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WHEN THE CREATOR AND AI DISAGREE: THE EFFECTS OF HUMAN CREATOR VERSUS AI SHOPPING RECOMMENDATIONS ON CONSUMER TRUST AND RETAIL PURCHASE DECISIONS

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Abstract: The rapid integration of social commerce creators alongside autonomous artificial intelligence recommendation systems has transformed contemporary retail, frequently exposing shoppers to discordant purchase advice. Grounded in source credibility and attribution theories, this empirical research investigates consumer trust evaluation and purchase decision dynamics when human creator endorsements directly conflict with algorithmic recommendations. Administering an empirical survey across 125 active digital consumers in Tiruchirappalli (Trichy), Tamil Nadu, the study evaluates an expanded multi-factor model comprising Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Perceived Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk. Parametric and non-parametric statistical analyses including percentage distribution, Cronbach's alpha reliability, composite reliability, Pearson correlation, multiple linear regression, paired samples t-testing, Mann-Whitney U testing, and Kruskal-Wallis H testing demonstrate a definitive human advisory primacy. Consumers predominantly adhere to creator recommendations (55.2%) over AI suggestions (32.8%), driven by perceived authenticity and relational empathy. Nevertheless, AI recommendations retain substantial predictive weight when accompanied by operational transparency, while advisory conflict elevates purchase risk, precipitating a 12% cart abandonment rate. Marked gender and generational disparities emerge across algorithmic reliance. Strategic implications for hybrid e-commerce interface design, algorithmic explainability, and targeted creator collaborations are discussed.

Keywords: Social Commerce, Artificial Intelligence, Consumer Trust, Retail Purchase Decisions, Algorithmic Transparency, etc.,

I. Introduction

The modern retail ecosystem is experiencing a seismic paradigm shift characterized by the simultaneous integration of social commerce influencers and algorithmic artificial intelligence engines. Consumers no longer navigate digital marketplaces through static product directories alone; rather, their shopping journeys are actively shaped by social media content creators who offer emotional resonance, lived consumption experiences, and relational endorsements. Concurrently, e-commerce architectures deploy predictive and generative AI recommendation systems that process extensive datasets to provide objective, attribute-optimized, and hyper-personalized product evaluations. As contemporary retail platforms harmonize these two advisory streams within unified digital interfaces, consumers are frequently subjected to discordant guidance where a trusted human creator and an automated AI engine generate mutually contradictory product recommendations.

This convergence introduces significant cognitive dissonance into the online decision-making matrix. Grounded in source credibility theory and attribution theory, human creators command authority derived from perceived authenticity, empathy, and social connectivity, whereas AI recommendation agents derive credibility from computational competence, perceived objectivity, and exhaustive data synthesis. When these two guidance mechanisms diverge on identical retail choices, the consumer's internal calculus regarding information credibility, risk perception, and transactional commitment becomes exceptionally convoluted. Determining how retail shoppers negotiate this advisory friction, evaluate competing credibility cues, and finalize basket conversions constitutes an urgent inquiry in modern marketing and retail analytics.

II. Review of Literature

Gerlich (2025) made a study on "The Shifting Influence: Comparing AI Tools and Human Influencers in Consumer Decision-Making". This study shows that consumers demonstrate a dual-target persuasion pathway where algorithmic tools dominate utilitarian, attribute-driven product evaluations, whereas human influencers preserve persuasive superiority in emotionally salient, hedonic shopping categories.

Kim and Han (2025) made a study on "The Impact of AI Influencer Endorsements on Consumers' Purchase Intentions: The Serial Mediating Roles of Mind Perception and Brand Trustworthiness". This study shows that endorsement discrepancies trigger lower overall brand credibility, with consumers resolving contradictory recommendations by scrutinizing the commercial motives and perceived authenticity of the endorser versus the automated impartiality of the AI agent.

Mazzù et al. (2024) made a study on "The Impact of Humans vs. AI Recommendation on Consumer Reactions to Products Exposure: The Role of Transparency and Credibility". This study shows that when recommendation sources conflict, perceived operational transparency and recommender expertise interact significantly, determining whether the consumer experiences advice aversion or proceeds with transactional commitment.

Shen et al. (2023) made a study on "Artificial Intelligence or Human: When and Why Consumers Prefer AI Recommendations". This study shows that consumers favor algorithmic recommendations for material and objective product choices but systematically defer to human recommendations for experiential goods because human creators are credited with affective capacity and qualitative consumption experience.

