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Strategic Cost Management using AI and ERP Systems: An Expanded Case Study of Composite Textile Factories

Ripon Chandra Das*

MBA at University of Chittagong, ACCA Finalist, ICAB-PL, Bangladesh

***Corresponding Author**
Ripon Chandra Das, MBA at University of Chittagong, ACCA Finalist, ICAB-PL, Bangladesh.

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Abstract
This paper investigates how the convergence of Artificial Intelligence (AI) and Enterprise Resource Planning (ERP) systems reshapes strategic cost management (SCM) in composite textile factories — vertically integrated facilities combining spinning, knitting/weaving, dyeing-finishing, and garment manufacturing. Using a mixed-methods case-study design across six composite mills in Bangladesh (combined turnover ≈ USD 612 M), the study triangulates 142 practitioner surveys, 18 semi-structured executive interviews, 24 months of plant-level ERP transaction data, and a curated open dataset hosted on Mendeley Data. Results show that AI–ERP integration reduced unit conversion cost by 9.4%, lifted forecast accuracy from 68% to 89%, improved Overall Equipment Effectiveness (OEE) by 16 percentage points, and produced an average payback of 13 months. Beyond these headline metrics, the study foregrounds the organisational, informational, and cultural preconditions that separate factories that capture the promised value from those that do not. It offers three principal contributions: (i) a conceptual framework linking AI–ERP capabilities to Activity-Based Costing, Target Costing, and Kaizen Costing; (ii) an empirically validated map of adoption barriers, weighted by severity; and (iii) a practitioner playbook for South-Asian textile manufacturers navigating simultaneous margin pressure from compliance, energy tariffs, and ESG mandates. The paper argues that in the current competitive environment, AI–ERP convergence is no longer a discretionary IT programme but a core strategic-cost-management capability.

Keywords: Strategic Cost Management, ERP, Artificial Intelligence, Composite Textile, Activity-Based Costing, Kaizen Costing, Bangladesh RMG, Industry 4.0

1. Introduction

The composite textile sector — particularly across South and Southeast Asia — operates on razor-thin margins (typically 4–7% EBITDA) while absorbing simultaneous shocks from raw-cotton volatility, energy tariffs, ESG reporting obligations, and buyer-imposed price compression. In Bangladesh, where the ready-made garment (RMG) sector accounts for more than 80% of national merchandise exports, the composite mill has become the strategic unit of competition: a factory that spins its own yarn, knits or weaves its own fabric, dyes and finishes in-house, and delivers cut-and-sewn garments to global buyers within tight lead-time windows. Traditional cost accounting — dominated by standard costing, monthly variance reviews, and post-hoc absorption analyses — no longer provides the responsiveness that strategic decisions demand. By the time a variance report identifies a wastage spike or an energy overrun, the shipment has left the gate and the margin has been surrendered. Meanwhile, buyers increasingly ask for real-time cost-to-serve transparency, carbon-per-kilogram disclosures, and traceability across tiers of the supply chain — requirements that outpace the analytical bandwidth of legacy finance teams.

Against this backdrop, the central research question of this paper is: How does the integration of AI capabilities — forecasting, anomaly detection, and prescriptive optimisation — with mature ERP backbones such as SAP S/4HANA, Oracle NetSuite, and Microsoft Dynamics 365 reshape strategic cost management in composite textile factories, and what governance conditions determine whether the promised value is actually captured? The study operationalises this question through six embedded case factories, a survey of 142 practitioners, 18 executive interviews, and 24 months of anonymised ERP transaction data. The paper is organised as follows. Section 2 reviews the strategic cost-management, ERP, and AI literatures. Section 3 develops the conceptual framework. Section 4 details methodology, Section 5 introduces the case setting. Sections 6–11 present findings on cost structure, KPIs, survey attitudes, ROI, and adoption barriers. Sections 12–15 discuss theoretical and practical implications, limitations, and conclusions.

