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Design and Development of an MIS Dashboard for a Battery Pack Manufacturing Facility A Management Information Systems Perspective on Executive Decision-Support in Indian Manufacturing

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Abstract: *Battery pack manufacturing is a safety-critical, energy-intensive and economically sensitive process in the Indian manufacturing landscape. Operational data on production, quality, maintenance, cost, energy, inventory, traceability and environment are typically scattered across separate functional reports, delaying executive review and weakening cross-functional accountability. This paper presents the design and development of a plant-level Management Information System (MIS) dashboard for a commercial battery pack assembly plant. Using a Business Requirement Document (BRD), benchmarking and exploratory secondary research as primary inputs, the proposed dashboard integrates eight management dimensions: production/OEE, quality, maintenance, safety, cost/energy, traceability, inventory and environment, health and safety (EHS). Adopting a management-oriented design-science approach, the study benchmarks recent peer-reviewed literature (2021–2026) to derive KPI commonality, battery-specific measures, formula governance and Sustainable Development Goal (SDG) linkages. The central argument is that dashboard value is created not by visualization alone but by clearly defined KPI formulas, ownership, data-freshness rules, exception handling and traceability to source records. The result is a practical framework that turns distributed shop-floor data into a one-page decision-support system, with future scope for AI and digital-twin integration.*

Keywords: Plant manager dashboard; management information system; battery manufacturing; OEE; Industry 4.0; data governance; sustainability.

I. INTRODUCTION

Manufacturing managers increasingly operate in environments where production, quality, maintenance, finance, energy, supply-chain and environmental data are generated by different systems. The management challenge is therefore not data availability but the conversion of fragmented data into a coherent decision system. Battery manufacturing is particularly suited to such an approach because the production chain contains tightly coupled processes in which defects, downtime, energy consumption and material losses carry significant operational and financial consequences. Fragmented reporting can delay executive review, weaken accountability and make it difficult for a Plant Head to separate urgent exceptions from routine variation.

The supplied BRD defines the proposed Plant Manager MIS dashboard as an executive decision-support view for a mock battery pack assembly plant, positioned as a presentation and decision-support layer rather than a replacement for source systems. It identifies the management problem as the absence of a single, consistent executive view across production, quality, maintenance, EHS, finance, energy, inventory and serialization, and requires every KPI to be

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traceable to its source, formula, owner and timestamp. The paper has four purposes: to explain the managerial need for a unified dashboard; to review recent literature on digital manufacturing, battery production, quality, maintenance, sustainability and traceability; to describe the methodology that translates the BRD into a management framework; and to interpret the dashboard as a decision-support instrument with a practical implementation roadmap.

II. REVIEW OF LITERATURE

2.1 Digital manufacturing and management decision-making

Industry 4.0 has shifted manufacturing information from periodic reporting toward connected decision support, combining sensing, connectivity, analytics and control so that managers detect deviations earlier. Sartal et al. (2022) show that vertical and horizontal data integration supports plant performance when combined with lean practices, while Oluyisola et al. (2022) demonstrate that smart production planning and control systems can combine IoT, machine learning and decision support. These findings reinforce a core design principle: a dashboard should be built around decisions first and technologies second. Its value also depends on organisational capability, and Manoharan et al. (2025) and Choi et al. (2022) argue that digital transformation requires coordination beyond a single department. Accordingly, a Plant Manager dashboard is an organisational coordination mechanism, not merely a visual-analytics project — which is why the BRD assigns KPI ownership to functional roles.

2.2 Battery manufacturing as a data-intensive operation

Battery production has a long, strongly coupled process structure in which intermediate-product characteristics influence downstream quality and final battery performance (Liu, Wang & Lai, 2022). Digitalisation is repeatedly framed as an opportunity to improve data structures, modelling and process understanding, and to support quality control, predictive maintenance, traceability and process optimisation across the chain (Manoharan et al., 2025). Machine-learning studies for electrode quality, mass-load prediction, coating analysis, assembly and welding quality imply that managers need both outcome KPIs and leading indicators that reveal the causes of performance loss. The dashboard therefore separates broad management outcomes (OEE, FPY, cost/pack) from the operational variables that drive them.

