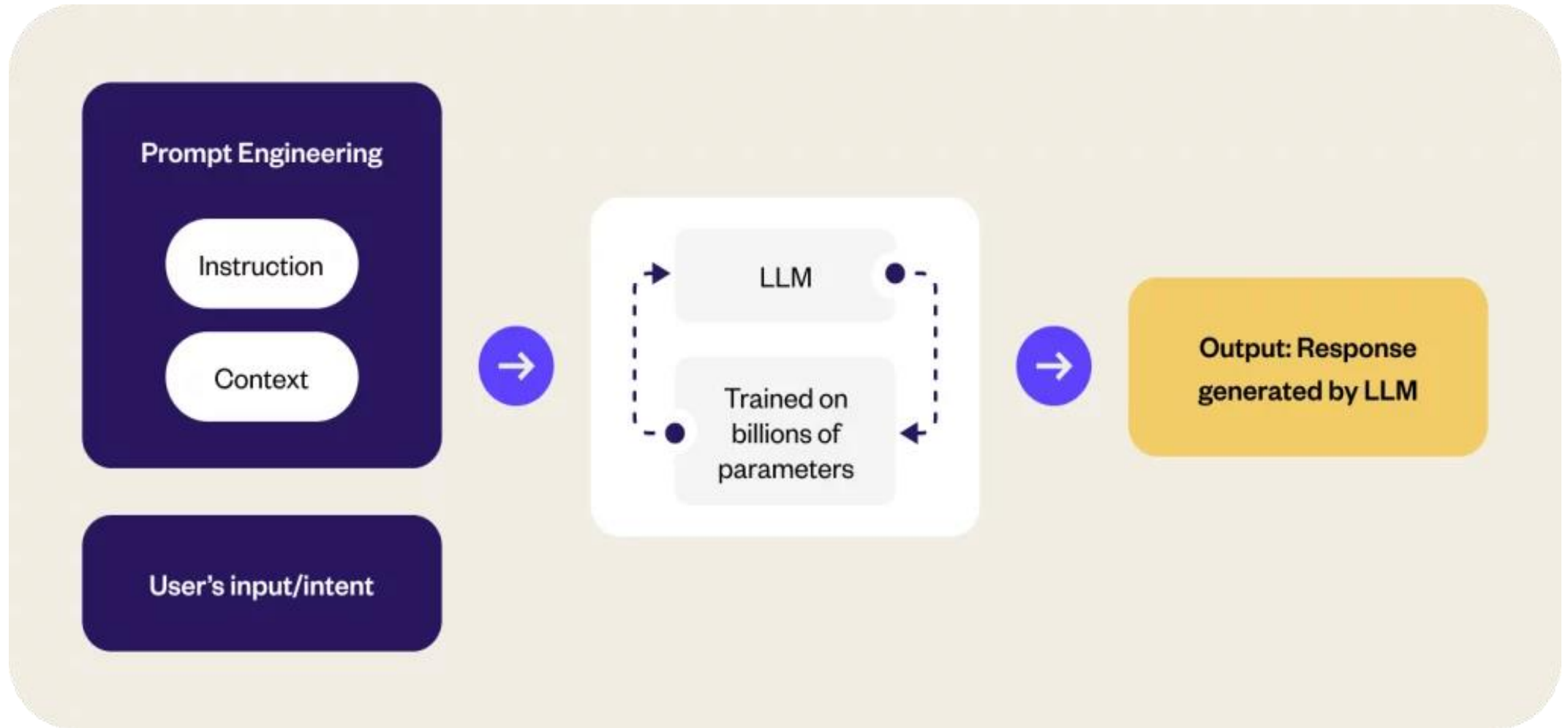
Exploring

Open-Source
Models

