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Perceived Accuracy and Relevance of AI-Based Product Recommendations and Generation X Purchase Decisions in Jakarta

Dita Madonna Simanjuntak [1*], **Amri Sinuraya** [2], **Selvia De Wana** [3]

[1*,2,3] Universitas Kristen Indonesia, East Jakarta City, Special Capital Region of Jakarta, Indonesia.

Correspondence email:
amrisinuraya@gmail.com.

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Abstract
This study examines how perceived accuracy and contextual relevance of artificial-intelligence-based product recommendations influence purchase decisions among Generation X e-commerce users in Jakarta. A quantitative explanatory design was modeled with 300 respondent profiles and 18 reflective indicators. Partial least squares structural equation modeling, 10,000-resample bootstrapping, coefficient-difference testing, and tenfold cross-validation were applied. Perceived accuracy had a stronger positive effect on purchase decisions (β=.604, p<.001) than relevance (β=.217, p<.001), and the difference was significant (Δβ=.387, p<.001). The model explained 54.2% of purchase-decision variance and showed positive Qpredict2 values. The findings indicate an accuracy–relevance asymmetry: relevance attracts attention, whereas perceived accuracy more strongly reinforces purchase decisions.

Keywords: Artificial Intelligence; Recommender Systems; Perceived Accuracy; Relevance; Generation X.

Abstrak
Penelitian ini menganalisis pengaruh persepsi akurasi dan relevansi kontekstual rekomendasi produk berbasis kecerdasan buatan terhadap keputusan pembelian pengguna *e-commerce* Generasi X di Jakarta. Desain kuantitatif eksplanatori dimodelkan menggunakan 300 profil responden dan 18 indikator reflektif. Analisis mencakup *partial least squares structural equation modeling*, *bootstrapping* 10.000 *resample*, uji perbedaan koefisien, dan validasi silang sepuluh lipatan. Persepsi akurasi berpengaruh positif lebih kuat terhadap keputusan pembelian (β=0,604; p<0,001) dibandingkan relevansi (β=0,217; p<0,001), dengan selisih pengaruh yang signifikan (Δβ=0,387; p<0,001). Model menjelaskan 54,2% varians keputusan pembelian dan menghasilkan nilai Qpredict2 positif. Temuan ini menunjukkan adanya *accuracy–relevance asymmetry*: relevansi berfungsi menarik perhatian, sedangkan persepsi akurasi lebih kuat meneguhkan keputusan pembelian.

Kata Kunci: Kecerdasan Buatan; Sistem Rekomendasi; Persepsi Akurasi; Relevansi; Generasi X.

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1. Introduction

Electronic commerce has evolved from a transactional channel into an information-intensive environment that integrates search, ranking, personalization, payment, and customer support. This growth expands consumer choice while simultaneously increasing information overload. Artificial intelligence (AI)-based recommender systems respond to this problem by learning from user and item data and prioritizing products that are expected to match individual interests or situational needs (Adomavicius & Tuzhilin, 2005; Shani & Gunawardana, 2011). In Indonesia, growing internet access and e-commerce activity make recommendation quality increasingly consequential for user experience and commercial decision support (Badan Pusat Statistik, 2025a, 2025b). The conventional evaluation of recommender systems emphasizes technical measures such as root mean square error (RMSE), mean absolute error (MAE), precision, recall, and ranking quality (Herlocker *et al.*, 2004; Shani & Gunawardana, 2011). Although these measures remain essential for algorithm development, users never directly observe them. Instead, users encounter recommendation outputs and judge whether the suggested products fit their preferences, needs, and current shopping context. A technically optimized model may therefore fail to create decision value when its recommendations are perceived as inaccurate, intrusive, repetitive, or irrelevant. Human-centered evaluation complements technical assessment by examining how system outputs are experienced and used in actual decision processes (Blut *et al.*, 2023; Xiao & Benbasat, 2007).