2.3 Maintenance, quality and digital twins

Because unplanned downtime affects availability, output, cost and sometimes quality, predictive maintenance is central to plant performance. Fordal et al. (2023) show how sensor data and neural networks support predictive maintenance, Rosati et al. (2023) integrate IoT and machine learning into a maintenance decision-support system, and Hassan et al. (2024) and Savolainen and Urbani (2021) demonstrate digital-twin approaches to maintenance optimisation. These justify the dashboard's use of top-failure ranking, critical-machine OEE and PM compliance. On the quality side, Filz et al. (2024) present a data-driven quality-management platform for multi-stage manufacturing, and Tercan and Meisen (2022) and Escobar et al. (2021) review predictive quality and Quality 4.0. The implication is that quality views should combine first-pass yield, scrap, defect concentration and end-of-line testing rather than rely on a single pass measure. The proposed dashboard is not itself a digital twin but a management interface that can become a front end for future digital-twin or advanced-analytics architectures (Kerin et al., 2023).

2.4 Sustainability, energy and environmental management

Battery manufacturing has significant energy and material requirements, making sustainability a core management dimension. Degen (2023) analyses scenarios for reducing energy consumption and greenhouse-gas emissions in European lithium-ion production; Chordia et al. (2021) and Clemente et al. (2025) examine the environmental implications of scaling; and Kannan et al. (2023) position smart manufacturing as a strategic tool for sustainable-manufacturing challenges. These studies support making energy and environmental metrics visible alongside productivity and quality. The dashboard therefore broadens a traditional production view into a triple-bottom-line one, treating EHS and energy as integral sections rather than optional additions.

2.5 Traceability and information integrity

Traceability is especially important in battery manufacturing because cells, components, modules and packs are linked through serialised records, enabling containment, genealogy, investigation and targeted recall. Recent battery-digitalisation research treats data structures and traceability as part of the manufacturing system rather than an afterthought, and this is reinforced by regulatory momentum toward a mandatory battery passport. The BRD translates this into two management indicators — digital genealogy and scan-match accuracy — which also test whether the genealogy data can be trusted.

III. RESEARCH GAP, OBJECTIVES AND QUESTIONS

The literature offers substantial work on individual technologies — machine learning, predictive maintenance, digital twins, quality inspection, energy modelling and process optimisation. A management-oriented gap remains: how can these fragmented dimensions be integrated into one executive dashboard with consistent KPI definitions, ownership, data freshness and action logic? This project addresses that gap from a management and business-analytics perspective rather than by developing a new algorithm. The study objectives are:

- Identify the major performance dimensions a Plant Manager must monitor.
- Examine common and battery-specific KPIs across the eight dimensions.
- Translate KPI definitions into controlled formulas, input variables, data sources and decision rules.
- Design a dashboard structure that supports exception-based decision-making.
- Assess how the dashboard supports sustainability and SDG priorities, and propose a governance roadmap. The study addresses four research questions: RQ1 — Which KPI dimensions should be integrated into a Plant Manager-level battery dashboard? RQ2 — How can KPI definitions, formulas and data sources be standardised to provide trustworthy information? RQ3 — How can a dashboard connect operational performance with management decisions, sustainability and traceability? RQ4 — What governance and implementation conditions are required for the dashboard to create sustained managerial value?

IV. RESEARCH METHODOLOGY

The research uses a management-oriented design and benchmarking methodology, treating the dashboard as a design case through which management information requirements can be analysed. No claim is made that its values represent actual production performance. Four source groups inform the work: the Business Requirement Document (background, source-system architecture, KPI requirements, formulas, freshness rules, business rules, acceptance criteria and roles); the representative dashboard construction, which provides illustrative KPI values; the supplied research brief; and recent academic literature, with emphasis on 2021–2026 Springer publications.

