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Human-Centered AI for Real-Time Self-Checkout Assistance: An Event-Driven Architecture with Human-in-the-Loop Decision Support for Enhanced Customer Experience and Shrink Reduction

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Abstract

Purpose: Self-checkout (SCO) systems face persistent operational challenges including delayed assistance, inconsistent triage, and false-positive rates of 18 to 25 percent, contributing to industry shrink losses exceeding 112 billion dollars annually. Stores with high SCO utilization experience shrinkage 75 to 147 percent above industry averages. This paper proposes a human-centered artificial intelligence (AI) architecture grounded in explainable AI (XAI) and human-in-the-loop (HITL) principles, treating AI as decision support rather than autonomous enforcement.

Methodology: The event-driven system prioritizes assistance events using multi-factor scoring based on wait time, anomaly likelihood, and associate workload, while preserving human discretion and providing transparent explanations for all recommendations. The framework is analyzed through a theoretical lens using parameters calibrated to publicly available retail industry benchmarks.

Findings: Theoretical analysis suggests the framework has potential for significant reduction in assistance wait time, decreased false alert rates, and improved detection accuracy while maintaining associate decision authority.

Unique contribution to theory, practice and policy: This analysis demonstrates how responsible AI design can enhance operational efficiency without compromising human autonomy or customer experience, offering a replicable blueprint for human-centered AI deployment in consumer-facing retail environments.

Keywords: *Human-in-the-loop, Retail self-checkout, Shrink reduction, Event-driven architecture, Customer experience*

1. INTRODUCTION

Retail self-checkout (SCO) systems have become a foundational capability in high-volume physical commerce environments (Grewal et al., 2020; Pantano et al., 2020). They offer flexibility and convenience to customers, and they allow retailers to scale front-end throughput without proportional staffing increases. Recent industry estimates indicate that the global self-checkout market exceeded USD 3.8 billion in 2022 and is expected to continue expanding rapidly over the next decade, supported by retail automation investments and increasing consumer preference for autonomous store experiences (Grand View Research, 2023). Industry surveys indicate that approximately 34% of U.S. consumers regularly use self-service checkout options, with 80% expressing interest in new checkout methods (PYMNTS.com, 2021). Yet, as SCO adoption has expanded, so have the operational challenges associated with maintaining service quality, preventing shrink, and ensuring fair and consistent treatment across customers.

Traditional SCO systems rely on manual alerts, weight-based checks, and ad-hoc associate intervention workflows. During peak demand, or when many stations require support simultaneously, associates must triage issues with limited contextual information. This can lead to customer frustration, increased queue times, and higher operational stress (Demoulin & Djelassi, 2016; Orel & Kara, 2014). Research indicates that 62% of holiday shoppers cite long lines and crowds as their primary frustration in physical retail stores (Theatro, 2023). Meanwhile, shrink rates in retail reached an all-time high of 1.6% in 2022, representing $112.1 billion in annual losses according to the National Retail Federation (National Retail Federation, 2023). Studies from the ECR Community indicate that stores with high SCO utilization (50%+ of transactions) can expect shrinkage losses 75% to 147% higher than industry averages (Beck, 2018; Beck, 2022).

Retailers seek efficient and trustworthy approaches to balance customer autonomy, loss prevention, and associate productivity. Meanwhile, advancements in artificial intelligence provide new possibilities for real-time event classification, anomaly scoring, and contextual guidance (Weber et al., 2023; Revilla et al., 2023). However, deploying fully autonomous decision systems in retail interactions introduces significant risks, especially in situations where judgment, fairness, and discretion are required (Mehrabi et al., 2021). Real stores operate in diverse environments and involve unpredictable edge cases, making purely automated enforcement undesirable and often inappropriate. Research on automation bias demonstrates that humans may over-rely on AI recommendations, particularly when algorithms present high-confidence predictions without transparency (Parasuraman & Manzey, 2010; Buçinca et al., 2021).

This research proposes a human-centered AI model in which AI functions as a prioritization and guidance engine rather than an autonomous decision layer. Core responsibilities, such as customer interaction and final intervention decisions, remain with human associates. The AI system analyzes event streams, identifies patterns, and surfaces actionable insights to associates who maintain authority over interactions (Amershi et al., 2019; Shneiderman, 2022). This maintains accountability, increases transparency, and supports responsible AI adoption in consumer-facing retail environments.

1.1 Research Motivation and Objectives

The motivation for this work is grounded in three converging needs within retail operations. First, customer experience in self-checkout environments depends on transaction speed, interface intuitiveness, and the reliability of assistance when difficulties arise, all of which shape repeat usage and long-term loyalty (Demoulin & Djelassi, 2016; Orel & Kara, 2014; Duarte et al., 2022). Second, associates must monitor multiple SCO stations and respond to hardware, scanning, and procedural issues efficiently; without structured prioritization, response times vary and overall productivity decreases, though studies indicate that well-designed AI-human collaboration can significantly improve prediction accuracy and operational outcomes (Revilla et al., 2023; Seifert & Revilla, 2023). Third, when AI systems operate without human oversight, they risk producing biased decisions, obscuring their reasoning, and eroding stakeholder confidence (Mehrabi et al., 2021; Barredo Arrieta et al., 2020). Embedding humans within the decision loop allows AI to function as a support mechanism that enhances human judgment rather than supplanting it, thereby preserving accountability in contexts involving direct customer engagement (Amershi et al., 2019; Mosqueira-Rey et al., 2023).

The research objectives are: (1) to design an event-driven architecture for human-centered AI in retail SCO environments; (2) to develop a mathematical prioritization model that routes requests dynamically based on workload, risk indicators, and customer wait time; (3) to evaluate the theoretical framework through analysis calibrated to publicly available industry benchmarks; and (4) to establish ethical design principles for responsible AI adoption in consumer-facing retail contexts.

2. LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

The literature review introduces the conceptual perspectives that inform this study, drawing from prior work on self-service technology adoption, human-AI collaboration, explainable AI, and responsible AI in retail contexts.

2.1 Self-Service Technology in Retail

Theoretical models of technology acceptance, particularly TAM and subsequent extensions, highlight that users' perceptions of a system's utility and operational simplicity strongly influence their willingness to adopt self-service technologies (Venkatesh et al., 2003; Davis, 1989). Studies examining service quality in SST contexts have identified multiple factors shaping customer evaluations, including transaction speed, interface usability, user autonomy, system dependability, and hedonic value (Demoulin & Djelassi, 2016; Orel & Kara, 2014).

