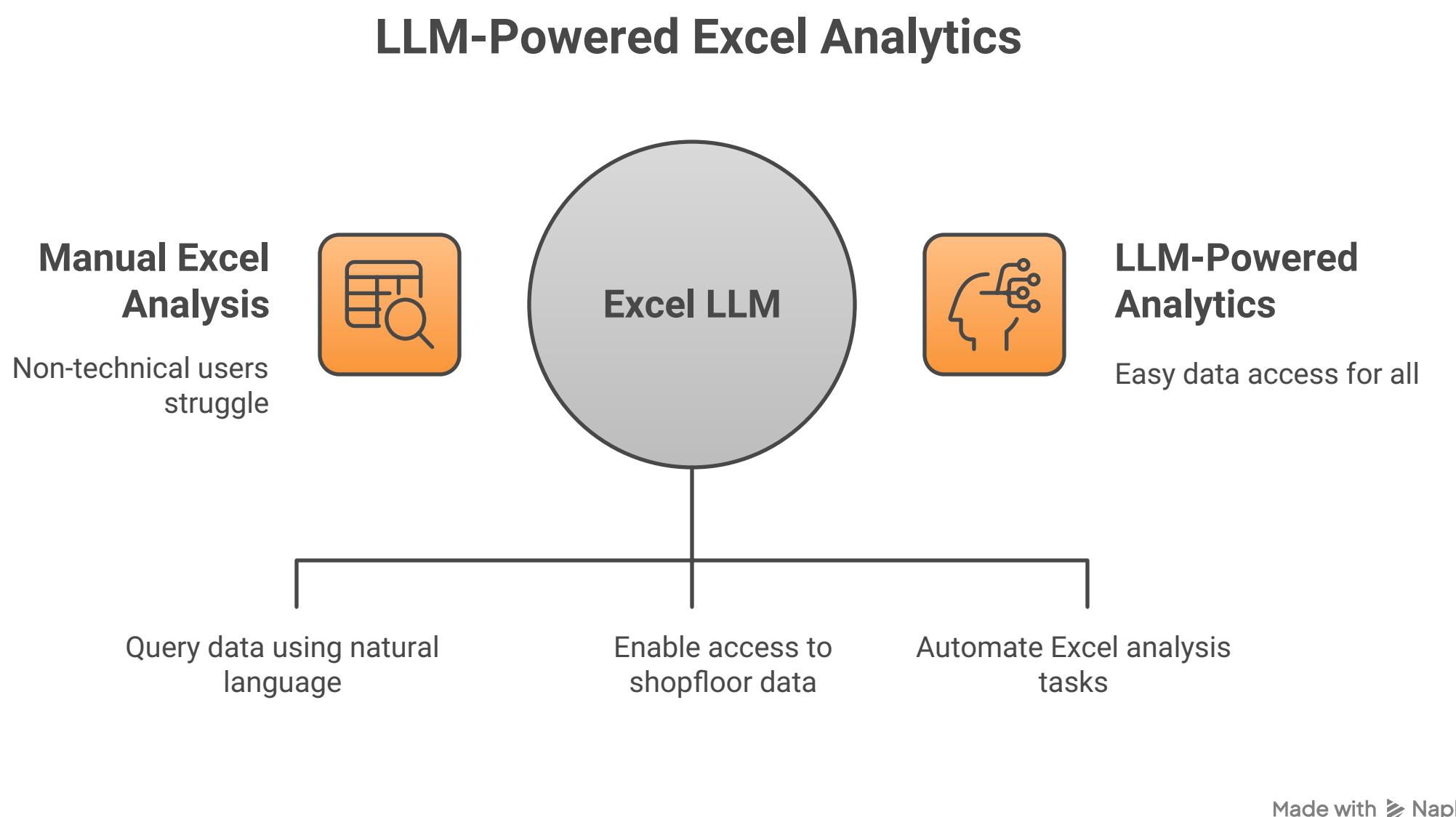


Excel LLM

Project Overview

I am building an **LLM-powered Excel analytics assistant** specifically for MSME manufacturing shopfloor data. The goal is to enable non-technical users to query production, quality, maintenance, and inventory data using natural language instead of manual Excel analysis.