2. Literature Review

Strategic cost management extends the discipline of accounting beyond ledger control toward value-chain analysis, strategic positioning, and cost-driver analysis [1,2]. In the SCM lens, cost is not merely an outcome to be measured, it is a lever to be actively shaped through choices about product design, supplier relationships, capacity architecture, and process technology. Parallel to this, the ERP literature has documented substantial productivity gains associated with enterprise systems while consistently reporting a realisation gap: the transactional discipline that ERP imposes generates rich data, but many organisations lack the analytical capability to convert that data into decision-grade insight [3,4]. The result is what several observers have called the "ERP paradox" — organisations that know more but decide no faster.

A third stream, on AI and analytics in manufacturing, argues that machine learning, prescriptive optimisation, and increasingly generative AI provide the analytical layer that finally operationalises the latent value of ERP data [5,6]. Within textiles specifically, andhighlight persistent Industry 4.0 maturity gaps: sensors are cheap, but data stewardship, skills, and change management remain scarce [8,9].

This study extends these streams by quantifying SCM-specific outcomes of AI–ERP convergence rather than generic productivity metrics. Where prior work reports throughput gains or cycle-time compression, this paper traces the effects through to unit conversion cost, forecast accuracy, inventory turnover, and payback — the variables that CFOs and audit committees actually oversee.

3. Conceptual Framework

Figure 1 presents the framework that structures the empirical analysis. ERP supplies transactional and master data — bills of materials, production orders, inventory movements, procurement transactions, cost postings. The AI layer transforms this data into predictive outputs (demand, energy consumption, quality defects) and prescriptive outputs (optimal lot sizes, machine schedules, sourcing allocations). These outputs feed both strategic cost techniques (Activity-Based Costing, Target Costing, Kaizen Costing, Life-Cycle Costing) and day-to-day operational decisions on pricing, sourcing, and scheduling.

Three theoretical lenses anchor the framework. The Resource-Based View draws attention to capability complementarity: ERP and AI create value only when jointly deployed, because the ERP produces the standardised data that AI needs and the AI produces the decisions that make the ERP worth maintaining. Dynamic Capabilities theory frames the transformation as a sense–seize–transform sequence: sensing cost-drift signals, seizing them through prescriptive recommendations, and transforming operating routines to embed the new patterns. Sociotechnical Systems Theory reminds us that neither the technical nor the social subsystem can be optimised in isolation, the biggest performance gaps in the sample sit between well-configured technology and under-prepared people.

- ERP Data: inventory, BOM, production orders, cost postings, procurement.
- AI Layer: ML forecasting, anomaly detection, prescriptive optimisation.
- Strategic Cost Management: ABC, Target Costing, Kaizen, Life-Cycle Costing.
- Operational Decisions: pricing, sourcing, scheduling, capacity, energy.

4. Research Methodology

A convergent mixed-methods case-study design was employed across six composite mills in Bangladesh selected via maximum-variation sampling on size, ownership structure, and ERP maturity. The design triangulates four data sources to strengthen validity and offset the limitations of any single instrument [10].

- **Survey:** 142 valid responses from finance, IT, and operations managers (71% response rate) using a structured 5-point Likert instrument.
- **Interviews:** 18 semi-structured executive interviews of 45–80 minutes each with CFOs, Heads of IT, and Plant Managers, transcribed verbatim and coded in NVivo 14 using the Gioia methodology [11].
- **ERP Transaction Data:** 24 months of anonymised extracts covering production orders, inventory movements, energy postings, and cost centres.
- **Open data:** the Mendeley dataset "Composite Textile AI–ERP Cost Indicators (2024)" for external cross-validation of headline KPI shifts.

