The Influence of Artificial Intelligence-Generated Content on Consumers' Purchase Decision in E-commerce: An Action Mechanism Study

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Abstract. Consumers making choices in e-commerce are now organized by artificial intelligence-generated and -orchestrated content (AIGC). This study looks at two typical surfaces, namely, algorithmic recommendations and urgency cues, through an exploratory secondary analysis of a survey (N=102) of young and digitally active shoppers. This paper has constructed concise variables on the basis of the questionnaire, and reports descriptive statistics, chi-square screens as well as two parsimonious logistic regressions. Results indicate that reported influence by recommendations is positively associated with comfort about data collection and shopping frequency, while chatbot exposure shows a negative association; dynamic-pricing exposure shows a borderline positive signal. Reported influence by urgency messages is predicted by perceived preference accuracy and trust in AI over human service. AI familiarity, perceived intrusiveness, perceived bias, overall satisfaction, and basic demographics do not reach conventional significance in either model; chi-square tests similarly show no detectable segmentation by gender or education in the tested outcomes. Together, the findings suggest that influence depends less on generic awareness and more on situated perceptions (accuracy, trust, data comfort) and context of use (task readiness). This paper translates these patterns into actionable guidance on transparency, explainability, pricing fairness cues, chatbot orchestration, and responsible urgency, while noting limitations of sample scope, self-reporting, and model convergence.

Keywords: AIGC, e-commerce, recommender systems, consumer trust, urgency cues.

1. Introduction

Artificial intelligence has developed the AIGC that found its place in e-commerce through recommendation boxes, chatbots, and price cut banners [1]. The features minimize the amount of search and evaluation as well as personalizing the message to the villain [2]. At the center of the algorithmic mediation issue is the threat of privacy, which is indicative of the personalization-privacy paradox in online attention spaces [3].

The role of AIGC is conceptualized in a three-part process, such as reduction of decision-cost, alignment and trust of values, and conversion. Interactive decision aids and recommenders reduce the information overload and increase presumed diagnosticity of possibilities and thus reduce the choice frictions [4]. There is material difference in the design preference of the mode of explaining the recommendations, which affects acceptance and satisfaction [5].

The value alignment is based on what the system looks like in order to understand user preferences and behave in trustworthy and fairways [6]. The construction of trust is multi-dimensional, and it predicts e-commerce adoptions and purchasing intention [7]. The aspect of trusting and mistrusting beliefs in e-commerce websites influence the buying behavior online by facilitating or deterring the exchange [8]. Directed persuasion is intrusive and destroys the desire to interact with AI-driven products [9]. In the case of algorithmic pricing, perceptions of fairness in price also tend to be very sensitive with implications of trust and search behaviors [10].

The conversion step is partly regarding the intention to action in time and uncertainty. Meta-analytic evidence demonstrates that urgency and scarcity as signs of scarcity are effective shortcutters of deliberation and nudges purchases of products in any environment [11]. The current studies of the augmented reality show that more detailed try-on and visualization options prompt interest and desire to purchase by lowering uncertainties in fits [12]. The social dynamics of service encounters are changed by the AI chatbot disclosure and anthropomorphic cues and may shift the purchase outcomes [13]. Fairness concerns remain cross-cutting as bias perceptions affect acceptance of AI systems in recommender environments [14]. Model-agnostic explanations may bolster trust when they are faithful and comprehensible to lay users [15]. New research on visual explanation design for recommenders emphasizes rigorous, user-centered visualization strategies that make rationales actionable [16]. Social proof from online reviews also operates as a powerful heuristic that interacts with algorithmic guidance under bounded rationality [17].

Several gaps motivate the study. Much evidence focuses on a single modality or construct, which limits comparison across AI touchpoints in the same journey [2]. Platform- or feature-specific findings can be hard to generalize beyond the studied context [13]. Many studies prioritize attitudinal constructions such as the privacy calculus over behavioral endpoints, leaving a gap between perceptions and reported purchase influence [18]. Advocacy for explanations has outpaced evidence on how perceived preference accuracy and trust versus human service predict actual influence by AI content [19].