Longoni and Cian (2022) made a study on "Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The Role of Competence and Warmth Perceptions". This study shows that an "algorithm aversion" phenomenon frequently manifests when subjective judgment and aesthetic preferences are required, causing shoppers to discount algorithmic outputs when they directly conflict with human advisory consensus.

III. Need of the Study

The rapid proliferation of algorithmically curated e-commerce interfaces alongside creator-driven social shopping has created an unprecedented operational tension: direct recommendation conflict between human endorsers and synthetic algorithms. While prior scholarship has extensively explored influencer persuasiveness in isolation and algorithmic adoption separately, substantial gaps exist concerning how multi-factor constructs such as perceived commercial bias, operational transparency, brand authenticity, parasocial interaction, and perceived risk interact to drive purchase behavior when these two sources deliver contradictory guidance. For digital retailers and platform architects, unravelling this multi-variable interplay is critical to optimize user experience designs, prevent cart abandonment, and strategically balance promotional budgets. Moreover, examining consumer behavior within tier-II emerging urban commercial centres like Tiruchirappalli provides rare empirical visibility into high-growth, mobile-first consumer segments whose adjudication between human authenticity and algorithmic precision remains largely unexplored in retail literature.

IV. Statement of the Problem

The rapid integration of algorithmic recommendation engines within creator-monetized retail platforms presents a major theoretical and practical dilemma: the emergence of direct advisory conflict. When a human digital creator advocates for a specific brand or item based on lifestyle appeal while an embedded artificial intelligence recommendation agent presents an alternative product backed by comparative specifications, pricing metrics, or algorithmic matching, consumers face severe informational dissonance. This conflicting environment alters consumer perceptions of commercial bias, challenges platform trust, elevates perceived purchase risk, and dampens conversion velocity. Existing empirical inquiries have seldom investigated the integrated structural relationship among multi-dimensional advisory trust, algorithmic transparency, parasocial interaction, creator authenticity, perceived purchase risk, and resulting retail basket decisions during direct advisory discrepancies. Understanding how consumers balance conflicting informational cues to complete transactions is paramount for sustainable digital commerce. To systematically resolve this research problem, the study addresses three core research questions: (1) What are the comparative levels of consumer trust, perceived competence, and perceived authenticity attributed to human creators versus AI recommendation engines when contradictory advice occurs? (2) How do multiple advisory and psychological factors specifically Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Perceived Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk collectively influence and predict final retail purchase decisions during advisory disagreement? and (3) Do consumer demographic characteristics (such as gender and age cohorts) significantly differentiate advisory trust, risk perceptions, and ultimate purchase choices when human and algorithmic recommendations clash?

V. Objectives of the Study

To maintain rigorous alignment with the statement of the problem and the research questions, the study sets forth the following three specific objectives:

1. To evaluate and compare the levels of consumer trust, perceived competence, authenticity, and risk perceptions regarding human content creators versus AI recommendation engines during instances of conflicting retail recommendations.
2. To examine the multi-factor relationships and predictive power of Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Perceived Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk on final retail purchase decisions under advisory conflict.
3. To identify whether significant demographic variations (gender and age cohorts) exist in consumer trust evaluations, advisory preferences, and purchase decisions during recommendation disagreements.

VI. Hypotheses of the Study

H01: There is no significant correlation between the study factors (Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk) and retail purchase decisions during advisory disagreement.

H1: There is a significant correlation between the study factors (Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk) and retail purchase decisions during advisory disagreement.

H02: The expanded multi-factor model (Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk) does not significantly predict retail purchase decisions under advisory conflict.
H2: The expanded multi-factor model (Human Creator Trust, AI Recommendation Trust, Algorithmic Transparency, Creator Authenticity, Parasocial Interaction, and Perceived Purchase Risk) significantly predicts retail purchase decisions under advisory conflict.
H03: There is no significant difference in consumer trust toward AI recommendations, human creator recommendations, and perceived risk across gender cohorts during advisory disagreement.
H3: There is a significant difference in consumer trust toward AI recommendations, human creator recommendations, and perceived risk across gender cohorts during advisory disagreement.
H04: There is no significant difference in final retail purchase decisions and source choice resolution across different consumer age groups during advisory conflict.
H4: There is a significant difference in final retail purchase decisions and source choice resolution across different consumer age groups during advisory conflict.
H05: There is no significant difference between consumer trust placed in Human Creators versus AI Recommendation Engines under conflicting advisory conditions.
H5: There is a significant difference between consumer trust placed in Human Creators versus AI Recommendation Engines under conflicting advisory conditions.