Key Requirements I've Noted

1. Model Approach

- Use open-source SLMs (Llama 2, Mistral, or Falcon)
- Fine-tune using LoRA/PEFT for efficiency
- Domain-specific training on manufacturing/shopfloor terminology

2. Core Functionality

- Parse and normalize diverse Excel formats automatically
- Semantic understanding of manufacturing data structures
- Convert natural language queries to data operations
- Generate both textual insights AND visualizations

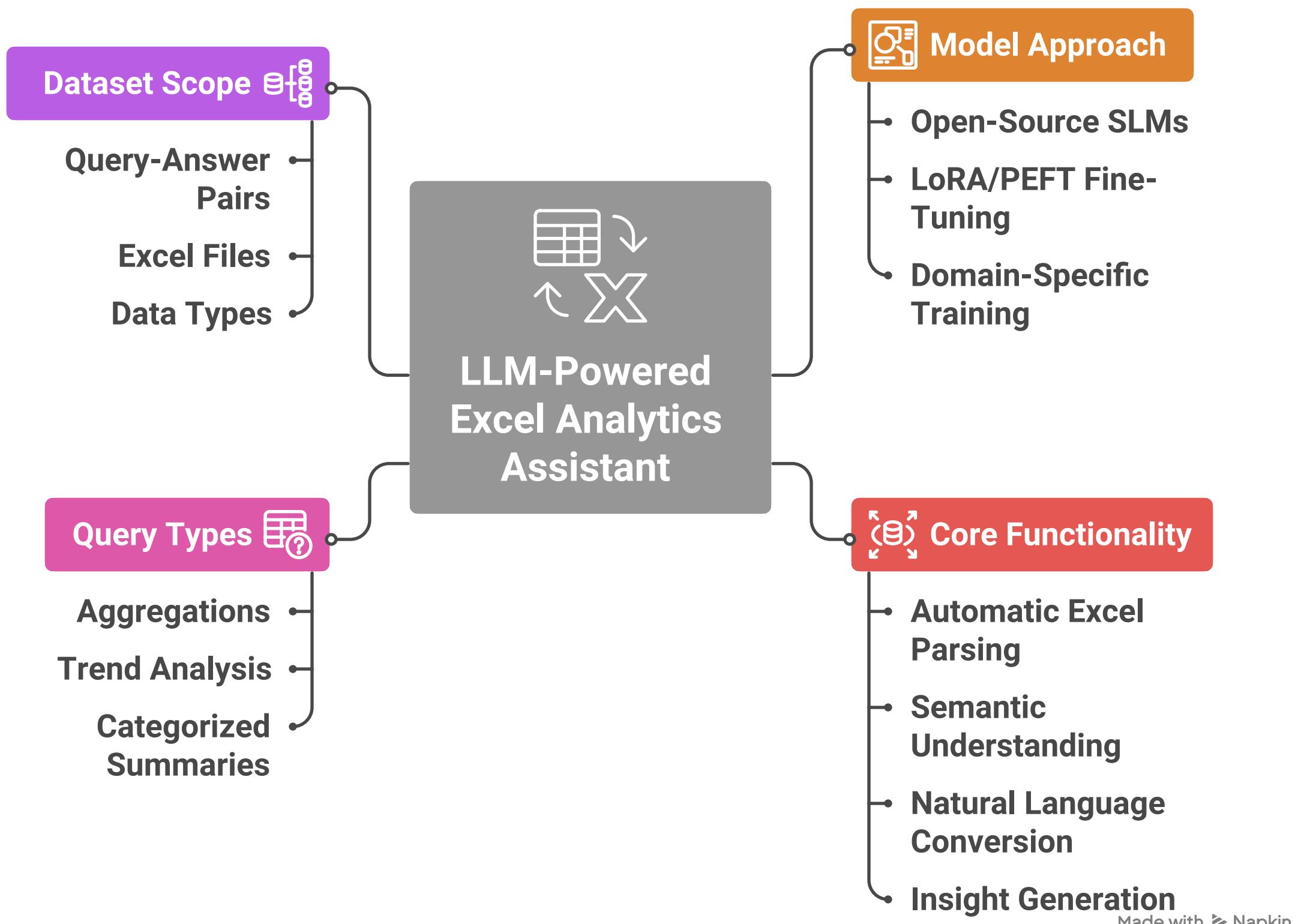
3. Query Types to Handle

- Aggregations ("most rework this quarter")
- Trend analysis ("daily efficiency trends")
- Categorized summaries ("rejected batches by defect type")

4. Dataset Scope

- ~2,000 query-answer pairs
- 50-100 Excel files
- Multiple data types: production logs, QC reports, inventory, maintenance