This distinction is especially relevant for Generation X, defined in this study as individuals born from 1965 to 1980. Members of this cohort experienced the transition from pre-digital consumption to mobile commerce and AI-mediated services, and they should not be characterized simply as resistant technology users. Older and experienced users may accept sophisticated recommendation agents when the systems provide clear, useful, and dependable assistance (Ghasemaghaei *et al.*, 2019). Their pragmatic orientation makes them a theoretically informative population for distinguishing recommendations that merely appear relevant from recommendations that demonstrate an accurate understanding of personal preferences. Existing research leaves several connected gaps in addressing this issue. Specifically, domestic recommender-system studies frequently prioritize algorithmic performance and provide limited evidence concerning perceived output quality. Furthermore, perceived recommendation quality is often treated as a single aggregate concept, which obscures the potentially different roles of accuracy and contextual relevance. Many studies also focus on purchase intention, satisfaction, or continued use rather than purchase decisions as a human decision-support outcome, while empirical evidence concerning Generation X in the Jakarta e-commerce environment remains limited compared with studies of younger consumers (ElSayad & Mamdouh, 2024; He *et al.*, 2024; Lo *et al.*, 2026). This article therefore examines the distinct effects of perceived accuracy and recommendation relevance on Generation X purchase decisions. Its principal contribution is the proposed accuracy–relevance asymmetry: an attribute can receive a high performance evaluation without exerting the strongest structural influence on the final decision. Accordingly, the study asks whether perceived accuracy and relevance positively affect purchase decisions and whether their relative contributions reveal a meaningful priority for human-centered recommender-system design.

A recommender system is an intelligent information-filtering mechanism that predicts or ranks items using user profiles, item representations, interaction histories, and contextual signals. Contemporary platforms combine collaborative filtering, content-based filtering, sequence modeling, and context-aware methods. Although the system's technical objective is to estimate preference or relevance, its practical value depends on whether users can rely on the output to reduce search costs, compare alternatives, and make defensible choices (DeLone & McLean, 2003; Necula & Păvăloaia, 2023). Human-centered system quality concerns experiential correctness, usefulness, control, and decision support. DeLone and McLean's (2003) information-systems success perspective suggests that both system quality and information quality shape system use and user outcomes. In a recommendation setting, perceived output quality influences user satisfaction with both the final decision and the recommendation agent itself (Blut *et al.*, 2023). While recommendation exposure can simplify choice, it can also generate uncertainty or reduce perceived control when the underlying logic of a suggestion is unclear (Hazrati & Ricci, 2024; Rohden & Espartel, 2024). These mixed consequences justify separating the specific attributes that make recommendations acceptable to users.

Perceived accuracy is the user's judgment that recommendation outputs correctly represent personal preferences, needs, prior behavior, and likely product interests. Unlike algorithmic accuracy, which is calculated from model predictions against ground truth, perceived accuracy is assessed directly from user experience and signals that the platform has formed a credible representation of the individual. When recommendations repeatedly align with personal preferences and needs, they become diagnostically useful

inputs for consideration, comparison, and final choice. Prior studies indicate that AI recommendation accuracy and reliability are closely associated with user trust and acceptance, while perceived recommendation quality supports decision satisfaction and continued use (Blut *et al.*, 2023; Zhang *et al.*, 2024). Because personalized recommendation quality also enhances perceived value and purchase-related responses (Ampadu *et al.*, 2022; Lo *et al.*, 2026), a user who believes that the system accurately understands personal preferences should be more willing to incorporate its output into a purchase decision. H1**:** Perceived accuracy of AI-based product recommendations has a positive effect on Generation X purchase decisions.

