Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

Transforming Grocery Retail and E-Commerce Through Large Language Models

Sanjay Basu
TATA Consultancy Services (TCS), USA

ARTICLE INFO
Received: 06 Jan 2026
Revised: 08 Jan 2026

ABSTRACT
In light of the rise of multimodal AI and big language models, the landscape for grocery, physical retailers, and e-commerce is rapidly changing. By leveraging complex models, digital commerce, omnichannel, and supply chain operations can benefit from natural language understanding, the ability to process information from multiple modalities, and the ability to make autonomous decisions. Recent work shows the effectiveness of conversational LLM experiences for product discovery, website navigation, and customer experiences through live meal preparation, optimized shopping baskets, personalized promotions, and smart product substitutions in online buying experiences. In addition, LLM applications have proven effective in automating e-commerce workflows, such as summarizing customer feedback, improving search and recommendation systems, and automating product classification. These are key functions for the online merchandising at scale. LLM-based solutions help improve the resiliency of the supply chain via dynamic inventory management, demand forecasting, and fulfillment routing. Omnichannel, computer vision, last-mile logistics, and robotics deliver additional capabilities to improve product identification and picking accuracy for online grocery fulfillment. This essay discusses how grocery retail and digital businesses are evolving due to the growing prominence of LLM technologies, with the support of recent academic and business literature. It resolves planned, operational, and ethical issues for future AI-enabled environments.

Keywords: Large Language Models, Grocery Retail, E-Commerce, Supply Chain Optimization, Artificial Intelligence

1. Background and Current Research

1.1 Foundational Context

With the concept of artificial intelligence, particularly massive language models, having reached operational maturity, grocery retail and e-commerce organizations experience transformational shifts. Initial digital retail concepts concentrated on the rudimentary search engines and non-portable web interfaces. Modern merchants build shopping experiences that can dynamically adapt to preferences and situations using mental, verbal, and non-verbal intelligence over digital media. Grocery ecommerce poses special challenges: the customers require fast product searches, reliable substitutes, an automatic refill concept, and complete allergen, freshness, and nutritional value information. The traditional recommendation systems and search algorithms are not very good at fulfilling these requirements because they are based primarily on organized data and past trends. To address these shortcomings, multimodal LLMs are capable of concurrently analyzing text, images, nutrition labels, user preferences, and inventory levels in their homes and offer contextualized decision support in most purchasing scenarios [1][2].

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

1.2 Historical Development of Retail AI

The retail AI appeared due to the use of machine-learning algorithms oriented to demand forecasting, price algorithms, and customer segmentation. ARIMA models and simple regression frameworks were refined into deep learning models, such as LSTMs and temporal convolutional networks, which can now predict inventory planning with a significant level of accuracy. Simultaneous changes in the ecommerce sphere brought out search-ranking algorithms and collaborative filtering systems that customized product collections and boosted conversion levels. Research has always shown that algorithmic recommendations increase the size of baskets, customer loyalty, and frequency of purchase. This means that such systems rely heavily on structured behavioral data, and therefore, they cannot understand product descriptions, customer inquiries, social media posts, or photos of food, which are essential in grocery shopping experiences. Computer vision technology was used to automate checkout procedures and support real-time shelf tracking and improved SKU recognition using advanced convolutional architectures with large datasets. Amazon Go is a good example of using computer vision, sensor networks, and probabilistic models to automate the physical retail experience. In e-commerce fulfillment, visioned robotics reinforced accuracy in picking and recovery in micro-fulfillment facilities. This early AI provided automation and data insights but was not interpretable, adaptable, and multimodal, which is now being filled by LLMs [1][2].

