

# Human–AI Iterative Knowledge Value Creation: An AKCV Framework for AI-Assisted Retail Marketing Decisions

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## Abstract

*This study investigates how domain knowledge can be systematically transformed into actionable value in the retail sector through a human–AI collaborative decision framework. Focusing on the hypermarket format, the research challenges the conventional managerial assumption that customers who have been dormant for more than 120 days are not worth further promotional investment. We propose the Analytical **Data-Knowledge-Model-Environment (AKCV)** framework, which integrates customer transaction records (Data, D), dynamic value segmentation and product association rules (Knowledge, K), automated rule-based inference mechanisms (Model, M), and contextual environmental constraints (Environment, E). The empirical case study from a Taiwanese hypermarket demonstrates that, compared to conventional mass promotion strategies yielding an 18–19% return rate, the proposed approach achieves a significantly improved customer return rate of **45%** through personalized recommendations and targeted interventions. Furthermore, by quantifying mobility friction through the novel environmental variable (E), the framework enables alternative strategies like transportation subsidies, minimizing reliance on price discounts while mitigating the risks of pure AI decisions undermining customer value.*

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Date of Submission: 29-09-2026

Date of Acceptance: 09-10-2026

## 1. Introduction

The retail industry is inherently tied to public livelihoods and significantly impacts national GDP growth. Modern traditional retail face three critical characteristics and pain points:

1. **Shortening product life cycles contrasted with expanding Customer Lifetime Value (CLV):** Product life cycles are increasingly compressed, whereas the long-term potential value generated by individual customers over time continues to grow.
2. **Proliferation of product assortments concealing critical underlying insights:** The hypermarket sector manages highly complex and vast product assortments (SKUs), burying high-value behavioral characteristics deep within the granular layers of inventory records.
3. **Imperative utilization of auto-identification and information technologies for data externalization:** Retailers must leverage advanced information technologies—such as data mining—to externalize and visualize massive big data, transforming raw information into actionable business intelligence.

Recently, the adoption of Artificial Intelligence (AI) by marketers has surged from 29% in 2018 to 84% in 2020 for demand forecasting, inventory optimization, and personalized offers. However, misguided or purely automated AI initiatives often destroy customer value—such as through customers experiencing a perceived loss of control or privacy concerns. To drive successful strategic upgrading, retail digital transformation must be anchored by three critical pillars:

- **Shifting Managerial Paradigms:** Moving from subjective "gut-feeling" executive heuristics to empirical intelligence and algorithmic governance. Traditional Decision Support Systems (DSS) must evolve into Intelligent Decision Support Systems (IDSS) powered by machine learning to provide prescriptive insights. Managerial experience is mathematically formalized as boundary conditions within feature engineering.
- **Advancing Customer Value Evaluation:** Upgrading retrospective, lagging RFM (Recency, Frequency, Monetary) metrics to dynamic predictive analytics. This includes incorporating machine learning models to estimate Time-to-Next-Purchase (TTNP) and Churn Probability, while integrating micro-behavioral data (clickstream trajectories and omnichannel preferences) to construct 360-degree algorithmic customer profiles.
- **Integrating Advanced Marketing Decision Variables:** Leveraging exponential computational capacity to transition from mass static metrics to real-time parameters, such as Location-Based Services (LBS), localized weather fluctuations, and instantaneous inventory levels. Continuous optimization frameworks (e.g., Multi-Armed Bandit algorithms) are deployed to dynamically optimize discount rates and recommendation timing in real time.

Through a longitudinal case study of a hypermarket, this research addresses the persistent research gap concerning the systematic fusion of human domain expertise and data-driven inference.