This paper addresses these gaps with an exploratory analysis of a public survey of AI in e-commerce (N=102) focused on a young, digitally active population. Two behavioral outcomes are operationalized: self-reported influence by AI recommendations and by urgency messages. Predictors capture decision-cost reduction (AI familiarity), value alignment (perceived preference accuracy and trust in AI), experience quality (overall satisfaction), and privacy/ethics attitudes (comfort with data collection, perceived intrusiveness, perceived bias). Usage context is represented by shopping frequency and exposure to recommendation engines, chatbots, dynamic pricing, and voice assistants.

This study contributes in three ways. First, it offers a compact mechanism-driven lens that links decision aids, trust/privacy calculus, and conversion cues in one empirical setup [4]. Second, it offers comparative evidence of what perceptions and touchpoints predict reported influence by recommending versus urgency prompts while foregrounding intrusiveness and fairness issues [9]. Third, it relates managerial levers (transparency, data practices, and tool mix) to active e-commerce cohort observable outcomes [1]. The remainder proceeds with Method, Data Analysis, Findings & Recommendations, and Conclusion, with implications for fairness-aware and explainable AIGC pipelines highlighted in closing [20].

2. Methodology

2.1. Research Design and Data

This study employs a quantitative, cross-sectional design using a public survey titled The Influence of AI in E-Commerce(N=102), which primarily captures young, digitally active consumers suited to examining AIGC in shopping contexts [1]. Because responses are self-reported and collected at a single time point, the analysis is exploratory and emphasizes associations rather than causality [6]. The conceptual framing follows an AIGC mechanism spanning decision-cost reduction, value alignment and trust, and conversion outcomes that are salient in e-commerce interfaces [2].

Data was prepared via a reproducible Python pipeline (pandas, SciPy, statsmodels), with long question texts renamed to concise analytic labels (e.g., ai_familiarity, rec_influence, urgency_influence) to support transparent modeling and explainable presentation of outputs [19]. The multi-select AI-tool item was expanded into binary indicators—tool_reco(recommendation engines), tool_chatbot (chatbots/virtual assistants), tool_dynprice (dynamic pricing systems), and tool_voice (voice assistants)—plus a tool_count summary to represent exposure intensity, following standard practice in recommender-systems analysis [11]. This representation aligns with recent accounts of heterogeneous user touchpoints in fairness-aware recommender ecosystems [17].

2.2. Measures and Variable Construction

Reported behavioral influence is measured with two binary outcome variables: recinfluencebin equals 1 when the respondents indicated that the algorithmic recommendations influenced their purchases and 0 otherwise, and urgencyinfluencebin equals 1 when the messages of urgency influenced their purchases and 0 otherwise [4].Operationalization of the mechanism in the explanatory variables is as follows: decision-cost minimization through aifamiliarity (0-3) reflecting the awareness of platform AI capabilities which have the ability to compress search and evaluation time [2]. Value alignment and trust via pref_accuracy(0–2) and trust_ai (0/0.5/1), capturing whether the system seems to understand the user and whether AI is preferred to human service in customer support contexts [8].

Usage-context controls include shop_freq (0–2) and the four tool indicators to account for differential exposure to recommendation, conversational, pricing, and voice interfaces embedded in e-commerce journeys [1].

2.3. Analytical Strategy

Descriptive statistics were employed to characterize the empirical backdrop of a youth-skewed e-commerce cohort. Data was reported on numbers and percentages of age, gender, education, occupation, and shopping frequency with a distribution summary on AI familiarity, perceived preference accuracy, trust of AI and human services, overall shopping satisfaction, and privacy/ethical attitudes. Presentation was deliberately given in a sparse manner in order to have face validity of respondents being active online shoppers who frequently see AIGC surfaces [1].

Pearson chi-square tests of independence with a=0.05 were selected as the screening test of bivariate relationships between demographics and focal outcomes. The use of contingency tables and precise p-values were used to demonstrate the strength of evidence but not causality. Cell counts were observed as expected; sparse or weak cells had been considered an interpretive warning, and non-rejections were scored as no detectable segmentation instead of finding evidence of equivalence. To reduce the risks of multiple comparison in a small sample and focus tests on the constructs emphasized in recent syntheses of buyer trust and mistrust on e-commerce sites, the screening of the hypothesis was narrowed down to three pre-specified pairs: gender x trust in AI, education x recommendation influence, and gender x urgency influence [10].