Technology Generation	Time Period	Primary Capabilities	Key Applications	Limitations
Traditional ML Models	2000-2015	ARIMA forecasting, Basic regression, Rule-based systems	Demand forecasting, Price optimization, Customer segmentation	Limited to structured data, no unstructured content interpretation, Manual feature engineering required
Deep Learning Era	2015-2020	LSTMs, CNNs, Collaborative filtering, Computer vision	Advanced forecasting, Image recognition, Personalized recommendations, Automated checkout	Unimodal processing, Limited contextual understanding, Poor interpretability
LLM & Multimodal AI	2020-Present	Transformer architectures, Multimodal processing, Agentic systems, Natural language understanding	Conversational commerce, Dynamic catalog management, Autonomous operations, Intentbased search	Requires extensive data, Computational complexity, and Bias management needed

Table 1: Evolution of AI Technologies in Grocery Retail and E-Commerce [1][2]

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

1.3 Recent Progress in Language Models and Multimodal Systems

Transformer-based LLMs constitute substantial advancement in machine information processing and generation. Models including GPT-4, PaLM 2, and Gemini achieve remarkable results across text generation, strategic planning, dialogue management, and contextual comprehension. Contemporary models incorporate multimodality, processing images, audio, video, and structured data within unified frameworks. This capability matters for retail because understanding products requires synthesizing nutritional labels, ingredient lists, package images, customer reviews, shelf photographs, planograms, and environmental sensor data. Investigation demonstrates that multimodal LLMs outperform single-mode models in product categorization, attribute extraction, and recommendation generation, yielding better customer experiences and operational intelligence. Agentic LLM systems mark another development—these models plan, decide, and execute tasks across tools, APIs, and enterprise workflows. They update product metadata autonomously, generate substitutions for unavailable items, classify extensive e-commerce catalogs, and perform SKU-level analytics without human intervention. This autonomy drives productivity gains in digital retail environments managing vast, constantly changing assortments. LLMs improved natural-language search, allowing ecommerce platforms to interpret complex intent-based queries like "kid-friendly gluten-free snacks" or "budget meals for a family"—capabilities that keyword-based search cannot achieve [3][4].

1.4 Knowledge Deficits and Article Organization

Despite these advances, academic literature contains notable deficits. Most investigations focus on isolated applications rather than integrated architectures spanning customer experience, merchandising, fulfillment, and supply-chain operations. Few peer-reviewed investigations evaluate frontier LLMs in actual grocery or omnichannel settings, even though these models apply effectively to inventory tracking, product recognition, and fulfillment routing. Minimal investigation examines how shoppers interact with conversational agents for grocery navigation, basket curation, or nutritional guidance—all highly relevant for e-commerce. Literature on privacy, fairness, explainability, and AI regulation in retail remains fragmented, particularly for use cases involving personal health data like allergens and dietary restrictions. The emerging domain of autonomous AI agents coordinating warehouses, robots, human workers, and delivery fleets lacks thorough examination in e-commerce and grocery logistics. This article addresses these deficits through a comprehensive analysis spanning customer experience, merchandising optimization, supply chain transformation, and strategic governance frameworks.

2. Reshaping Customer Interactions Through LLMs

2.1 Individualized E-Commerce Journeys

E-commerce platforms leverage LLMs to establish adaptive, individually tailored shopping experiences. Dynamic basket optimization assists families in constructing balanced weekly menus by suggesting fresh vegetables for planned dinners or recommending alternative proteins for dietary restrictions. This approach increases basket size while addressing nutritional needs proactively, elevating customer satisfaction. Intent-aware search allows platforms to parse complex queries—"lowsodium meals for two" or "vegan snacks for a toddler"—and map them to relevant products, substitutions, and recipe suggestions. This capability extends considerably beyond keyword matching. Personalized content generation tailors product descriptions, promotional messages, and recipe ideas to individual shoppers, strengthening engagement across platforms. Instacart and Amazon Fresh demonstrate these capabilities in practice, where LLM-driven engines suggest complementary items and recipe bundles directly within user interfaces [1][3].