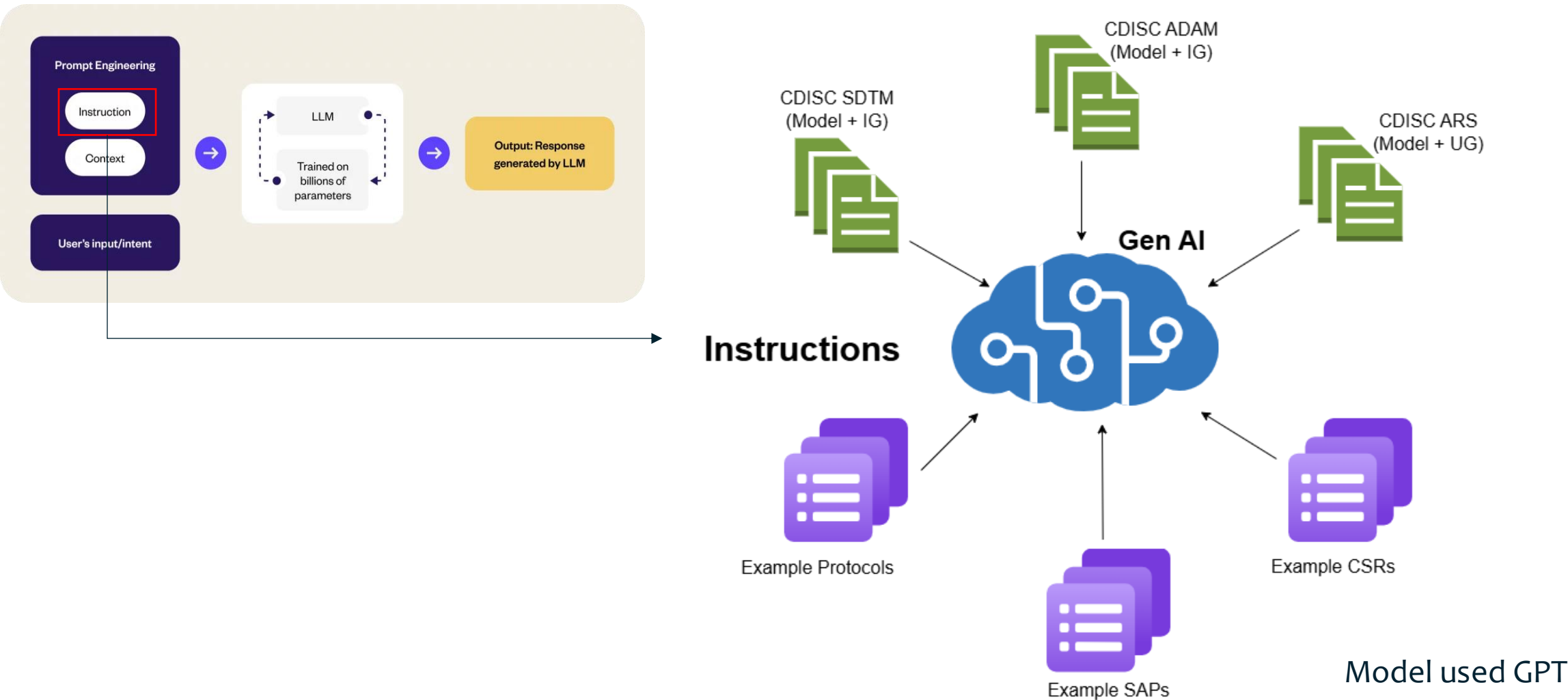


Presenting on

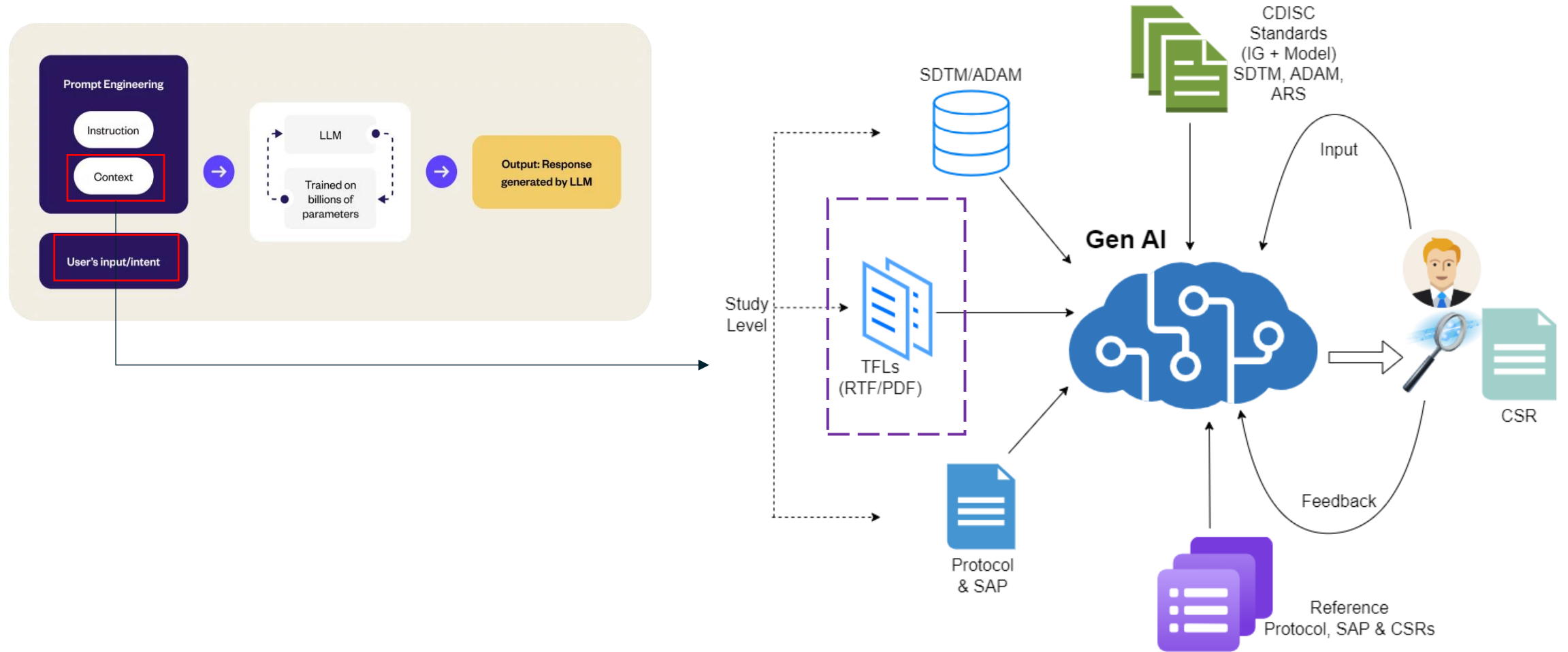
Prompt Engineering – Instruction, Context and User's Input



