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THE MAIN PRINCIPLES OF DECISION SUPPORT AI-BASED SYSTEM FOR RETAIL ENTERPRISES

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Abstract. Against the backdrop of global retail digitalization – characterized by omnichannel integration, volatile consumer demands, and intensifying competition – AI-based Decision Support Systems (AI-DSS) have become a critical tool for retailers to optimize operations. However, a 2024 survey by the China Retail Digitalization Alliance shows that only 38 % of Chinese retail enterprises achieve expected outcomes from AI-DSS implementation, with failures often stemming from unclear retail-specific principles, data silos, and misalignment between technology and business scenarios. To address this gap, this master's dissertation systematically explores the concept, theoretical foundations, application status, core design principles, and implementation strategies of retail-oriented AI-DSS, aiming to provide theoretical guidance and practical references for retail enterprises to realize data-driven intelligent decision-making.

Keywords: AI-based Decision Support System (AI-DSS), Retail Enterprises, Core Design Principles (Data-Driven, Scenario Adaptation, Human-Machine Collaboration), Implementation Barriers, Chinese Retail Cases, Inventory Management, Dynamic Pricing, Customer Segmentation, Digital Transformation.

1. THEORETICAL FOUNDATIONS OF AI-BASED DECISION SUPPORT SYSTEMS FOR RETAIL ENTERPRISES.

1.1. Concept, Core Components and Classification of Retail-Oriented AI-DSS.

Defines retail-oriented AI-DSS as a scenario-tailored system integrating AI tech, multi-source data, and retail models – distinct from traditional DSS (no autonomous learning) and generic AI (ignores retail traits like fresh produce shelf-life) [6]. It details 5 core components (Data Acquisition/Integration, AI Algorithm Engine, Scenario-Specific Decision Module, User Interaction, System Integration) and classifies AI-DSS by decision scenario (inventory optimization, dynamic pricing, customer engagement), technical architecture (cloud/on-premises/hybrid), and enterprise scale (SME/large retailer) [2].

1.2. Theoretical Connection Between AI-DSS and Retail Decision-Making (Rational/Behavioral/Supply Chain Coordination Theories).

Links AI-DSS to 3 theories: Rational Decision-Making Theory (solves info asymmetry via multi-source data integration and real-time processing, e. g., Walmart's inventory system); Behavioral Decision-Making Theory (mitigates biases like loss aversion with interpretable AI and scenario simulation, e. g., Carrefour's pricing system); Supply Chain Coordination Theory (reduces bullwhip effect via shared data hubs and collaborative optimization, e. g., JD.com's supply chain system) [3].

2. ANALYSIS OF AI-DSS APPLICATION STATUS IN CHINESE RETAIL ENTERPRISES.

2.1. Application of AI-DSS in Core Retail Decision Scenarios (Inventory Management, Dynamic Pricing, Customer Segmentation).

Analyzes AI-DSS in 3 core scenarios: Inventory Management (uses LSTM/XGBoost for demand forecasting, unifies omnichannel stock – JD cuts stockouts by 25 %, Freshippo reduces cross-channel stockouts by 35 %); Dynamic Pricing (monitors competitors in real time, calculates SKU-specific elasticity – Suning boosts price match rate to 90 %, Amazon lifts non-food gross margin by 8 %); Customer Segmentation (integrates behavioral/psychographic data for dynamic grouping – Tmall raises marketing conversion by 12 %, Sephora improves in-store redemption by 22 %) [4].

2.2. Case Studies of AI-DSS Implementation in Representative Chinese Retail Enterprises.

Presents 3 cases: Hema Fresh (AI reduces fresh waste from 20 % to 7.2 % via freshness decay models); Walmart China (cuts peak stockouts to 3.8 % with demand forecasting and supplier collaboration); HLA (accelerates inventory turnover from 1.2 to 2.1x annually via regional assortment planning). Normalized data shows all achieve efficiency gains (Hema's efficiency metrics reach 250 % of pre-implementation levels) [1].

3. KEY PRINCIPLES AND OPTIMIZATION STRATEGIES FOR RETAIL AI-DSS IMPLEMENTATION.

3.1. Core Design Principles of Retail AI-DSS (Data-Driven, Scenario Adaptation, Human-Machine Collaboration).

Proposes 3 core principles: Data-Driven (builds "data collection – integration – value conversion" loops, e. g., Walmart's data hub integrating 20+ systems); Scenario Adaptation (customizes modules for retail pain points – Hema's fresh inventory module, HLA's regional preference mapping); Human – Machine Collaboration (defines roles: AI handles daily replenishment, humans manage strategy – Walmart's LLM interface boosts adoption to 95 %) [5].

3.2. Implementation Barriers and Principle-Based Optimization Paths of Retail AI-DSS.

Identifies 4 barriers (data silos, tech-scenario mismatch, human-machine friction, resource constraints) and solutions: low-cost data integration (Alibaba Cloud's $200/month Retail Data Link); scenario module iteration; human-machine responsibility matrices; phased budget allocation. A regional supermarket pilot (Anhui) verifies feasibility: $8k initial budget cuts fresh waste to 9 % and achieves 6-month ROI [3].

CONCLUSIONS.

Theoretically, this dissertation constructs a "Scenario-Principle-Function" matching framework for retail AI-DSS, bridging the gap between AI technology and retail management theory. Practically, it provides size-specific guidance: SMEs use cloud-based tools and prioritize core scenarios; large retailers adopt customized modules. The findings confirm that AI-DSS is not a "luxury" but a "necessity" for retail digitalization – by adhering to data-driven, scenario-adapted, and human-machine collaborative principles, retailers can turn data into decisions that reduce waste, improve efficiency, and enhance competitiveness.

This study enriches retail AI-DSS theory and provides size-specific guidance (SMEs use cloud tools; large retailers adopt custom modules) for retail digital transformation.

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