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

2.2 Interactive Shopping Across Distribution Channels

Dialogue-driven shopping becomes intuitive and efficient through LLM deployment. Chatbots and voice assistants handle questions like "Which brands of almond milk are sugar-free and in stock nearby?" by returning ranked options based on availability, price, and nutrition. Within physical stores, mobile kiosks and smart carts guide shoppers to specific aisles or suggest substitutes for unavailable items. Unlike rule-based chatbots, LLMs maintain context across multiple exchanges, enabling natural conversations. A shopper might refine an earlier query—"Show me options with lower pricing for the items you suggested"—and receive updated recommendations instantly. Proactive recommendation capabilities allow systems to nudge customers based on real-time signals: fresh seasonal produce, special promotions matching purchase history, or complementary items for planned meals. This demonstrates how conversational commerce anticipates needs rather than merely responding to requests, reducing friction throughout decision-making [3][4].

2.3 Physical Store Support and Wayfinding

Physical grocery stores benefit from LLM-enhanced experiences that bridge digital intelligence with real-world navigation. Mobile apps and smart carts provide guided directions to locate items quickly—a shopper seeking gluten-free pasta receives aisle directions alongside recipe suggestions and complementary product recommendations. Product substitution alerts monitor shelf inventory through camera feeds or store sensors, recommending alternatives or directing customers to online purchase options when items are unavailable. Staff assistance takes on new dimensions as LLMs function as in-store copilots, helping associates answer queries about product origins, dietary concerns, or promotions while providing step-by-step restocking and planogram compliance guidance. These applications enhance efficiency, accuracy, and overall shopping quality, establishing value for customers and store staff alike [4].

3. Optimizing Product Management and Pricing Strategies

3.1 Automated Classification and Content Enhancement

E-commerce platforms manage tens of thousands of SKUs, with new products arriving daily. Automated SKU classification allows LLMs to analyze product descriptions, images, nutritional information, and supplier metadata, then accurately categorize items within hierarchical taxonomies. An online grocery platform might automatically classify a new plant-based cheese under "Dairy Alternatives → Cheese Substitutes," ensuring discoverability in search and recommendations. Attribute extraction generates structured metadata—flavor profiles, sizes, dietary information, allergen warnings—improving search precision and building customer trust. E-commerce platforms already deploy AI-driven content enrichment to reduce manual effort and improve data consistency, demonstrating tangible operational benefits across large-scale catalog management [5][6].

3.2 Tailored Product Selection Strategies

Dynamic assortment optimization tailors product selections to customer segments, geographic regions, or individual households. Personalized recommendations draw on historical purchases, browsing patterns, and dietary constraints to suggest curated product subsets with high appeal. A household with a peanut-allergic child receives safe alternatives across snack categories automatically. Micro-localized digital shelves adjust online assortments based on regional trends, seasonality, and inventory availability. Northern platforms might emphasize winter root vegetables more than southern counterparts while ensuring alternative delivery options for high-demand items. Integration with in-store merchandising allows systems to recommend promotions or displays aligned with online engagement patterns, establishing omnichannel consistency [5][6].

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

3.3 Adaptive Price Management and Search Enhancement

Data-driven pricing strategies benefit from LLM capabilities in scenario simulation, competitor analysis, historical sales integration, and real-time inventory tracking. Dynamic promotions deliver time-sensitive discounts personalized to shopping history, while in-store displays adjust based on predicted demand or stock levels. Price elasticity reasoning predicts how price changes affect basket size and total revenue, helping retailers optimize margins and customer satisfaction simultaneously. Scenario simulation generates "what-if" analyses for e-commerce campaigns, evaluating promotional bundles or flash sales before implementation. Intent-based product search interprets queries like "quick vegan dinner for four" and maps them to relevant products, meal kits, or recipe bundles. Enhanced recommendation pipelines rank products by contextual fit—customer preferences, prior purchases, pantry inventory data—rather than just popularity. Cross-channel integration ensures online browsing recommendations inform in-store displays and mobile guidance, establishing seamless omnichannel experiences [5][6].

