

DRIVING FINANCIAL OWNERSHIP IN SEMICONDUCTOR OPERATIONS GEARED TOWARDS ARTIFICIAL INTELLIGENCE (AI)

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ABSTRACT

Web-based platforms have advanced rapidly, enabling real-time, data-driven solutions. However, this digital shift still faces challenges in semiconductor manufacturing, where high-volume data, strict traceability, site variability, and legacy systems add significant complexity.

To address these challenges, we developed a centralized, web-based platform designed to automate data consolidation, apply AI-driven analytics, and standardize site-dependent reporting with automated alarm system and assistive intelligence, thereby enabling active ownership of cost on a daily basis.

The solution enabled 18% cost improvement, in addition to significant hours and storage saved. Through fine-tuning of the AI model in the future, the tool is set to provide more comprehensive look-ahead responses catering demand changes in the market.

1. 0 INTRODUCTION

In the semiconductor industry, cost-related data tends to be fragmented across siloed systems, with each site operating under varying processes, legacy system setups, and localized reporting formats. This lack of standardization burdens engineers with time-consuming manual efforts to consolidate, clean, and validate cost reports—introducing inconsistencies and delaying critical cost-control decisions in an industry where efficiency and margin optimization are vital.

These challenges highlighted the need for a centralized, web-based platform. Blind spots in cost data—especially during non-working days—led to surprise expenses, while manual reporting created delays, storage issues, and limited transparency. Without real-time visibility, engineers tend to be disengaged from financial decisions. This underscored the urgency for a system to automate reporting, unify cost data across sites, and drive timely, transparent spending insights. Figure 1 demonstrates the improved workflow to standardize and streamline the site-variable processes.

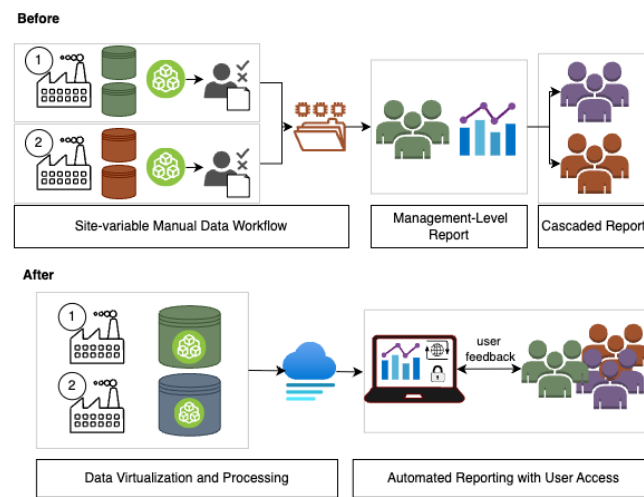


Fig. 1. Current Cost Monitoring Workflow versus Improved Workflow through Data Virtualization and Artificial Intelligence.

1.1 Data Silos & Blind Spots

In semiconductor operations, data can be trapped in disconnected systems, ranging from long-standing legacy platforms to newer digital tools. It may also vary across sites, market demand, and product portfolio. These silos result in blind spots where critical cost signals are delayed or lost. Without integrated access, cross-functional teams make decisions in isolation, increasing risk and inefficiency.

1.2 Cost Surprises

Without synchronized, real-time cost tracking across procurement and production, surprise material deliveries can occur without proper budget alignment or site readiness. This disrupts planning and may result in unutilized inventory or rushed approvals.

1.3 Manual Workflow

Engineers often generate cost and operational reports manually using local spreadsheets, leading to high storage overhead, poor version control, and difficulty in auditing past

data. This method is inefficient, risks data loss or inconsistencies, and ultimately creates bottlenecks in data availability and transparency.