Providing Instructions / Examples to the AI Model

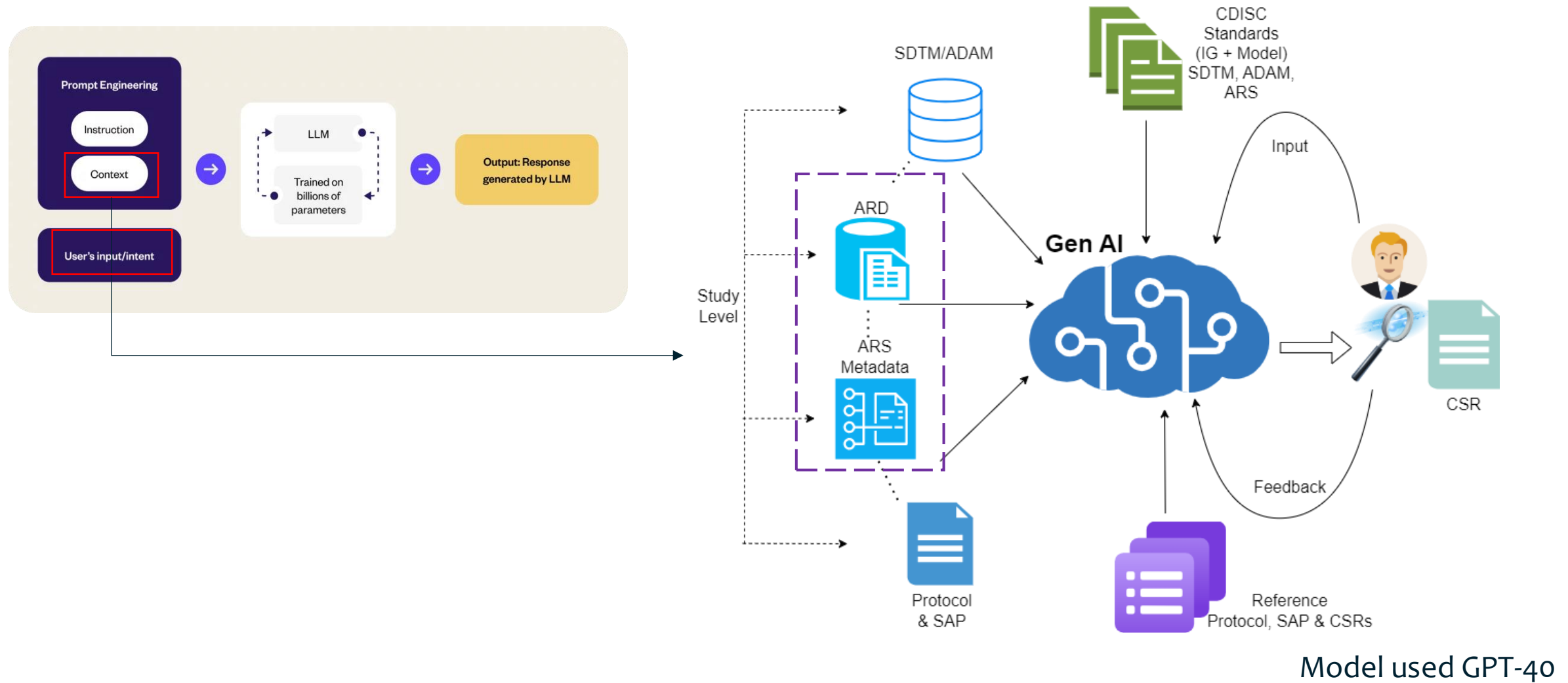


Providing **Context** to the AI Model [TFLs in RTF or PDF]



Model used GPT-4o

Providing **Context** to the AI Model [ARS Metadata and ARD]



Is Providing ARS Metadata + ARD Better Than TFLs ?

CDISC Analysis Results Standard - a Logical Data Model



Analysis Results Standard (ARS) v1.0



Large trials generate many analysis results in the form of tables, figures, and written reports, yet these results are rarely output in a form that is machine-readable. Previously, there has been no standard way of describing and organizing these results, making it difficult to automate their generation, make them reproducible, trace their origin, or enable them to be reused in other outputs.

To address these inefficiencies, CDISC has developed the [Analysis Results Standard \(ARS\)](#), which aim to facilitate automation, reproducibility, reusability, and traceability of analysis results data.

Features of ARS v1.0

- A Logical Data Model that describes analysis results and associated metadata.
- A User Guide to illustrate and exercise the model with common safety displays.

<https://cdisc-org.github.io/analysis-results-standard/>

Analysis Results Standard (ARS)

Schema Diagram

Classes

Slots

Enumerations

Types

Subsets

Analysis Results Standard (ARS)

Logical model to support both the prospective specification of analyses and the fully contextualized representation of the results of the analyses.

