AI-Enabled Retail Operating Efficiency Improvement: A Comparative MIS Study of Walmart and Costco

RICC: A Retail Strategic Intelligence Center Prototype for Benchmarking, Forecasting, and Evidence-Based Insights

EBA203 Management Information Systems (MIS) — Class 01, Group 5

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Abstract

The global supermarket retail industry has shifted from growth-driven expansion to a mature, efficiency-centered competitive phase. Retailers face rigidly rising costs (rent, labor, logistics), supply chain coordination frictions (simultaneous overstock and stockouts), insufficient depth of digital transformation (fragmented systems and limited analytics), and increasing difficulty in building customer loyalty amid omnichannel fragmentation. This project examines two representative U.S. retail leaders—Walmart and Costco—to identify how differences in information systems (SCM, POS data utilization, inventory management, and CRM/loyalty mechanisms) translate into observable differences in operating efficiency and financial outcomes. Building on the comparative analysis, we propose and prototype an AI-enabled MIS artifact—RICC(Retail Intelligence Command Center)—that integrates standardized financial metrics, benchmarking, forecasting, and evidence-constrained generative insights (RAG-style) from annual disclosures (e.g., 10-K MD&A and Risk Factors). We also develop a go-to-market strategy (Option 2) including positioning, target customers, pricing tiers, pilot KPIs, and governance measures. The deliverable is a management-oriented, decision-support blueprint that links system design to measurable performance and actionable managerial recommendations.

Keywords: MIS; retail analytics; Walmart; Costco; SCM; POS; CRM; inventory management; benchmarking; forecasting; generative AI; RAG; decision support

Executive Summary (Management View)

Decision context. U.S. grocery and general merchandise retail has become an efficiency-led arena where value creation is driven by (i) cost-to-serve discipline, (ii) inventory and working capital efficiency, and (iii) loyalty and demand predictability across omnichannel fragmentation.

What we compared. We benchmarked Walmart and Costco across four MIS capability areas—SCM coordination, POS-driven demand sensing, inventory/working capital control, and CRM/loyalty mechanisms—and linked these capabilities to operational and financial outcomes (DIO/CCC, ROA/ROE, cash generation). Results are supported by standardized metric pipelines and evidence from disclosures.

What we built. We prototyped RICC, an AI-enabled MIS decision-support system integrating:

- **Standardized financial metrics and mapping governance** for cross-firm comparability;
- **Benchmarking dashboards** for efficiency/returns/cash diagnostics;
- **Forecasting** as trend/scenario support (multi-model options);
- **Evidence-constrained GenAI (RAG-style)** where every claim must be accompanied by retrieved metrics and/or filing excerpts.

Managerial implication. "Digital transformation" is only valuable when it closes the loop from *data* → *evidence* → *insight* → *action*. Our artifact operationalizes this loop with auditability and metric governance designed for management settings.

Deliverables (what the report contains).

- Comparative mechanism analysis (Walmart vs. Costco) linked to KPIs;
- RICCarchitecture and implementation evidence;
- Option-2 go-to-market plan and pilot KPI framework;
- Risks, governance, and reproducibility notes.

Contents

List of Figures

1 Introduction

1.1 Context: From Expansion to Efficiency Competition

The supermarket retail sector has entered a stage characterized by slower demand growth and heightened competitive intensity. In such a "stock-based" market, firms compete less on expansion and more on operating excellence: superior supply chain execution, disciplined inventory and working capital management, and loyalty systems that stabilize demand. Digital capabilities—data integration, analytics, and decision support—are increasingly decisive for sustaining competitive advantage (Bharadwaj, 2000, Bharadwaj, 2000).

1.2 Industry-Wide Pain Points

This project is motivated by four widely observed pain points in supermarket retail operations:

1. **Rigid cost inflation:** rising rent, labor, and logistics expenses, alongside investments required for compliance and sustainability, compress margins.

2. **Insufficient supply chain coordination:** multi-tier distribution and global sourcing can lead to simultaneous overstock and stockouts, with sluggish replenishment responses.

3. **Shallow digital transformation:** many retailers remain at surface-level digitalization with fragmented systems and limited analytics, lacking predictive and prescriptive capabilities.

4. **Difficulty building customer loyalty:** fragmented omnichannel experiences and homogenized membership benefits limit stickiness; consumers have more choice and higher switching propensity.