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## 2. Literature Review

This research evaluates existing literature across three core constructs to connect the theoretical and practical gaps:

- **AI-Driven Retail Transformation:** Mika Yrjölä et al. (2025) examine how retailers leverage AI to build dynamic Customer Value Propositions (CVPs), while Vidushi Sharma (2024) illustrates how recommendation systems and dynamic pricing enhance consumer experiences. However, prior studies focus heavily on e-commerce settings, creating a distinct lack of empirical investigation into how offline retail formats redefine customer value determinants (such as the conventional RFM framework) in the AI epoch.
- **Human-AI Iterative Decision-Making:** Han Li & Feng Tian (2025) identify four distinct collaborative paradigms (autonomous execution, guided resolution, collaborative exploration), and Angelo Gordini (2025) focuses on the cognitive aspects of Explainable AI (XAI) within DSS design. Yet, a profound gap remains regarding a structured framework to rationalize and formalize tacit managerial knowledge into computable rules.
- **Knowledge-Value Creation:** Grounded in Nonaka & Takeuchi's (1995) SECI model, knowledge management aims to transform personal tacit experience into shared explicit capabilities through Socialization, Externalization, Combination, and Internalization. In marketing applications, Lanlan Cao (2021) uncovers value creation logics driven by automation, hyper-personalization, complementarity, and innovation.

**Synthesis of Research Gaps:** Existing retail analytics models suffer from three structural gaps: (1) they are mostly descriptive and lack actionable decision structures; (2) recommendation engines underutilize spatial, geographic, and environmental context; and (3) they fail to integrate situational human judgment and adaptive feedback loops. The proposed AKVC framework is designed to bridge these precise lacunae.

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## 3. Methodology & Framework Operationalization

This study adopts a longitudinal three-phase case study design to trace the technological evolution of the investigated retailer over more than a decade:

- **Phase 1 (2015–2019): Data Mining & Rule-Based DSS:** Utilizing Data Lake-based Business Intelligence (BI) and market basket analysis, the research team overturned the manager's long-standing intuition-based 120-day dormancy assumption. By analyzing customer transaction trajectories within the previous 240 days, the team inferred household structures, marital status, and social roles (e.g., father vs. husband role). Mailing eight targeted complementary products via direct mail (DM) boosted the customer recall rate from 18% to 45%.
- **Phase 2 (2021–2025): Pure AI-Driven Decision Systems:** Implementing automated software modules (Predict\_Purchase, Recommendation\_Product, and Optimize-Promotion) improved purchase prediction accuracy by 61%–70%. However, it introduced severe "algorithmic blind spots" and "decision rigidity," resulting in over-promotion, resource waste, and a lack of contextual flexibility. Dormant customers remained inactive unless additional managerial interventions were deployed.
- **Phase 3 (2026): Human-AI Collaborative Knowledge Co-Creation (AKVC):** Establishing a continuous human-AI iterative learning loop where store managers transform experiential context into computable decision rules alongside AI inference mechanisms.

### The AKVC Core Inference Mechanism

The global effectiveness function of the framework is operationalized as:  $V = f(M, K, D, \text{Inference}, \text{Action})$ . To model geographic realities, the innovative **Environmental Accessibility Factor (E)** captures contextual mobility friction and is defined as:

$$E = W_{\text{store}} \times W_{\text{customer}}$$

$E \uparrow \Rightarrow$  Higher contextual friction

Based on empirical observations in Taipei, urban center stores face extreme land costs and heavy traffic, leading to highly restricted parking capacity (assigned a store accessibility weight of  $W_{\text{store}} = 0.4$ , whereas suburban stores provide abundant parking spaces  $W_{\text{store}} = 0.8$ ). Conversely, urban customers exhibit higher private parking ownership and convenience  $W_{\text{customer}} = 0.7$  compared to suburban residents  $W_{\text{customer}} = 0.3$ . A higher calculated E value indicates higher contextual mobility friction. When friction peaks, standard price discounts lose efficacy, necessitating alternative situational actions.

### Decision logics for AKVC framework

Decision-making is structured through conditional logic that integrates customer value and environmental context. For example:

High-value customers with high environmental scores receive transportation subsidies instead of price discounts. Medium-value customers receive combined promotional incentives.

Low-value customers are targeted with standard promotions.