VII. Research Methodology

Research Design: Descriptive, cross-sectional empirical survey design deploying parametric and non-parametric multivariate statistical tools.
Research Study Area: Tiruchirappalli (Trichy), Tamil Nadu, India an urban commerce and higher-education center exhibiting rapid adoption of digital retail, livestream shopping, and social commerce platforms.
Sample Size: 125 active retail e-commerce consumers.
Sampling Technique: Non-probability purposive and convenience sampling, screening for respondents who actively follow digital content creators and regularly use algorithmically tailored shopping platforms (Amazon, Myntra, Flipkart, Ajio, Instagram Shop).
Data Collection: A structured, self-administered questionnaire containing multi-item psychometric scales on a 5-point Likert continuum (1 = Strongly Disagree to 5 = Strongly Agree), administered through digital schedules and field distribution across major retail and commercial nodes in Tiruchirappalli.
Sources of Data: Both primary and secondary data were integrated. Primary data were gathered firsthand from the 125 respondents regarding trust metrics, advisory conflict resolution, and purchase behavior. Secondary data were sourced from peer-reviewed journals across ABDC, Scopus, and Web of Science databases, retail industry reports, and e-commerce analytics.
Operationalization of Research Constructs: The conceptual framework operationalizes seven distinct constructs: (1) Human Creator Trust [HCT - 4 items], (2) AI Recommendation Trust [AIT - 4 items], (3) Algorithmic Transparency [AT - 3 items], (4) Perceived Creator Authenticity [PCA - 3 items], (5) Parasocial Interaction [PSI - 3 items], (6) Perceived Purchase Risk [PPR - 3 items], and (7) Retail Purchase Decision [RPD - 4 items].

VIII. Analysis and Discussion

Percentage Analysis

Table No. 01

Dimension	Classification	Frequency (N=125)	Percentage (%)
Gender	Male	68	54.4%
	Female	57	45.6%
Age Group	18-25 Years	74	59.2%
	26-35 Years	38	30.4%
	Above 35 Years	13	10.4%
Education Level	Undergraduate	62	49.6%
	Postgraduate / Professional	63	50.4%
Monthly Online Shopping Frequency	1-3 Orders	42	33.6%
	4-6 Orders	56	44.8%
	Above 6 Orders	27	21.6%
Dominant Category Purchased	Fashion & Lifestyle	58	46.4%
	Consumer Electronics & Tech	43	34.4%
	Beauty & Personal Care	24	19.2%
	Follow Human Creator	69	55.2%

Choice Resolution When Sources Disagree	Follow AI Engine Recommendation	41	32.8%
	Abandon / Postpone Purchase	15	12.0%

Source: Primary data

The percentage distribution reveals a young, active digital cohort with 59.2% of consumers between 18 and 25 years, and 30.4% between 26 and 35 years. Online purchasing is well established, with 66.4% ordering online four or more times each month. In situations where human creator recommendations clash directly with AI suggestions, 55.2% prioritize the human creator, 32.8% adhere to the algorithmic recommendation, and 12.0% postpone or abandon the transaction due to informational uncertainty.

Scale Reliability and Construct Validity

Table No. 02

Construct Factor	Items	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE	Validity / Reliability Status
Human Creator Trust (HCT)	4	0.842	0.894	0.678	Confirmed (α > 0.80, AVE > 0.50)
AI Recommendation Trust (AIT)	4	0.817	0.879	0.645	Confirmed (α > 0.80, AVE > 0.50)
Algorithmic Transparency (AT)	3	0.805	0.866	0.683	Confirmed (α > 0.80, AVE > 0.50)
Perceived Creator Authenticity (PCA)	3	0.831	0.887	0.724	Confirmed (α > 0.80, AVE > 0.50)
Parasocial Interaction (PSI)	3	0.824	0.882	0.713	Confirmed (α > 0.80, AVE > 0.50)
Perceived Purchase Risk (PPR)	3	0.812	0.874	0.698	Confirmed (α > 0.80, AVE > 0.50)
Retail Purchase Decision (RPD)	4	0.856	0.902	0.697	Confirmed (α > 0.80, AVE > 0.50)

Source: Primary data

As demonstrated in Table No. 02, all seven research constructs surpass the standard psychometric threshold of 0.80 for Cronbach's alpha and 0.85 for Composite Reliability. The Average Variance Extracted (AVE) values range from 0.645 to 0.724, substantially exceeding the 0.50 benchmark, thereby confirming convergent validity in accordance with Fornell-Larcker criteria.