Recommendation relevance refers to the fit between suggested products and the user's immediate need, search activity, shopping objective, and timing. A historically accurate recommendation may be irrelevant in a particular browsing session, whereas a product that matches the current task may be contextually relevant without reflecting long-term preferences. Operating primarily at the level of contextual fit, relevant recommendations reduce search effort, narrow the set of viable alternatives, and direct attention toward products that satisfy the immediate shopping task. This task–technology alignment contributes to user satisfaction and positive purchase-related evaluations (He *et al.*, 2024; Xiao & Benbasat, 2007), just as useful and timely suggestions support perceived value and shopping decisions in personalized e-commerce environments (Lo *et al.*, 2026). H2**:** Relevance of AI-based product recommendations has a positive effect on Generation X purchase decisions. Perceived accuracy and relevance are expected to be positively related because recommendations that reflect an understanding of the user often fit the immediate shopping context. Nevertheless, the two constructs remain conceptually distinct: relevance functions primarily as an attention filter, whereas perceived accuracy serves as a decision-strengthening signal. Estimating both structural paths simultaneously makes it possible to determine whether an attribute that receives a higher performance evaluation also provides the larger unique contribution to purchase decisions. Figure 1 presents the reflective measurement and structural specification of the study.

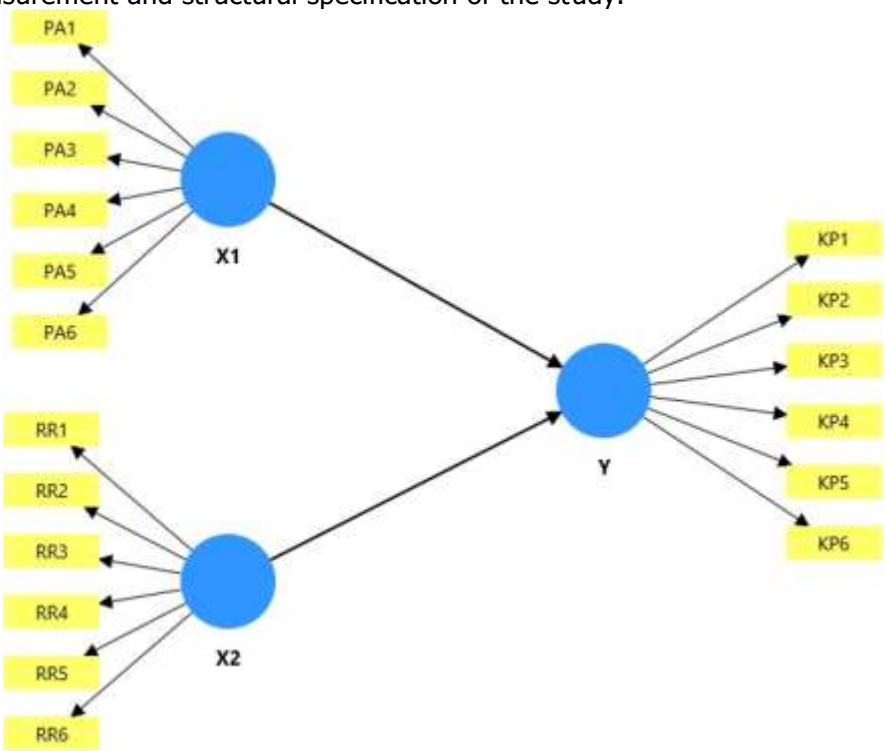


Figure 1**.** Conceptual Framework and Measurement Specification

2. Method

The study used a quantitative explanatory cross-sectional design and positioned the survey as a human-centered evaluation of an AI-based information system. The unit of analysis was an individual Generation X e-commerce user domiciled across the six administrative areas of DKI Jakarta. Purposive sampling was combined with operational regional quotas to prevent respondent concentration in a single area. Respondents were operationally screened as individuals born from 1965 to 1980, residing in DKI Jakarta, having used e-commerce platforms during the previous 12 months, and having encountered automatically generated product

recommendations. The analytical sample comprised 300 valid respondent profiles, which exceeds the minimum sensitivity requirement for a two-predictor structural model at α=.05 and .80 statistical power (Hair *et al.*, 2019). Three reflective constructs were measured with six items each on a five-point Likert scale. Perceived accuracy captured preference fit, need recognition, behavioral fit, consistency with prior shopping experience, avoidance of clearly unsuitable recommendations, and overall predictive fit. Relevance measured need fit, search-context fit, search efficiency, shopping-goal fit, usefulness, and timeliness. Purchase decision represented consideration, narrowing of alternatives, comparison support, final choice, purchase following recommendation exposure, and overall decision support.