LLM-Powered Excel Analytics Assistant for MSME Manufacturing



Questions for Clarification

Before we dive deeper, I'd like to understand:

1. **Data Heterogeneity**: How varied are the Excel structures? [Different column names, formats, or relatively standardized templates?]
2. **Query Complexity**: Should the model handle multi-step reasoning [e.g., "Compare rework rates between products A and B, then show which defect types are common to both"]?
3. **Deployment Context**: Will this run locally on MSME machines, or cloud-based? [Important for model size selection]
4. **Visual Output**: What chart types are priorities? [Line charts for trends, bar charts for comparisons, pie charts for distributions?]
5. **Real-time vs Batch**: Should this process queries in real-time or is batch processing acceptable?

Understanding MSME Shopfloor Operations

1. Core Production Areas to Model

Production/Manufacturing

- What gets tracked: Output quantities, cycle times, machine utilization, shift performance
- Why it matters: Efficiency, capacity planning, bottleneck identification
- Typical questions: "Are we meeting targets?" "Which shift performs best?" "Where are delays happening?"

Quality Control (QC)

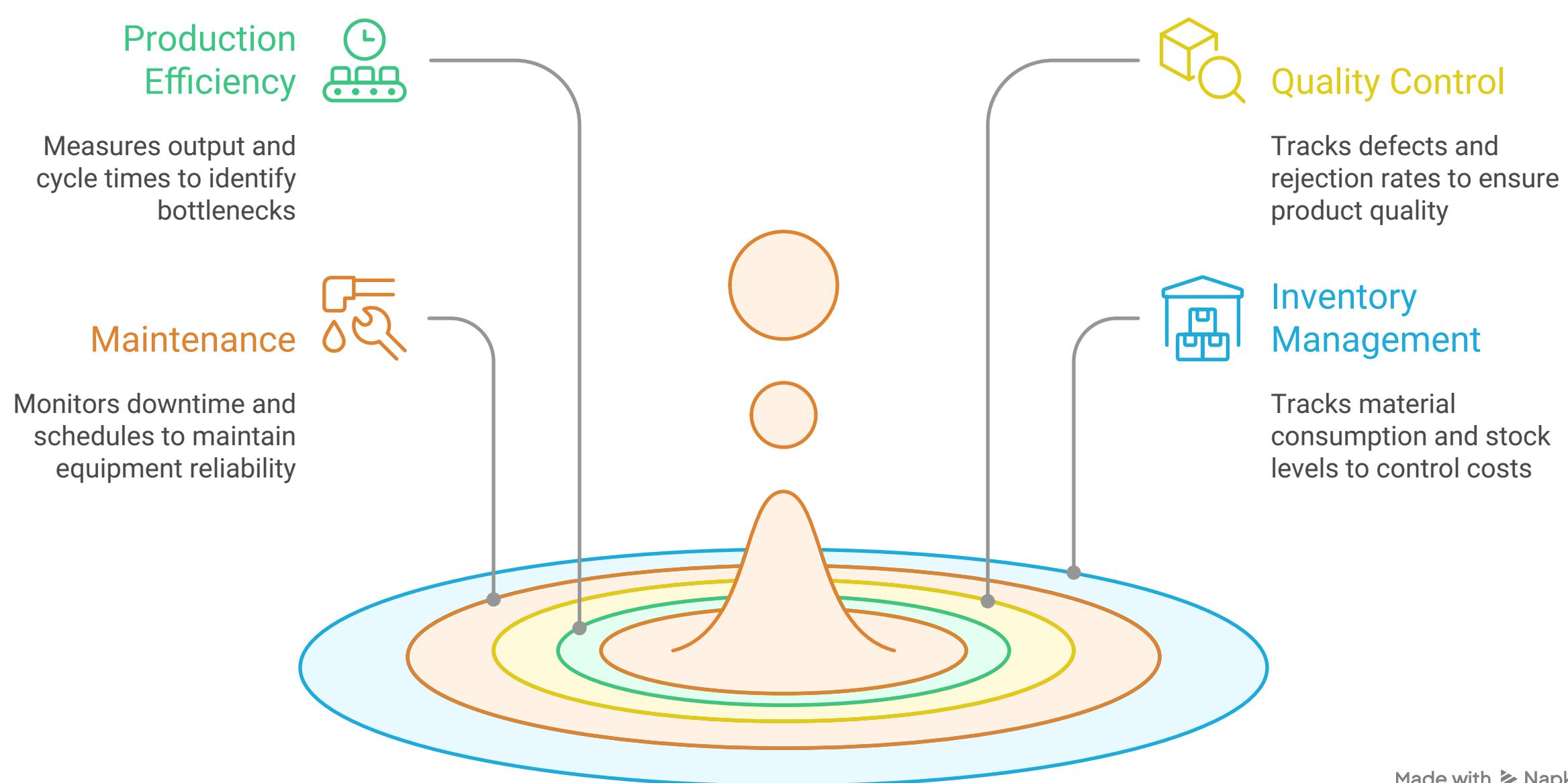
- What gets tracked: Inspection results, defect types, rejection rates, rework counts
- Why it matters: Product quality, cost of poor quality, compliance
- Typical questions: "What defects are most common?" "Which batches failed?" "Is quality improving?"

