

Future use of artificial intelligence for SKU promotion in retail : Applications, perceptions, and strategic challenges

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Abstract

The implementation of Artificial Intelligence (AI) in retail promotional strategies marks a paradigm shift from mass marketing to granular, stock-keeping unit (SKU) level customization. AI-driven SKU promotion can stimulate consumer interest through contextual, geo-fenced and inventory-friendly offers, while real-time data streams allow retailers to surface high-conversion SKUs, optimize stock rotation and minimize holding costs. AI recommendations also reduce search fatigue and encourage exploration of new product categories. However, privacy concerns, algorithmic bias and ethical risks, particularly when behavioral patterns are inferred without the direct consent of the user, constrain large-scale adoption. This paper examines how AI systems use customer behavior data, transaction history, demographic segmentation and contextual triggers to promote SKUs to particular groups of consumers. A quantitative, cross-sectional design was adopted, surveying 150 retail consumers exposed to AI-based solutions such as virtual try-ons, smart shelves and recommendation engines. Findings indicate that perceived AI accuracy,

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transparency and reduced cognitive load have a significant effect on trust and purchase intention, while omnichannel integration enhances satisfaction. The privacy problem remains but is mitigated by perceived usefulness and transparency. The paper underscores the need to align AI potential with data governance and ethical execution in order to gain sustainable competitive advantage in the retail business.

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1. Introduction

AI is transforming retail marketing, merchandising, and customer interaction by replacing mass promotions with data-driven, personalized SKU-level targeting based on real-time transactional, behavioral, contextual, and geographic data. AI-driven recommendation and promotion systems improve conversion rates, basket size, inventory efficiency, and decision-making, while reducing stock obsolescence, holding costs, search effort, and choice overload [1], [2], [3], [4]. They also enable personalized tools such as virtual try-ons, smart shelves, and smart kiosks, shifting merchandising toward algorithmic decision-making and creating integrated omnichannel retail experiences.

AI adoption in retail is constrained by privacy concerns, algorithmic bias, opaque decisions, and the personalization–privacy paradox, which can affect trust, consent, and ethical control [5], [6], [7]. Retailers also face fragmented data systems, skill gaps, strategic misalignment, and weak data governance that limit measurable AI value [8], [9]. This study therefore uses a quantitative cross-sectional design to examine how consumers exposed to AI-based shopping tools perceive SKU promotion, focusing on AI accuracy, cognitive load reduction, and omnichannel integration and their effects on trust, privacy concerns, and purchase intention, with implications for responsible and sustainable AI adoption.

2. Literature Review

AI is now embedded in marketing, merchandising and operational decision-making in retail [3], enabling personalized, SKU-level engagement from real-time consumer data, transaction history and contextual cues [4]. Industry research suggests AI-driven personalization can raise retail sales by 10–30 percent while reducing inventory costs and demand shortages

[1], [2], and AI-enhanced recommendation systems improve perceived relevance, lower search costs and strengthen decision confidence [3]. Digital and social media promotion likewise shapes brand awareness, brand image and purchase decisions [10]. Yet consumer fears about data privacy, transparency and the ethics of AI-based persuasion [5], and retailers' lack of integrated data structures, analytical capabilities and cross-functional readiness [9], [8], remain key barriers. This study addresses these gaps through an empirically grounded, multi-dimensional framework covering consumer perception, behavioral effects and implementation concerns [6].

2.1 AI in Retail and the Shift to SKU-Level Promotion

AI has transformed retail from rule-based approaches to data-driven SKU-level targeting, enabling personalized promotions and predictive demand management [4], which can improve conversion and reduce inventory stagnation [3]. AI, IoT, and cloud-based ML further enable real-time tracking of customer behavior and SKU-level recommendations, improving decision-making and context-based promotions [11]. Explainable AI research highlights that transparency and interpretability increase user confidence and acceptance, making transparency and perceived usefulness essential for trust in AI-based SKU promotion [12].