Pearson Correlation Analysis

Table No. 03

Construct Variables	Mean	SD	1. HCT	2. AIT	3. AT	4. PCA	5. PSI	6. PPR	7. RPD
1. Human Creator Trust (HCT)	3.82	0.74	1.000	-	-	-	-	-	-
2. AI Recommendation Trust (AIT)	3.41	0.81	-0.198*	1.000	-	-	-	-	-
3. Algorithmic Transparency (AT)	3.28	0.85	-0.114	0.482**	1.000	-	-	-	-
4. Perceived Creator Authenticity (PCA)	3.95	0.71	0.592**	-0.176*	-0.082	1.000	-	-	-
5. Parasocial Interaction (PSI)	3.78	0.76	0.614**	-0.215*	-0.128	0.548**	1.000	-	-

6. Perceived Purchase Risk (PPR)	3.52	0.82	-0.342**	-0.284**	-0.395**	-0.312**	-0.268**	1.000	-
7. Retail Purchase Decision (RPD)	3.76	0.69	0.584**	0.312**	0.364**	0.521**	0.472**	-0.418**	1.000

Source: Primary data ***Note: *Significant at p < 0.05 level;***

***** Significant at p < 0.01 level (2-tailed).***

The correlation matrix in Table No. 03 confirms that Retail Purchase Decisions correlate positively and strongly with Human Creator Trust (r = 0.584, p < 0.01), Perceived Creator Authenticity (r = 0.521, p < 0.01), and Parasocial Interaction (r = 0.472, p < 0.01). On the technological front, AI Recommendation Trust (r = 0.312, p < 0.01) and Algorithmic Transparency (r = 0.364, p < 0.01) exhibit positive associations with purchase decisions. Conversely, Perceived Purchase Risk demonstrates an inverse relationship with purchase decisions (r = -0.418, p < 0.01). The negative correlation between HCT and AIT (r = -0.198, p = 0.027) reflects the inherent psychological friction between human and algorithmic advisory mechanisms. Since all factors correlate significantly with purchase decisions, null hypothesis H01 is rejected.

Multiple Linear Regression Analysis

Expanded Model Summary: Model Summary: R = 0.791, R^2 = 0.626, Adjusted R^2 = 0.607, Standard Error of the Estimate = 0.432, F(6, 118) = 32.94, p < 0.001, Durbin–Watson = 1.968.

Table No. 04

Predictor Factors	Unstandardized B	Std. Error	Standardized Beta (β)	t-value	Sig. (p)	Tolerance	VIF
(Constant)	0.982	0.298	-	3.295	0.001	-	-
Human Creator Trust (HCT)	0.294	0.065	0.315	4.523	<0.001	0.548	1.825
Perceived Creator Authenticity (PCA)	0.198	0.064	0.204	3.094	0.002	0.612	1.634
AI Recommendation Trust (AIT)	0.176	0.051	0.207	3.451	0.001	0.741	1.350
Algorithmic Transparency (AT)	0.134	0.049	0.165	2.735	0.007	0.732	1.366
Parasocial Interaction (PSI)	0.142	0.058	0.156	2.448	0.016	0.584	1.712
Perceived Purchase Risk (PPR)	-0.168	0.048	-0.200	-3.500	0.001	0.814	1.228

Source: Primary data

The regression equation formulated from Table No. 04 is: RPD = 0.982 + 0.294(HCT) + 0.198(PCA) + 0.176(AIT) + 0.134(AT) + 0.142(PSI) - 0.168(PPR). Incorporating the expanded set of behavioral and technological factors increases the explained variance to 62.6% (R^2 = 0.626, F = 32.94, p < 0.001). All six predictors demonstrate statistically significant beta weights (p < 0.05). Collinearity diagnostics verify model robustness with all VIF values below 2.0. Human Creator Trust exerts the strongest positive influence (β = 0.315), followed by AI Recommendation Trust (β = 0.207), Creator Authenticity (β = 0.204), and Algorithmic Transparency (β = 0.165), while Perceived Purchase Risk exerts a significant inhibiting effect (β = -0.200). Null hypothesis H02 is decisively rejected.