Merchandising Function	Traditional Approach	LLM-Enhanced Approach	Operational Benefits	Performance Metrics
Product Classification	Manual categorization, Rule-based taxonomies, Periodic updates	Automated SKU analysis, Multimodal data processing, Realtime classification	Reduced manual effort, Faster product launch, Improved accuracy	Classification accuracy, Time to market, Error reduction
Catalog Enrichment	Manual attribute entry, Limited metadata, Inconsistent descriptions	Automated attribute extraction, Comprehensive metadata generation, Standardized content	Enhanced search precision, Better customer trust, Consistent quality	Metadata completeness, Search effectiveness, Customer satisfaction
Assortment Planning	Segment-based selection, Quarterly reviews, Regional clustering	Individual-level personalization, Real-time adjustment, Microlocalization	Higher relevance, Better inventory turns, Regional optimization	Conversion rate, Inventory turnover, Customer retention
Dynamic Pricing	Historical pricing models, Competitor monitoring, Manual adjustments	Scenario simulation, Elasticity reasoning, Realtime optimization	Improved margins, Better competitiveness, Faster response	Margin improvement, Price competitiveness, Revenue growth

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

Product Discovery	Keyword matching, Category browsing, Filter-based search	Intent-based search, Contextual ranking, Crosschannel integration	Enhanced findability, Reduced search time, Better recommendations	Search success rate, Time to purchase, Recommendation CTR

Table 2: Merchandising and Pricing Optimization Through LLMs [5][6]

4. Revolutionizing Supply Networks and Logistics

4.1 Predictive Demand Analysis and Planning

Grocery and e-commerce operations require accurate forecasting given perishable inventory and extensive SKU diversity. E-commerce demand prediction analyzes historical orders, browsing data, search queries, and customer preferences to generate detailed forecasts at SKU and household levels. Platforms anticipate demand spikes for frozen vegetables during holiday weekends or winter months, enabling proactive replenishment. In-store demand sensing integrates POS data, shelf imaging, local weather, and regional events to predict store-level demand, helping grocery chains optimize restocking schedules, reduce stockouts, and minimize perishable waste. Scenario simulation and risk analysis model supply disruption impacts, promotional effects, and demand spikes, providing actionable mitigation recommendations across supply chain ecosystems [7][8].

4.2 Real-Time Stock Management and Warehouse Coordination

Real-time inventory management spans e-commerce warehouses, fulfillment centers, and physical stores. Warehouse optimization coordinates multi-robot picking, packing, and replenishment by integrating inventory levels, order priorities, and delivery schedules. E-commerce fulfillment centers use AI-enabled systems to route robots and human pickers efficiently. Omnichannel inventory alignment connects warehouse, store, and online inventory data to prevent overselling and improve fulfillment accuracy. Shoppers placing online orders can be directed to pick up items from the nearest store with available stock. Perishable goods management includes shelf rotation recommendations, dynamic markdowns, and bundle promotions to reduce spoilage, directly affecting profitability and sustainability while minimizing food waste [7][8].

4.3 Store Workflow Optimization and Delivery Improvements

Physical store operations increasingly rely on LLM applications that complement digital and ecommerce workflows. Shelf replenishment and planogram compliance analysis uses real-time shelf images to detect low stock, misplaced items, or planogram deviations. Store staff receive actionable restocking or rearrangement instructions, reducing labor-intensive audits. Task prioritization guides daily operational decisions: which aisles need immediate restocking, which promotions require signage updates, which customer inquiries demand attention. In-store customer support connects operational insights with customer-facing systems, enabling associates to provide instant guidance on product locations, substitutions, and nutritional information. Dynamic route planning optimizes delivery routes by integrating order locations, traffic patterns, and time constraints, reducing delivery times and operational costs. Order prioritization suggests substitutions for unavailable items or recommends combining multiple orders to maximize efficiency. E-commerce platforms leverage AIdriven systems for automated substitution suggestions and batch routing. Predictive customer communication generates automated, context-aware messages about expected delivery times, substitutions, or delays, improving transparency and satisfaction throughout fulfillment [7][8].