Reported influence predictors were then measured using two maximum-likelihood logistic regressions using parsimonious specifications to control overfitting. Model 1 targeted rec_influence_bin (influence by recommendations); Model 2 targeted urgency_influence_bin (influence by urgency messages). Each model included mechanism-aligned covariates—AI familiarity (0–3), perceived preference accuracy (0–2), trust in AI (0/0.5/1), shopping satisfaction (−2…+2), comfort with data collection (0–2), perceived intrusiveness of ads (0–3), and perceived AI bias (0–2)—alongside usage-context controls (shopping frequency, plus indicators for recommendation engines, chatbots, dynamic pricing, and voice assistants) and sociodemographic factors entered as categorical terms for gender and education. Ordinal items were encoded as ordered scores to preserve monotonicity and interpretability, avoiding unnecessary parameter proliferation typical of fully saturated dummy schemes for graded responses [7].

3. Data Analysis

3.1. Sample Characteristics

The sample size of this study is 102 (N=102), and the sample structure shows distinct group characteristics, with young people and students as the core, and generally with high education level and high-frequency contact with e-commerce, which is highly consistent with the mainstream user portraits in the current online consumer market. The sample (N=102) is predominantly young and student-oriented, with high educational attainment and regular exposure to e-commerce. Table 1 consolidates the core descriptors. Respondents are mostly 18–25 (87.3%) and students (68.6%); males account for 62.7%. Nearly 90% have undergraduate or postgraduate education. Shopping frequency is concentrated in occasional (once/month) and frequent (once/week+) segments (47.1% and 28.4%, respectively), indicating an active online-shopping population.

Table 1. Sample characteristics (N=102)

Variable	Category	n	%
Age group	18–25	89	87.3
	26–40	11	10.8
	Above 40	2	2
Gender	Male	64	62.7
	Female	37	36.3
	Prefer not to say	1	1
Education	Postgraduate	50	49
	Undergraduate	41	40.2
	High School or below	8	7.8
	Doctorate/Professional	3	2.9
Occupation	Student	70	68.6
	Employed	16	15.7
	Unemployed	13	12.7
	Self-employed	2	2
	Retired	1	1
Shopping frequency	Occasionally (once a month)	48	47.1
	Frequently (once a week or more)	29	28.4
	Rarely	23	22.5
	Never	2	2

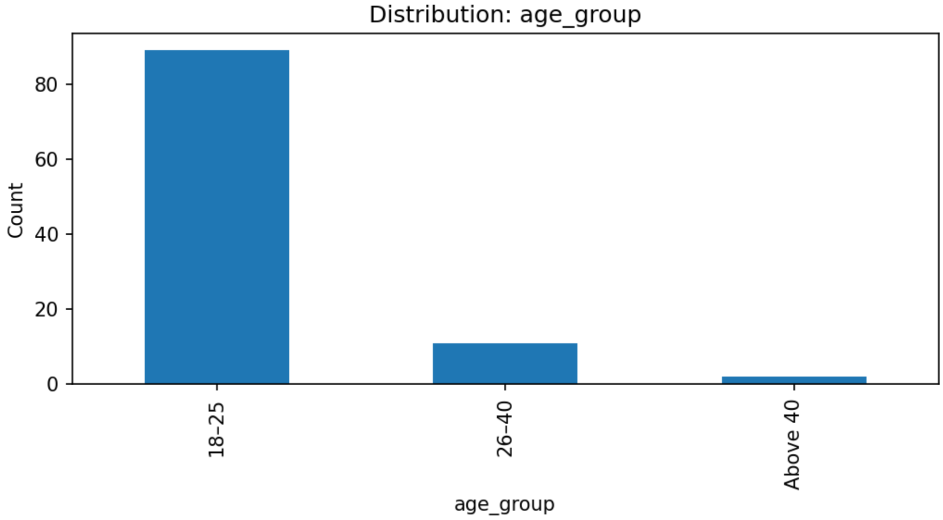

Figure 1. Age distribution (dominant 18–25 cohort)

As shown in Figure 1, the sample is heavily youth-skewed, with ages 18–25 comprising about 87 percent, 26–40 about 11 percent, and above 40 roughly 2 percent.