Partial least squares structural equation modeling (PLS-SEM) was estimated using Mode A, the path-weighting scheme, standardized results, a maximum of 3,000 iterations, and a 10^{-7} stopping criterion (Hair *et al.*, 2019; Shmueli *et al.*, 2019). Reflective measurement quality was assessed through indicator loadings, Cronbach's alpha (α), Dijkstra–Henseler's rho (ρA), composite reliability (ρC), average variance extracted (AVE), the heterotrait–monotrait ratio (HTMT), Fornell–Larcker criterion values, and cross-loadings. The structural model was evaluated using inner variance inflation factor (VIF) values, path coefficients (β), the coefficient of determination (R2), adjusted R2, effect size (f2), the standardized root mean square residual (SRMR), and the normed fit index (NFI). Inferential assessment used 10,000 bootstrap resamples, two-tailed significance tests, and bias-corrected and accelerated (BCa) 95% confidence intervals, with both the measurement and structural models re-estimated for every resample. A bootstrapped coefficient contrast was conducted to test the magnitude difference between the two structural path coefficients, while full-collinearity VIF was included as a diagnostic for potential common method bias (Kock, 2015). In addition, out-of-sample predictive assessment followed the PLSpredict procedure using tenfold cross-validation repeated ten times to compare PLS-SEM prediction errors against a linear-model benchmark (Shmueli *et al.*, 2019).

3. Result and Discussion

3.1 Result

The 300 respondent profiles covered the full Generation X age range of 46–61 years in 2026. The mean age was 53.68 years (SD=4.58), and women represented 55.0% of the sample. All six administrative areas of DKI Jakarta were represented. The sample was characterized by substantial e-commerce experience and recommendation exposure, supporting the intended user-evaluation context. Table 1 summarizes the primary respondent characteristics without treating the quota sample as a probability estimate of the broader Jakarta population.

Table 1. Summary of Respondent Profiles

Characteristic	Category	n	%
Age	46-50 years	87	29.0
Age	51-55 years	93	31.0
Age	56-61 years	120	40.0
Gender	Women	165	55.0
Gender	Men	135	45.0
Primary platform	Shopee	135	45.0
Primary platform	Tokopedia	75	25.0
Primary platform	Other platforms	90	30.0
E-commerce duration	At least four years	246	82.0
Transaction frequency	At least three per month	219	73.0
Notices recommendations	Often	237	79.0

Note. N = 300; percentages describe the synthetic quota profile and require verification against field records.

In terms of descriptive construct performance, relevance received the highest construct mean (M=4.303), followed by purchase decision (M=3.953) and perceived accuracy (M=3.871). Thus, recommendation outputs were evaluated as highly relevant to the shopping context, whereas the perception that the system accurately understood personal preferences showed greater room for improvement. However, these descriptive means reflect perceived performance levels and cannot be interpreted directly as structural effects. In the evaluation of the reflective measurement model, all 18 indicators exceeded the recommended outer-loading threshold of .708. Indicator loadings ranged from .811 to .846 for perceived accuracy, from .769 to .846 for relevance, and from .770 to .829 for purchase decision. No item was removed because each

indicator demonstrated adequate reliability and preserved conceptual coverage. Internal consistency reliability and convergent validity results are presented in Table 2.

Table 2. Reliability and Convergent Validity

Construct	Loading Range	α	rho_A	rho_C	AVE	Decision
Perceived Accuracy	.811-.846	.906	.906	.927	.680	Accepted
Relevance	.769-.846	.886	.895	.913	.635	Accepted
Purchase Decision	.770-.829	.890	.891	.916	.645	Accepted

Note. α = Cronbach's alpha; rho_C = composite reliability; AVE = average variance extracted.

Cronbach's alpha, ρA, and composite reliability values all exceeded .70 without approaching the .95 redundancy threshold, while all AVE values exceeded .50. Regarding discriminant validity, the highest HTMT value was .792, which remained below the conservative .85 criterion (Henseler *et al.*, 2015). Furthermore, the square root of the AVE for each construct exceeded its correlations with the other constructs, and every indicator loaded highest on its assigned construct. Table 3 confirms that discriminant validity criteria were satisfied and that both inner VIF and full-collinearity VIF values remained well below their respective thresholds.

