Generative AI for DRAM Manufacturing

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Background

DRAM semiconductor manufacturing is among the most complex and precise industrial processes in the world. The global DRAM market generates over $120 billion in annual revenue[1], and the fabrication of each wafer involves hundreds of tightly controlled process steps across dozens of specialized tools. Even small deviations in process conditions can introduce variability that carries significant syield and economic impact.

In this project, we investigate how generative AI can accelerate the development of predictive machine learning models that identify which process steps, equipment, and sensors drive wafer-level variability. Our aim is to leverage AI tools to build a faster, more accessible data science workflow for process engineers while producing models to aid in reducing product variability.

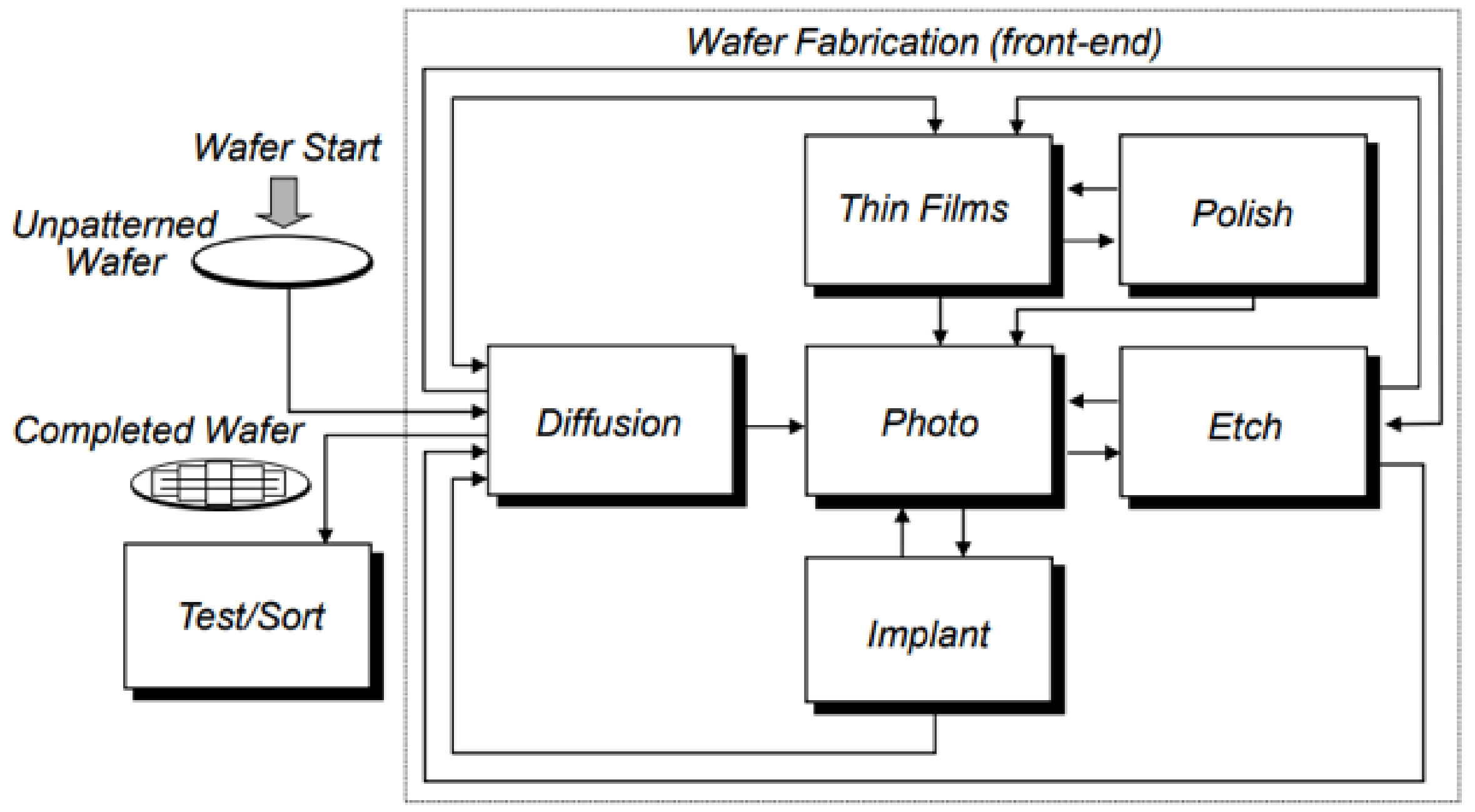
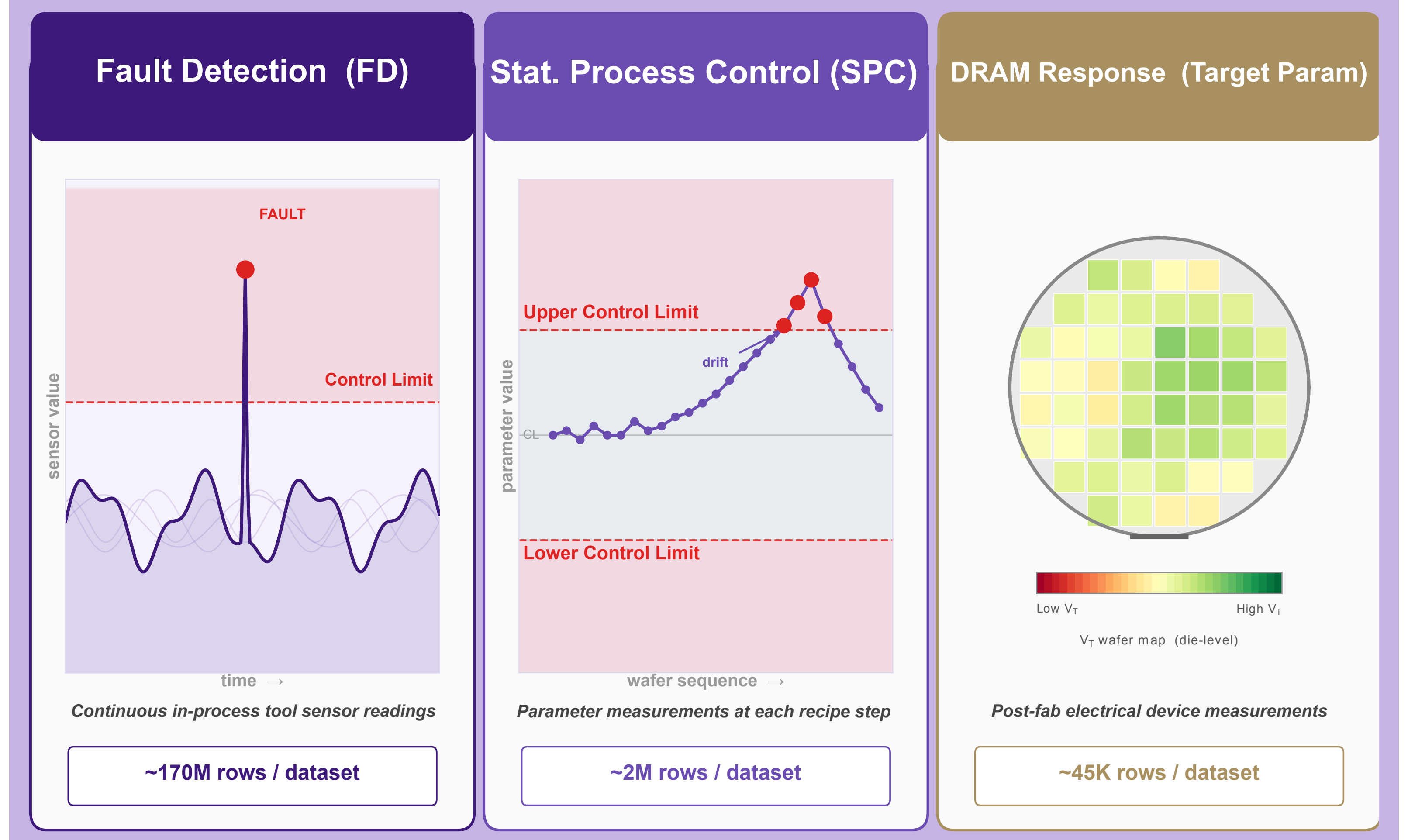