3.2. AI Exposure and Usages

Self-reported familiarity with AI features clusters at the upper end of the 0–3 scale (histogram mass around scores 2–3), and overall shopping satisfaction skews positive (−2…+2 agreement scale concentrated near +1 to +2). Regarding concrete touchpoints, product-recommendation engines dominate user interaction, followed by chatbots, dynamic pricing, and voice assistants (Table 2).

Table 2. AI tools encountered (count and share)

Tool	n	%
Recommendation engines	66	64.7
Chatbots / virtual assistants	42	41.2
Dynamic pricing systems	32	31.4
Voice-based shopping assistants	22	21.6

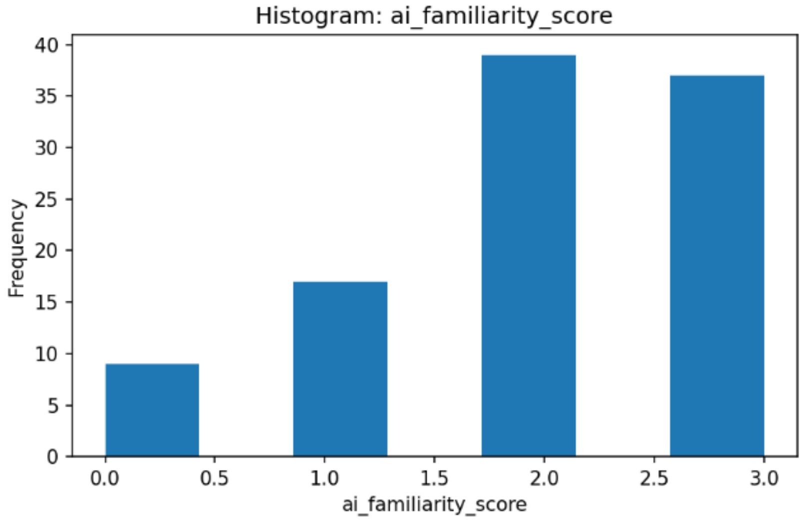

Figure 2. AI familiarity score (0–3) — mass at 2–3.

As shown in Figure 2, AI familiarity is skewed toward the upper end, with most respondents reporting scores of two or three and relatively few at zero or one.

3.3. Cross-Tabulations

Pearson chi-square tests were used to screen for bivariate associations between demographics and focal outcomes. None of the tested pairs reached conventional significance (α=0.05), indicating no detectable demographic segmentation in these specific splits (Table 3).

Table 3. Chi-square tests (summary)

Pair	χ^2	df	p
Gender × Trust AI (binary)	3.04	2	0.218
Education × Influenced by AI recommendations	1.56	3	0.668
Gender × Influenced by urgency messages	1.42	2	0.492

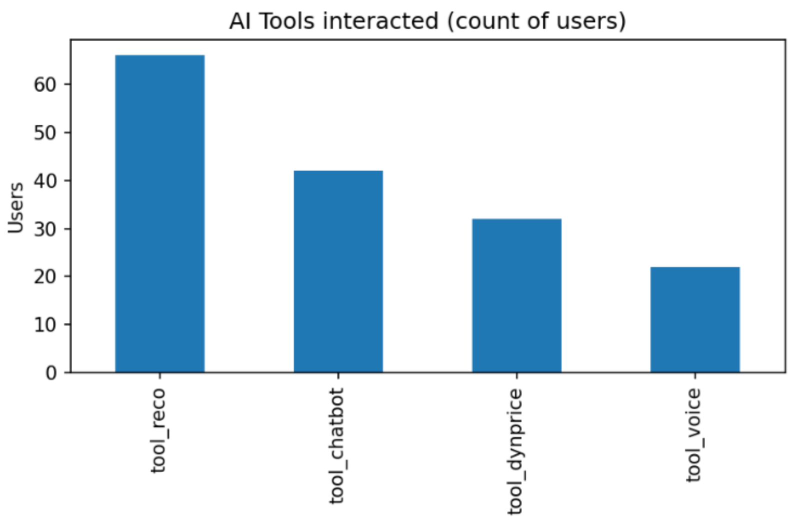

Figure 3. Most frequent touchpoint is recommendation engines

As shown in Figure 3, recommendation engines are the dominant touchpoint, followed by chatbots, then dynamic pricing, with voice assistants least encountered.

