

# Innovation & Advancing GMP

“APPLYING AI/ML TO DEVIATION  
TREND ANALYSIS”

Mary Coyne, Quality Advisor Eli Lilly

*Lilly*

## THE CHALLENGE

### Deviation Trending — A Manual, Labour Intensive Subjective Process



#### High Volume

A large volume of deviations with rich free-text descriptions — too many to manually review for hidden patterns.



#### Category Dependency

Traditional trending relies on pre-defined categories selected by authors — subtle cross-category themes are missed.



#### Reviewer Variability

Different reviewers may identify different trends from the same data, introducing subjectivity into the process.

**WHAT IF WE COULD ANALYSE THE LANGUAGE IN DEVIATION DESCRIPTIONS (NOT THE CATEGORIES) TO IMPROVE EVALUATION WHERE SIMILAR EVENTS ARE CLUSTERING?**

## THE ORIGIN

# Innovation from Within Quality

This project didn't start in IT or Data Science. It started with a Quality professional recognising that the language used in deviation records held untapped insight — and partnering with a Data Engineer to unlock it.

### 1 Identify the Opportunity

A Quality Professional recognised that free-text descriptions contain richer trend signals than pre-defined categories alone employed in traditional trending.

### 2 Cross-Functional Partnership

Quality expertise paired with Data Engineering skills to design an ML pipeline purpose-built for deviation data.

### 3 Prototype & Validate

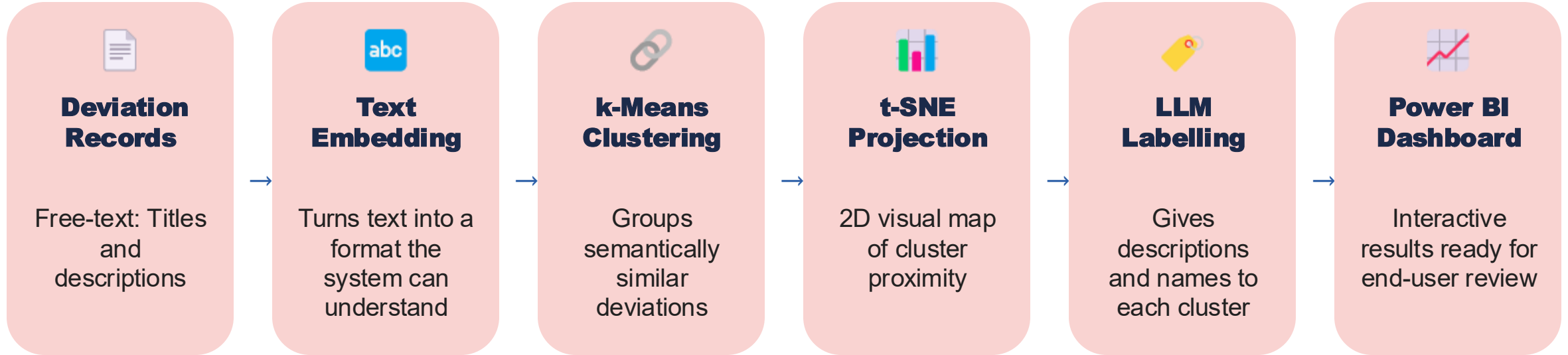
Built a working tool and validated outputs with area experts to confirm clusters reflected real-world trends.

### 4 Expand the Use Case

Same engine repurposed for inspection preparation — one investment, multiple returns.

## HOW IT WORKS

# The ML Pipeline — Fully Automated, End to End



### Unsupervised

No labelled training data needed

### Language-Based

Clusters by meaning, not keywords

### Adaptive

Reflects trend shifts automatically

### Scheduled

Models refresh automatically

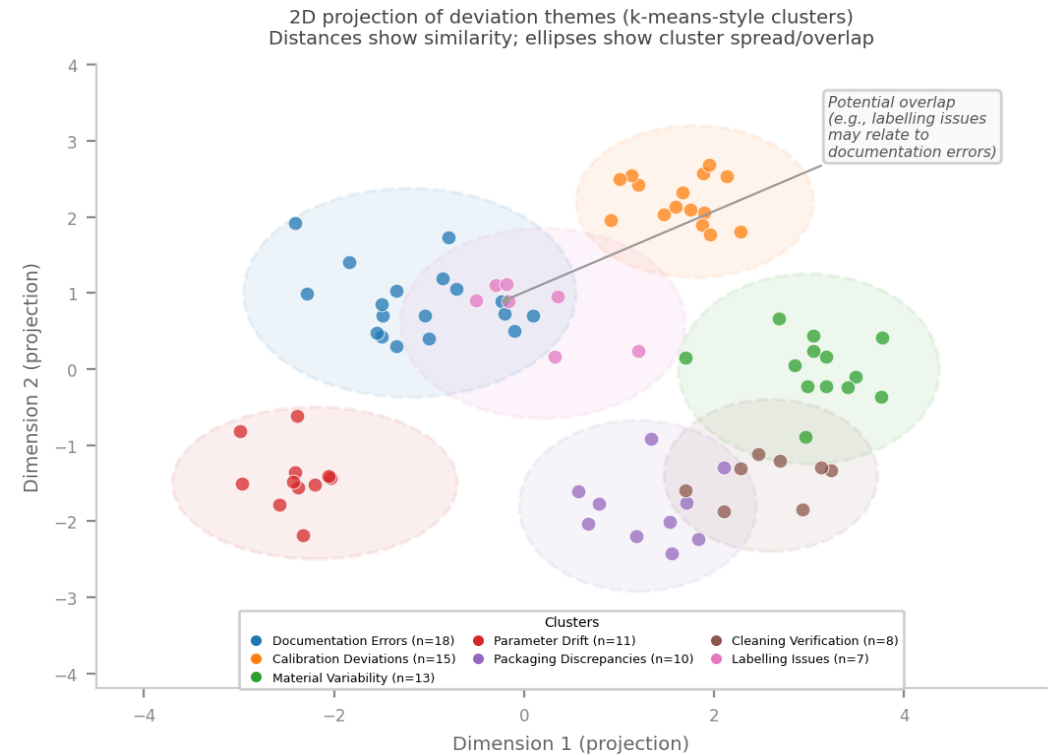
# Cluster Map — Deviation Trend Detection