Paired Samples t-Test (Direct Mean Comparison of Trust Sources)

Table No. 05

Paired Constructs	Mean	N	Std. Deviation	Mean Difference	t-statistic	df	Sig. (2-tailed)	Hypothesis Decision
Human Creator Trust (HCT)	3.82	125	0.74	0.41	4.085	124	<0.001	Significant (Reject H05)
AI Recommendation Trust (AIT)	3.41	125	0.81					

Source: Primary data

To directly compare consumer confidence levels between the two guidance mechanisms during advisory conflict, a paired samples t-test was conducted. As detailed in Table No. 05, the mean score for Human Creator Trust (3.82 ± 0.74) is significantly higher than that for AI Recommendation Trust (3.41 ± 0.81), yielding a mean difference of 0.41 (t(124) = 4.085, p < 0.001). This provides conclusive statistical confirmation of human advisory primacy, rejecting null hypothesis H05.

Mann-Whitney U Test (Gender-Based Differences)

Table No. 06

Construct Variable	Gender	N	Mean Rank	Sum of Ranks	Mann-Whitney U	Z-value	Asymp. Sig. (2-tailed)	Test Result
AI Recommendation Trust (AIT)	Male	68	71.45	4858.5	1363.5	-2.748	0.006	Significant (Reject H03)
	Female	57	52.92	3016.5				
Algorithmic Transparency (AT)	Male	68	69.88	4752.0	1470.0	-2.284	0.022	Significant (Reject H03)
	Female	57	54.79	3123.0				
Perceived Authenticity (PCA)	Male	68	55.10	3747.0	1401.0	-2.541	0.011	Significant (Reject H03)
	Female	57	72.42	4128.0				
Parasocial Interaction (PSI)	Male	68	56.24	3824.5	1478.5	-2.186	0.029	Significant (Reject H03)
	Female	57	71.06	4050.5				
Perceived Purchase Risk (PPR)	Male	68	58.12	3952.0	1606.0	-1.624	0.104	Not Significant ($p > 0.05$)
	Female	57	68.82	3923.0				

Source: Primary data

The Mann-Whitney U test in Table No. 06 confirms distinct gender disparities across multiple advisory dimensions. Male shoppers report significantly higher AI Recommendation Trust (Mean Rank = 71.45, $p = 0.006$) and demand for Algorithmic Transparency (Mean Rank = 69.88, $p = 0.022$). Conversely, female shoppers exhibit significantly higher scores for Perceived Creator Authenticity (Mean Rank = 72.42, $p = 0.011$) and Parasocial Interaction (Mean Rank = 71.06, $p = 0.029$). These findings confirm that male shoppers place greater weight on computational attributes while female shoppers are guided more strongly by relational social cues. Null hypothesis H03 is therefore rejected.

Kruskal-Wallis H Test (Age-Cohort Variance)

Table No. 07

Construct Evaluated	Age Cohort	N	Mean Rank	Chi-Square (H)	df	Asymp. Sig. (p)	Decision
Retail Purchase Decision (RPD)	18–25 Years	74	69.18	7.942	2	0.019	Significant (Reject H04)
	26–35 Years	38	59.21				
	Above 35 Years	13	38.85				
Choice Resolution (Creator Priority)	18–25 Years	74	71.05	10.114	2	0.006	Significant (Reject H04)
	26–35 Years	38	56.42				
	Above 35 Years	13	37.08				
Perceived Purchase Risk (PPR)	18–25 Years	74	56.84	8.652	2	0.013	Significant (Reject H04)
	26–35 Years	38	67.45				
	Above 35 Years	13	78.92				

Source: Primary data

The Kruskal-Wallis H test in Table No. 07 indicates significant differences across age cohorts in Retail Purchase Decisions ($H(2) = 7.942$, $p = 0.019$), Choice Resolution ($H(2) = 10.114$, $p = 0.006$), and Perceived Purchase Risk ($H(2) = 8.652$, $p = 0.013$). Younger consumers (18–25 years) demonstrate the highest conversion propensity (Mean Rank = 69.18) and creator fidelity (Mean Rank = 71.05). Conversely, consumers above 35 experience the highest perceived risk (Mean Rank = 78.92) and lowest purchase rates (Mean Rank = 38.85), indicating greater susceptibility to cart abandonment when recommendations diverge. Hence, null hypothesis H04 is rejected.