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

4.4 Cross-Channel Operational Synchronization

Synchronizing online, warehouse, and in-store operations represents the full potential of LLM deployment. Unified inventory visibility provides real-time views across channels, improving fulfillment accuracy and reducing stock discrepancies. Operational feedback loops ensure insights from online sales, store transactions, and delivery performance continuously inform forecasting, warehouse routing, and store-level decisions. Adaptive resource allocation dynamically assigns staff, robotics, and delivery resources based on real-time demand, ensuring operational efficiency and responsiveness across retail ecosystems. Multimodal reasoning and predictive intelligence establish unified operational ecosystems that align supply-chain efficiency with superior customer experiences [7][8].

Operational Domain	LLM Capability	Data Inputs	Automated Decisions	Efficiency Gains
Demand Forecasting	Autonomous demand sensing	POS data, Browsing patterns, Weather data, Regional events, Search queries	SKU-level predictions, Storelevel forecasts, Seasonal adjustments, Promotion impact analysis	Forecast accuracy improvement, Reduced stockouts, Lower waste
Inventory Management	Dynamic optimization	Multi-location inventory, Order priorities, Delivery schedules, Perishability data	Reorder quantities, Warehouse allocation, Stock transfers, Markdown timing	Inventory reduction, Better fill rates, and Spoilage minimization
Warehouse Operations	Multi-robot coordination	Inventory levels, Order queues, Robot positions, Picker locations, Time constraints	Picking routes, Task assignments, Packing sequences, and Resource allocation	Throughput increase, Labor productivity, Order accuracy
Store Operations	Shelf compliance monitoring	Real-time shelf images, Planograms, POS transactions, and Staff schedules	Restocking priorities, Task assignments, Compliance alerts, Display adjustments	Audit reduction, Better compliance, Staff efficiency
Last-Mile Delivery	Route and order optimization	Delivery addresses, Traffic patterns, Order contents, Time windows, Vehicle capacity	Route planning, Order batching, Substitution recommendations, Customer notifications	Delivery cost reduction, Time savings, Customer satisfaction

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ Research Article

Omnichannel Sync	Unified visibility	Online sales, Store transactions, Warehouse data, Delivery performance	Channel allocation, Fulfillment routing, Inventory rebalancing, Resource assignment	Fulfillment accuracy, Stock optimization, Channel efficiency

Table 3: Supply Chain and Operations Transformation with LLMs [7][8]

5. Strategic Positioning, Governance Frameworks, and Deployment

5.1 Competitive Positioning Through Differentiation

Retailers differentiate increasingly through how effectively they match customer needs with product offerings rather than through assortment breadth alone. LLMs enable shifts from segment-level targeting to individual-level understanding, synthesizing dietary habits, cultural preferences, health goals, and real-time intent. Grocers establish hyper-personalized meal planning based on budgets, time constraints, and health considerations. E-commerce platforms offer context-aware product bundles like diabetes-friendly pantry resets or vegetarian weekly essentials. Retailers with advanced recommendation engines see measurable gains in basket size, conversion rates, and repeat purchase probability. This personalization becomes a strategic asset difficult for competitors to replicate without comparable data depth and modeling capabilities. Operational excellence emerges as a competitive advantage through dynamic workforce guidance, predictive supply chain capabilities, and automated customer support, establishing productivity gaps between retailers who operationalize LLMs and those maintaining manual or static workflows [9][10].

5.2 Information Stewardship and Privacy Safeguards

LLM adoption introduces significant opportunities alongside critical ethical, governance, and compliance considerations. As LLMs interact with sensitive customer data, operational information, and supplier intelligence, retailers must balance innovation with accountability, transparency, and fairness. LLMs require access to extensive data streams: customer purchase histories, browsing behavior, dietary preferences, health-related information like allergen sensitivities, and nutrition tracking. Proper data governance frameworks protect privacy and ensure regulatory compliance. Platforms must obtain explicit consent for data collection and use, allowing users to opt into personalized nutrition recommendations while anonymizing purchase data for broader analytics. Secure data handling processes sensitive information using encryption and secure protocols to prevent unauthorized access, breaches, or misuse. Grocery chains handling loyalty program data must ensure alignment with GDPR, CCPA, and other privacy regulations. Data used for LLM training or fine-tuning requires anonymization to prevent individual customer or household identification [9][10].