3.4. Logistic Regressions

Two parsimonious logit models quantify predictors of (i) being influenced by AI recommendations and (ii) being influenced by urgency cues. Both models use listwise deletion (N=90) and report odds ratios (OR) with 95% CIs; software flags non-convergence, so estimates are interpreted cautiously, though model LLR tests are significant.

As shown in Figure 4, the recommendations model fits reasonably well with pseudo-R squared 0.381, AIC 101.83, and a significant likelihood ratio test. Reported influence rises with comfort about data collection with odds ratio 3.93 and with shopping frequency with odds ratio 4.16, whereas chatbot exposure relates negatively with odds ratio 0.13. Dynamic pricing shows a borderline positive signal with odds ratio 6.05, and other attitudinal and demographic factors are not significant at the conventional five percent level.

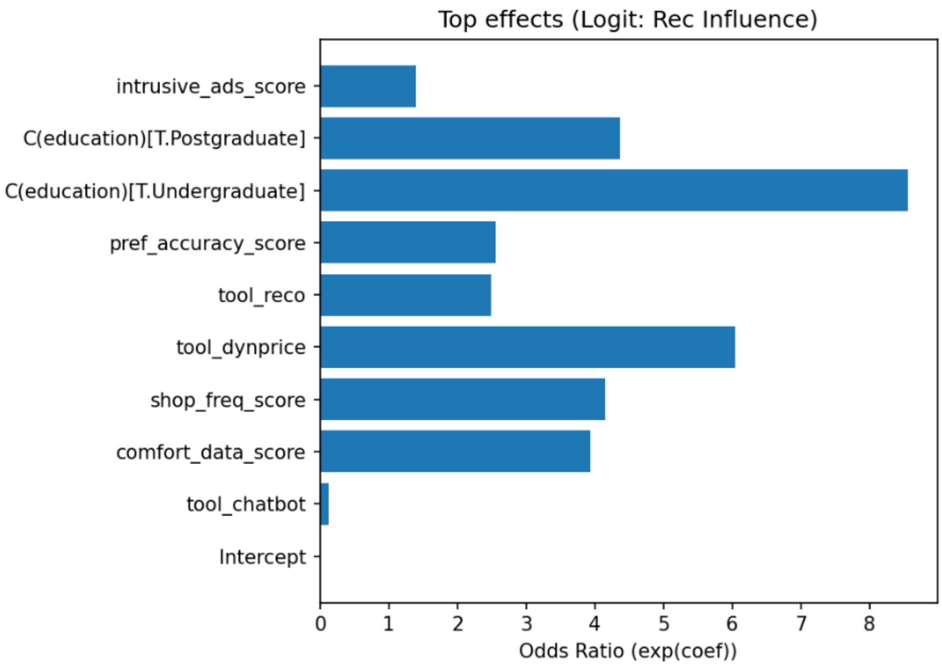

Figure 4. Top effects (OR) — influenced by recommendations

As shown in Figure 5, the urgency model demonstrates reasonable fit with a pseudo-R squared of 0.417, an AIC of 107.03, and a highly significant likelihood ratio test with a p value of 0.0000308. Reported influence by urgency messages increases with perceived preference accuracy, with an odds ratio of 5.84 and a ninety five percent confidence interval from 1.20 to 28.47 and a p value of 0.029, and it also increases when respondents trust AI over human service, with an odds ratio of 12.21 and a ninety five percent confidence interval from 1.39 to 107.43 and a p value of 0.024.