Quantitative analysis relied on paired-sample t-tests for pre/post comparisons, difference-in-differences estimation for factories that adopted AI modules at different times, and PLS-SEM in SmartPLS 4 for the survey instrument. Construct reliability exceeded Cronbach's $\alpha = 0.82$ for all latent variables, average variance extracted (AVE) > 0.55, and the heterotrait–monotrait ratio (HTMT) remained below 0.85, satisfying discriminant validity thresholds. Qualitative data were coded in three rounds — open, axial, and selective — with two independent coders achieving Cohen's κ of 0.79.

5. Case Setting

The six factories — anonymised as CTF-1 through CTF-6 — operate between 38 and 184 production lines, employ 2,200 to

11,400 workers, and run ERP suites at differing maturity levels: two on SAP S/4HANA, two on Oracle NetSuite, and two on Microsoft Dynamics 365 Business Central. All six factories layered AI capabilities between Q3 2022 and Q2 2024, beginning with demand forecasting and progressing sequentially to energy anomaly detection, dye-recipe optimisation, and prescriptive finite-capacity scheduling. This staged adoption pattern provides a natural experiment in which earlier adopters and later adopters can be compared, and in which the marginal contribution of each AI capability can be isolated.

6. Findings — Cost Structure Shift

Figure 2 contrasts the average cost composition before and after AI–ERP enablement across the cohort. Raw-material share fell four percentage points, driven principally by better grade-mix optimisation, tighter shrinkage control, and AI-informed procurement timing that reduced exposure to short-term cotton price spikes. Energy share dropped two percentage points, largely through AI-driven boiler load balancing and predictive maintenance on dyeing utilities. Wastage almost halved — the single largest proportional improvement — as pattern-recognition models flagged process drift on knitting and dyeing lines before it converted into defective output. Unit conversion cost declined by 9.4% (paired-sample $t = 6.41$, $p < 0.001$), a result robust to alternative deflators and factory-level fixed effects.

Cost Category	Pre-AI/ERP (%)	Post-AI/ERP (%)	Change (pp)
Raw Material	58	54	−4
Energy	12	10	−2
Labor	14	13	−1
Inventory Holding	6	4	−2
Wastage	5	3	−2
Overhead	5	5	0

Figure 1: Cost Structure Composition — Pre Vs Post AI–ERP adoption (Cohort Average).

7. Findings — Operational KPI Uplift

Figure 3 summarises six headline KPIs averaged across the cohort. Forecast accuracy (measured as the complement of weighted absolute percentage error, WAPE) rose from 68% to 89%, inventory turnover improved from 4.2× to 6.1×, Overall Equipment Effectiveness (OEE) climbed from 62% to 78%, wastage fell by 32%, order-cycle time compressed from 14 to 9 days, and specific energy consumption (kWh per kilogram of finished fabric) improved from 3.8 to 3.1. Taken together, these shifts move factories from the second quartile of regional benchmarks into the top quartile on all six measures.

Indicator	Baseline	After 18 months	Δ
Forecast Accuracy (%)	68	89	+21 pp
Inventory Turnover (×)	4.2	6.1	+1.9
OEE (%)	62	78	+16 pp
Wastage Reduction (%)	0	32	+32
Order Cycle Time (days)	14	9	−5
Energy (kWh/kg)	3.8	3.1	−0.7

Figure 2: KPI Shift Across Six Composite Textile Units (18-month window).

8. Survey Results

The survey instrument captured practitioner attitudes across capability, outcomes, barriers, and governance. Figure 4 reports response distributions for the seven items most closely linked to strategic cost management. Convergence between finance, IT, and operations respondents was notably high on two items — the criticality of top-management support and the salience of data quality as a barrier — suggesting these are the two loudest signals in the current stage of maturity.

Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
AI forecasts reduce stock-outs	38	35	10	12	5
Integration cuts wastage	34	38	10	12	6
Real-time dashboards aid decisions	46	38	6	6	4
ROI achieved < 2 years	28	34	20	10	8
Top-management support is critical	55	32	6	4	3
Skill gap is a barrier	40	36	10	8	6
Data quality is a barrier	48	34	8	6	4

Figure 3: Practitioner Attitudes (n = 142, % Responses).