$V=f(M, K, D, \text{Inference}, \text{Action})$

$AKVC=f(R, F, M, X, E)$

RFM: Customer Behavior

Future Set X : ( Customer Features , Basket Features, Temporal Features)

E: Environmental Features

AI Feature Schema

Customer Features: (R, F, M, Tenure, New/Returning)

Basket Features: (Item co-occurrence, Category preference, Association, Substitution)

Temporal Features: (Purchase interval, Recency trend, Seasonal pattern)

Environmental Features: (Location, Parking convenience)

AI and human knowledge co-evolve through iterative feedback loops, where each iteration refines both decision quality and knowledge representation.

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#### 4. Empirical Case Study and Results

The empirical case is drawn from a hypermarket operation in Taiwan handling 21 product categories, 81,000 SKUs, and 29,000 active members. Under the collaborative framework, the system first executes **dynamic customer value segmentation** based on cumulative 120-day spending thresholds:

- **High-Value VIP Customers:** Spending NT\$60,000 within the past 120 days, holding the retailer's co-branded credit card, averaging 4 visits annually, and exhibiting low price sensitivity but high sensitivity toward quality differentiation.
- **Mid-Value Potential Customers:** Spending between NT\$1,600 and NT\$59,999.
- **Low-Value General Customers:** Spending NT\$1,600.

#### Implementation of Context-Aware Promotion Strategies

The rule-based model was deployed via a spreadsheet prototype using data-cleansing and string-matching rule structures such as XLOOKUP and IFERROR(VLOOKUP(CLEAN(TRIM())))) to simulate automated AI matches. The empirical outcomes reveal powerful business improvements:

1. **Behavioral Reversal of Suburban VIPs:** Facing high environmental barriers E, suburban VIP customers responded exceptionally well to the **Taxi Transportation Subsidy** program, which **increased repurchase intention by 8%**. In stark contrast, traditional discount coupons only yielded a minor 2% increase in intention, proving that high-value segments prioritize time efficiency over minor price markdowns.
2. **Price Incentives for Mid-to-Low Value Segments:** For suburban potential and general customers, discount coupons remained the most powerful activation tool, driving a **6% increase** in repurchase intentions across both groups.
3. **Comprehensive Turnaround in Operational Metrics:** By formalizing human insights into algorithmic constraints, the human-AI iteration paradigm significantly outperformed standalone human management across all key dimensions:
  - **Customer Traffic:** Increased by **54%** under human-AI iteration, representing an absolute improvement of 36% over the 18% increase from traditional human management.
  - **Average Spend per Customer:** Rose by **26%**, a net improvement of 17% over human management alone (9%).
  - **Revenue and Campaign ROI:** Revenue growth reached 18% (7% net improvement), while **global ROI jumped to 17%** (a 10% net improvement over the 7% from human management).

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#### 5. Discussion & Conclusions

The empirical results vividly illustrate two vital paradigms shaping modern retail analytics: the "**Contrast Phenomenon**" and the strategic rule that "**Contrast Phenomenon**"

And:

「**Promotion ≠ Discount**」

Traditional retail practices frequently treat promotions as synonymous with margin erosion, which degrades brand equity over time. The AKVC framework proves that by mathematically embedding human tacit insights—regarding accessibility, location, and regional friction—into the feature engineering of an IDSS, firms achieve optimal resource allocation. This approach bypasses the immense computational costs and opaque "black-box" issues associated with complex machine learning models, delivering a highly transparent, explainable, and context-sensitive inference mechanism.

Furthermore, the case study demonstrates a paradigm shift in retail value generation: shifting from a traditional buyer-seller dyad to a **Human-AI-Customer collaborative value ecosystem**. Experiential initiatives, such as "AI-assisted cooking workshops" and "family-oriented AI learning camps," turn passive shoppers into active co-producers of value, community diffusers, and experiential contributors.

**Future Research Directions:** Future studies can extend the AKVC framework across diverse retail formats, such as fresh-food e-commerce and micro-convenience stores. Models should integrate highly dynamic signals—including real-time weather fluctuations and micro-behavioral sentiment valence—while exploring continuous experimental optimization via causal inference and dynamic uplift modeling.