Figure 1. Schematic of DRAM Wafer production flow. In total, this process consists of 1000+ Steps. Our investigation includes 500.

Objectives

1. Establish baseline procedures for how to effectively use Gen AI while retaining integrity, security, and reproducibility.
2. Use Gen AI principles to construct predictive model; Identifying key drivers of wafer target parameter variability.

Datasets at a glance



Fault Detection (FD)

Continuous in-process tool sensor readings

~170M rows / dataset

Stat. Process Control (SPC)

Parameter measurements at each recipe step

~2M rows / dataset

DRAM Response (Target Param)

Post-fab electrical device measurements

~45K rows / dataset

Figure 2. Overview of categories of data available for model construction.

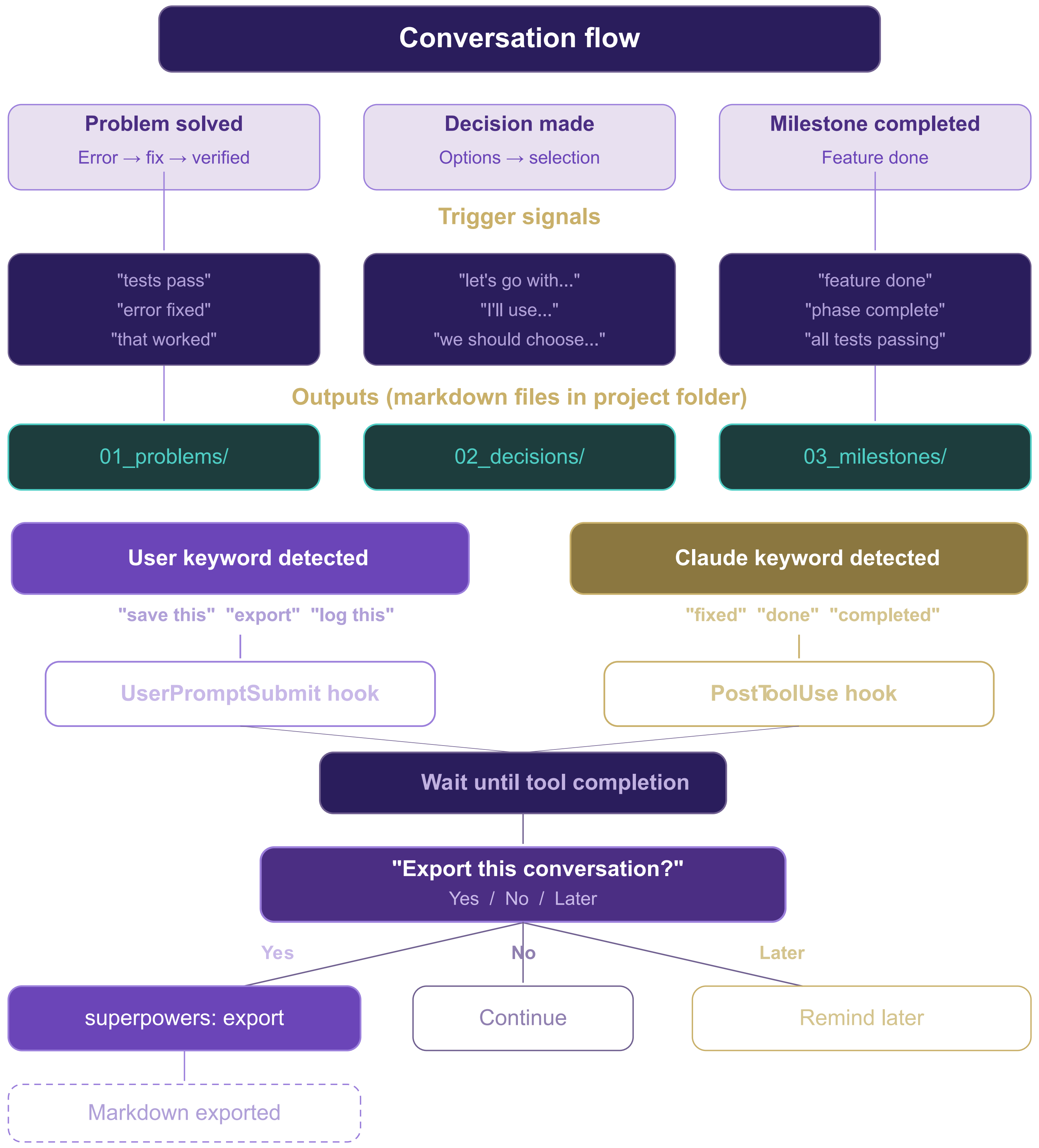
Datasets at a glance

Total Size	FD Rows (est.)	Time Period
DS1 19.99 GB 561 files	DS1 170.8M Mean + Standard Deviation	DS1 2021-05 — 2021-10 Dataset 1 Period
DS2 30.06 GB 186 files	DS2 182.3M Mean + Standard Deviation	DS2 2023-08 — 2024-12 Dataset 2 Period

Figure 3. Overview of scale of datasets.

Methods

1. A set of LLM "Best Practices" were established based on literature, learned experience, and documentation.
2. To evaluate usage of Gen AI in Capstone Team's development of predictive model, an automatic conversation export tool was developed and package for use in Claude Code.
3. Using this framework, the team used Claude Code to aid in generation of a predictive model.



Conversation flow

Problem solved
Error → fix → verified

Decision made
Options → selection

Milestone completed
Feature done

Trigger signals

"tests pass"
"error fixed"
"that worked"

"let's go with..."
"I'll use..."
"we should choose..."

"feature done"
"phase complete"
"all tests passing"

Outputs (markdown files in project folder)

01_problems/

02_decisions/

03_milestones/

User keyword detected
"save this" "export" "log this"
UserPromptSubmit hook

Claude keyword detected
"fixed" "done" "completed"
PostToolUse hook

Wait until tool completion

"Export this conversation?"
Yes / No / Later

Yes: superpowers: export → Markdown exported

No: Continue

Later: Remind later

Figure 4. Flowchart illustrating the Claude Conversation Export Guidelines and hook-based implementation, highlighting discrete locations of interest where data export is valuable.