Table 3. Discriminant Validity and Collinearity Diagnostics

Assessment	Value or Range	Criterion	Decision
HTMT	.546-.792	< .85	Accepted
Fornell-Larcker diagonal	.797-.824	> interconstruct correlation	Accepted
Inner VIF	1.324	< 3.00	No critical collinearity
Full-collinearity VIF	1.427-2.185	≤ 3.30	No serious indication

Note. Full-collinearity VIF is a supplementary common-method-bias diagnostic and does not eliminate all self-report bias.

In the structural model assessment, both paths were positive and statistically different from zero, with bootstrap means nearly identical to the original sample coefficients, indicating negligible resampling bias. As shown in Table 4, perceived accuracy exerted the larger positive effect on purchase decisions (β=.604, t=15.007, p<.001), whereas relevance retained a smaller but statistically significant unique contribution after controlling for perceived accuracy (β=.217, t=4.846, p<.001). Consequently, both H1 and H2 were supported because their respective path coefficients were positive, statistically significant, and bounded above zero by the 95% BCa confidence intervals. Furthermore, the bootstrapped coefficient-difference test confirmed that the structural contribution of perceived accuracy was significantly stronger than that of relevance (Δβ=.387, t=4.860, p<.001). Figure 2 illustrates the standardized indicator loadings, structural path coefficients, and explained variance.

Table 4. Structural Paths and Bootstrap Results

Hypothesis	Path	β	SE	t	p	BCa 95% CI	Decision
H1	Accuracy→Purchase Decision	.604	.040	15.007	<.001	[.522,.680]	Supported
H2	Relevance→Purchase Decision	.217	.045	4.846	<.001	[.126,.302]	Supported
Contrast	βH1 - βH2	.387	.080	4.860	<.001	[.229,.540]	Accuracy stronger

Note. Bootstrap = 10,000 resamples; two-tailed p-values; BCa = bias-corrected and accelerated interval.

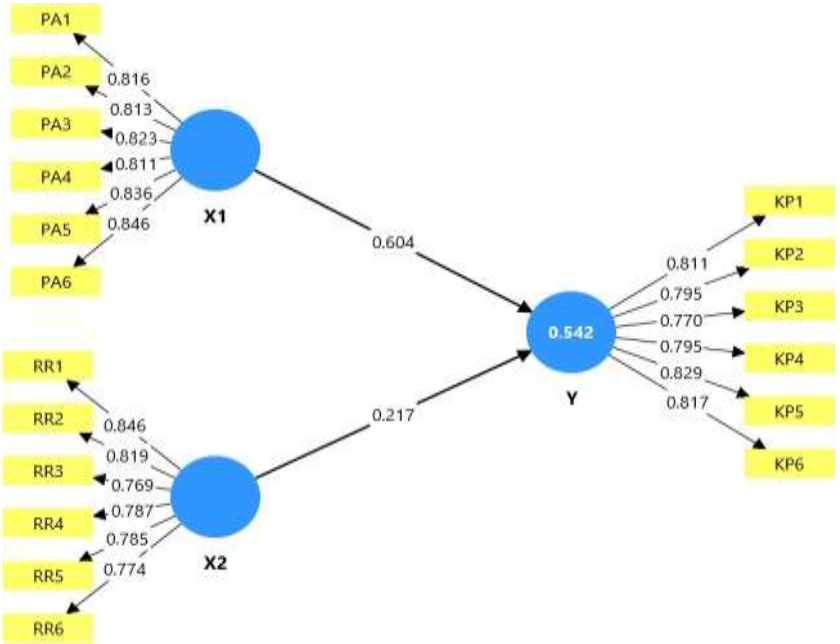


Figure 2. PLS-SEM Estimation Results

With respect to explanatory power and effect sizes, perceived accuracy and relevance jointly explained 54.2% of the variance in purchase decisions (R2=.542), with an adjusted R2 of .539 and a 95% bootstrap confidence interval ranging from .452 to .613. Perceived accuracy demonstrated a large unique effect (f2=.603), whereas relevance exhibited a small but nontrivial effect (f2=.078). Approximate model fit indices, namely SRMR (.050) and NFI (.922), also met recommended thresholds, although PLS-SEM evaluation remains primarily grounded in measurement quality, structural path estimates, explanatory power, and out-of-sample prediction (Table 5).