2.2 Consumer AI Accuracy Perceptions and Cognitive Ease

Consumers increasingly regard AI as more accurate than human judgment in objective pattern-recognition tasks such as size or shade matching, particularly in large assortments [13], and this perceived technical efficiency builds trust in recommendations. AI-based personalization also reduces cognitive load: by narrowing large collections to relevant SKUs, it limits choice fatigue and enhances shopping efficiency and the feeling of control [14]. Research on online shopping behavior likewise stresses the need to understand purchasing patterns in technology-mediated retail decisions, providing a basis for examining how AI recommendations influence purchase intention [15].

2.3 Omnichannel Expectations, Trust and the Privacy Paradox

Trust in AI systems is multidimensional, resting not only on accuracy but also on perceived benevolence and openness: customers are receptive to AI recommendations when the system appears to serve their interests rather than retailer objectives such as stock clearance, and when they

understand the rationale behind them [6], [16]. This coincides with the personalization–privacy paradox: consumers voice strong worries about data collection and abuse, yet are conditionally willing to provide personal, even biometric, data when the AI system is believed to be highly useful and transparent [7], [5].

2.4 Immersive Technologies and AI-Enabled Automation

Store automation through smart shelves, self-checkouts and interactive kiosks is widely tolerated for its perceived time and convenience benefits, provided the systems are reliable [17]. Immersive technologies such as virtual try-ons and smart mirrors directly reduce purchase uncertainty and enhance consumer confidence [18]. Positive experiences with these AI interfaces foster continued-use intention and word-of-mouth promotion, consistent with technology acceptance models [19].

3. Hypotheses Development and Conceptual Framework

The study adopts the Stimulus–Organism–Response (S-O-R) paradigm [20] (Figure 1), proposing that AI-enabled SKU promotion influences consumer perceptions, which shape behavioral outcomes. Key perceptions include AI accuracy, cognitive load reduction, omnichannel integration, transparency, and perceived usefulness, affecting trust, efficiency, privacy concerns, satisfaction, and acceptance of reduced human interaction. Accordingly, H1–H6 propose positive effects of AI accuracy on trust, reduced cognitive load on shopping efficiency, omnichannel integration on satisfaction, transparency on trust, usefulness on reducing privacy concerns, and perceived automation efficiency on

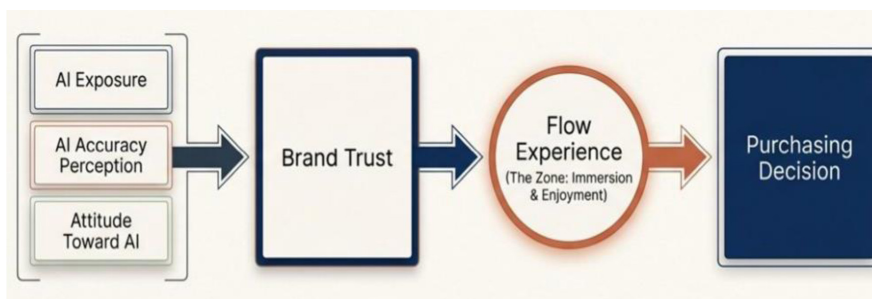


Figure 1
The Flow Model

acceptance of less human service. H7 proposes that trust, efficiency, and reduced cognitive load increase purchase intention, while H8 links purchase intention with future usage intention and advocacy.

4. Research Methodology

4.1 Research Design and Sample

A quantitative, cross-sectional design was adopted. Data were collected through a structured online survey distributed to a purposive sample of 150 retail consumers exposed to AI-enabled shopping tools (e.g., recommendation engines, virtual try-ons, AI kiosks), of whom 78% had consciously used such tools.

4.2 Measures and Data Analysis

Multi-item scales on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), based on the existing literature [13], [14], [7], measured all constructs. Data were analyzed using SPSS and AMOS; Cronbach’s alpha and confirmatory factor analysis assessed reliability and validity. Structural Equation Modeling (SEM) was chosen to simultaneously test the hypothesized relationships among the latent constructs.