5.3 Equity, Justice, and Explainability in AI Systems

LLMs may inadvertently propagate biases present in training data, affecting recommendations, promotions, and operational decisions. Models trained on historical purchase data might overrepresent certain brands or demographics, unintentionally disadvantaging minority customer segments. Dynamic pricing algorithms require monitoring to prevent discriminatory pricing or unfair targeting—systems offering higher discounts only to certain zip codes may inadvertently reinforce inequities. Continuous evaluation, bias audits, and model retraining with diverse datasets ensure equitable outcomes. LLMs function as complex systems where explainability becomes crucial for operational trust and customer confidence. Shoppers interacting with recommendations or substitutions should understand why certain products are suggested. Store managers, warehouse operators, and e-commerce staff must interpret LLM-generated instructions for stocking, routing, and promotions. Transparent reasoning supports faster human validation and error correction [9][10].

Journal of Information Systems Engineering and Management
2025, 10(63s) e-ISSN: 2468-4376 https://www.jisem-journal.com/ **Research Article**

5.4 Compliance Requirements and Implementation Pathways

Retailers deploying LLMs navigate a rapidly evolving regulatory landscape. Models must ensure product recommendations, nutritional guidance, and promotional messages comply with local laws and advertising standards. LLM-powered systems providing dietary guidance or allergen warnings must align with labeling regulations, avoiding misrepresentation. LLM-generated decisions and recommendations require logging for internal audits and external regulatory reporting. Strategic roadmaps begin with establishing governance, data quality, and ethical frameworks while building unified customer and product data layers and deploying LLMs for low-risk internal use cases. Subsequent phases involve launching personalized meal planning and budget-aware recommendations, integrating LLMs into loyalty programs and retail media, connecting LLMs to supply chain and store operations systems, and ultimately co-developing models with cloud partners while monetizing insights through LLM-enhanced targeting. Retailers reaching advanced implementation stages build competitive differentiators powered by proprietary data, seamless customer experiences, and comprehensive AI integration, establishing structural advantages including the ability to train proprietary models tailored to grocery semantics and enhanced monetization through higher-quality retail media targeting [9][10].

Implementation Phase	Timeline	Key Activities	Required Capabilities	Success Metrics	Risk Mitigation
Phase 1: Foundation	0-6 months	Governance framework establishment, Data infrastructure unification, Ethical guidelines development, Low-risk pilot deployments	Data quality management, Privacy compliance, Bias detection tools, Internal analytics capacity	Data completeness, Governance coverage, Pilot success rate, Compliance adherence	Staged rollout, Extensive testing, Clear accountability, and Regular audits
Phase 2: Customer Value	6-12 months	Personalized meal planning launch, Loyalty program integration, Naturallanguage navigation, Retail media enhancement	Customer data platform, Recommendation engines, Conversational interfaces, Content generation	Customer engagement, Basket size growth, Retention improvement, Media effectiveness	User feedback loops, A/B testing, Performance monitoring, Privacy safeguards

Phase 3: Operational Scale	12-18 months	Supply chain integration, Store operations connection, Merchandising automation, Decision intelligence deployment	API integration, Real-time data pipelines, Multimodal processing, Workflow automation	Operational efficiency, Cost reduction, Accuracy improvement, Resource optimization	Change management, Staff training, System redundancy, Fallback procedures
Phase 4: Ecosystem Leadership	18-24 months	Proprietary model development, Cloud partner collaboration, Insight monetization, Brand differentiation	Model training infrastructure, Partner ecosystems, Advanced analytics, Competitive intelligence	Market differentiation, Revenue growth, Operational advantage, Customer lifetime value	Continuous innovation, Competitive monitoring, Ethical boundaries, Regulatory compliance

Table 4: Strategic Implementation Roadmap for LLM Adoption [9][10]