The literature review was organised into five themes — Industry 4.0 and digital transformation; battery manufacturing and process optimisation; quality and predictive maintenance; sustainability and energy; and traceability and data governance. Benchmarking aimed not to replicate existing designs but to identify recurring management concepts that support the selected KPI families. Common manufacturing KPIs (OEE, availability, performance, quality, FPY, scrap, maintenance compliance, safety rates, cost and energy intensity) were separated from battery-specific indicators (EOL pass rate, genealogy, scan accuracy, cell-buffer days). For each KPI, the analysis identifies minimum input variables, reporting dimensions, owner, formula and required freshness, following a controlled calculation sequence: identify the reporting window, retrieve approved inputs, validate timestamps and master data, apply exclusions, aggregate, calculate, compare against target, assign status and store calculation metadata.

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Fig. 1 Proposed MIS information flow: source systems → integration/API → validation & master data → KPI calculation → dashboard & alerts.

V. DASHBOARD DESIGN AND KPI ARCHITECTURE

The eight sections form a balanced scorecard for plant operations. Production answers whether the plant is producing effectively; quality, whether correctly; maintenance, whether assets are reliable; safety, whether operations are safe; cost/energy, whether output is economically efficient; traceability, whether product history is trustworthy; inventory, whether materials are available; and EHS, whether performance is sustainable and compliant.

Table 1 Eight-dimensional Plant Manager performance model

Dashboard domain	Primary KPIs	Management purpose
Production / OEE	OEE; availability; performance; quality; packs/shift; trend	Identify production losses and plan-output gaps
Quality	FPY; scrap; defect PPM; EOL pass rate	Detect deterioration and initiate containment
Maintenance	Top failures; critical-machine OEE; PM compliance	Prioritise chronic equipment and reliability losses
Safety	TRIR; LTIFR; days without LTI; leading controls	Escalate incidents and monitor preventive discipline
Cost and energy	Cost/good pack; energy/good pack; budget variance	Connect operational performance with economic intensity
Traceability	Cell–component–pack genealogy; scan-match accuracy	Support containment, investigation and recall readiness
Inventory	Raw material; finished goods; cell-buffer days	Identify shortage, excess and continuity risks
EHS	Renewable energy; recycling; water; audit compliance	Integrate sustainability and compliance into plant review

A distinctive strength of the design is that data freshness is set by the decision a metric supports, not by a blanket demand for real-time data. Event-level safety and traceability issues require immediate information, whereas monthly safety rates and financial measures require validated, closed records — faster data is not automatically better data.

Table 2 Data-freshness classes and management rationale

Class	Target freshness	Examples and management reason
RT-1 Event / alarm	≤ 5 seconds	Machine stop, EOL failure, traceability mismatch — immediate intervention
RT-2 Near-real-time KPI	1–5 minutes	OEE, availability, performance, quality — shift-level action
RT-3 Short-lag operational	15–30 minutes	Energy/pack, inventory, PM compliance — operational monitoring

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D-1 Shift / daily	Shift close / next day	FPY, scrap, days without LTI, cost/pack — aggregation & reconciliation
D-2 Periodic / monthly	Daily-to-monthly close	TRIR/LTIFR, renewable share, budget variance — validated reporting

Table 3 Core KPI definitions and decision logic

KPI	Controlled formula	Primary management use
OEE	Availability × Performance × Quality	Separate downtime, speed and quality losses
Availability	Run time ÷ planned production time × 100	Monitor stoppage-related losses
Performance	(Ideal cycle time × total count) ÷ run time × 100	Identify slow cycles and minor stops
First-pass yield	First-pass good units ÷ total processed × 100	Expose rework and process instability
Defect PPM	Defective units ÷ inspected units × 1,000,000	Track normalised defect intensity
Cost per pack	Allocated actual plant cost ÷ good packs	Measure economic efficiency on a consistent base
Energy per pack	Relevant measured kWh ÷ good packs	Measure energy intensity and sustainability
Scan accuracy	Correct serial matches ÷ required scans × 100	Test whether genealogy data can be trusted
Cell-buffer days	Usable cell stock ÷ expected daily consumption	Convert inventory into continuity coverage