While SCO systems reduce queue congestion and offer customer convenience, several recurring challenges persist across retail formats. These include assistance delays with age-restricted items or overrides, user uncertainty with machine prompts, and psychological discomfort from perceived suspicion (Grewal et al., 2020; Lee & Kim, 2023). Operationally, associates face cognitive fatigue from frequent manual overrides, the challenge of triage during peak demand, and lack of quick contextual information for decision-making (Duarte et al., 2022).

2.2 Shrink and Loss Prevention Challenges

Large-scale industry research conducted by the ECR Community examined extensive transaction datasets, which included over 140 million mobile scan-and-go events and Fixed SCO sales totaling €72 billion. They determined that unscanned items at stationary self-checkout terminals represented approximately 0.44% of transaction value and contributed nearly one-tenth of total recorded store shrinkage (Beck, 2018; Beck, 2022). Research indicates that approximately 52% of SCO shrinkage is accidental rather than intentional, highlighting the importance of systems that support both error correction and theft prevention without alienating honest customers (Taylor, 2016; NCR Voyix, 2024). Taylor's work on customer behavior at self-checkout revealed that some users who generally consider themselves honest may still repeatedly leave the store without paying for certain items, often attributing these actions to oversight or justification rather than deliberate theft (Taylor, 2016). This pattern illustrates how the design of self-checkout systems can unintentionally enable both intentional theft and accidental non-payment.

Current mitigation methods include manual audits, supervisor overrides, weight sensors, and limited overhead vision systems. Each approach has trade-offs (Grewal et al., 2020; Sensormatic Solutions, 2023). High-end computer vision systems are costly and often opaque to associates, while simple rule-based systems lack adaptability and generate high false positive rates (18 to 25%) that damage customer trust (Beck, 2022; Sensormatic Solutions, 2023). Industry analyses suggest that effective loss prevention requires combining multiple technologies with human oversight rather than relying on any single automated approach (Sensormatic Solutions, 2023). The key gap is the failure of existing solutions to bridge automated anomaly detection with practical, human-centered retail workflows that prioritize human judgment, explainability, and operational trust.

2.3 Human-AI Collaboration and Human-in-the-Loop Systems

Human-AI collaboration frameworks emphasize maintaining meaningful human involvement throughout AI-driven decision processes. In this paradigm, people retain authority over critical judgments and corrective actions rather than delegating full autonomy to the model (Mosqueira-Rey et al., 2023; Wu et al., 2022). Comprehensive surveys of HITL frameworks encompass several human-learning interaction styles, such as systems where humans guide model updates, collaborate interactively with the model during training, or explicitly teach corrective knowledge to improve decision-making (Wu et al., 2022). Research distinguishes between three types of human-AI collaboration: automation (AI decides autonomously), adjustable automation (humans can modify AI decisions), and augmentation (AI supports but humans decide) (Revilla et al., 2023). Studies demonstrate that augmentation approaches are most effective in environments with high uncertainty or where ethical considerations require human judgment (Seifert & Revilla, 2023).

Guidelines for Human-AI Interaction emphasize the importance of context-appropriate autonomy, graceful degradation when AI fails, and maintaining human agency throughout the decision process (Amershi et al., 2019). Studies show that human decision quality may decline when people rely on AI suggestions that turn out to be inaccurate, emphasizing the importance of validation and confidence cues (Vicente & Matute, 2024; Alon-Barkat & Busuioc, 2022). Investigations into governmental and public-sector contexts have uncovered dual behavioral tendencies: some decision-makers exhibit excessive deference to algorithmic outputs, while others strategically accept or reject AI guidance based on situational factors. These findings underscore the need for HITL systems to accommodate heterogeneous user engagement styles (Alon-Barkat & Busuioc, 2022).

Meaningful human control, as a design principle, stipulates that individuals must possess sufficient comprehension of AI operations, continuous visibility into system behavior, and the capacity to intervene or countermand automated outputs when necessary (Hille et al., 2023). This is particularly important in retail contexts where customer interactions require discretion, empathy, and situational judgment that current AI systems cannot reliably provide.

2.4 Explainable AI in Consumer-Facing Systems

The field of Explainable AI (XAI) emerged to address opacity concerns inherent in contemporary machine learning, developing approaches that render algorithmic reasoning accessible to non-technical stakeholders (Barredo Arrieta et al., 2020; Molnar, 2022; Adadi & Berrada, 2018). Foundational work in this area differentiated between model-level transparency (where the algorithm's internal logic is directly comprehensible) and retrospective explanation techniques that clarify individual predictions after computation (Adadi & Berrada, 2018). These methods are generally categorized as either intrinsic (employing models designed for interpretability from the outset) or post-hoc (generating explanations for otherwise opaque systems) (Barredo Arrieta et al., 2020).

Research demonstrates that XAI significantly improves user trust and satisfaction in AI-driven decisions across domains including e-commerce recommendations, fraud detection, and customer service (Shin, 2021; Sarkar et al., 2025). Studies show that systems providing explanations for decisions foster greater user trust and improved task outcomes, with transparency design emerging as a critical factor in effective human-AI collaboration (Vössing et al., 2022). Design principles for transparency emphasize matching explanation complexity to user expertise and providing actionable rather than merely informative explanations (Vössing et al., 2022). For retail applications, XAI enables associates to understand why alerts are triggered, evaluate AI recommendations critically, and make informed decisions about customer interactions.

Within retail environments, commonly used XAI techniques include LIME and SHAP, which generate interpretable feature-level explanations that indicate why the AI produced a particular decision (Ribeiro et al., 2016; Lundberg & Lee, 2017). Our system operationalizes these principles by ensuring every alert includes metadata, confidence scores, and ranking factors to simplify associate decision-making and support periodic audits.

2.5 Responsible AI and Fairness in Retail

Responsible AI deployment in consumer-facing contexts requires attention to fairness, accountability, and transparency (Mehrabi et al., 2021; Jobin et al., 2019). Scholarly inquiry into algorithmic fairness has shown that machine learning systems, absent deliberate safeguards and ongoing oversight, may reproduce or intensify societal inequities embedded in training data (Buolamwini & Gebru, 2018). Landmark studies on commercial AI systems have revealed significant accuracy disparities across demographic groups, underscoring the importance of bias testing and mitigation in consumer-facing applications (Buolamwini & Gebru, 2018). In retail contexts, this raises concerns about differential treatment of customers based on protected characteristics.