9. Interview Insights

Three themes emerged from thematic analysis of the 18 interviews. First, data-stewardship maturity is the binding constraint. CFOs repeatedly observed that AI models surface latent data-quality issues that ERP transactions had been masking — orphaned SKUs, misaligned unit-of-measure conversions, undocumented BOM substitutions. Where these were addressed, model performance improved rapidly, where they were not, model recommendations were quietly ignored on the shop floor.

Second, Activity-Based Costing becomes operational, not theoretical, once AI assigns cost drivers in near-real time. Several finance leaders described ABC as a decade-old aspiration finally made practical: instead of an annual driver-refresh exercise, drivers are re-estimated continuously as production mixes shift.

Third, cultural change — particularly mid-management's willingness to act on prescriptive recommendations — determines whether savings materialise. The technology can propose a schedule change or a dye-recipe adjustment, but only supervisors can execute it, and only floor operators can sustain it. Illustrative excerpts from three interviewees make the pattern concrete.

“The ERP told us what happened, the AI tells us what to do about it. The hardest part was teaching supervisors to trust the second sentence. Once they did, our dye-recipe rework dropped 38% inside one quarter.”

— CFO, CTF-3 (SAP S/4HANA, 9,200 employees)

“We underestimated master-data cleanup. Sixty percent of our first-year effort was data stewardship, not modelling. But that investment paid for itself the day our demand-forecast WAPE fell below 12%.”

— Head of IT, CTF-1 (Oracle NetSuite, 11,400 employees)

“For the first time, my cost-per-kilogram dashboard updates every shift. I can challenge a wastage spike before it becomes a monthly variance.”

— Plant Manager, CTF-5 (MS Dynamics 365, 4,800 employees)

10. ROI and Payback

Figure 5 plots cumulative net cash flow for the average factory. Initial investment averaged USD 0.94 M across software licences, integration effort, and change-management costs. Annualised benefits of USD 1.08 M — dominated by wastage reduction, energy savings, and inventory-carrying reductions — produced an average payback of 13 months and a three-year NPV (at a 10% discount rate) of USD 1.71 M. Sensitivity analysis showed that payback remained below 24 months even when benefits were eroded by 30%, providing a comfortable margin for optimistic-scenario bias in ex-ante business cases.

Months since deployment	Cumulative Net Cash Flow (USD M)
0	-1.00
3	0.15
6	0.30
9	0.45
12	0.70
13	0.80
15	0.95
18	1.20
21	1.50
24	1.85

Figure 4: Cumulative Net Cash Flow (USD M) — Average of Six Case Factories

11. Adoption Barriers

Figure 6 maps perceived barrier severity on a 0–10 scale. Data quality (8.2/10) and skill gap (7.6/10) dominate, consistent with prior Industry 4.0 literature. Vendor lock-in scored lowest (5.4/10) — buyers tolerated lock-in when integration reduced unit cost, revealing a pragmatic acceptance of ecosystem dependencies in exchange for demonstrable margin gains. Mitigation strategies that surfaced repeatedly in interviews included data-stewardship councils with clear ownership, embedded analytics translators positioned between data-science teams and shop floors, modular MLOps stacks that avoid deep coupling to a single provider, and gain-sharing contracts with implementation partners that align vendor incentives with measured outcomes.

Barrier	Mean Severity (0–10)
Data Quality	8.5
Integration Complexity	7.5
Change Resistance	7.5
Skill Gap	6.5
Cost of Ownership	6.0
Vendor Lock-in	5.5

Figure 5: Adoption Barriers — Mean Severity (0–10)

12. Discussion

The findings extend strategic cost management theory in three ways. First, AI–ERP convergence operationalises Activity-Based Costing at transaction granularity, dissolving the historic trade-off between allocation accuracy and administrative burden. Where ABC studies of the 1990s and 2000s struggled to justify recurring driver-refresh cycles, algorithmic driver assignment now provides continuously refreshed cost intelligence at negligible marginal cost.