1.3 Research Objective and Contributions

We study Walmart and Costco to (i) identify key differences in their MIS capabilities across SCM, POS, inventory management, and CRM; (ii) explain how these differences map to operating efficiency outcomes (inventory turnover, working capital cycle, cost control, loyalty); and (iii) design an AI-enabled MIS solution (RICC) that operationalizes benchmarking and evidence-based insights for managers.

Consistent with a design-science orientation in MIS (Hevner et al., 2004, Hevner et al., 2004), our artifact (RICC) is positioned as a practical decision support prototype, complemented by an Option-2 product strategy (positioning, pricing, acquisition funnel, pilot KPIs).

2 Company and Industry Description

2.1 Walmart: Scale, Omnichannel Complexity, and Platformization

Walmart is the world's largest retailer, operating a highly complex portfolio across stores, e-commerce, and omnichannel fulfillment. Its competitive advantage is traditionally associated with scale economics, supply chain sophistication, and price leadership. The operating model requires robust data integration and end-to-end coordination to manage product variety, demand volatility, and fulfillment trade-offs.

2.2 Costco: Membership-Based Discipline and High-Turnover Simplicity

Costco is a benchmark membership-based warehouse retailer. Its business model emphasizes a limited SKU selection, high inventory turnover, and customer loyalty supported by membership fees. This structure enables disciplined operating processes and strong bargaining power with suppliers, translating into a distinct efficiency and profitability profile.

2.3 Why This Pair is an Informative Benchmark

Walmart and Costco represent two successful but structurally different strategic configurations within the same sector. This contrast allows us to link MIS design choices and system capabilities to measurable performance differences while controlling for broad industry context.

3 Conceptual Background and Analytical Lens

3.1 MIS as a Source of Capability and Advantage

MIS can shape competitive advantage through operational capabilities and information processing capacity (Bharadwaj, 2000, Bharadwaj, 2000). In retail, the strategic value of MIS often lies in enabling: (i) supply chain visibility and coordination (SCM), (ii) real-time demand sensing and store execution (POS analytics), (iii) inventory and working capital discipline (IMS/WMS), and (iv) personalized engagement and loyalty management (CRM).

3.2 Retail Value Chain Perspective

We apply a value-chain logic (Porter, 1985, Porter, 1985) to structure the analysis: how upstream sourcing and logistics (SCM) interacts with in-store execution and demand signals (POS), which in turn influences inventory policies and working capital outcomes, and ultimately customer loyalty and revenue stability (CRM).

3.3 Design-Science Perspective for the Artifact

Following design-science research (Hevner et al., 2004, Hevner et al., 2004), we view RICCas an artifact intended to improve managerial decision-making by integrating standardized metrics, benchmarking, forecasting, and evidence-based narrative insights.

4 Research Design and Methodology

4.1 Data Sources

We rely on:

- **Structured data:** financial statements (income statement, balance sheet, cash flow statement) and derived operational/financial metrics.
- **Unstructured text:** annual disclosure narratives (e.g., 10-K sections such as Business Overview, MD&A, and Risk Factors).
- **Supporting materials:** investor relations presentations, company websites, and reputable public data platforms for cross-checking.

4.2 Metric System and Comparability

Cross-firm comparison requires consistent definitions and alignment:

- **Field mapping:** standardizing heterogeneous line-item naming across firms (e.g., "Net sales" vs. "Total revenues").
- **Time alignment:** using annual, quarterly, and trailing-twelve-month (TTM) constructs where appropriate to reduce distortions from incomplete fiscal years.
- **Missing-data discipline:** logging missing items and applying conservative treatment (no numeric invention in KPI computation; only clearly labeled interpolation when used for visualization).

4.3 Analytical Components

1. **Benchmarking and diagnostics:** profitability (gross/net margin), returns (ROA/ROE), operating efficiency (DIO/DSO/DPO/CCC), and cash generation (CFO/Capex/FCF).
2. **Predictive analytics:** time-series forecasting (multi-model options) for revenue and key efficiency metrics, with uncertainty awareness and scenario framing.

3. **Generative analytics with evidence constraints:** retrieval-augmented generation (RAG-style) that injects relevant metrics and disclosure excerpts into prompts, enforcing a "claim–evidence–impact–recommendation" structure.

5 Prototype Implementation: RICCas an MIS Artifact

This section makes the engineering work visible in the report, bridging your system build with managerial credibility.