- What gets tracked: Machine downtime, breakdown frequency, preventive maintenance schedules
- Why it matters: Equipment reliability, production continuity
- Typical questions: "Which machines break down most?" "Are we maintaining on schedule?"

Inventory/Materials

- What gets tracked: Raw material consumption, stock levels, material wastage
- Why it matters: Cost control, preventing stockouts
- Typical questions: "Are we running low on materials?" "What's our wastage rate?"

Production Tracking Metrics



2. Key Manufacturing Metrics (KPIs)

Before we create training data, we need to know what MSMEs actually measure:

Efficiency Metrics

- OEE (Overall Equipment Effectiveness) = Availability × Performance × Quality
- Production per shift/hour
- Cycle time vs. target time

Quality Metrics

- First Pass Yield (FPY): % of products passing without rework
- Defect rate per 1000 units (PPM - parts per million)
- Rework percentage

Operational Metrics

- Downtime hours
- Changeover time (switching between products)
- Resource utilization rates

3. Typical Excel Data Structures in MSMEs

Let me describe what these Excel sheets usually look like:

Production Log Example Structure:

| Date | Shift | Line/Machine | Product | Target Qty | Actual Qty | Downtime (min) | Operator |
|------|-------|--------------|---------|------------|------------|----------------|----------|
|------|-------|--------------|---------|------------|------------|----------------|----------|

Batch ID | Product | Inspection Date | Inspected Qty | Passed | Failed | Defect Type | Inspector

Maintenance Log:

Machine ID | Date | Issue Type | Downtime (hrs) | Repair Cost | Maintenance Type (Breakdown/Preventive)

4. Industry-Specific Challenges

Understanding these helps us design better queries and responses:

Data Quality Issues:

- Inconsistent naming [Product-A vs ProductA vs Prod_A]
- Missing entries
- Manual data entry errors
- Date format variations