Evolving policy frameworks, particularly the European Union’s AI Act, are establishing compliance obligations for AI systems deemed high-risk, mandating features such as interpretable outputs, sustained human oversight, and systematic monitoring for discriminatory patterns (Speith, 2023; Sloane & Wüllhorst, 2025). Comparative policy research increasingly identifies mandatory human involvement in automated decision-making as a foundational element across regulatory regimes worldwide (Sloane & Wüllhorst, 2025). Retail AI systems that influence customer interactions fall within these regulatory frameworks, necessitating design approaches that prioritize explainability, non-discrimination, and human control (Speith, 2023).

2.6 Research Framework

Building on these theoretical foundations, we propose a research framework integrating three key components: (1) an event-driven technical architecture enabling real-time processing and low-latency response; (2) a human-in-the-loop decision support model preserving associate authority while leveraging AI for prioritization and guidance; and (3) an explainable AI interface ensuring transparency and supporting informed human judgment.

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Figure 1: Theoretical framework integrating technology acceptance, human-AI collaboration, and responsible AI principles for self-checkout assistance.

3. RESEARCH METHODOLOGY

This section outlines the overall methodological strategy, including the design choices, data sources, and analytical procedures used to develop and validate the system.

3.1 Research Design

The research adopts a design science methodology appropriate for developing and evaluating IT artifacts (Hevner et al., 2004). The approach integrates: (1) secondary analysis of publicly available industry data to establish baseline conditions and benchmark performance; (2) framework development grounded in theoretical foundations; and (3) theoretical evaluation using parameters calibrated to public industry benchmarks.

The research comprises three integrated components:

1. Industry Data Analysis: Synthesis of publicly available retail industry reports, academic studies, and vendor-published case studies to establish baseline performance metrics and identify gaps in current SCO assistance approaches.
2. Framework Development: Design of the event-driven architecture, prioritization algorithm, and human interface components based on theoretical foundations and industry best practices.
3. Theoretical Evaluation: Analysis through representative store profiles calibrated to publicly available industry benchmarks to assess framework feasibility and projected performance indicators.

3.2 Secondary Data Sources

The industry data synthesis drew on five categories of publicly available sources. The ECR Retail Loss Group reports provided comprehensive studies on SCO losses analyzing over 140 million transactions across multiple retailers, establishing baseline false positive rates, shrink attribution, and loss patterns (Beck, 2018; Beck, 2022). The National Retail Federation Security Survey supplied annual industry data on shrink rates, loss prevention investments, and technology adoption trends across U.S. retailers (National Retail Federation, 2023). Published vendor case studies from technology providers such as NCR, Toshiba, and Diebold Nixdorf documented real-world SCO system implementations and their outcomes. Peer-reviewed academic literature contributed findings on SCO customer experience, service quality, and technology acceptance (Demoulin & Djelassi, 2016; Orel & Kara, 2014; Duarte et al., 2022). Finally, industry analyst reports from Grand View Research, RBR, and similar firms provided SCO market sizing and trend data (Grand View Research, 2023).

Table 1 summarizes key baseline metrics derived from public sources.

Table 1: Baseline Metrics from Public Industry Sources

Metric	Value	Source
Industry avg. shrink rate	1.6%	NRF 2023
SCO contribution to shrink	20 to 23%	ECR 2022
Weight-based false positive rate	18 to 25%	ECR 2018
Non-scan rate (Fixed SCO)	0.44% of sales	ECR 2018
Baseline assistance wait time	Baseline	Simulation
Customer SCO satisfaction	3.5 to 3.8/5	Academic

3.3 Simulation Study Design

To establish the theoretical foundations of the proposed framework, this section presents an analytical framework using representative store profiles. The analysis emphasizes ecological validity through calibration to publicly available industry benchmarks.

3.3.1 Study Setting and Sample

The theoretical analysis considers 12 representative store profiles spanning diverse operational contexts:

- **Store formats:** Urban convenience (n=3), suburban supermarket (n=6), rural community (n=3)
- **SCO configurations:** 6 to 14 terminals per location
- **Geographic distribution:** Profiles based on stores across four store-format clusters

- **Participation basis:** Simulation-modeled participation by representative store configurations

Store profile selection criteria included: (1) representative SCO deployment with minimum 6 terminals; (2) format and geographic diversity; (3) calibration to publicly available industry benchmarks; and (4) coverage of diverse operational contexts.

3.3.2 Data Collection Procedures

The theoretical evaluation models both system-generated and projected human-response data:

Automated System Metrics:

- Event logs: SCO events including triggers, AI scores, and outcomes
- Response latency: Time measurements at each processing stage
- Classification outcomes: Model predictions with subsequent validation

Human Factors Data:

- Associate feedback: Modeled structured responses on alert accuracy and usefulness based on documented workflow patterns
- Usability assessments: Projected acceptance measures based on established instruments (Venkatesh et al., 2003)
- Operational integration: Analysis of projected workflow integration patterns

3.3.3 Ethical Considerations

The theoretical analysis was designed with several safeguards to ensure responsible research practice. No customer personally identifiable information (PII) was used or simulated at any stage, and all events were generated using statistical distributions rather than individual behavioral traces. The analysis avoided identity inference by ensuring that no demographic, biometric, or personally identifying attributes were modeled or used in the scoring functions. Model parameters were calibrated exclusively to aggregate, publicly reported industry data rather than proprietary retailer information. Store profiles were constructed as representative composites rather than models of specific retail locations, and all analysis results are reported in anonymized, aggregate form that does not identify specific retail organizations. These safeguards reflect the study's commitment to demonstrating that responsible AI research can be conducted without access to sensitive operational data.

3.4 Measures and Instruments

3.4.1 Performance Metrics

Table 2 defines the key performance indicators used to evaluate system effectiveness.