5.1 System Architecture (Four-Layer MIS Stack)

RICCfollows a four-layer MIS structure:

- **ETL layer:** extraction, normalization, and mapping into a consistent schema;
- **Data layer:** relational storage for standardized financial data, mappings, and text blocks;
- **Application layer:** Streamlit dashboard for interactive benchmarking and reporting;
- **AI layer:** LLM-based summary, risk analysis, and strategy comparison constrained by retrieved evidence.

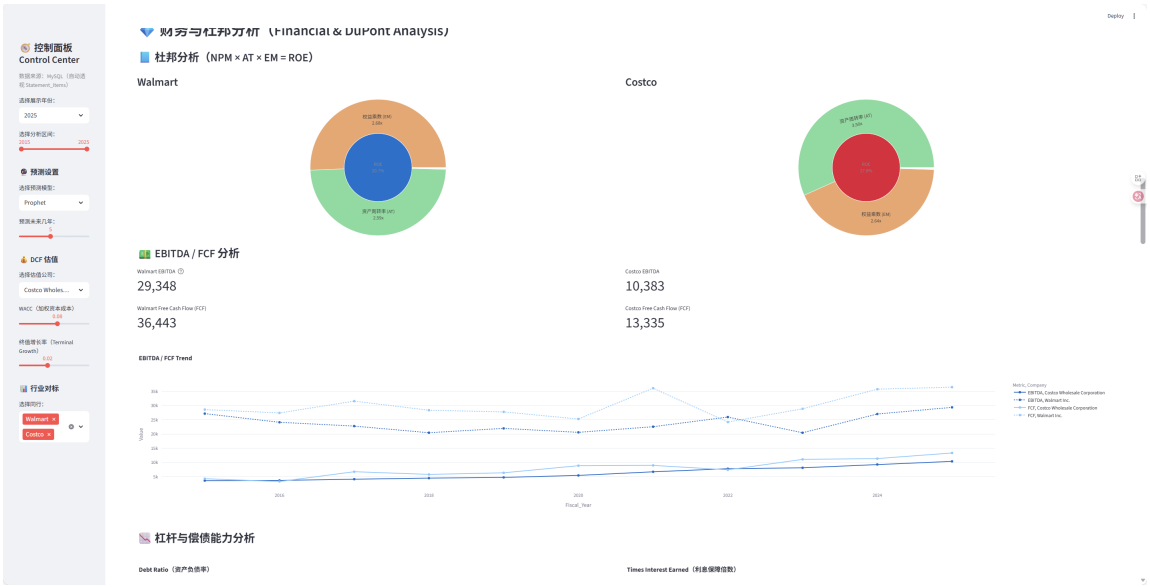


Figure 1: RICCprototype dashboard (Streamlit + database backend): benchmarking controls and key financial modules.

5.2 Standardization and Mapping Governance

A central implementation barrier is inconsistent financial statement labeling across firms and years. To ensure comparability, RICCimplements:

- **Field detection rules:** identifying revenue, net income, COGS, inventory, payables, etc., from heterogeneous labels;
- **Mapping tables and overrides:** allowing controlled manual mapping when automated rules are insufficient;
- **Audit-friendly logging:** recording missing items and mapping decisions to reduce "metric disputes" in management meetings.

5.3 Forecasting as Scenario Support (Not Deterministic Promise)

Retail time series exhibit seasonality and structural changes. RICCuses forecasting to support planning conversations:

- Multi-model options (e.g., linear/polynomial trends, SARIMA/Prophet variants) selected by data coverage and stability;
- Outputs framed as **trend/scenario** with uncertainty rather than point promises;
- A managerial "driver" explanation layer (what could plausibly move revenue/efficiency).

5.4 Evidence-Constrained GenAI (RAG-Style)

In management contexts, AI value depends on credibility. RICCenforces an explainability contract:

1. **Claim:** a manager-relevant conclusion;
2. **Evidence:** retrieved metrics (with dates/values) and/or cited disclosure excerpts;
3. **Impact pathway:** why the evidence affects cost, turnover, cash, or loyalty;
4. **Recommendation:** concrete actions with priority and rationale.

This design reduces hallucination and supports auditability in decision processes.

6 Findings: Walmart vs. Costco (Comparative Insights)

Because this project is positioned as a management-oriented MIS study, we report findings as mechanisms that link *system capability* → *operating process* → *observable performance*.