URI: <https://www.cdisc.org/ars/1-0> Name: ars_idm

Schema Diagram

Classes

Classes provide templates for organizing data. Data objects instantiate slots (aka fields, attributes) that are applicable to it. See [LinkML docs](#)

Class	Description
NamedObject	An object with a name
ReportingEvent	A set of analyses and o requirements...
ListOfContents	A structured list of ana

cdisc

Analysis Results Standard User Guide

Version 1.0 (Final)

Prepared by the
Analysis Results Standard Team

Notes to Readers

- This is the final Version 1.0 of the Analysis Results Standard User Guide.
- This document is based on ADaM v2.1 and Analysis Results Metadata (ARM) v1.0 for Define-XML v2.0

Revision History

Date	Version
2024-04-19	Final

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<https://wiki.cdisc.org/display/ARSP/Analysis+Results+Standard+User+Guide+v1.0>

CDISC ARD - holding Results and associated Metadata

Analysis Results Datasets

id		operation_id	resultGroup1_groupingId	resultGroup1_groupId	resultGroup2_groupingId	resultGroup2_groupId	rawValu	formattedVal
An03.02_AgeGrp_ByTrt		Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	14	14
An03.0	id	operation_id	resultGroup1_groupingId	resultGroup1_groupId	resultGroup2_groupingId	resultGroup2_groupId	rawValu	formattedVal
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	14	14
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	72	72
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	72	72
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	14	14
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	72	72
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_2	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	8	8
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An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_3	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	11	11
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_1_n	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_3	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	73	73
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_2_pct	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	16.27907	(16.3)
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_2_pct	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_1	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	83.72093	(83.7)
An03.0	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_2_pct	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_2	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	9.52381	(9.5)
	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_2_pct	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_2	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	90.47619	(90.5)
	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_2_pct	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_3	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_1	13.09524	(13.1)
	An03.02_AgeGrp_ByTrt	Mth01_CatVar_ByGrp_2_pct	AnlsGrouping_02_Trt	AnlsGrouping_02_Trt_3	AnlsGrouping_03_AgeGp	AnlsGrouping_03_AgeGp_2	86.90476	(86.9)

Analysis Results Datasets (ARD) are structured datasets containing the results of statistical analyses performed on clinical trial data, along with metadata that provides **context**, **traceability**, and **machine-readable** summaries to support TFLs and regulatory submissions.

Final Verdict

Final Verdict: ARD > TFLs in RTF

ARDs provide a more structured, efficient, accurate, and regulation-aligned input for Gen AI-driven CSR generation compared to TFLs in RTF. While TFLs in RTF are useful for human review, ARDs unlock the full potential of automation, contextual consistency, and seamless integration with modern tools like Gen AI models.



Why Bother With Summarized Results (ARD)? Can't We Just Provide Patient-Level Data?

Using ARD as the Primary Input

Conclusion

- **Performance:** ARDs improve processing efficiency by 3–5x compared to patient-level data.
- **Accuracy:** ARDs significantly reduce the risk of misinterpretation and statistical errors.
- **Compliance:** ARDs simplify traceability and ensure compliance with CDISC and regulatory expectations.
- **Narrative Quality:** ARDs enhance AI's ability to produce clear, objective-driven narratives.

Recommendation:

Use ARDs as the primary input for Gen AI-driven CSR generation. Patient-level data can be used for exploratory or hypothesis-generating analyses but is less suitable for structured regulatory narratives.



Regulatory Perspective

Verdict:

From a **regulatory perspective**, summarized results like ARDs are a **requirement** to demonstrate that analyses were performed according to the study's Statistical Analysis Plan (SAP). Regulatory bodies such as the **FDA** and **EMA** expect that clinical summaries are based on **validated, human-reviewed results**, not directly on raw patient-level data.

Additionally, for a **drug product tied to patient safety and efficacy**, you want **human intervention** in the analytical process to ensure that **critical safety signals are not missed**, statistical methodologies are correctly applied, and conclusions are reliable for regulatory decisions.