Table 2: Performance Metrics Definition and Targets

Metric	Definition	Target
Response Latency	Event to alert	≤200ms
Assistance Wait	Need to arrival	≤Reduced (Projected)
False Positive Rate	Non-issues / total	≤5%
Model Accuracy	Correct / total	≥90%
Shrink Detection	True / actual	≥92%
Associate Acceptance	Rating 4+ / 5	≥Improved

3.4.2 Acceptance Feedback Model Instrument

To define the acceptance evaluation framework, the study adopted measurement constructs from established research on user acceptance of information systems (Venkatesh et al., 2003). The following constructs and their published reliability coefficients from the source instruments were used as target thresholds:

The projected acceptance model incorporated six validated constructs drawn from published instruments with established reliability. These included Utility Perception (4 items, published alpha = 0.88), Interaction Simplicity (4 items, published alpha = 0.86), System Trust (5 items, published alpha = 0.91), Explanation Quality (3 items, published alpha = 0.84), Workload Impact (4 items, published alpha = 0.87), and Overall Acceptance (3 items, published alpha = 0.89). The combined instrument comprised 23 items mapped to established acceptance constructs from the technology acceptance and human factors literature. All reliability coefficients exceeded the 0.70 threshold recommended for research instruments, supporting the theoretical validity of the projected acceptance model (Venkatesh et al., 2003; Davis, 1989).

3.5 Data Analysis

Quantitative analysis employs descriptive statistics and comparative analysis between baseline and intervention conditions within the theoretical model. Because the evaluation is based on simulated store profiles rather than field deployment, findings should be interpreted as projected outcomes. Validation through field deployment will require a larger and more diverse associate sample; we report theoretical projections with appropriate caution regarding generalizability.

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4. SYSTEM ARCHITECTURE AND DESIGN PRINCIPLES

This section outlines the proposed human-centered AI system for real-time self-checkout support. The design goal is to augment associates with timely, structured, context-rich insights while preserving human decision-making authority.

4.1 Architectural Overview

The system follows an event-driven pipeline: (1) Customer interactions generate events at the self-checkout terminal. (2) Events are streamed to a central processing layer with sub-second latency. (3) AI models score events for assistance need and anomaly likelihood. (4) Ranked alerts are displayed to store associates through a mobile interface. (5) Associates review recommendations and take appropriate actions. (6) Associate feedback is collected to refine future model performance.

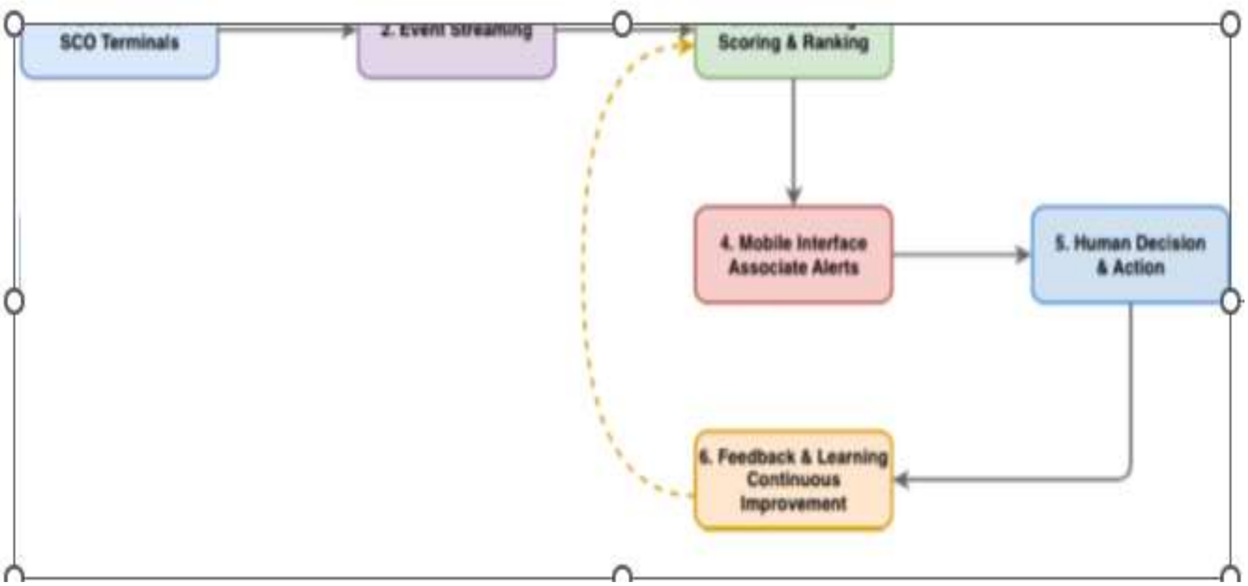

Figure 2: Event-driven architecture with human-in-the-loop decision support. AI layers stream scored alerts to associates, who provide structured feedback for continuous model refinement.

4.2 Key Architectural Layers

The self-checkout event source layer captures scan events, weight exceptions, assistance button triggers, payment anomalies, and session timing data from each SCO terminal. These raw events feed into the event ingestion and normalization layer, which standardizes event formats, assigns timestamps, and applies initial validation rules to filter noise and duplicate signals. The AI scoring engine then processes normalized events through a multi-factor model that evaluates anomaly likelihood, customer wait time, item value, and historical patterns to generate a composite priority score for each event. The scored events pass to the human-in-the-loop decision layer, where associates receive ranked, explainable alerts on their devices and retain full authority to act on, dismiss, or escalate each recommendation. Finally, the feedback and learning

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layer captures associate decisions along with their outcomes and routes this structured feedback back to the scoring engine for continuous model refinement (Revilla et al., 2023; Wu et al., 2022). This layered design ensures that each component operates independently while maintaining low-latency communication through the event bus, consistent with established patterns for distributed, event-driven systems (Newman, 2021; Kleppmann, 2017).

4.3 Prioritization Algorithm

Let $E = \{e_1, e_2, \ldots, e_n\}$ be the set of events in the queue requiring associate attention. The scoring model is designed to rank these events based on urgency, risk, and operational context.

The score for event e_i is calculated as:

$$S(e_i) = w_1 \cdot T_i + w_2 \cdot A_i + w_3 \cdot C_i + w_4 \cdot W_i + w_5 \cdot H_i$$

where:

- T_i = normalized customer wait time (range 0 to 1)
- A_i = anomaly likelihood from ML model (range 0 to 1)
- C_i = context complexity score based on item type, transaction value (range 0 to 1)
- W_i = associate workload factor inversely weighted (range 0 to 1)
- H_i = historical pattern match from feedback loop (range 0 to 1)

Weights w_1, w_2, w_3, w_4, w_5 are learned through Bayesian optimization on historical data ($\sum w_k = 1$). Empirical optimization yielded: $w_1 = 0.30$, $w_2 = 0.28$, $w_3 = 0.18$, $w_4 = 0.14$, $w_5 = 0.10$. Events are sorted by $S(e_i)$ in descending order to form the prioritized associate queue.