Each dot is a deviation positioned by semantic similarity. Clusters are ranked by density. Related clusters overlap — e.g., labelling issues and documentation errors share boundary points.

**Illustrative demo only (not company data); themes use generic deviation categories common across the industry; dots/counts are synthetically generated placeholders (not from any internal/company systems or records).**

## Cluster Rankings, AI Labels & Descriptions

Rank	AI Label	AI Description	Size
1	<b>Documentation &amp; Record Errors</b>	This cluster includes trends such as incomplete batch records, missing signatures, transcription errors, and logbook discrepancies across multiple production areas.	18
2	<b>Calibration Deviations</b>	This cluster includes trends such as out-of-tolerance instrument readings, missed calibration schedules, and drift detected during routine verification checks.	15
3	<b>Material Variability</b>	This cluster includes trends such as incoming raw material specification deviations, supplier lot inconsistencies, and excipient attribute variation affecting process performance.	13
4	<b>Process Parameter Drift</b>	This cluster includes trends such as gradual shifts in mixing speed, temperature, or pressure parameters outside validated ranges during extended campaigns.	11
5	<b>Packaging Discrepancies</b>	This cluster includes trends such as incorrect carton counts, seal integrity failures, and blister pack defects detected during in-process or final inspection.	10
6	<b>Cleaning Verification Gaps</b>	This cluster includes trends such as residue above acceptance criteria, swab sample failures, and hold-time exceedances between cleaning and next use.	8
7	<b>Labelling Issues</b>	This cluster includes trends such as mismatched lot numbers on labels, incorrect expiry dates, and label reconciliation discrepancies at the end of packaging runs.	7



Note: Cluster overlap (visible in the scatter plot) indicates semantically related deviation categories that may share root causes or contributing factors.

# Zero Technical Effort for End Users

Data  
Extraction



Text  
Embedding



Clustering



Labelling



Visualisation

Workflow 100%  
Automated

Models are pre-computed and refreshed on schedule. End users open a Power BI dashboard — no configuration, no ML knowledge required. The User role is to apply expertise and professional judgement to assess whether clusters represent meaningful trends requiring action



## Top Clusters

Ranked clusters with AI labels and interactive visual representation



## Clusters by Area

Same map colour-coded by operational area



## Formation Timeline

Cumulative view showing patterns vs. emerging clusters



## Drill-Through

Click into any cluster to read deviation details for SME assessment

# One Engine — Multiple Applications

## Operational Excellence

**Cluster deviations to detect systemic trends and prioritise improvement initiatives across operational areas.**

- ✓ Deviation trending across all areas
- ✓ Human error analysis per team
- ✓ Configurable time periods (quarterly, rolling)

**SAME  
ENGINE**

## Proactive Oversight

**Review historical deviations for signals to support informed quality oversight and demonstrate proactive site awareness.**

- ✓ Highlight recurring themes
- ✓ Inform areas of routine quality focus
- ✓ Demonstrate data-driven site awareness
- ✓ Strengthen clarity of CAPA effectiveness

***Agnostic Functionality — applicable to any text-rich dataset***

Complaints

CAPAs

Change  
Controls

## IMPACT

# Benefits to Operations



### Speed

Automated pipeline can replace days of manual trending — models refresh on a scheduled basis



### Depth

Analyses meaning of free-text descriptions — revealing cross-cutting themes that categories miss



### Consistency

Every reviewer sees the same algorithmically-derived clusters, removing subjective variability



### Inspection Confidence

Data-driven evidence of site awareness and proactive management that supports inspection readiness

## Decision-Support, Not Decision-Making

The tool surfaces signals — the SME makes the final call. This maintains human oversight while dramatically increasing the speed of trend analysis.

## LESSONS LEARNED

# Reflections on Innovating Within Quality

- 1 Quality SMEs are Innovators**

The most impactful innovation came from deep domain knowledge. Technology was the enabler — Quality expertise was the driver.
- 2 Start with the Problem, Not the Tech**

We didn't start with 'let's use AI.' We started with 'our trending process has limitations' — then found the right tools.
- 3 Build Once, Apply Many Times**

One pipeline serves OpEx trending, human error analysis, QC models, and inspection preparation.
- 4 Keep the Human in the Loop**

AI outputs are signals, not conclusions. This maintains stakeholder ownership of the data and conclusions.

INNOVATION DOESN'T ALWAYS COME FROM  
OUTSIDE.

SOMETIMES IT STARTS WITH A QUALITY  
PROFESSIONAL ASKING  
"WHAT IF WE COULD DO THIS BETTER?"

Mary Coyne, Quality Advisor  
& Cian Linehan, Data Engineer



Thank  
you

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**A MEDICINE COMPANY**