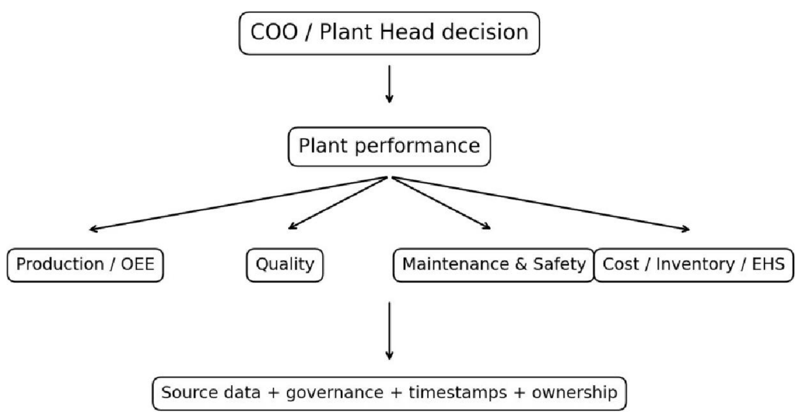

Fig. 2 Management-oriented KPI hierarchy — decision at the top, plant performance in the middle, data governance at the foundation.

VI. RESULTS AND DISCUSSION

OEE is the central production KPI because it combines availability, performance and quality, but it should never be read alone: a low value can arise from downtime, slow cycles or poor quality, each requiring a different response. The dashboard therefore shows the headline outcome and its component drivers together, reducing the need for separate reports from Production and Quality. The illustrative profile — availability 91%, performance 95%, quality 99% and OEE 86% — is used only to demonstrate the logic.

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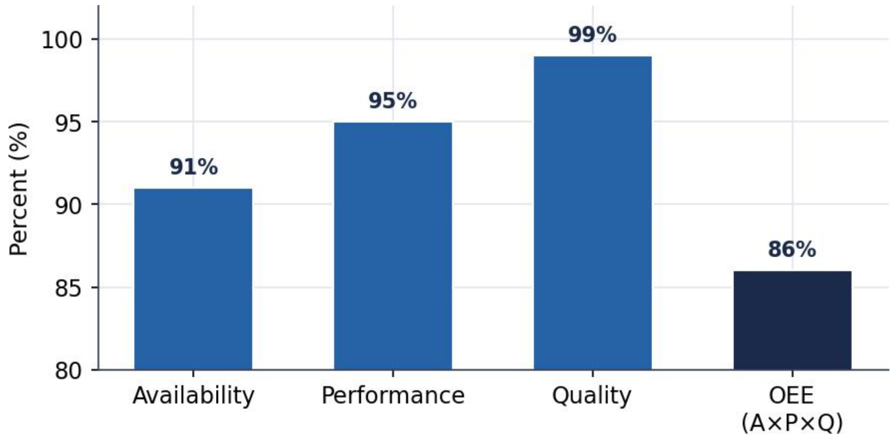

Fig. 3 OEE and its component losses (Illustrative values).

The quality section combines FPY, scrap, defect PPM and EOL pass rate. FPY is valuable because it focuses on first-pass success and prevents reworked units from appearing artificially successful, while EOL testing adds a final performance gate. For management the key is escalation: a rising defect PPM should trigger review of defect concentration and affected stations, and an EOL failure should trigger containment — without claiming a root cause the source data does not confirm.

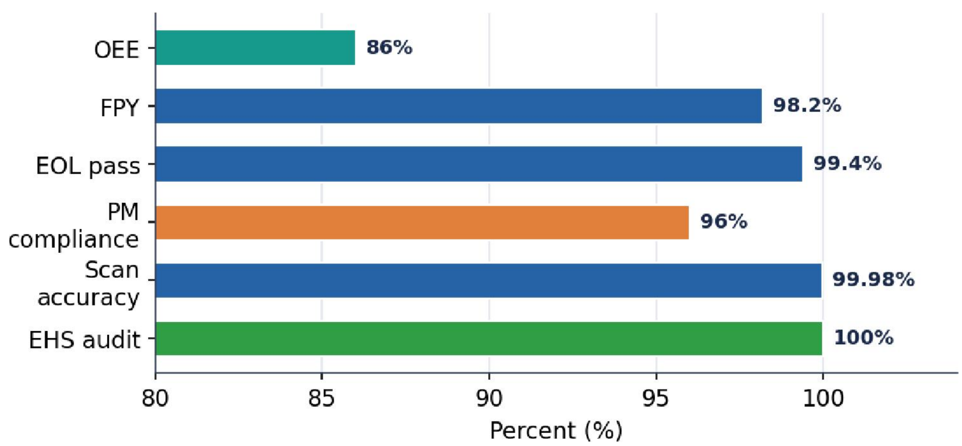

Fig. 4 Illustrative KPI profile across the dashboard's principal dimensions.