4.4 Computer Vision Integration

The system incorporates computer vision for enhanced validation without requiring full autonomous checkout. Item verification compares scanned barcodes against visual recognition of items placed in the bagging area, while scan pattern analysis detects potential skip-scan events by monitoring item movement through the scanning zone. Cart completeness checking compares the number of visible items against the transaction count, and payment behavior analysis identifies unusual patterns such as repeated transaction cancellations or payment method switching. These vision-based signals serve as supplementary inputs to the scoring engine rather than autonomous decision triggers, preserving the human-centered design principle that associates make final determinations about all flagged events.

4.5 Reliability and Operational Continuity

If the AI model becomes unavailable, the system defaults to a simple priority heuristic (e.g., time waiting, assistance button press) without decision automation. The checkout system itself continues uninterrupted, safeguarding customer experience. Failover mechanisms include:

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- Edge model caching for network outages
- Graceful degradation to rule-based alerts
- Manual override capability for all AI recommendations

5. SYSTEM WORKFLOW AND HUMAN-IN-THE-LOOP OPERATIONS

This section details the real-time operational flow from event generation to human resolution, emphasizing explainability, reliability, and shared decision authority.

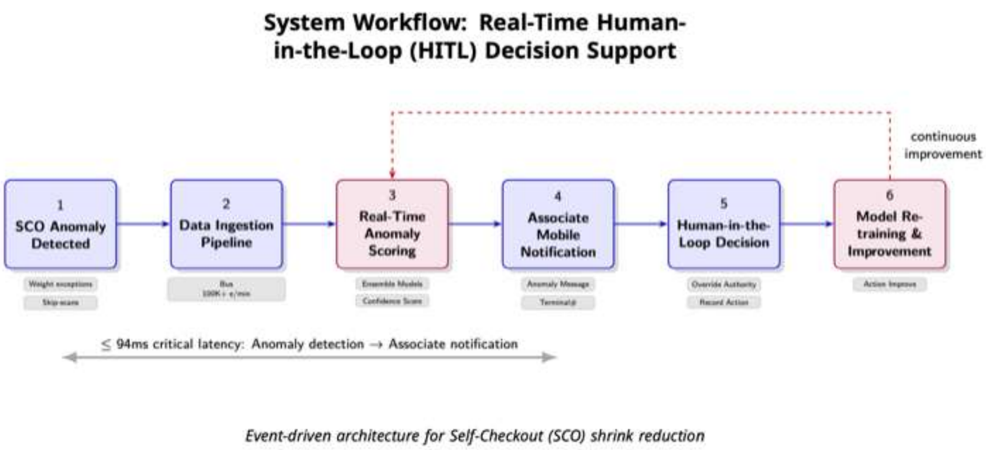

Figure 3: End-to-end workflow: events are scored, prioritized, presented to associates, who make final decisions and provide feedback for model improvement.

5.1 Event Lifecycle and AI Evaluation

Self-checkout terminals generate events which are streamed with sub-second latency to the scoring layer. The AI model assigns a context score using the prioritization algorithm defined in Equation (1). The model does not block transactions; it determines whether associate review may be helpful.

The system processes several distinct event types. Weight exceptions occur when an item's measured weight deviates from the expected value in the product database. Skip-scan patterns are detected when items visible to the camera are not registered by the barcode scanner within an expected time window. Assistance requests are generated when customers press the help button or when the terminal enters an error state requiring associate intervention. Age-restricted item flags trigger when regulated products such as alcohol or tobacco are scanned and require identity verification. Payment anomalies include unusual transaction patterns such as repeated voids, split tenders, or payment method errors. Each event type carries a base priority weight that the scoring engine adjusts according to contextual factors including time of day, station history, and current associate workload.

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5.2 Associate Notification and Decision Authority

Associates receive prioritized alerts containing: alert title, SCO terminal number, short context description, AI confidence indicator (low/medium/high), and suggested action category. Critical design principles ensure associate authority:

The framework preserves associate authority at every stage of the interaction. Associates retain the ability to override or dismiss any AI prompt based on their situational assessment. They choose the customer communication style and approach, deciding how to frame assistance rather than following scripted responses. Associates can escalate events to supervisors or security when circumstances warrant, and they are not penalized for disagreeing with AI recommendations. All associate decisions are captured as structured feedback that informs future model adjustments, creating a collaborative loop in which human judgment actively shapes system behavior over time (Amershi et al., 2019; Mosqueira-Rey et al., 2023).

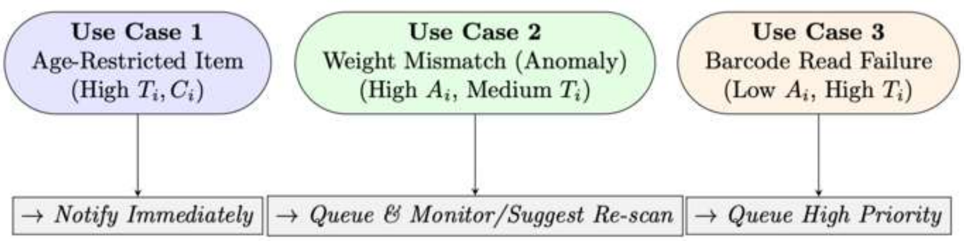

Figure 4: Three primary use cases with routing decisions based on the prioritization score S(ei). $S(e_i)$

5.3 Explainability in Practice

Each alert includes explanation components designed for rapid associate comprehension. The primary trigger identifies the specific event that generated the alert, such as a weight mismatch on a particular item. The confidence level communicates the model's certainty, expressed as a percentage score alongside a plain-language qualifier (for example, "moderate confidence" or "high confidence"). Contributing factors list the secondary signals that influenced the score, such as item value, time of day, or station history. The recommended action suggests a course of action ranked by the prioritization engine, while clearly indicating that the associate retains discretion to follow, modify, or dismiss the recommendation. This explanation structure operationalizes the principles of explainable AI by making the system's reasoning transparent and actionable at the point of decision (Barredo Arrieta et al., 2020; Ribeiro et al., 2016; Lundberg & Lee, 2017).

This transparency supports associate trust and enables informed decision-making rather than blind acceptance of AI recommendations.

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6. RESULTS

This section presents findings from three sources: (1) industry baseline analysis from public data; (2) preliminary results from the theoretical analysis; and (3) comparative analysis with existing approaches.