1.4 Isolated Decision Points

Cost data is typically accessible only to select management roles, leaving engineers and frontline personnel—such as cost component owners and material handlers—passively engaged from the financial implications of their actions on a daily basis. This limited visibility made it difficult to instill a sense of ownership and accountability across the broader organization. Without transparent, timely insights, daily operational decisions were often made in isolation from their cost impact.

2.0 REVIEW OF RELATED WORK

Refer to 1.0 Introduction.

3.0 METHODOLOGY

This section presents the overall system architecture and database management system (DBMS) principles to enable automated report with assistive intelligence.

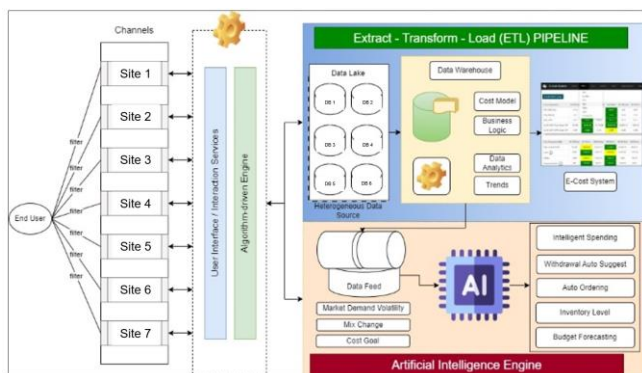


Fig. 2. Software Architecture. Extract-Transform-Load (ETL) principle enables consolidation of data from multiple sources.

The system was built from the ground up using Spring MVC framework paired with Oracle SQL to build the fundamental data structure. Figure 2 illustrates the Extract-Transform-Load (ETL) pipeline implemented to process data from each site, guided by the Atomicity-Consistency-Isolation-Durability (ACID) principle in database management to handle high-volume data while maintaining integrity and continuous data availability.

1.4 Atomicity

Each cost transaction (e.g., material withdrawal, cost allocation, report update) is treated as a single, indivisible unit. Either all components of the transaction succeed, or none do. This prevents partial updates that could corrupt cost records or lead to mismatched data between sites.

1.4 Consistency

For fixed costs—such as commodities that are only reflected at month-end—figures must be analyzed in advance relative to the set budget to avoid unexpected variances when the actual costs are posted. Proactive monitoring ensures better financial control and eliminates last-minute surprises. To address this, Figure 3 summarizes cost linearization, allowing partial estimation of figures relative to the monthly goal. This involves using projected or placeholder values to simulate expected costs for the remaining days of the month, providing a clearer picture before actual month-end figures are posted.

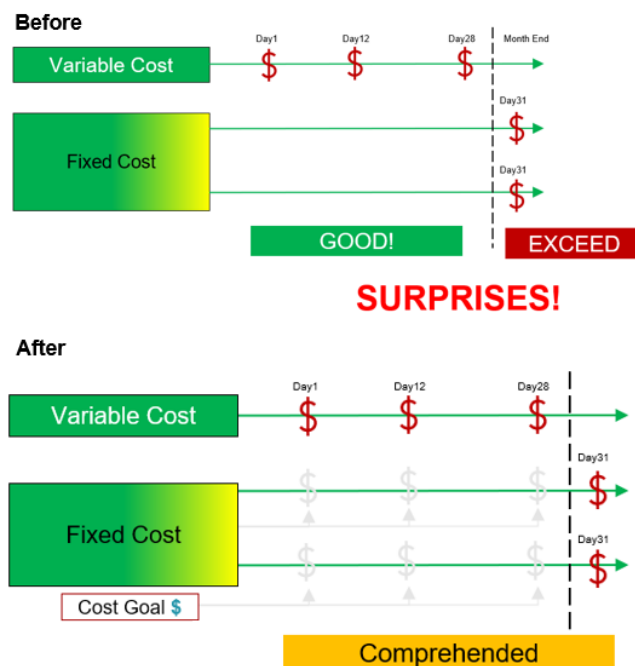


Fig. 3. Application of cost linearization for data consistency and early comprehension of financial numbers.