Conclusion

This article examined how large language models fundamentally transform grocery retail and ecommerce ecosystems. Through integrated analysis spanning customer experience, merchandising and catalog management, supply chain operations, and strategic governance, it was demonstrated that LLMs represent paradigmatic shifts in retail value creation and competitive dynamics rather than merely incremental technological advancement. Academic research and industry applications demonstrate that LLMs enable unprecedented personalization, operational intelligence, and omnichannel integration across retail value chains. From hyper-personalized e-commerce experiences and conversational commerce to dynamic catalog enrichment, intelligent demand sensing, and autonomous store operations, LLMs reshape modern retail dimensions. Their multimodal reasoning capabilities—integrating text, images, structured data, and real-time contextual signals—provide retailers with cognitive infrastructure that transcends traditional rule-based systems and isolated machine learning models. However, the transformative potential of LLMs requires rigorous attention to data governance, ethical deployment, and responsible AI practices. Privacy protection, algorithmic fairness, transparency, and regulatory compliance constitute central imperatives for sustainable LLM adoption rather than peripheral concerns. Retailers embedding ethical principles and governance frameworks into AI strategies will mitigate risks while building trust and differentiation in increasingly competitive markets. From strategic perspectives, LLMs establish structural competitive advantages for early adopters, enabling differentiation through superior customer experiences, operational excellence, and data-driven decision-making. The integration of LLMs into grocery retail and e-commerce represents defining moments in intelligent commerce evolution, requiring technological sophistication alongside strategic foresight, organizational agility, and unwavering commitment to ethical principles.

References

[1] Rashed Haq, "AI in E–E-E-Commerce and Retail," IEEE Xplore, 2020. Available: https://ieeexplore.ieee.org/document/10950773

[2] Iskren Tairov et al., "Enhancing E-commerce with Artificial Intelligence," in 2024 5th International Conference on Communications, Information, Electronic and Energy Systems (CIEES), 31 December 2024. Available: https://ieeexplore.ieee.org/document/10811370

[3] Farooq Shareef, "Enhancing Conversational AI with LLMs for Customer Support Automation," in 2024 2nd International Conference on Self-Sustainable Artificial Intelligence Systems (ICSSAS), 28 November 2024. Available: https://ieeexplore.ieee.org/abstract/document/10760403

[4] Mrinal Verghese, et al., "User-in-the-Loop Evaluation of Multimodal LLMs for Vision-Powered Assistants," in 2025 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), 08 April 2025. Available: https://ieeexplore.ieee.org/document/10943568

[5] G. Yamuna, et al., "Machine Learning-Based Price Optimization for Dynamic E-commerce," in 2024 Ninth International Conference on Science, Technology, Engineering, and Mathematics (ICONSTEM), 28 June 2024. Available: https://ieeexplore.ieee.org/document/10568763

[6] Amantra AI (Case Study Team), "Intelligent Product Classification with LLMs: Transforming Retail Catalog Management," Amantra Case Study, 2025. Available: https://amantra.ai/casestudy/intelligent-product-classification-with-llms-transforming-retail-catalog-management/

[7] Adrian E. Coronado Mondragon, "Large language models (LLMS) for supply chains: identifying opportunities for development using a systematic literature review," in International Conference on Applied System Innovation (ICASI 2025), 03 September 2025. Available: https://ieeexplore.ieee.org/abstract/document/11148326

[8] Lin Xiong, et al., "Research and Application of Multimodal LLMs DeepSeek in Power Enterprise Electronicization of Vouchers," in 2025 IEEE International Symposium on the Application of Artificial Intelligence in Electrical Engineering (AAIEE), 2025. Available: https://ieeexplore.ieee.org/document/11100298

[9] Marco Vieira, et al., "Leveraging LLMs for Trustworthy Software Engineering: Insights and Challenges," IEEE Xplore, 26 June 2025. Available: https://ieeexplore.ieee.org/document/11052849

[10] BSI Group (British Standards Institution), "Trust in AI Governance Retail Overview," BSI Insights Whitepaper, 2023. Available: https://www.bsigroup.com/en-US/insights-andmedia/insights/whitepapers/trust-in-ai-governance-retail-overview/