Maintenance uses a ranked top-five failure view and critical-machine OEE; ranking directs attention to the most frequent or costly losses, provided the ranking basis (occurrence or downtime) is documented. Cost/pack and energy/pack translate plant activity into business terms, and their denominators matter: using good packs rather than total production prevents a quality deterioration from making cost per pack appear artificially better. Energy/pack is especially important in energy-intensive battery production, affecting both cost and environmental impact. Traceability adds an information-control dimension — genealogy and scan accuracy support containment and recall readiness — while cell-buffer days convert inventory into a time-based measure of continuity risk.

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Fig. 5 Illustrative seven-day OEE trend against a target line, supporting shift-level review.

Read together, the eight sections let a manager move from an outcome KPI to a contributing KPI, to the responsible function, and finally to the underlying source record. The dashboard's status logic — Above Target, On Target, Below Target, Stale, Unavailable — turns the management meeting from "What happened?" into "Where is the deviation, who owns it, and what action is required?"

Table 4 Dashboard alignment with selected Sustainable Development Goals

SDG	Relevant indicators	Management connection
SDG 7 – Affordable & Clean Energy	Energy per pack; renewable-energy share	Energy intensity and renewable sourcing
SDG 8 – Decent Work & Economic Growth	OEE; cost per pack; safety indicators	Productivity, efficiency and safe work
SDG 9 – Industry, Innovation & Infrastructure	Digital dashboard; predictive maintenance; traceability	Smart and resilient manufacturing
SDG 12 – Responsible Consumption & Production	Scrap; recycling; waste; material efficiency	Resource efficiency and circularity
SDG 13 – Climate Action	Energy; renewable share; environmental savings	Reduction of operational environmental impact

Consolidating the eight dimensions produces the single executive view shown in Fig. 6. All displayed values are illustrative and do not represent actual plant performance.

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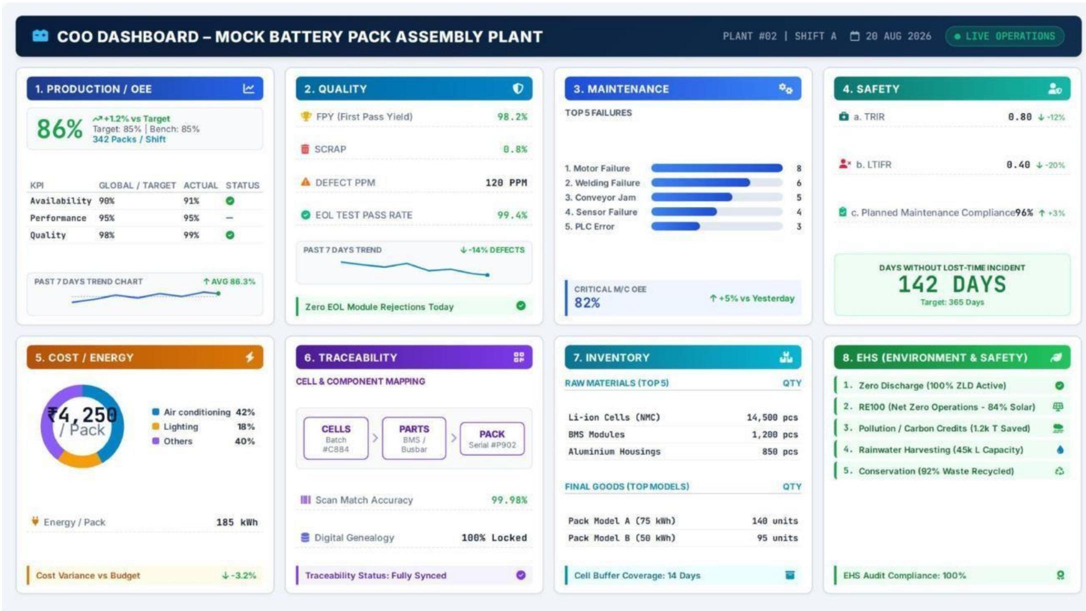

Fig. 6 Proposed one-page Plant Manager MIS dashboard for the battery pack assembly plant (illustrative values).