1.4 Isolation

Even when multiple users across different sites interact with the database simultaneously (e.g., generating reports, recording expenses), transactions are isolated from one another. This prevents race conditions or conflicting updates, ensuring each user sees a coherent and stable view of cost data.

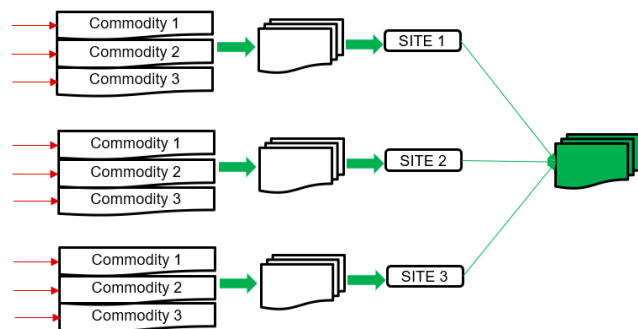


Fig. 4. Isolated Job Schedulers for each commodity per site.

1.4 Durability

Once a transaction is committed (e.g., an expense posted, a report saved), it is permanently stored—even in the event of power failures or system crashes. This ensured data persistence is enabled through integration of the consolidated data warehouse with Denodo, a data virtualization platform that supports live data access and web services.



Fig. 5. Data Virtualization Architecture with Denodo Layer for AI

While the data warehouse helped consolidate fragmented data sources, the resulting structured data required scripts and access layers. To ensure data reliability, a data virtualization layer, Denodo, was integrated to handle data across disparate systems, allowing AI models to access real-time information without replication, effectively accelerating model development, deployment, and insight generation.

4.0 RESULTS AND DISCUSSION

The implemented system enabled record-breaking cost improvement, with a significant efficiency gain equivalent to removing over 20 days of workload per quarter, and storage optimization by over 25%, improving system responsiveness and scalability. It was further fanned out to other Assembly/Test sites to support manufacturing and engineering teams obtain better visibility of cost data in a timely manner.

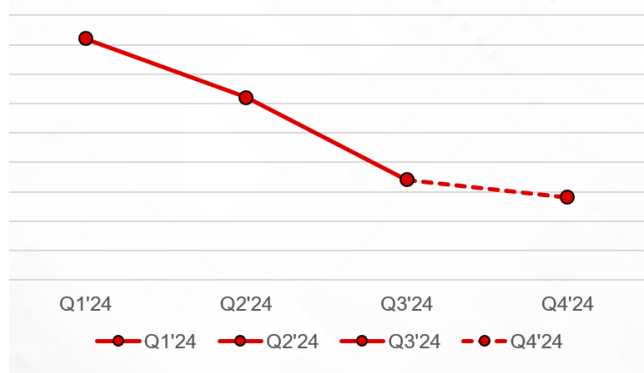


Fig. 6. Cost Improvement of 18% from Q1'2024 – Q4'2024.

1.1 Centralized Daily Access

Through a centralized page with daily breakdown of cost spending, the previous practice of top-down reporting is supplemented with an accessible platform that provides data visibility among line personnels and cost component owners without dependence on other localized reports.

In addition, a deep dive of spending on a transaction level is enabled by data clickables to aid in historical assessment and risk analysis from reflected financial numbers.

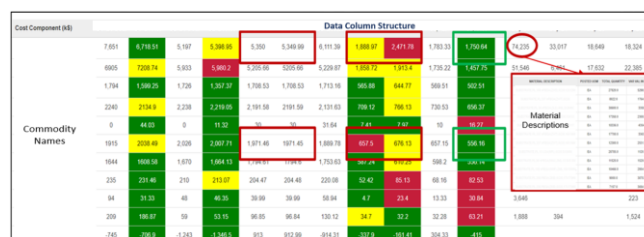


Fig. 7. Daily summary reporting with visual indicator of cost spend status for each commodity relative to the set budget goal: (1) red: critically exceeded goal; (2) slightly exceeded goal; (3) within budget.