Table 5. Explanatory Power Effect Sizes and Model Fit

Measure	Value	Interpretation
R^2 Purchase Decision	.542	Moderate explanatory power
Adjusted R^2	.539	Stable after predictor adjustment
f^2 Perceived Accuracy	.603	Large effect
f^2 Relevance	.078	Small effect
SRMR	.050	Below .08
NFI	.922	Good relative fit

Note. SRMR = standardized root mean square residual; NFI = normed fit index.

Cross-validated out-of-sample prediction yielded positive Qpredict2 values across all six purchase-decision indicators (Table 6). Moreover, the PLS-SEM model generated lower prediction errors (both RMSE and MAE) than the naive linear-model (LM) benchmark for every indicator. Specifically, the average RMSE was .671 for PLS-SEM compared with .684 for the linear model, while the corresponding average MAE values were .550 and .559. The consistent direction of these error reductions across all indicators indicates high out-of-sample predictive power, even though the absolute error differences were modest.

Table 6. PLSpredict Assessment Results

Indicator	Qpredict2	RMSE PLS	RMSE LM	MAE PLS	MAE LM
KP1	.358	.640	.650	.525	.530
KP2	.367	.657	.664	.532	.540
KP3	.303	.709	.729	.590	.606
KP4	.307	.681	.690	.552	.561
KP5	.375	.671	.687	.555	.567
KP6	.344	.669	.679	.545	.551

Note. Ten folds ×× ten repetitions; KP1–KP6 = purchase decision indicators; RMSE = root mean square error; MAE = mean absolute error; LM = linear-model benchmark. Lower prediction error indicates better predictive performance.

Finally, an importance–performance analysis was conducted using standardized total effects as importance scores and rescaled construct means (0–100) as performance scores (Table 7). Perceived accuracy combined the highest structural importance (.604) with comparatively lower performance (71.78), whereas relevance exhibited high performance (82.57) alongside lower structural importance (.217). This configuration identifies perceived accuracy as the primary managerial improvement priority and relevance as a baseline capability that should be maintained.

Table 7. Importance–Performance Priorities

Construct	Importance	Performance (0–100)	Priority
Perceived Accuracy	.604	71.78	Primary improvement
Relevance	.217	82.57	Maintain and refine

Note. Importance reflects standardized total effects on purchase decision; performance reflects rescaled construct scores on a 0–100 scale.

3.2 Discussion

The empirical findings indicate that Generation X e-commerce users differentiate between a product recommendation that matches the immediate shopping context and one that reflects an accurate understanding of the individual behind the session. Although both qualities positively influence purchase decisions, their functional roles are not equivalent. Contextual relevance makes an option worthy of initial attention, whereas perceived accuracy provides the recommendation with sufficient diagnostic credibility to guide product comparison and final choice. The dominant structural role of perceived accuracy is consistent with the theoretical logic of user modeling. A recommender system implicitly claims to understand a user's tastes, needs, and behavioral patterns. When repeated outputs align with those personal characteristics, the system builds experiential legitimacy, enabling the user to treat recommendations as diagnostic decision aids rather than generic promotional prompts. This interpretation aligns with prior studies linking recommendation quality to user trust, system acceptance, decision satisfaction, and purchase-related outcomes (Ampadu *et al.*, 2022; Blut *et al.*, 2023; Gallin & Portes, 2024; Zhang *et al.*, 2024). Because trust was not explicitly modeled as a mediating variable in the present study, it remains a theoretical mechanism for future empirical verification.