Table 1
Sample Demographic Profile

Variable	Category	Frequency	Percentage (%)
Age	22–25 years	57	38.0
	26–40 years	69	46.0
	Above 40 years	24	16.0
Gender	Male	78	52.0
	Female	69	46.0
	Prefer not to say	3	2.0
Shopping Frequency	Weekly	62	41.3
	Monthly	61	40.7
	Quarterly	27	18.0
Prior AI Tool Usage	Yes	117	78.0
	No	33	22.0

Source: Data Analysis

5. Data Analysis and Results

5.1 Sample Profile

The purposive sample of 150 retail customers (Table 1) is digitally active and predominantly young to middle-aged (84% aged 22–40), shops frequently (82% weekly or monthly) and has substantial prior exposure to AI retail tools (78%), ensuring respondents can evaluate AI-driven SKU promotion meaningfully.

5.2 Descriptive Statistics and Scale Reliability

Table 2
Descriptive Statistics and Reliability of Constructs

Construct	Items	Mean	Standard Deviation	Cronbach's α
AI Accuracy Perception	3	3.92	0.81	0.81
Cognitive Load Reduction	3	4.01	0.74	0.84
Omnichannel Integration	2	3.78	0.88	0.79
Transparency	3	3.74	0.86	0.82
Trust in AI	4	3.88	0.79	0.86
Perceived Usefulness	3	3.91	0.77	0.84
Privacy Acceptance	3	3.65	0.85	0.78
Privacy Concerns	3	3.42	0.91	0.81
Perceived Efficiency	3	4.06	0.71	0.83
Automation Acceptance	3	3.89	0.79	0.85
Satisfaction	3	3.86	0.82	0.87
Purchase Intention	3	3.84	0.83	0.85
Future Usage Intention	2	4.12	0.69	0.82
Word-of-Mouth Advocacy	2	3.97	0.76	0.81

Note: All constructs measured on 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree). *Source:* Data Analysis

Table 2 shows generally positive results across all constructs, with every mean above the scale midpoint of 3.0. Future Usage Intention received the highest mean (4.12), closely followed by Perceived Efficiency (4.06), while Privacy Concerns received the lowest (3.42), in line with prior studies on privacy concerns. All constructs showed good to excellent internal consistency, with Cronbach's alphas above 0.70.

5.3 Confirmatory Factor Analysis (Measurement Model)

Confirmatory Factor Analysis (CFA) was employed to test the validity of the measurement model (Table 3).

Table 3
Convergent Validity Assessment

Construct	Items	Factor Loadings	CR	AVE
AI Accuracy Perception	ACC1–ACC3	0.82, 0.78, 0.81	0.88	0.65
Cognitive Load Reduction	CLR1–CLR3	0.79, 0.83, 0.82	0.89	0.67
Omnichannel Integration	OMI1–OMI2	0.84, 0.87	0.85	0.74
Transparency	TRA1–TRA3	0.81, 0.84, 0.79	0.86	0.67
Trust in AI	TRU1–TRU4	0.84, 0.81, 0.83, 0.82	0.90	0.69
Perceived Usefulness	PU1–PU3	0.80, 0.84, 0.83	0.88	0.71
Privacy Acceptance	PA1–PA3	0.78, 0.82, 0.80	0.85	0.65
Privacy Concerns	PC1–PC3	0.81, 0.85, 0.79	0.87	0.69
Perceived Efficiency	EFF1–EFF3	0.80, 0.86, 0.85	0.88	0.71
Automation Acceptance	AA1–AA3	0.83, 0.81, 0.85	0.88	0.71
Satisfaction	SAT1–SAT3	0.86, 0.82, 0.84	0.89	0.73
Purchase Intention	PI1–PI3	0.84, 0.87, 0.82	0.89	0.73
Future Usage Intention	FUI1–FUI2	0.88, 0.90	0.89	0.80
Word-of-Mouth Advocacy	WOM1–WOM2	0.86, 0.89	0.87	0.77

Note: CR = Composite Reliability; AVE = Average Variance Extracted. Source: Data Analysis

All factor loadings exceeded 0.70, composite reliability values exceeded 0.80 and AVE values exceeded 0.50, indicating adequate convergent validity for all constructs [21]. Discriminant validity was also adequate, as the square root of the AVE of each construct was greater than its correlation with every other construct.