VII. MANAGERIAL IMPLICATIONS

The dashboard shifts management from report collection to exception-based management: rather than waiting for departmental reports, the Plant Manager sees whether each KPI is above target, below target, stale or unavailable. Because it integrates multiple functions, it also reduces silos — a production loss can be linked to a maintenance failure, a quality loss to process conditions, an energy increase to lower output. Equally important, the design shows that data governance is a management responsibility, not merely an IT task: a single source of truth, controlled master data, timestamp integrity, visible stale status and reconciliation with source reports protect decisions from misleading numbers. Finally, analytics should support rather than overwhelm managers — the view shows the result, the main driver, the trend and the next action, with detailed machine-learning outputs available through drill-downs.

VIII. RECOMMENDED IMPLEMENTATION ROADMAP

The roadmap follows the BRD's sequence: freeze KPI definitions, map sources, build validation and the calculation layer, implement the dashboard, run a two-to-four-week parallel validation, and obtain sign-off with change control. This ordering prevents building an attractive dashboard before the underlying numbers are agreed. A KPI is accepted only when it has an approved definition, formula, source, owner, refresh SLA and unit, and reconciles with the relevant approved report.

Table 5 Recommended implementation roadmap

Phase	Focus	Key activity	Output
1	KPI governance	Freeze definitions, formulas, units, owners, targets, thresholds	Approved KPI master
2	Source mapping	Map approved inputs to operational, quality, EHS and business records	Validated source map
3	Data quality	Timestamp, unit, completeness, duplicate and master-data checks	Trusted data layer

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4	KPI engine	Formula logic, exclusions, status rules, trends and versioning	Reproducible calculations
5	Dashboard	Build one-page view with freshness indicators and alerts	Operational dashboard
6	Parallel validation	Compare outputs with official reports for two to four weeks	Reconciled results
7	Governance & scale	Sign-off, change control and justified advanced analytics	Sustained MIS

IX. LIMITATIONS AND FUTURE SCOPE

The plant is a mock facility; its values are illustrative, and actual database tables, APIs, PLC tags and source-system names remain unconfirmed. Benchmark values and some KPI conventions require plant-specific approval, and the study is a design- and literature-based analysis rather than a longitudinal empirical test of dashboard impact. Future work should validate every KPI against plant-approved data, compare management performance before and after deployment — measuring response time to deviations, downtime reduction and quality containment — and progressively introduce diagnostic, predictive and digital-twin capabilities once definitions and governance controls are stable.

X. CONCLUSION

This paper presents the design and development of a Plant Manager MIS dashboard for a commercial battery pack assembly plant from a management perspective. Its central finding is that an executive dashboard is valuable not because it places many KPIs on one screen, but because it creates a controlled link between data, performance interpretation and managerial action. The eight-section structure integrates production/OEE, quality, maintenance, safety, cost/energy, traceability, inventory and EHS into a single decision-support view, supported by clear formulas, data ownership, freshness rules, exception messages and auditability. The next step is not more visual elements but validation of every KPI against plant-approved data and governance rules; once that foundation is stable, advanced analytics and digital-twin capabilities can be introduced progressively, allowing the dashboard to evolve from a mock-up into a reliable MIS for data-driven battery manufacturing.

XI. DECLARATIONS

Funding: No specific funding was received. Competing interests: The authors declare none. Ethics approval: Not applicable; the study uses secondary research and a mock dashboard design. Use of generative AI: Language-refinement and reference-formatting tools were used; the authors accept full responsibility for the content.

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