Wafer Variation Predictive Model Results

1. Utilizing a CatBoost based model on dataset 1, platen input temperature at **Step IM0013** is identified to be a key driver of threshold voltage variation, with feature importance of 6.74.

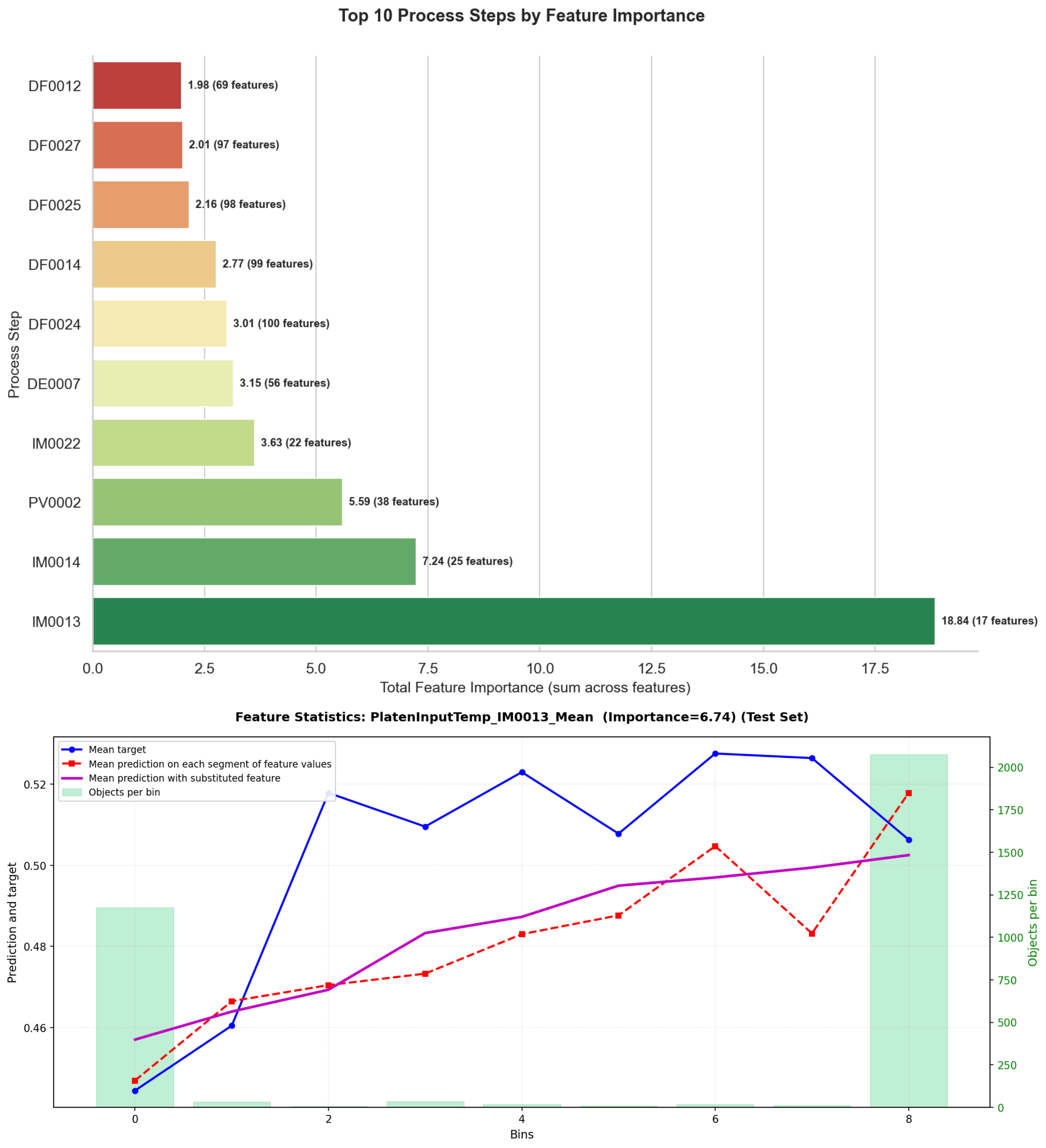


Figure 5. Binned SHAP importance of critical step in prediction of target params.

Discussion

- Through the use of generative AI, a machine learning model was developed and revealed the key steps which have the largest contributions towards wafer quality.
- An automatic toolkit was developed, enabling engineers to track and analyze their interactions with generative AI, increasing efficacy and quality of work.
- AI tools fundamentally alter the structural approach to project coding, shifting emphasis from implementation to design and analysis.
- Domain expertise remains essential for critical decision-making, with AI serving in an advisory capacity rather than an authoritative one

References and Acknowledgments

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https://www.fortunebusinessinsights.com/dram-market-109251[1]