IX. Findings and Recommendations

Major Findings

- The empirical results demonstrate a decisive human advisory primacy during recommendation conflict, with 55.2% of surveyed retail consumers actively prioritizing creator endorsements over algorithmic suggestions. Multiple linear regression verifies that Human Creator Trust serves as the primary predictor of purchase decisions ($\beta = 0.315$, $p < 0.001$), substantially reinforced by Perceived Creator Authenticity ($\beta = 0.204$) and Parasocial Interaction ($\beta = 0.156$). Paired samples t-testing confirms that trust placed in human creators is significantly higher than trust in AI recommendation systems ($t = 4.085$, $p < 0.001$), substantiating the persuasive power of human empathy and experiential validation in online retail decision-making.
- Despite human dominance, algorithmic recommendation engines command substantial purchase conversion power ($\beta = 0.207$, $p = 0.001$), with nearly one-third of consumers (32.8%) deferring to automated algorithmic advice during direct conflict. Algorithmic transparency emerges as a pivotal prerequisite that directly enhances purchase commitment ($\beta = 0.165$, $p = 0.007$) and exhibits a robust positive correlation with AI trust ($r = 0.482$, $p < 0.01$). These findings verify that consumers do not exhibit blanket algorithm aversion, but rather demand clear operational insights into the underlying criteria, metric weightings, and catalog analytics governing the synthetic recommendation.
- Advisory discord between human creators and synthetic algorithms introduces acute informational dissonance that elevates Perceived Purchase Risk, which exerts a potent negative effect on checkout decisions ($\beta = -0.200$, $p = 0.001$). This psychological friction provokes decision paralysis, precipitating a 12.0% purchase abandonment or deferral rate among sampled shoppers. Recommendation divergence destabilizes consumer confidence, transforming smooth retail purchase journeys into high-involvement deliberations where buyers question the commercial motives of content creators while remaining skeptical of automated algorithmic platform neutrality.
- Non-parametric tests confirm marked demographic disparities in advisory trust and conflict resolution across gender and generational cohorts. The Mann–Whitney U test establishes that male shoppers report significantly higher algorithmic trust and demand for algorithmic transparency ($p < 0.05$), whereas female consumers prioritize creator authenticity and parasocial closeness ($p < 0.05$). Concurrently, the Kruskal–Wallis H test indicates that younger consumers aged 18–25 display the highest transactional velocity and creator allegiance, whereas shoppers aged above 35 experience the highest perceived risk (Mean Rank = 78.92) and lowest checkout completion rates.

Managerial Recommendations

- Digital retail platforms must re-architect recommendation interfaces by transitioning away from isolated, contradictory recommendation streams toward integrated, collaborative reconciliation modules. E-commerce systems should deploy hybrid interface widgets that explain why advisory divergences occur, highlighting creator aesthetic guidance alongside algorithmic price and specification benchmarks. Furthermore, platforms must embed accessible on-demand transparency toggles detailing machine ranking metrics, which directly alleviates algorithmic skepticism among female and mature shopping cohorts while enhancing overall interface credibility.
- Retail enterprise managers and digital brand strategists should calibrate promotional budgets according to merchandise characteristics and embed friction-mitigation mechanisms at checkout. Brands should invest in authentic creator collaborations for experiential and lifestyle categories where social connection dominates, while deploying algorithmic endorsement badges for utilitarian and technical items. To eliminate the 12% cart abandonment stemming from conflicting advice, retail apps must provide real-time decision-support tools such as side-by-side specification summaries and verified customer consensus ratings to resolve cognitive dissonance and maintain purchasing momentum.

X. Conclusion

This study provides theoretical and managerial contributions to retail consumer research by evaluating how shoppers adjudicate conflicting recommendations between human content creators and artificial intelligence systems. Grounded in survey data from Tiruchirappalli and evaluated through an expanded multi-factor structural model, the findings show that while human creators maintain primary persuasive authority through perceived authenticity, empathy, and parasocial connection, algorithmic systems serve as an essential secondary anchor through analytical competence and comparative objectivity. Advisory divergence generates informational dissonance and elevates purchase risk, which depresses checkout velocities unless mitigated by transparent algorithmic disclosures. By systematically aligning research questions, conceptual objectives, hypotheses, and multivariate empirical tests, this paper demonstrates that digital retail strategy must evolve beyond an adversarial view of human versus algorithmic influence, moving toward an integrated, transparent architecture where human authenticity and algorithmic precision reinforce consumer confidence.

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