1.3 Visibility on Operational Efficiency

Through a tailored report that compares daily manufacturing output against daily material withdrawals, the system enables more accurate and consistent monitoring of operational efficiency. This comparison helps identify discrepancies between materials consumed and products produced, revealing potential issues such as over-withdrawals, wastage, or process inefficiencies. By providing clear visibility into daily performance, it empowers manufacturing and engineering teams to take immediate corrective actions, optimize resource usage, and improve overall production effectiveness.

Commodity Name					
POSTING DATE	Withdrawal vs. Output	Commodity Withdrawal	Commodity Cost	Output	Line Inventory
01-Jun-2025	206.39	3,066,694	113,509	1,485,857	1,580,837
02-Jun-2025	115.73	1,934,251	71,221	1,671,415	1,843,673
03-Jun-2025	104.07	1,614,955	59,056	1,551,807	1,906,821
04-Jun-2025	83.29	1,387,594	52,461	1,666,070	1,628,345
05-Jun-2025	90.86	1,671,996	69,612	1,840,093	1,460,248
06-Jun-2025	113.03	1,716,376	69,153	1,518,466	1,658,158
07-Jun-2025	106.74	1,854,496	64,477	1,737,411	1,775,243

Fig. 8. Package-based Output vs Withdrawal Daily Automated Reports

1.1 Project Fall Through Monitoring

Enabling users to see project fall-through at a glance, the system consolidates shipment and spend data across sites, down to part number level information, to provide visibility on project performance, underutilized materials, and potential execution gaps. By correlating what was planned versus what was actually shipped or consumed, the system helps stakeholders identify delays, cancellations, or inefficiencies early—allowing for timely intervention, better forecasting, and resource reallocation across teams.



Fig. 5. Commodity Spend vs Output Monitoring.

Component		Q1 Goal	Q1 Act	Q1 Var	Sites										Q2 Goal	Q2 Act	Q2 Var	Sites									
Commodities		1,000	1,000	0	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
		1,000	1,000	0	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	0	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
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Fig. 9. Simplified Sites Reporting per Commodity

1.2 AI-Powered Forecasting & Alerts

Through Denodo platform integration, creating data views are relatively faster due to a centralized virtual data source. This, in turn, allows creation of customized dataset for

specific business problems, allowing the AI model to have niche-based knowledge of cost across the sites.

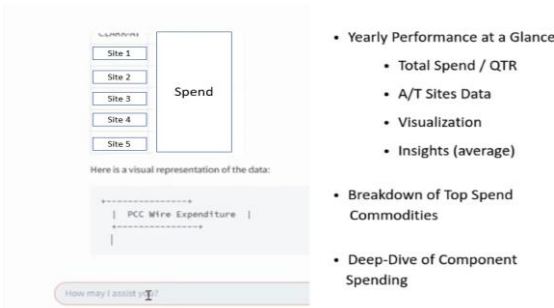


Fig. 10. AI-driven chatbot for descriptive analytics.

5.0 CONCLUSION

The implemented system presented a shift in approach towards cost leadership through a streamlined monitoring workflow and unified practice of data analysis. By proactively managing high-volume data partnered with AI-powered analytics, a paradigm shift in cost monitoring is introduced while establishing a web platform for use.

6.0 RECOMMENDATIONS

While large historical data has been aggregated from various sources into Denodo, the AI model’s capability to forecast is in its early stages. By utilizing shipments, demand forecasts, market trends, and raw material availability—the AI model can learn patterns and generate predictive insights that could include:

- Anticipated demand fluctuations across regions or product categories
- Projected material shortfalls or oversupply
- Forecasted financial impacts of supply chain or market changes
- Recommended adjustments to production plans or inventory levels

7.0 ACKNOWLEDGMENT

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