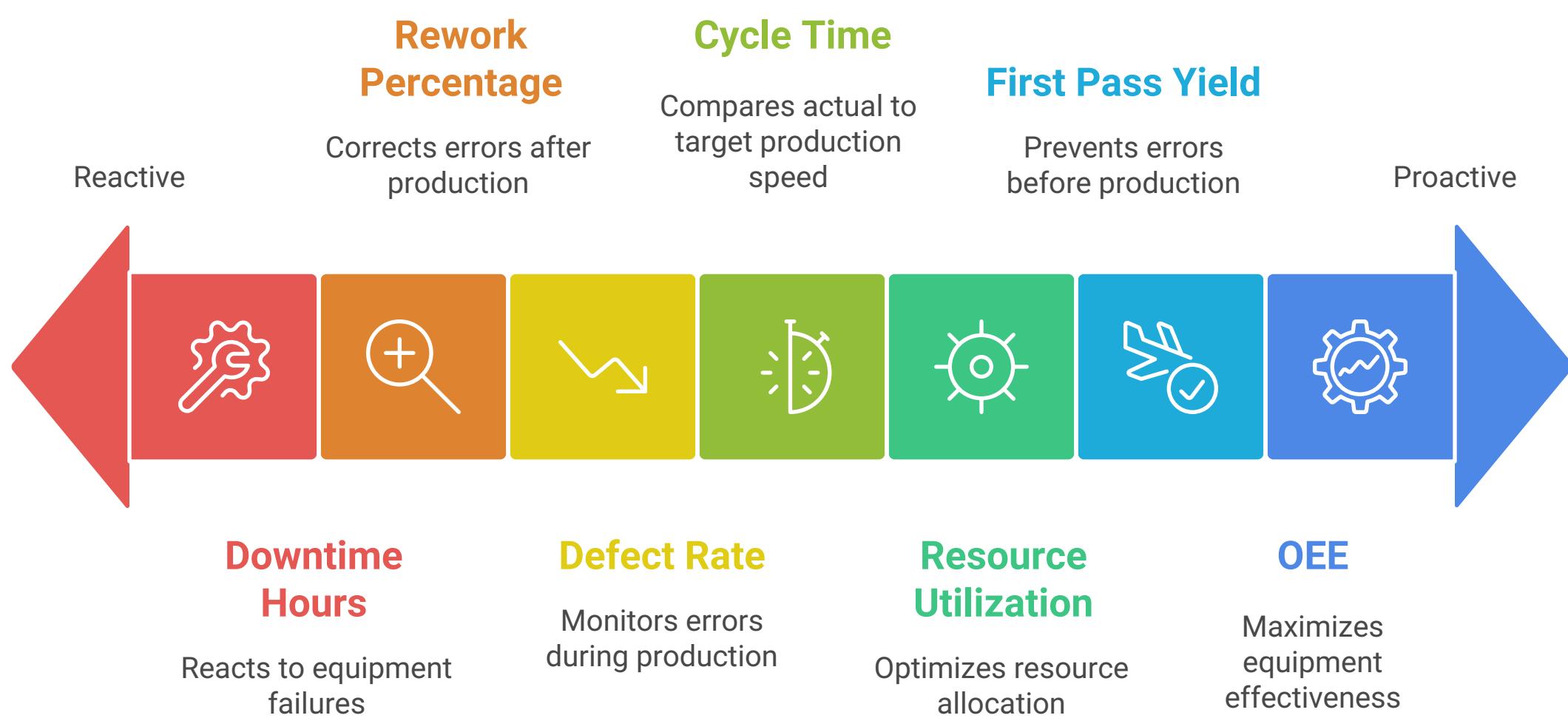
Domain Language:

- Shopfloor terminology [rework, scrap, batch, lot, SKU]
- Abbreviations [FG = Finished Goods, WIP = Work In Progress]
- Machine-specific codes

Decision Context:

- MSMEs need quick, actionable insights [not complex statistical models]
- Visual dashboards matter more than raw numbers
- Comparison over time is crucial [this month vs last month]

Manufacturing metrics range from reactive to proactive approaches.



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Refined Roadmap

Phase 1: Industry Selection & Intelligent Data Generation

Step 1.1: Choose Industry

- **Decision Point:** Walmart Retail/Logistics OR Manufacturing MSME?
- **Output:** Industry context document [terminology, KPIs, relationships]

Step 1.2: Smart Data Generator [Gemini-Powered]

Architecture:

```
Previous Data State → Gemini API → Generate New Related Data → Append to
Excel/CSV
```

Key Features :

- **Stateful Generation:** Each new batch references previous data
- **Relationship Preservation:**
 - Customer "Shivam" who bought Product A → next time buys complementary Product B
 - Machine that broke down → needs maintenance → shows reduced efficiency
 - Seasonal patterns (Q4 sales spike)
- **Realistic Variations:** Not random, but story-driven

Implementation Plan:

- **Script:** data_generator.py
- **Input:** Industry type, row count, existing CSV (if continuing)
- **Output:** Incremental CSV files with relationship metadata
- **Gemini Call:** Batch generation (50-100 rows per call to maintain context)

Phase 2: Intelligent Question Generator

Step 2.1: Question Generation System

Purpose: Auto-generate diverse, realistic queries for training

Features:

- **Auto-answer generation:** Use Gemini to also generate ground truth answers
- **Metrics extraction:** Identify which KPIs each question targets
- **Benchmark categories:** Group questions by complexity for evaluation

Phase 3: LLM Selection & Fine-Tuning Pipeline

Step 3.1: Model Evaluation Matrix

Benchmark Tests Before Fine-Tuning:

| Model | Size | Speed | Zero-Shot Accuracy | SQL Generation | Reasoning |
|--------------|------|--------|--------------------|----------------|-----------|
| Llama 3.2 3B | 3B | Fast | ? | ? | ? |
| Mistral 7B | 7B | Medium | ? | ? | ? |
| Phi-3 Mini | 3.8B | Fast | ? | ? | ? |