CDISC ARD: The Clear Winner for Gen AI-Driven CSR Writing!

What Sections of the CSR is Supported by Gen AI?

Sections of the CSR Supported by Gen-AI

1. Synopsis (Section 1)

- Study Objectives, Endpoints, and Summary
- Key Efficacy and Safety Results
- Statistical Methods Summary
(Requires inputs from Protocol, SAP, ARD, and ARS)

2. Introduction (Section 2)

- Study Rationale and Background
(Primarily Protocol-driven; minimal data input required)

3. Study Objectives (Section 3)

- Primary, Secondary, and Exploratory Objectives
(From Protocol and SAP)

4. Study Design (Section 4)

- Description of Study Population, Treatment Groups, and Randomization
(Protocol and SAP-driven)

5. Efficacy Evaluation (Section 8)

- Primary and Secondary Endpoint Results
- Statistical Analysis Details (e.g., Hypothesis Testing, Model Outputs)
- Tables, Listings, and Figures (TLFs) generated from ARD/ARS metadata
(Requires ADaM datasets, ARD, ARS, SAP)

6. Safety Evaluation (Section 9)

- Adverse Events Analysis
- Laboratory Parameters, Vital Signs, ECGs
(Generated using ARD/ARS with ADaM datasets)

7. Statistical Methods (Section 11)

- Detailed Statistical Analysis Procedures
(Derived from SAP and ARS metadata)

8. Results (Section 12)

- Demographic and Baseline Characteristics
- Disposition of Subjects
- Efficacy and Safety Outcomes
(Primarily data-driven using ARD, ARS, and ADaM datasets)

9. Conclusions (Section 13)

- Automatically generate draft conclusions based on statistical outputs and key efficacy/safety findings
(Can provide initial draft; human oversight recommended)

10. Appendices (Section 16)

- Tables, Listings, and Figures (TLFs)
- ADaM Dataset Metadata Documentation
- Analysis Results Metadata Documentation (ARS/ARD)

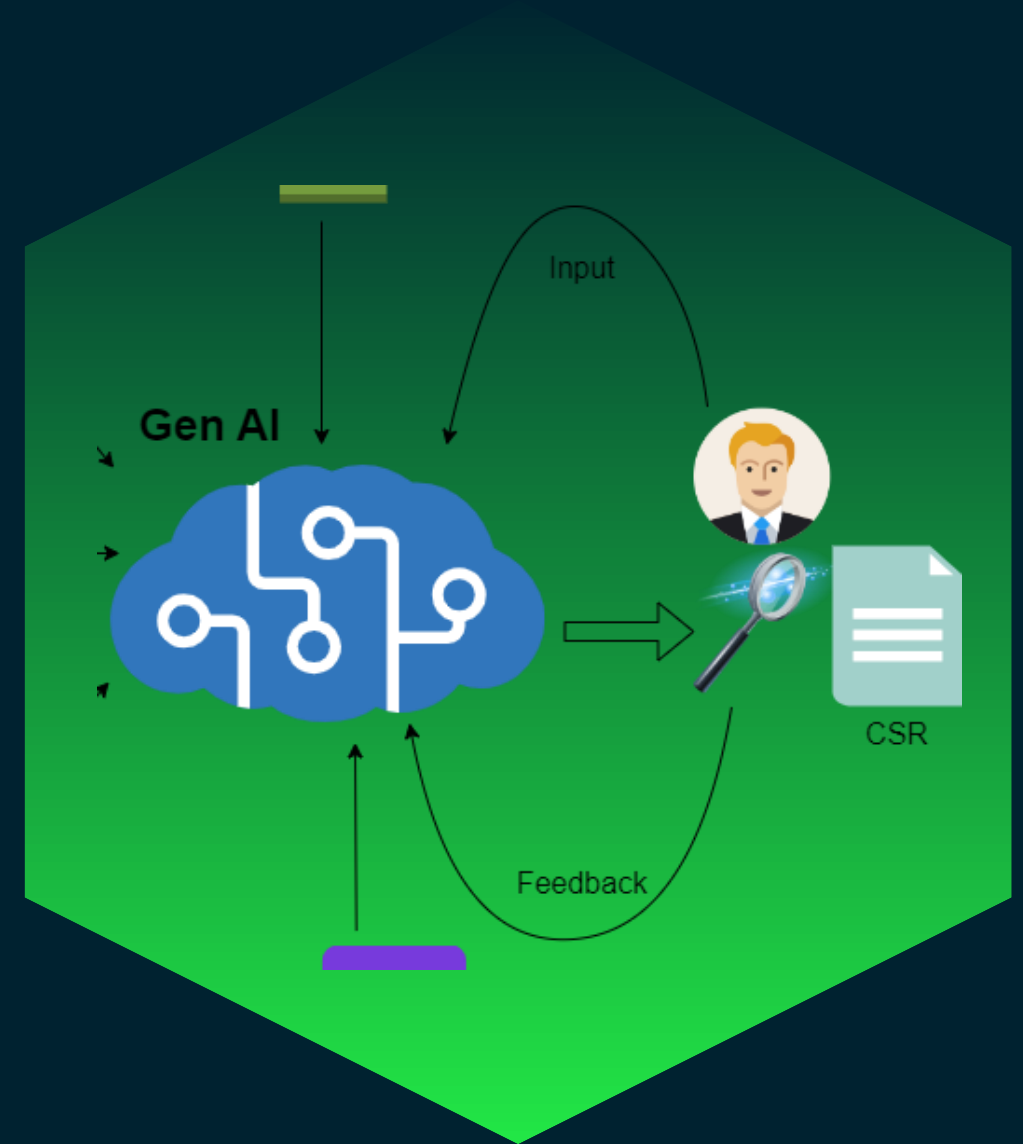
Let's See Gen AI Produced CSR Sections!