5.4 Structural Model and Hypothesis Testing

SEM was employed to test all hypothesized relationships; Table 4 presents the path coefficients, critical ratios (t-values) and test results.

Table 4
Structural Model Results and Hypothesis Testing

Hypothesis	Path	Path Coeff. β	t-value	p-value	Result
H1	AI Accuracy $\rightarrow$ Trust in AI	0.37	4.82	<0.001	Supported
H2	Cognitive Load Reduction $\rightarrow$ Perceived Efficiency	0.29	3.36	<0.01	Supported
H3	Omnichannel Integration $\rightarrow$ Satisfaction	0.31	3.89	<0.001	Supported
H4	Transparency $\rightarrow$ Trust in AI	0.41	5.12	<0.001	Supported
H5	Perceived Usefulness $\rightarrow$ Privacy Concerns	-0.33	4.01	<0.001	Supported
H6	Perceived Efficiency $\rightarrow$ Automation Acceptance	0.35	4.25	<0.001	Supported
H7	Trust + Efficiency + CLR $\rightarrow$ Purchase Intention	0.41	4.92	<0.001	Supported
		0.33	4.11	<0.001	
		0.28	3.36	<0.01	
H8a	Purchase Intention $\rightarrow$ Future Usage Intention	0.48	6.12	<0.001	Supported
H8b	Purchase Intention $\rightarrow$ Word-of-Mouth Advocacy	0.44	5.67	<0.001	Supported

Note: CLR = Cognitive Load Reduction. Source: Data Analysis

The model explained substantial variance in the key endogenous variables: Trust in AI ($R^2 = 0.58$), Perceived Efficiency ($R^2 = 0.47$), Purchase Intention ($R^2 = 0.62$), Future Usage Intention ($R^2 = 0.53$) and Word-of-Mouth Advocacy ($R^2 = 0.49$).

5.5 Model Fit Indices

As shown in Table 5, all standard model fit indices met or exceeded the recommended thresholds, indicating that the proposed structural model adequately fits the observed data [22].

Table 5
Model Fit Indices

Fit Index	Recommended	Obtained	Interpretation
Chi-square χ^2/df	< 3.0	2.18	Good fit
Comparative Fit Index (CFI)	> 0.90	0.94	Good fit
Tucker-Lewis Index (TLI)	> 0.90	0.93	Good fit
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.06	Good fit
Standardized Root Mean Square Residual (SRMR)	< 0.08	0.05	Good fit

Source: Data Analysis

6. Discussion

The findings support the proposed S-O-R model in the context of AI-based SKU promotion. AI accuracy and transparency were positively associated with consumer trust, with transparency strengthening trust by helping consumers understand AI recommendations, while reduced cognitive load improved perceived efficiency; trust, efficiency and cognitive ease together drove purchase intention.

The explained variance of purchase intention ($R^2 = 0.62$) highlights the potential of AI-based SKU promotion to contribute to retail outcomes such as conversion and basket size. However, effective implementation requires transparency, responsible data management and seamless omnichannel integration.

7. Conclusion

This research finds that AI-driven SKU promotion is a strong predictor of modern shopper behavior: improved accuracy, decreased cognitive load, transparency and seamless interactions all result in increased trust, purchase intention and word of mouth. The paper moves the discourse on AI in retail from technical possibility to the interdependencies between algorithmic potential, consumer behavior and the ethical application of the technology. For practitioners, the greatest value will come from combining strategic technology investment with open communication protocols, trust-building data practices and organization-wide digital literacy.

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