Test on:

- 50 sample questions (before fine-tuning)
- Measure: Accuracy, hallucination rate, response time

Step 3.2: Fine-Tuning Strategy

Phase 4: LangChain Multi-Tool Agent System

Step 4.1: Tool Architecture

```
tools = [
    # 1. Data Retrieval Tool
    Tool(
        name="ExcelDataRetriever",
        func=retrieve_relevant_rows,
        description="Fetch relevant rows from Excel based on semantic search"
    ),
    # 2. Calculation Tool
    Tool(
        name="DataCalculator",
        func=perform_calculations,
        description="Perform aggregations, averages, sums, etc."
    ),
    # 3. Trend Analysis Tool
]
```

```

        name="TrendAnalyzer",
        func=analyze_trends,
        description="Identify patterns over time, seasonality, outliers"
    ],

    # 4. Comparison Tool
    Tool[
        name="ComparativeAnalyzer",
        func=compare_entities,
        description="Compare products, time periods, categories"
    ],

    # 5. Visualization Recommender
    Tool[
        name="ChartRecommender",
        func=suggest_visualization,
        description="Recommend best chart type based on data and query"
    ],

    # 6. SQL Generator (optional, for complex queries)
    Tool[
        name="SQLGenerator",
        func=generate_sql,
        description="Convert natural language to SQL for complex operations"
    ]
]

```

Step 4.2: ReAct Agent with Industry Context

system_prompt = f"""
You are an expert {industry} data analyst assistant.

Available tools: {tool_descriptions}

When answering:

1. Break down complex queries into steps
2. Use appropriate tools in sequence
3. Validate data before calculating
4. Provide context with industry benchmarks
5. Recommend visualizations

Industry Benchmarks:

{industry_kpis}

Respond in this format:

Thought: [reasoning]
Action: [tool_name]
Action Input: [tool_input]
Observation: [tool_output]
... [repeat as needed]
Final Answer: [comprehensive response with visualization spec]

"""