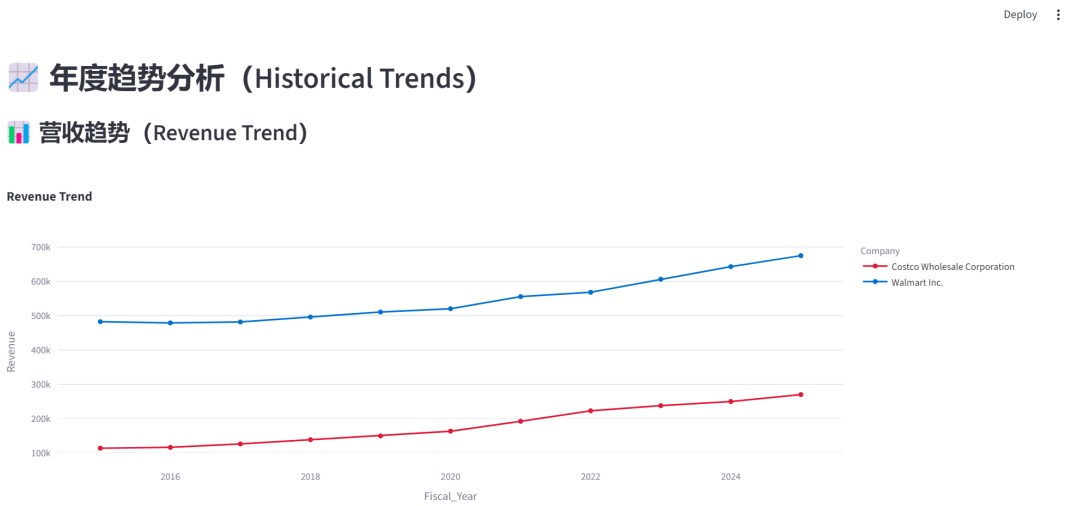


Figure 2: Revenue trend comparison between Walmart and Costco (FY2015–FY2025).

6.1 Supply Chain Management (SCM): Coordination and Responsiveness

Mechanism. Stronger SCM capability improves replenishment responsiveness and reduces both overstock and stockouts, improving inventory efficiency and cost control. **Comparative interpretation.** Walmart's omnichannel complexity increases coordination requirements; Costco's limited-SKU discipline and membership-driven repeat demand enable a simpler, high-turnover operating rhythm.

6.2 POS Data Utilization: Demand Sensing and Execution Feedback

Mechanism. POS data enables demand sensing and real-time operational feedback. Integrated POS-to-replenishment loops reduce latency, improve service levels, and stabilize inventory policies. **Comparative interpretation.** Both firms leverage POS data, but business-model constraints differ: Walmart balances breadth and variety, while Costco benefits from a tightly managed assortment that simplifies forecasting and replenishment.

6.3 Inventory and Working Capital: Cash Conversion Discipline

We use the cash conversion cycle (CCC) to connect operations with cash outcomes:

$$\text{CCC} = \text{DIO} + \text{DSO} - \text{DPO}.$$

Lower (or negative) CCC is typically associated with stronger working capital efficiency, indicating the ability to convert sales into cash quickly and/or extend payables effectively.

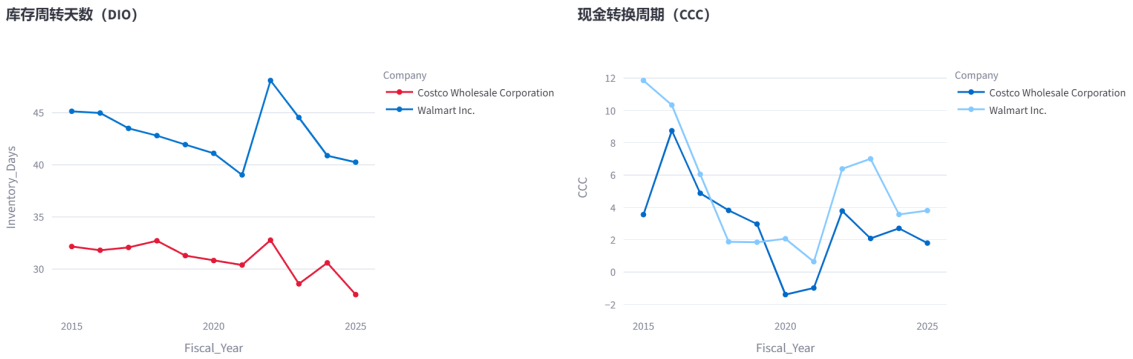


Figure 3: Working capital efficiency comparison: inventory days (DIO) and cash conversion cycle (CCC), FY2015–FY2025.