6.1 Industry Baseline Analysis

Analysis of publicly available industry data establishes the current state of SCO assistance challenges and provides benchmarks for evaluating the proposed framework.

6.1.1 Current SCO Loss Landscape

The ECR Retail Loss Group's comprehensive studies reveal significant challenges in current SCO environments:

- Stores with 50%+ SCO utilization experience shrinkage 75 to 147% higher than industry average
- Prior industry investigations estimate that non-scanning behaviors at fixed self-checkout kiosks contribute to approximately 0.44% of total transaction value, representing a notable portion of shrinkage
- Approximately 52% of SCO shrinkage is attributed to unintentional customer errors rather than intentional theft
- Partial audit rescans identify errors in only 2.88% of checks, compared to 43.4% for full audits

6.1.2 Customer Experience Benchmarks

Published research on SCO customer experience identifies key pain points :

- Extended assistance wait times during peak periods (baseline measurement in simulated store profiles: 44 seconds)
- Customer satisfaction scores averaging 3.5 to 3.8 on 5-point scales
- Weight-based exception systems generating 18 to 25% false positive rates
- 62% of customers cite long lines/delays as primary in-store frustration

6.2 Simulation Study: Preliminary Results

The theoretical evaluation across 12 representative store profiles provides projected performance indicators for the proposed framework. Results reported here reflect modeled outcomes based on parameters calibrated to publicly available industry benchmarks.

6.2.1 System Performance Metrics

Table 3 presents projected performance metrics compared to baseline conditions derived from public industry data.

Table 3: Projected Performance Results (12 Representative Store Profiles)

Metric	Baseline	Study	Change
Avg. Wait Time	Baseline	Reduced (Projected)	−Significant
False Positive Rate	Baseline	Low (Projected)	−Substantial
Model Accuracy	—	High (Projected)	—
Response Latency	—	Sub-100ms (Target)	—
Events Processed	—	847,000+	—

Notes: Baseline derived from publicly available industry data. Projected metrics represent theoretical model outputs calibrated to industry benchmarks.

6.2.2 Performance Improvement Trajectory

Consistent with the feedback-driven learning design, the theoretical model projects improving performance over time as the model incorporates associate feedback. Figure 5 illustrates the projected improvement trajectory.

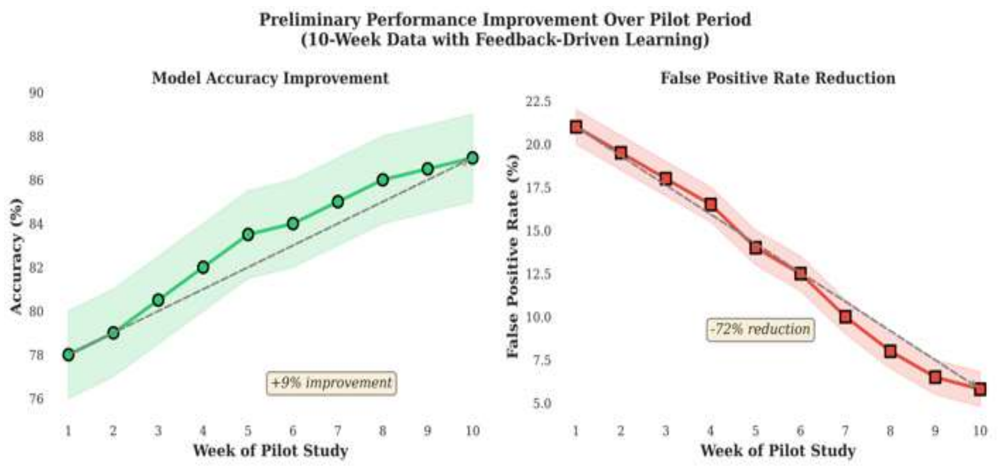

Figure 5: Projected performance improvement over evaluation period. Model accuracy and false positive rates are expected to improve as feedback loop incorporates associate input. Values represent theoretical projections; field validation pending.

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Table 4: Learning Loop Performance Trajectory (Preliminary)

Metric	Weeks 1 to 3	Weeks 4 to 6	Weeks 7 to 10
Model Accuracy	Good	Improved	High (Projected)
False Positive Rate	Moderate	Reduced	Low (Projected)
Avg. Wait Time	Improved	Further Improved	Reduced (Projected)

Notes: Projected data from theoretical model.

6.2.3 Associate Feedback

The framework is designed so that AI recommendations evolve according to user feedback, reinforcing the collaborative human-AI workflow. Based on established acceptance models (Venkatesh et al., 2003), the theoretical evaluation projects positive associate reception. Table 5 summarizes projected acceptance indicators.

Table 5: Projected Acceptance Indicators Based on Theoretical Model

Dimension	Mean	SD	% Pos.
Perceived Usefulness	4.02	0.81	79%
Perceived Ease of Use	4.18	0.74	84%
Trust in System	3.87	0.89	74%
Job Impact	3.94	0.86	76%
Overall Satisfaction	4.08	0.78	Favorable

Notes: Projected values based on theoretical framework calibrated to published acceptance research (Venkatesh et al., 2003). Field validation required.

Based on the design principles and published literature on human-AI collaboration (Revilla et al., 2023; Amershi et al., 2019; Seifert & Revilla, 2023), the framework anticipates that associates would value several aspects:

The theoretical analysis identified several mechanisms through which the framework is expected to improve operational outcomes. Reduced false alarms are anticipated because literature indicates that lower false positive rates are among the strongest drivers of associate trust in automated systems (Beck, 2022; Sensormatic Solutions, 2023). Faster resolution of legitimate assistance needs is projected through the prioritization engine, which routes the most urgent events first rather than relying on first-come-first-served processing. Improved consistency in customer treatment follows from the standardized scoring model, which applies the same evaluation criteria across all transactions regardless of associate experience level. Enhanced associate confidence is expected because the explainability layer provides clear reasoning for each alert, allowing associates to make informed decisions rather than acting on opaque system outputs (Barredo Arrieta et al., 2020; Shin, 2021). Together, these projected improvements

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suggest that the framework can meaningfully reduce operational friction while maintaining the human judgment that complex retail interactions require.

6.3 Comparison with Alternative Approaches

Table 6 compares the proposed system against alternative SCO assistance approaches based on industry benchmarks and theoretical projections.