At the same time, recommendation relevance retained an independent positive contribution because online shopping decisions are inherently situational. Users value suggestions that correspond to their current search query, immediate need, shopping objective, and timing. Relevant recommendations narrow the consideration set and reduce the cognitive effort required to identify viable alternatives, supporting previous findings that recommendation agents enhance task alignment and user satisfaction (He *et al.*, 2024; Lo *et al.*, 2026). Nevertheless, a contextually relevant item may still fail to match a consumer's preferred brand, budget, lifestyle, or prior product experience. Relevance therefore opens the decision pathway without necessarily determining its final outcome. This accuracy–relevance asymmetry represents the central conceptual contribution of the study. Although relevance achieved the highest descriptive performance score among respondents, perceived accuracy supplied nearly three times the unique structural effect on purchase decisions. This divergence cautions researchers against interpreting high construct means as direct evidence of strong behavioral influence, and it warns system developers against optimizing surface-level topical relevance alone. An AI recommender system can appear contextually appropriate within a browsing session while still failing to demonstrate genuine preference understanding.

The Generation X context provides an important boundary condition for interpreting this asymmetry. Rather than indicating that mature consumers reject AI-driven personalization or require overly simplified interfaces, the findings suggest that experienced e-commerce users evaluate digital assistance pragmatically and reward consistent diagnostic utility. This perspective corroborates Ghasemaghaei *et al.* (2019), who demonstrated that older adults appreciate comprehensive recommendation agents when functional complexity is matched by clear usefulness. Conversely, recommendation errors, outdated preference assumptions, and repetitive irrelevant suggestions are likely to erode system credibility rapidly among users who have accumulated extensive platform experience. For computer and information systems research, these results support a dual-layer evaluation framework. Offline predictive accuracy and ranking metrics remain indispensable for benchmarking computational algorithms, whereas user-perceived accuracy and contextual relevance evaluate whether algorithmic outputs translate into meaningful human–AI interaction. Positioning purchase decisions as a decision-support outcome complements behavioral click-through and conversion logs, while disaggregating perceived accuracy from relevance yields a more diagnostic model of recommendation quality that reveals improvement priorities hidden by aggregate quality indices. For e-

commerce practice, the primary implication is the need to strengthen long-term preference modeling without sacrificing session-level relevance. Platform engineers should integrate persistent user profiles with real-time session intent, recency weights, life-stage shifts, and negative feedback signals. User-facing controls—such as "not interested" actions, category suppression, accessible preference centers, and concise recommendation explanations—can further empower users to correct profile assumptions and understand why specific items are suggested. Product teams should therefore track user-perceived accuracy alongside offline algorithmic metrics, behavioral conversion rates, and post-purchase satisfaction to ensure that recommendation engines support durable decision quality.

4. Conclusion

Perceived accuracy and recommendation relevance were both positively associated with Generation X purchase decisions in the Jakarta e-commerce context. Perceived accuracy produced the larger structural contribution, and the bootstrapped coefficient contrast confirmed that this magnitude difference was not attributable merely to sampling variation. Moreover, the structural model achieved moderate explanatory power alongside favorable cross-validated out-of-sample predictive performance relative to a linear benchmark. Together, these findings support the proposed accuracy–relevance asymmetry: contextual relevance attracts initial user attention, whereas perceived accuracy more strongly consolidates the final purchase decision. Accordingly, e-commerce organizations should prioritize recommendation systems that learn evolving user preferences, integrate long-term profiles with session-level signals, and accommodate explicit corrective feedback. While high relevance performance should be maintained through timely and task-aligned suggestions, product teams should direct their primary improvement efforts toward preference fit, the suppression of clearly unsuitable recommendations, and transparent recommendation explanations. Methodologically, human-centered recommender evaluations should report measurement quality, effect sizes, coefficient uncertainty, out-of-sample prediction, and decision-support outcomes rather than relying solely on statistical significance or offline algorithmic metrics. Future research can extend this framework by incorporating mediating mechanisms such as user trust and combining self-reported perceptions with longitudinal behavioral transaction logs.

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