Takeaway: Gen AI can generate good-quality CSR narratives, but...

“Gen AI can make mistakes.”

Human-in-the-loop Validation

Human-in-the-loop validation is necessary to maintain clinical accuracy and regulatory compliance.



Key Considerations for Gen AI-Based CSR Writing



Create Training
Pairs

(Input / Output Examples)



Fine-Tuning
Strategy



Validation and
Testing



Continuous
Refinement

Prompt Engineering – Instruction, Context and User's Input

Tell us about the Benefits, Challenges and Considerations?

Key Benefits

- **Increased Efficiency:** Reduces manual effort, accelerates reporting, and streamlines CSR generation.
- **Enhanced Accuracy:** Minimizes human errors with automated quality control to detect inconsistencies.
- **Improved Consistency:** Ensures uniform interpretation and standardization across CSRs.



Challenges and Considerations



Regulatory Compliance

Strict adherence to ICH, FDA, and EMA guidelines to ensure regulatory approval.

Maintain audit trails and document every AI-driven decision for transparency.



Data Privacy

Secure handling of sensitive clinical data using HIPAA and GDPR standards.

Implement data anonymization and end-to-end encryption for confidentiality.



Model Interpretability

Ensure transparency in AI decision-making with explainable AI (XAI) techniques.

Provide traceability from data inputs to narrative outputs.



Adaptability

Handle study-specific nuances by fine-tuning models for different therapeutic areas.

Allow customization to align with study protocols and statistical methods.

Next Steps?

Gen AI for CSR Writing: An Inevitable Step Toward Efficiency and Innovation

Incorporate Learnings & Complete Embedded Model

1st POC

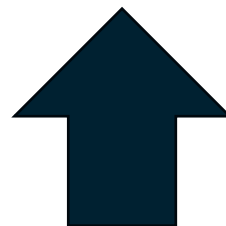
Prompt-Based
Models

2nd POC

Embedding
Models

Exploring

Open-Source
Models



Complete by Q2 '25



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