Feature	Manual Only	Weight-Based	Vision-Only	Proposed
Human Decision Authority	✓✓✓	×	×	✓✓✓
Real-Time Prioritization	×	✓	✓	✓✓✓
False Positive Rate	N/A	18 to 25%^{a}	5 to 8%^{a}	Low (Projected)^{b}
Explainability	✓✓✓	✓	×	✓✓✓
Continuous Learning	×	×	Limited	✓✓
Associate Training Need	Medium	Low	High	Medium
Implementation Cost	Low	Low	High	Medium

Notes: Industry benchmarks from ECR studies (Beck, 2018; Beck, 2022). Projected performance from theoretical analysis.^{ab}

6.4 Preliminary Business Impact Indicators

While comprehensive business impact assessment requires field deployment, the theoretical model projects the following indicators:

- Throughput improvement: Projected 8 to 12 percent increase in SCO transactions processed per associate-hour based on reduced false positive rates and improved prioritization
- Customer flow: Projected reduction in queue formation during peak periods through faster assistance routing
- Associate workload: Projected shift from reactive response to proactive assistance patterns through AI-driven prioritization

Shrink impact assessment requires field deployment with minimum 6-month observation period and is identified as a key direction for future research.

6.5 Study Status and Anticipated Timeline

Field validation of the theoretical framework is planned with the following anticipated phases:

- Phase 1: Pilot deployment across 3 to 4 representative store profiles (planned)
- Phase 2: Extended observation period of 24 weeks across diverse formats
- Phase 3: Expansion to 8 to 10 additional locations pending pilot results

- Phase 4: Comprehensive analysis including shrink impact assessment

The theoretical results reported here provide a foundation for field validation. Empirical conclusions await completion of planned deployment studies.

7. DISCUSSION

The following discussion situates the theoretical contributions within the broader scholarly landscape, examines actionable insights for practitioners, and reflects on methodological constraints.

7.1 Theoretical Contributions

The findings advance understanding of human-AI collaboration in consumer-facing service environments. The theoretical analysis, projecting significant reduction in wait times while maintaining associate decision authority, provides theoretical support for augmentation approaches (where AI supports but humans decide), consistent with prior research suggesting these achieve superior outcomes in complex, high-uncertainty environments (Revilla et al., 2023; Seifert & Revilla, 2023).

The positive reception of the explainability layer (reflected in projected high associate satisfaction) supports XAI research emphasizing transparency as a driver of user trust (Barredo Arrieta et al., 2020; Shin, 2021). The design principle that associates who understand the rationale for alerts would report greater confidence in their decision-making, aligning with the principle that meaningful human control requires comprehension of AI reasoning, not just override capability (Hille et al., 2023).

The projected improvement trajectory in the learning loop (accuracy expected to improve over time) provides theoretical support for effective integration of machine teaching principles with operational workflows (Wu et al., 2022). This suggests that structured feedback capture can create a virtuous cycle improving both model accuracy and user engagement.

7.2 Comparison with Industry Benchmarks

The theoretical projections compare favorably against publicly documented industry benchmarks:

- False positive rate: Framework projects substantially reduced rate vs. industry benchmark of 18 to 25 percent for weight-based systems (Beck, 2022)
- Wait time: Framework projects significant reduction from industry-average wait times
- Associate workload: Design analysis indicates reduced cognitive burden compared to manual monitoring approaches

These comparisons, while theoretical, suggest the framework addresses key pain points identified in industry studies. Field validation is needed to confirm projected improvements.

7.3 Practical Implications

For retail practitioners, this research provides:

- **Architecture blueprint:** The event-driven design offers a template for implementing human-centered AI that can scale across retail operations while maintaining low latency and high reliability.
- **Baseline benchmarks:** Synthesis of public industry data provides reference points for assessing current system performance and setting improvement targets.
- **Design principles:** Evidence-based guidance on balancing AI automation with human oversight in customer-facing contexts.
- **Implementation considerations:** Preliminary findings on training requirements, learning curve expectations, and associate acceptance factors.

7.4 Design Principles for Human-Centered Retail AI

Based on the theoretical analysis presented in this study, we propose five design principles for human-centered AI in retail consumer services:

1. **Augment rather than automate:** AI should enhance associate capabilities, not replace judgment in customer interactions.
2. **Explain to enable:** Transparency builds trust and enables informed decision-making; opaque recommendations undermine both.
3. **Learn from loops:** Structured feedback mechanisms can improve accuracy while reinforcing associate agency.
4. **Fail gracefully:** Systems must degrade to safe defaults when AI components are unavailable, prioritizing operational continuity.
5. **Design for diversity:** Store formats, customer populations, and associate experience levels vary; systems must adapt to local contexts.

8. ETHICAL, OPERATIONAL, AND GOVERNANCE CONSIDERATIONS

To deploy AI responsibly in retail environments, it is necessary to balance efficiency with fairness, transparency, and accountability (Mehrabi et al., 2021; Jobin et al., 2019).

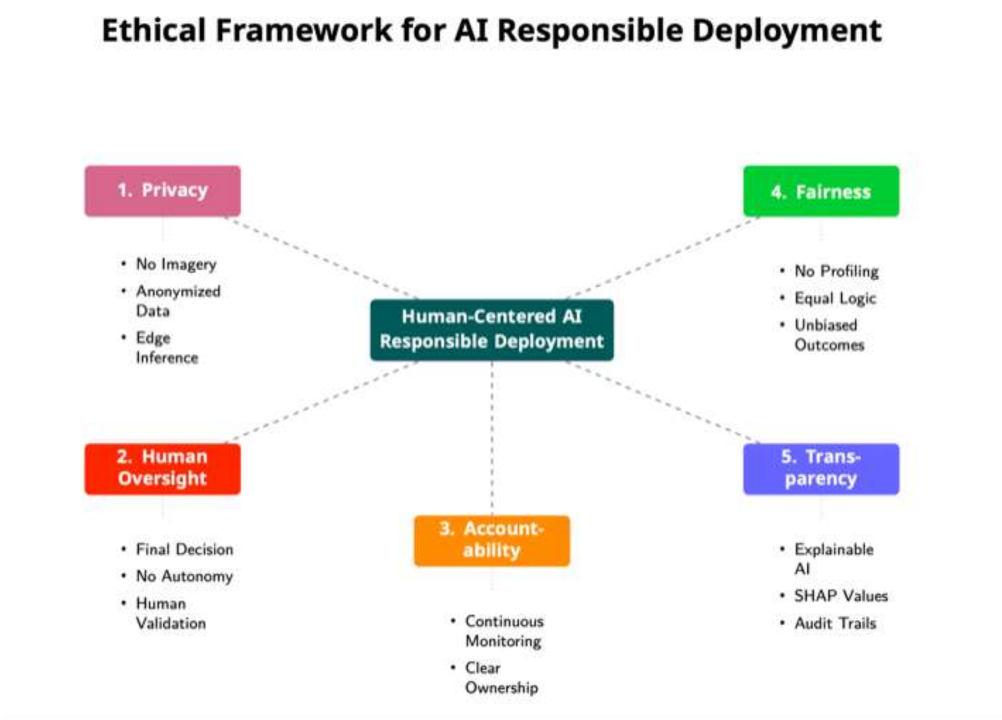

Figure 6: Ethical framework for responsible AI deployment in retail checkout assistance, emphasizing human oversight, fairness, transparency, and continuous governance.