6.4 CRM and Loyalty: Revenue Stability and Predictability

Mechanism. Loyalty systems increase repeat purchase and demand predictability, improving planning accuracy and inventory discipline. **Comparative interpretation.** Costco's membership fee model creates a distinctive loyalty-driven profit structure; Walmart relies more on omnichannel engagement and broad customer reach, requiring stronger integration across touchpoints.

6.5 Financial Performance Linkages: Returns and Cash Generation

We interpret returns using DuPont logic:

$$\text{ROE} = \text{Net Profit Margin} \times \text{Asset Turnover} \times \text{Equity Multiplier}.$$

Cash generation is assessed via operating cash flow (CFO), capital expenditures (Capex), and free cash flow (FCF = CFO + Capex). Together, these measures connect operational efficiency to value creation and investment capacity.

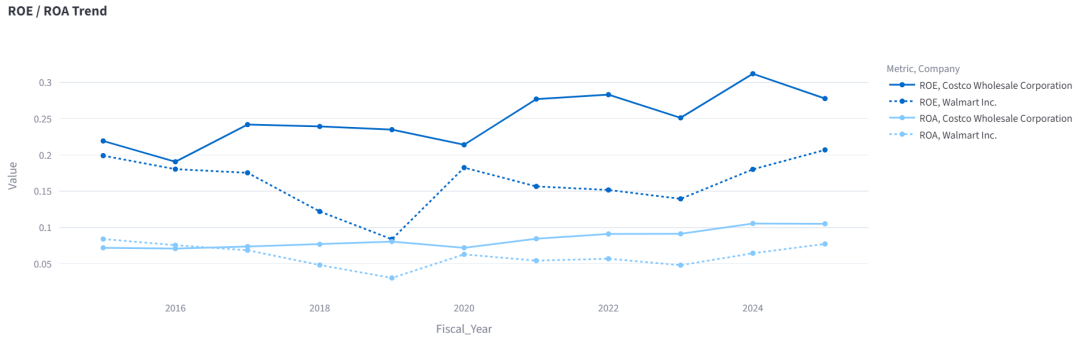


Figure 4: ROE and ROA trends for Walmart vs. Costco (FY2015–FY2025).

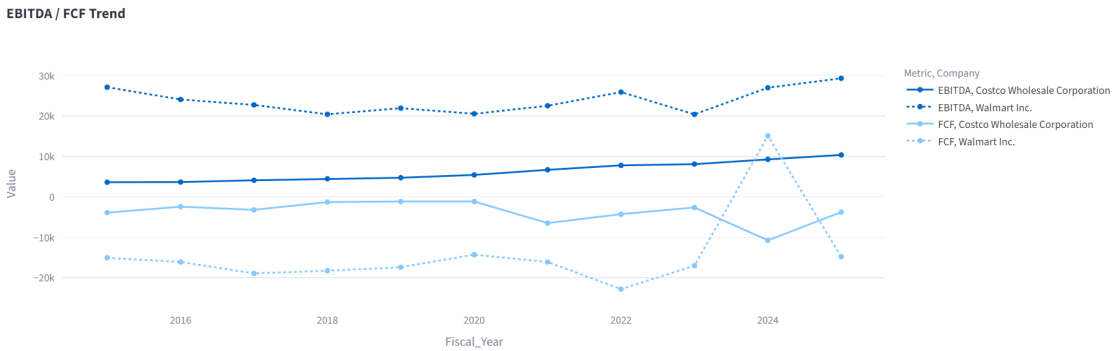


Figure 5: EBITDA and free cash flow (FCF) trends generated by RICC(FY2015–FY2025).

6.6 Key Findings at a Glance (Audit-Friendly)

Table 1 is designed for management review. Fill the numeric cells directly from RICCexports (recommended) or from the charts in Figures 2–5.