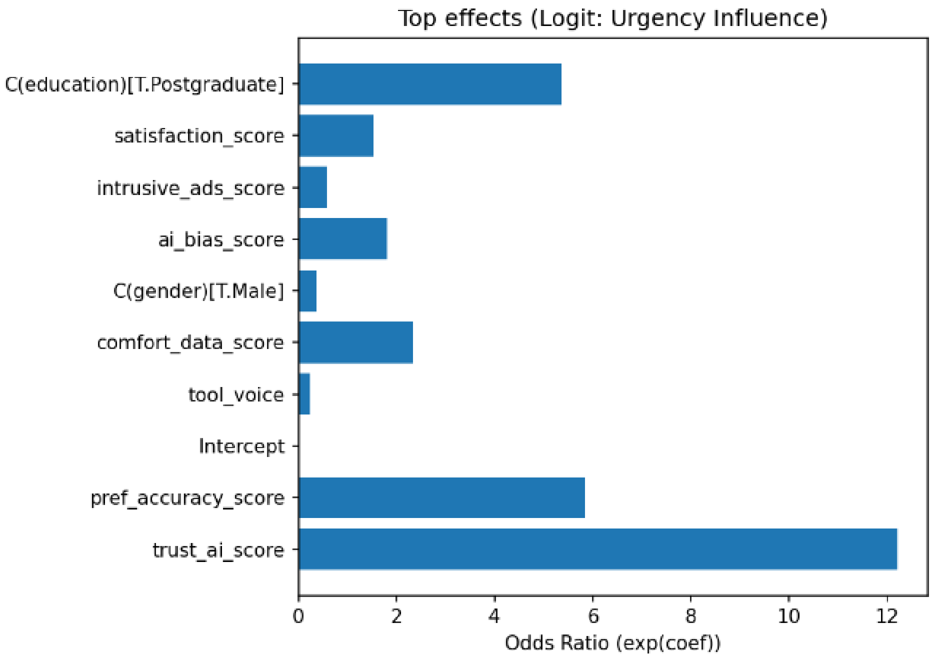

Figure 5. Top effects (OR) — influenced by urgency cues

4. Findings & Recommendation

4.1. Key Empirical Findings

Across outcomes and diagnostics, two clear patterns emerge. First, reported influence by AI recommendations rises with comfort about data collection and shopping frequency (Model 1: OR=3.93 and OR=4.16, both $p<.05$), while chatbot exposure is negatively associated with such influence (OR=0.13, $p<.05$). A borderline positive signal appears for dynamic-pricing exposure (OR=6.05, $p=.067$). In contrast, AI familiarity, perceived intrusiveness of ads, perceived bias, overall satisfaction, and gender/education indicators do not reach significance in this model. Model fit is acceptable for exploratory work (Pseudo $R^2=.381$; significant LLR), though estimation flags advise caution due to the modest sample.

Second, the reported influence of urgency messages is related to the perceived preference accuracy and trust in AI compared to human service (Model 2: OR=5.84 and OR=12.21, both $p<.05$). Other attitudinal and usage variables—including AI familiarity, satisfaction, privacy comfort, perceived intrusiveness/bias, shopping frequency, and tool indicators—do not reach conventional significance in this model. Fit again indicates meaningful explanatory power for a small-N survey (Pseudo $R^2=.417$; significant LLR), with the same caveat on convergence. Complementary chi-square screens reveal no detectable segmentation by gender or education in trust, recommendation influence, or urgency influence, suggesting that the drivers captured here operate within demographic groups rather than between them.

Taken together, the evidence points away from generic "AI awareness" as the lever and toward situated perceptions and context of use: recommendations are accepted when the environment feels safe and the shopper is already active, while urgency cues convert when personalization feels accurate and the AI agent is trusted.

4.2. What the Findings Implys

These findings are consistent with a mechanism perspective of AIGC in business. The recommendation effect is the most significant on decision-cost reduction among respondents with more frequent shoppers and are more comfortable with data practices. Practically, it means that the same recommendation unit can be used to carry out the same tasks under radically different conditions based on the level of the task readiness and privacy posture: extensive shoppers might view algorithmic recommendations as a filter, but this filter is still conditional upon the credible license to act issued through transparent and non-intrusive information manipulation. The absence of a substantial role of the familiarity of AI supports the idea that procedural trust (the way data is processed) is of more importance than declarative awareness (the awareness of AI features).