Phase 5: Graph Generation System

Step 5.1: LLM-Driven Visualization Specification

Step 5.2: Frontend Auto-Rendering

Phase 6: Evaluation & Benchmarking Dashboard

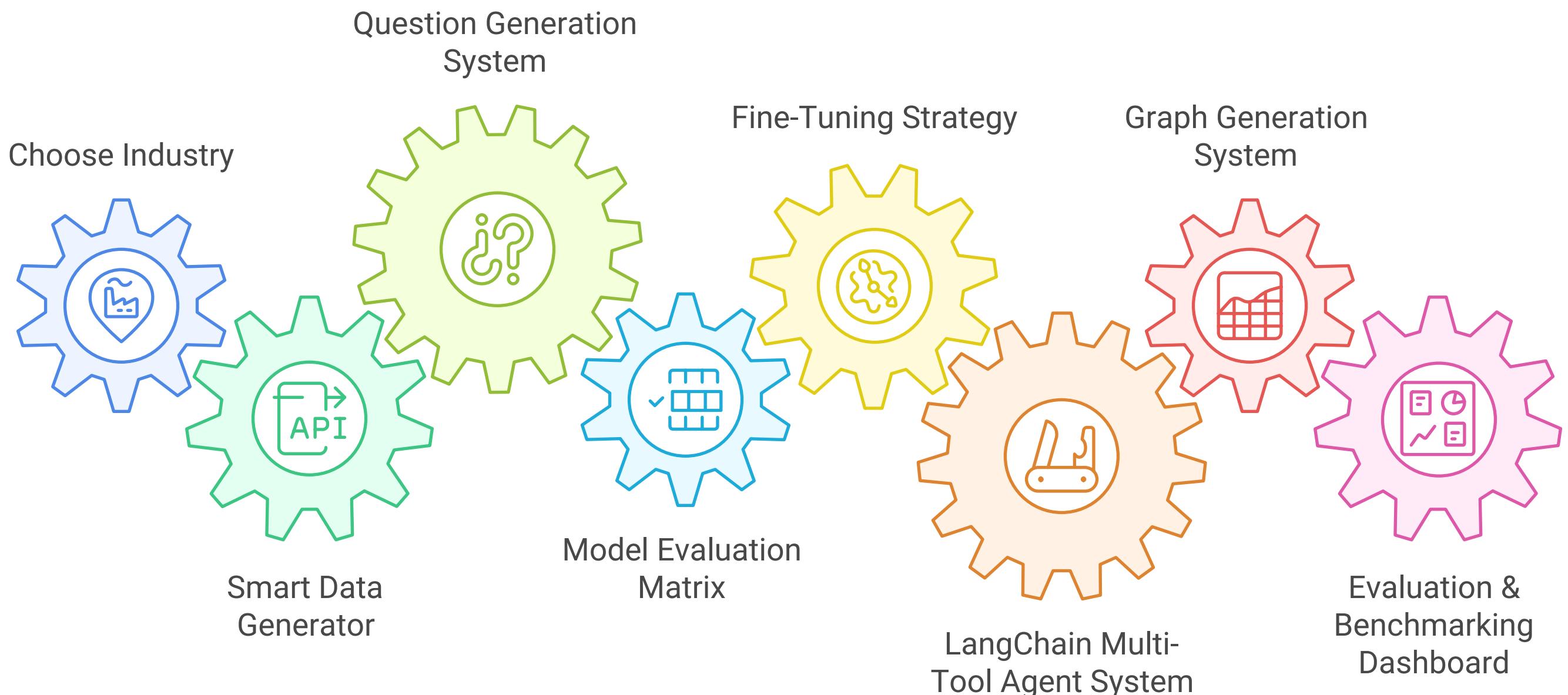
Step 6.1: Model Performance Metrics

Dashboard showing:

- **Accuracy by Question Type** [simple vs complex]
- **Hallucination Rate:** Incorrect facts generated

- **Tool Usage Efficiency:** How often agent picks right tool first
- **Visualization Appropriateness:** Chart type matches data

Refined Roadmap for Data Analysis System



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Revised Step-by-Step Execution Plan

Foundation

- Choose industry (Walmart logistics recommended)
- Build data generator script with Gemini
- Generate initial 10,000 rows with relationships
- Build question generator script
- Generate 500 questions with ground truth

Model Preparation

- Setup environment (Colab/Kaggle)
- Benchmark 3 base models (zero-shot)
- Select best performer
- Prepare fine-tuning dataset [questions + context + answers]
- Fine-tune with LoRA

Embedding & Retrieval

- Build embedding pipeline
- Setup ChromaDB
- Test semantic retrieval accuracy
- Create metadata layer

Agent System

- Implement 6 LangChain tools
- Build ReAct agent
- Test multi-step reasoning
- Create visualization recommender

Web Application

- Setup Vite + React + Tailwind
- Build FastAPI backend
- Implement file upload & processing
- Create query interface
- Build chart auto-renderer

Evaluation

- Build benchmarking dashboard
- Run 500 test queries
- Calculate all metrics
- Identify failure modes
- Iterate on prompts/tools

Polish

- UI/UX improvements
- Add export functionality (PDF reports)
- Optimize performance
- Documentation
- Demo video

Critical Improvements Needed

1. Missing: Data Preprocessing & Schema Normalization Layer

Roadmap jumps from data generation to embeddings, but MSMEs have messy Excel files.

You need:

- **Schema detection & auto-mapping** [handling "Product_Name" vs "ProductName" vs "Prod"]
- **Data cleaning pipeline** [null handling, date format standardization]
- **Column type inference** [is "123" a product code or quantity?]

Add: Phase 3.5 (between LLM selection and embeddings)

2. Missing: Ground Truth Generation for Evaluation

Mentioned "500 questions with ground truth" but don't detail HOW to generate accurate ground truth answers from synthetic data.

Solution: Use Gemini to generate query + execute pandas operations + verify = ground truth

3. Incomplete: Multi-Excel File Handling

Real MSMEs have 5-10 related Excel files (production, quality, inventory). Your roadmap doesn't clearly address:

- How to JOIN across multiple Excel files
- Which file contains what data [schema registry]
- How LLM knows which file to query

Add: Multi-file relationship mapping in Phase 1

4. Missing: Error Recovery & Fallback Mechanisms

What happens when:

- LLM generates invalid SQL?
- Visualization spec is malformed?
- User uploads corrupted Excel?

Add: Error handling strategy in each phase

5. Vague: "Fine-tuning with LoRA"

You need specifics:

- What training data format? [Instruction-tuning? QA pairs? SQL generation?]
- How many epochs? Validation strategy?
- How to handle domain-specific terminology [OEE, FPY, etc.]?

Shivam Tiwari
IIT Madras
DSA1