Table 1: Key Findings Summary (Data-Filled from RICC)

Dimension	Walmart (Evidence)	Costco (Evidence)
Revenue growth	Fig. 2; Revenue \$485.7B → \$681.0B; CAGR 3.4% (FY2015–FY2025)	Fig. 2; Revenue \$116.2B → \$275.2B; CAGR 9.0% (FY2015–FY2025)
Working capital	Fig. 3; median DIO 42.1 days; median CCC 3.7 days (FY2016–FY2025)	Fig. 3; median DIO 29.7 days; median CCC 2.6 days (FY2016–FY2025)
Returns	Fig. 4; median ROE 16.6%; median ROA 6.1% (FY2016–FY2025)	Fig. 4; median ROE 26.6%; median ROA 8.6% (FY2016–FY2025)
Cash generation	Fig. 5; median FCF \$15.9B; consistently positive by definition	Fig. 5; median FCF \$4.2B; consistently positive by definition
Loyalty mechanism	Omnichannel engagement and broad customer reach; higher system complexity	Membership fee model; demand predictability; simplified assortment and store execution

Note: Ratio-based medians use FY2016–FY2025 because average-balance mechanics make FY2015 ratios unavailable in the view. FCF is computed as Net OCF + Capital expenditures (capex is negative).

7 RICCSolution Design (Option 2 Artifact)

7.1 Product Positioning

RICCis positioned as a retail operating and strategy analytics copilot for managers and analysts. It unifies:

- **Standardized metrics** (consistent definitions and mappings),
- **Benchmarking** (cross-firm, cross-period comparisons),

- **Forecasting** (trend and scenario support),
- **Evidence-based generative insights** (LLM output constrained by retrieved metrics and disclosure excerpts).

7.2 Explainability Contract (Evidence-Constrained Output)

To reduce hallucination risk and increase auditability, RICCenforces a structured output template:

1. **Claim:** a manager-relevant conclusion.
2. **Evidence:** supporting metric changes (with dates/values) and/or cited disclosure excerpts.
3. **Impact pathway:** why the evidence affects cost, turnover, cash, or loyalty.
4. **Recommendation:** concrete actions with priority and rationale.

7.3 Target Users and Use Cases

- **Retail HQ functions:** strategy, finance, supply chain, and digital transformation teams for operating reviews and benchmarking.
- **Investment/consulting:** generating audit-friendly comparative briefs.
- **Management meetings:** aligning cross-functional teams around shared metrics and evidence-backed action plans.

7.4 Illustrative Tiering (Pricing/Packaging)

Table 2: RICCPackaging (Illustrative)

Tier	Scope	Key Features
Starter	Single firm	Core dashboards, notes, export of selected metrics
Pro	Multi-firm + forecasting	Cross-firm benchmarking, forecasting, reporting, configurable mappings
Enterprise	Governance	RBAC, audit logs, private deployment, metric governance, security controls

8 Go-to-Market Strategy (Option 2)

8.1 ICP and Buying Center

ICP: mid-to-large supermarket retail groups operating multiple regions/channels and facing recurring efficiency challenges. **Buying center:** CFO/COO or head of digital transformation; daily users include finance, strategy, supply chain, and operations analysts.

8.2 Value Proposition

- **Faster:** compress weekly manual analysis into minutes via standardized pipelines.
- **More reliable:** enforce metric definitions and mapping governance to reduce interpretive disputes.
- **More credible:** require evidence for generative outputs, improving trust and auditability.
- **More scalable:** extend across firms, periods, and teams with reusable templates and dashboards.

8.3 Acquisition Funnel and Pilot Design

- **Top-of-funnel:** publish benchmark briefs and industry snapshots generated from RICCto attract interest.
- **Mid-funnel:** interactive demo + co-designed pilot (2–4 weeks) focused on a narrow use case.
- **Bottom-of-funnel:** ROI narrative + governance plan to support procurement and scaling.

8.4 Pilot KPIs and ROI Logic

Efficiency KPIs: time-to-first-insight, analyst hours saved per report, reduction in manual data cleaning steps. **Effectiveness KPIs:** decision cycle time, adoption/active users, linkage between recommended actions and operational KPI movement.

$$\text{ROI} = (\text{time saved} \times \text{labor cost}) + (\text{decision improvement} \times \text{value estimate}) - (\text{deployment} + \text{subscription}).$$

9 Discussion

9.1 Linking MIS Capabilities to Business Model Logic

Our comparative findings support a consistent message: MIS capability is valuable when it aligns with business model constraints. Costco's membership-driven predictability and limited

SKU discipline facilitate simpler coordination and higher turnover, whereas Walmart's breadth and omnichannel structure demands stronger integration and more complex coordination. The managerial relevance is that digital transformation depth cannot be evaluated solely by technology spend; it must be evaluated by process fit, governance, and measurable outcomes.