On value alignment and trust, urgency messages only shift the behavior when the user is convinced that the system actually comprehends their preferences, and they trust the AI channel. Preference understanding is weak or the need to use AI is less acceptable than human service, and urgency will be discounted or even regarded as noise. The insignificance of perceived intrusiveness and bias in these models indicates that, in this case, with this young cohort, positive alignment cues (accuracy, trust) take a paramount role, not because dark patterns are benign, but merely because they were not significant in explaining variance in this study.

Lastly, the channel effects are important. These adverse effects of chatbot exposure and recommendation suggest that not all conversational experiences contribute to the insensitivity or difficulty at the browsing phase, which in turn diminishes the responsiveness to the subsequent stage of openness to recommendation. On the other hand, the positive but border correlation between fairness cues observed in dynamic pricing indicates that it is possible that this lever has an upside, but it also indicates that the lever is sensitive and will probably rely on transparency, reference points, and perceived boundaries.

4.3. Recommendations

For e-commerce firms. Replace blanket consent banners with plain-language notices, granular toggles, and just-in-time prompts that show specific value.

Strengthen alignment signals by improving preference modeling and giving users lightweight controls (“more/less like this,” hide brands/categories), then recycle those explicit signals into ranking. Use responsible urgency: personalize thresholds, avoid manipulative countdowns, cap frequency per session, and log both conversion uplift and complaint/opt-out rates to police overuse.

For regulators and standard-setters. Require clear AIGC labeling on key surfaces (recommendations, chatbots, urgency banners) so users can recognize automated content. Mandate succinct disclosures for dynamic pricing scope, guardrails, and recourse. Encourage periodic fairness and drift audits for recommendation and promotion pipelines, with outcomes tracked by segment.

For consumers. Treat urgency as a cue, not a command: compare alternatives and, where available, view price histories or benchmarks before acting. With time, those practices will boost the possibility of AI support being perceived as an extension and not obtrusive.

5. Conclusion

This study investigated the relationship between AI-mediated content and self-reported purchase influence in e-commerce and identified the difference in effects of algorithmic recommendation and urgency cues among a sample of young and digitally active individuals (N=102). This paper estimated how recommendation influence relates with a transparent variable construction and two parsimonious logistic models and discovered that the strongest relationship occurs between recommendation influence and comfort about data collection, as well as shopping frequency; exposure to chatbots has a negative relationship; dynamic pricing exposure has a marginal positive indicator. Probably, in contrast, urgency influence is associated with perceived preference accuracy and trust in AI more than to human service. On the complementary chi-square displays, this paper saw no apparent gender or education segmentation of the outcome tests conducted indicating that the driving operative levers in this cohort are perception of alignment or data practices and not the general demographics.

In substantive terms, these findings indicate a process whereby recommendations take hold when users are already involved in the task and where they believe that data practices provide a valid license to operate, whilst urgency takes place when the system appears to know the individual and the AI channel is rising to the occasion. However, it should be mentioned that generic AI familiarity, perceived intrusiveness, perceived bias, and overall satisfaction were not strongly expressed in both models that imply that particular and situational beliefs about accuracy, trust, and data comfort have a stronger impact on whether AI content influences decisions or not. The estimation diagnostics show that non-convergence is not observed, but both the likelihood-ratio tests and the effect sizes provide the same directionality of results.

The analysis accumulates the evidence-based view, which links decision-cost reduction, value alignment and trust, and conversion cues in one empirical model and transfers the relationship to product and policy levers. At the same time, the limitations of the sample size and bias toward the younger generation, cross-sectional and self-report data, and the smallness of the categories may result in the estimation of some factors. The suggested future studies should take into account the temporal priority of the survey by integrating it with behavioral telemetry and field experiments that would expand the demographic and cultural scope and introduce elements of fairness and explainability in accordance with the business Key Performance Indicators.

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