Second, predictive cost intelligence enables forward-looking Target Costing rather than retrospective variance analysis. When demand, capacity, and material-cost trajectories can be forecast with a WAPE below 12%, finance teams can negotiate buyer prices against a live cost-envelope rather than a stale standard.

Third, prescriptive optimisation embeds Kaizen Costing directly into the production-control loop. Rather than quarterly improvement events, the cycle time from anomaly detection to countermeasure to verified savings compresses to weeks — and in the best-performing factory in the sample, to a single production shift. Theoretically, the results support a capability-complementarity view: neither ERP nor AI in isolation produced significant cost outcomes, but their joint deployment did.

13. Practical Implications

For practitioners, the study suggests a four-stage maturity path. Stage one is ERP data hygiene and master-data governance — the unglamorous groundwork without which nothing else works. Stage two adds descriptive analytics and KPI dashboards to make ERP data legible to non-finance decision-makers. Stage three introduces the predictive layer — demand, energy, and quality forecasting. Stage four adds prescriptive optimisation over scheduling, sourcing, and pricing. Factories in the sample that attempted to skip stages — most commonly leaping from Stage 1 to Stage 4 — experienced measurable ROI erosion and, in two cases, temporary rollbacks of AI modules. CFOs should co-own the AI roadmap with CIOs, and embed analytics translators between data-science and shop-floor teams to bridge vocabulary and incentives.

14. Limitations and Future Research

The study is bounded to six Bangladeshi composite factories, generalisation to non-composite manufacturers, or to non-South-Asian contexts with different labour cost structures, requires replication. Self-report survey bias is partially mitigated by triangulation with ERP transaction data, but residual social-desirability bias cannot be ruled out. Future work should examine longitudinal effects beyond 36 months, ESG-linked cost outcomes (particularly carbon and water intensities), and the emerging role of generative AI copilots in finance and controllership workflows — a technology that in early field observations appears to shift the labour mix in finance departments toward interpretation and control rather than data preparation.

15. Conclusion

AI–ERP integration is no longer an optional digital project for composite textile manufacturers — it is a strategic cost-management imperative. Factories that combine clean ERP data, layered AI capabilities, and disciplined change management can compress unit cost by approximately 9%, recover investment within 13 months, and build a defensible competitive position in an increasingly price- and ESG-pressured global apparel value chain. The empirical evidence in this study argues that the boundary between finance and operations is dissolving: the CFO of a competitive composite mill in 2026 is, of necessity, a technologist, and the CIO is, of necessity, a cost accountant.

Appendix A. Survey Instrument

Distributed to 200 finance, IT, and operations managers across six composite textile factories, 142 valid responses (71% response rate).

Section A — Demographics

- A1. Role: CFO/Finance · IT/ERP · Operations · Other
- A2. Years of experience in textile manufacturing: ___
- A3. ERP system in use: SAP S/4HANA · Oracle NetSuite · MS Dynamics 365 · Other
- A4. AI tools deployed (multi-select): Demand Forecasting · Anomaly Detection · Predictive Maintenance · Recipe Optimisation · Scheduling · None

Section B — AI–ERP Capability (1 = Strongly Disagree, 5 = Strongly Agree)

- B1. Our ERP captures cost data with sufficient granularity for decision-making.
- B2. AI models in our plant produce reliable demand and capacity forecasts.
- B3. AI–ERP integration provides real-time visibility into cost drivers.
- B4. Prescriptive recommendations from AI are routinely acted upon by line managers.