9.2 Why Evidence-Constrained GenAI Matters in Management Settings

In management contexts, decision-making requires accountability and auditability. An evidence-constrained generative layer—paired with standardized metrics and traceable sources—improves trust, reduces black-box risk, and supports post-decision learning.

10 Managerial Implications and Action Roadmap

We recommend three practical directions for retail managers and MIS leaders:

1. **Treat data governance as a prerequisite:** standardize definitions, mappings, and lineage before scaling analytics or GenAI.
2. **Institutionalize explainable decision memos:** adopt claim–evidence–impact–recommendation templates for analytics and GenAI outputs.
3. **Pilot first, then scale:** start from a high-frequency, narrow scope (benchmarking + risk scanning), establish KPI baselines, and expand to forecasting and enterprise integration.

Table 3: Suggested Rollout Roadmap (Pilot to Scale)

Phase	Scope and Deliverables	KPIs (Examples)
0–30 days	Data ingestion + mapping governance; baseline dashboards; metric dictionary	Data coverage %; mapping disputes reduced; time-to-first-chart
30–90 days	Add forecasting + weekly review pack; implement evidence-constrained GenAI briefs	report cycle time; analyst hours saved; brief acceptance rate
90–180 days	Expand firms/regions; RBAC + audit logs; integrate internal operational telemetry if available	adoption (MAU); decision cycle time; KPI improvement linkage

11 Ethical, Legal, and Practical Considerations

- **Data consistency risk:** heterogeneous accounting labels and missing items can bias metrics. Mitigation: configurable mapping tables, missing-data logs, and manual overrides.

- **Hallucination and over-inference:** generative systems may extrapolate beyond evidence. Mitigation: evidence constraints, structured templates, disclaimers, and audit logs.
- **Forecasting uncertainty:** limited time points can yield unstable forecasts. Mitigation: present forecasts as scenarios/trends and report uncertainty.
- **Privacy and compliance:** enterprise deployments require RBAC, data classification, and access auditing.

12 Limitations and Future Work

Limitations. This study develops and evaluates an MIS prototype for retail benchmarking; consequently, several limitations apply. First, the empirical basis is dominated by public disclosures and structured financial statements, rather than internal operational telemetry (e.g., POS-level transactions, SKU-level inventory movements, supplier lead-time and service-level data). The lack of granular operational signals constrains inference about execution drivers and may under-represent within-period and store-/region-level heterogeneity. Second, data ingestion is affected by reporting-format heterogeneity (PDF tables, scanned figures, inconsistent line-item definitions). Without a fully automated extraction-and-normalization pipeline, measurement noise and label inconsistency can propagate into downstream analytics and impair comparability. Third, AI-assisted interpretation introduces model risk, including sensitivity to prompt design, dependence on retrieved text, and potential overfitting to externally available narratives rather than causal mechanisms. Finally, the prototype has not been validated in a production environment; reliability engineering, security controls, and organizational adoption factors are not empirically assessed.

Future work. Future research should prioritize (i) integrating operational datasets (POS, fulfillment, supplier lead times, inventory telemetry) to support mechanism-level analysis and finer-grained benchmarking; (ii) establishing an end-to-end ingestion pipeline that combines OCR and vision-based table structure recognition (document $\rightarrow$ table objects $\rightarrow$ normalized schema) with systematic data cleaning, validation, and reconciliation; (iii) adopting rigorous evaluation designs, including rolling-window backtesting with uncertainty quantification for forecasting and causal identification strategies for pilots (e.g., A/B testing where feasible, difference-in-differences, and synthetic control) to estimate impact rather than association; and (iv) formalizing governance and deployment practices (prompt/model versioning, audit trails, RBAC, monitoring, and security hardening) to enable reproducibility and safe scaling beyond a single prototype setting.

13 Conclusion

This MIS term project connects retail efficiency challenges to concrete system capabilities by comparing Walmart and Costco across SCM, POS, inventory management, and CRM. Building on the comparative mechanism analysis, we propose and prototype RICC, an AI-enabled decision-support system that integrates benchmarking, forecasting, and evidence-based narrative insights. The combined research and design output provides a practical roadmap for retailers to deepen digital transformation and strengthen operational competitiveness in an efficiency-driven market.