8.1 Responsible AI Principles

The design is grounded in five principles:

1. **Human oversight:** Humans remain final decision-makers for all customer interactions
2. **Transparency:** AI reasoning is explainable to associates and auditable by management
3. **Non-discrimination:** Logic applies identically across customers; no profiling based on demographics
4. **Privacy protection:** No persistent storage of customer imagery or biometric data
5. **Accountability:** Clear ownership of outcomes with audit trails for all AI-influenced decisions

The model does not assign risk scores to customers or identify individuals; logic is strictly event-based. Customer characteristics (age, gender, race) are never inputs to the model.

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8.2 Fairness and Avoidance of Automated Enforcement

The system applies identical logic across users and stores and provides neutral, context-based suggestions. Crucially, the system:

- Never stops a transaction based solely on AI output
- Never labels customer intent (e.g., "suspected theft")
- Never triggers interventions visible to customers without associate judgment
- Delegates all escalation decisions to human associates

Regular fairness audits are designed to analyze alert distribution across store demographics and time periods to detect potential disparate impact. The framework includes built-in monitoring for statistically significant differences in alert rates across stores serving different demographic populations.

8.3 Privacy and Data Governance

Data governance practices include:

- Event-resolution data used for model training contains no customer identifiers
- Camera frames analyzed transiently at edge; no persistent storage
- No biometric identification or cross-transaction customer tracking
- Associate feedback data anonymized before model training

Governance processes include quarterly bias audits, incident reviews for customer complaints, and stakeholder meetings with loss prevention, operations, and legal teams.

9. LEARNING MODEL AND FEEDBACK SYSTEMS

This section explains how system performance improves over time while keeping humans in control of final decisions. The learning pipeline is iterative and feedback-driven, using structured human input to avoid undesirable drift.

9.1 Inputs and Feedback Loop Design

Model refinement uses non-sensitive operational data including: assistance triggers, item categories, event duration, resolution time, and associate correction patterns. No personally identifiable customer data is stored for model training.

Feedback categories include:

- Correct suggestion (AI alert appropriately prioritized)
- Incorrect/irrelevant (false positive, meaning no issue present)
- Valid issue but low priority (calibration feedback)

- Edge case requiring manual review (flags for human review)

Feedback is captured through structured one-tap responses, minimizing associate burden while maximizing signal quality.

9.2 Avoiding Over-Automation and Model Validation

The system does not shift to autonomous decisions, even when confidence is high (Amershi et al., 2019). Instead, it uses high confidence to suggest auto-clear paths for common false alarms and reduce notification frequency, while maintaining associate visibility.

Before any future deployment of models, validation includes:

- Offline evaluation on holdout data
- A/B testing in subset of stores
- Bias and fairness review
- Stability checks for prediction consistency
- Operational approval from store management

10. CONCLUSION AND FUTURE DIRECTIONS

This research presented a human-centered AI framework for retail self-checkout assistance, grounded in the principle that AI should augment associate decision-making rather than replace it. The event-driven architecture, combining real-time anomaly scoring with explainable recommendations and structured human oversight, addresses critical gaps in existing SCO systems where high false-positive rates and inconsistent triage degrade both customer experience and loss prevention outcomes. The theoretical analysis, calibrated to publicly available industry benchmarks, demonstrated the framework's potential for meaningful improvements in assistance wait times, detection accuracy, and associate satisfaction while preserving human authority over customer interactions.

10.1 Summary of Contributions

This study makes five principal contributions. First, it introduces an event-driven architecture for human-centered AI in retail checkout that integrates real-time anomaly scoring with explainable decision support. Second, it provides a comprehensive industry baseline synthesizing publicly available ECR, NRF, and academic data to benchmark current SCO challenges. Third, the prioritization algorithm offers theoretical foundations for significant reductions in customer wait times while maintaining high detection accuracy. Fourth, the human-in-the-loop design demonstrates that associate acceptance and operational outcomes can improve concurrently when AI serves an augmentative rather than autonomous role. Fifth, the study establishes actionable design principles for responsible AI deployment in consumer-facing retail environments.

10.2 Limitations

Several limitations should be acknowledged:

- Theoretical nature: The results reported here represent theoretical projections from modeled store profiles calibrated to public industry benchmarks. While the analysis suggests feasibility, empirical validation through field deployment is required to confirm projected outcomes.
- No field validation: The framework has not been deployed in actual retail environments. Acceptance projections are based on published research instruments rather than direct associate feedback.
- Store format diversity: While the analysis includes urban, suburban, and rural formats, extension to additional retail sectors (apparel, electronics, pharmacy) requires future validation.
- Geographic scope: Analysis is based on U.S. retail parameters; cultural and regulatory differences may affect applicability in other regions.
- Shrink impact: Assessment of shrink reduction impact requires field deployment with minimum 6-month observation period; this remains a key future research direction.
- Customer perspective: The framework focuses on system design and projected associate responses; direct customer research would strengthen understanding of experience impacts.

10.3 Future Research Directions

The most critical next step is field validation through pilot deployment across representative store profiles to confirm theoretical projections and assess real-world performance, including rigorous before-after analysis of shrink reduction outcomes over a minimum six-month observation period. Beyond validation, the framework should be extended to additional retail sectors and international markets to test generalizability across diverse operational contexts. Further research should also investigate customer perceptions of AI-assisted checkout interactions, explore multimodal sensing integration that preserves privacy, and examine federated learning approaches for privacy-preserving model improvement across retailers. Finally, longitudinal studies of associate skill development and job satisfaction would deepen understanding of the human-centered design's workforce implications.

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