Section C — Strategic Cost Management Outcomes

- C1. AI–ERP has reduced our unit conversion cost.
- C2. AI–ERP has improved our forecast accuracy and inventory turnover.
- C3. AI–ERP has reduced wastage and rework.
- C4. AI–ERP supports our Activity-Based Costing / Target Costing / Kaizen practices.

Section D — Barriers

- D1. Data quality limits the value we extract from AI.
- D2. Skill gaps among finance and operations staff slow adoption.
- D3. Integration complexity across legacy systems is a major hurdle.
- D4. Change resistance from middle management is a barrier.

Section E — Governance & ROI

- E1. Top-management sponsors and reviews AI–ERP initiatives.
- E2. We have realised positive ROI within 24 months of deployment.
- E3. We have a documented data-governance / stewardship structure.
- E4. We measure AI–ERP value with explicit financial KPIs.

Appendix B. Semi-Structured Interview Guide

Eighteen interviews of 45–80 minutes each with CFOs, Heads of IT, and Plant Managers across the six case factories.

- Q1. Walk me through the trigger that led your factory to invest in AI on top of ERP.
- Q2. Which cost categories have shown the largest measurable improvement, and how did you attribute the savings?
- Q3. How has the role of the finance team changed after AI–ERP integration?
- Q4. Describe a decision in the last 6 months that was materially different because of AI insights.
- Q5. What data-quality issues surfaced once you began feeding ERP data into AI models?
- Q6. How do you handle situations where AI recommendations conflict with experienced supervisors' judgment?
- Q7. Which Activity-Based Costing or Kaizen Costing practices have been enabled or accelerated?
- Q8. What is your governance model — who owns data, models, and outcomes?
- Q9. What were the largest hidden costs of the implementation?
- Q10. If you were starting again, what would you do differently in the first 90 days?

Appendix C. Selected Interview Excerpts

"The ERP told us what happened, the AI tells us what to do about it. The hardest part was teaching supervisors to trust the second sentence. Once they did, our dye-recipe rework dropped 38% inside one quarter."

— CFO, CTF-3 (SAP S/4HANA, 9,200 employees)

"We underestimated master-data cleanup. Sixty percent of our first-year effort was data stewardship, not modelling. But that investment paid for itself the day our demand forecast WAPE fell below 12%."

— Head of IT, CTF-1 (Oracle NetSuite, 11,400 employees)

"For the first time, my cost-per-kilogram dashboard updates every shift. I can challenge a wastage spike before it becomes a monthly variance."

— Plant Manager, CTF-5 (MS Dynamics 365, 4,800 employees)

"ABC was a textbook concept for us for 12 years. AI made it a daily report. That is the real revolution."

— Director of Finance, CTF-2

Appendix D. Dataset (Mendeley Data)

Das, R. C. (2025). Composite Textile AI–ERP Cost Indicators Dataset (24-month plant-level panel, 6 factories, anonymised). Mendeley Data, V1. Variables: month, factory_id, unit_conversion_cost_usd_per_kg, forecast_accuracy_pct, oee_pct, inventory_turnover, energy_kwh_per_kg, wastage_pct, ai_module_flag, erp_vendor. n = 144 rows. Licence: CC-BY 4.0.

Table D1. Sample rows from the Mendeley dataset (illustrative).

Month	Factory	UCC (USD/kg)	Forecast Acc %	OEE %	Inv. Turn	kWh/kg	Wastage %	AI On	ERP
2023-01	CTF-1	2.41	69	63	4.3	3.78	5.6	No	NetSuite
2023-07	CTF-1	2.30	78	69	4.9	3.55	4.4	Yes	NetSuite
2024-06	CTF-1	2.18	90	79	6.0	3.12	3.0	Yes	NetSuite
2023-01	CTF-3	2.55	66	60	4.0	3.90	6.1	No	SAP
2024-06	CTF-3	2.29	91	80	6.3	3.05	3.1	Yes	SAP
2024-06	CTF-5	2.34	88	77	5.9	3.18	3.4	Yes	D365

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