Appendix A: KPI Formulas

Working Capital Efficiency

$$\text{DIO} = \frac{\text{Average Inventory}}{\text{COGS}} \times 365, \quad \text{DSO} = \frac{\text{Average Accounts Receivable}}{\text{Revenue}} \times 365,$$

$$\text{DPO} = \frac{\text{Average Accounts Payable}}{\text{COGS}} \times 365, \quad \text{CCC} = \text{DIO} + \text{DSO} - \text{DPO}.$$

Profitability and Returns

$$\text{ROA} = \frac{\text{Net Income}}{\text{Average Total Assets}}, \quad \text{ROE} = \frac{\text{Net Income}}{\text{Average Equity}}.$$

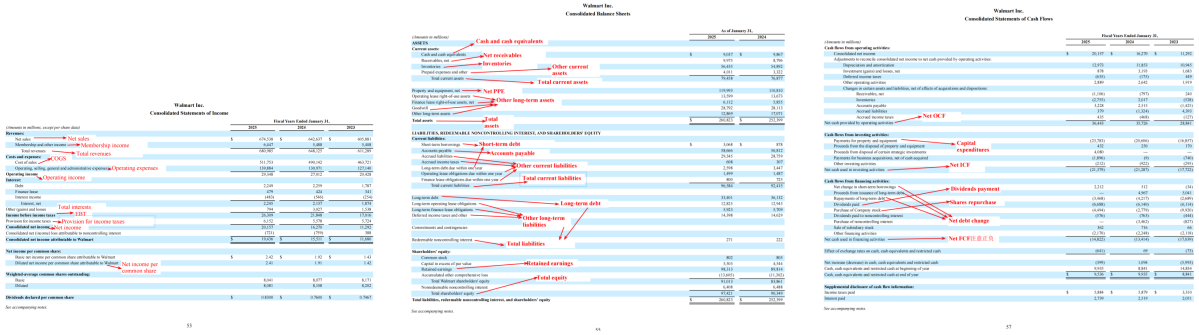
$$\text{DuPont ROE} = \text{Net Profit Margin} \times \text{Asset Turnover} \times \text{Equity Multiplier}.$$

Cash Metrics

$$\text{FCF} = \text{Operating Cash Flow} + \text{Capital Expenditures}.$$

Appendix B: Field Mapping Evidence (Examples)

To ensure cross-firm comparability, RICC standardizes heterogeneous statement line-items into a unified schema. Figure 6 provides representative mapping evidence from the original statements.



(a) Income statement mapping **(b)** Balance sheet mapping **(c)** Cash flow mapping

Figure 6: Representative examples of line-item mapping from original statements to the standardized schema used in RICC.

Appendix C: Prototype Workflow (Pseudo-Code)

The following pseudo-code summarizes the end-to-end workflow implemented in the RICC prototype (data loading, KPI computation, forecasting, valuation, and narrative AI modules).

```
# 1) Load normalized tables from MySQL
companies = read_table("Companies")
statements = read_table("Financial_Statements")
items = read_table("Statement_Items")

# 2) Pivot items to wide format, merge into analysis dataset
wide = pivot(items, index="statement_id", columns="item_name", values="
    item_value")
df = merge(statements, wide, on="statement_id")
df = merge(df, companies, on="company_id")

# 3) Quality patch (example): FCF = OCF + CapEx
df["FCF"] = df["OperatingCashFlow"] + df["CapEx"]

# 4) Compute KPIs (ROE/ROA/margins/DIO/CCC/EBITDA/FCF/growth)
df = compute_metrics(df)

# 5) UI controls: year, time window, peers, forecasting model, DCF params
params = sidebar_controls()

# 6) Visual analytics: trends, DuPont drivers, DIO/CCC, radar, etc.
render_charts(df, params)

# 7) Forecasting (Prophet/SARIMA/Regression) for selected series
forecast = forecast_series(df, model=params.forecast_model)

# 8) DCF valuation using FCF + WACC + terminal growth
value = dcf_valuation(df, wacc=params.wacc, tg=params.tg)

# 9) Narrative modules: display MD&A/Business/Risk, AI summary/risk/compare
ai_outputs = run_ai_modules(df, company=params.company)
```

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