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How AI-Driven Recommendation Accuracy and Novelty Shape Online Purchase Intention: The Mediating Roles of Perceived Value and Trust

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Abstract
Artificial intelligence recommendations must do more than reproduce a consumer's established preferences: they must also facilitate worthwhile discovery without undermining confidence in the platform. Drawing on the stimulus–organism–response framework, this study examines recommendation accuracy and recommendation novelty as two distinct system cues, perceived value and trust as parallel cognitive mechanisms, and online purchase intention as the behavioral response. The model was tested with 493 complete survey responses and 27 reflective indicators using partial least squares structural equation modeling in SmartPLS 4. Recommendation accuracy and novelty were positively related to both perceived value and trust. Perceived value, in turn, had a positive relationship with purchase intention. Trust also had a positive but comparatively weak relationship with purchase intention; this path met the conventional percentile-bootstrap criterion, although its bias-corrected confidence interval included zero. The specific indirect effects through perceived value were supported for both accuracy and novelty, whereas the corresponding trust-based indirect effects were not supported under conservative inference. The model explained 7.5% of perceived value, 3.4% of trust, and 4.0% of purchase intention, indicating that recommendation quality is a meaningful but limited part of the wider purchase decision. The findings distinguish relevance from discovery and show that the value pathway is more dependable than the trust pathway in translating AI recommendation quality into purchase intention.

Keywords: Artificial Intelligence, Personalized Recommendation, Recommendation Accuracy, Recommendation Novelty, Online Purchase Intention

1. Introduction

Artificial intelligence has become embedded in the ordinary architecture of digital commerce. Recommendation engines rank products, anticipate needs, personalize storefronts, and decide which alternatives become visible to a consumer. In doing so, they can reduce search costs and make very large assortments manageable. However, the same systems can also feel repetitive, opaque, or intrusive. The commercial problem is therefore not simply whether an algorithm can predict what a consumer is likely to prefer. It is about whether the recommendation experience feels both personally fitting and genuinely useful, and whether consumers are sufficiently confident in the system to act on its suggestions.

This problem matters because AI creates value in marketing through the quality of the decisions and interactions it enables, not through its technical sophistication alone (Davenport *et al*., 2020; Huang & Rust, 2021) [5, 14]. From the consumer's perspective, an AI recommendation is an encounter with an inferred judgment: the platform is effectively claiming to understand what is relevant, what may be worth discovering, and what should be considered next. Consumers evaluate that claim through experience. A recommendation that accurately reflects their needs may signal competence and save time. A recommendation that introduces an appealing but previously unconsidered option may create discovery value. Conversely, personalization that is poorly matched, inexplicable, or based on uncomfortable data practices may erode trust (Aguirre *et al*., 2015; Puntoni *et al*., 2021) [1, 22].

Research on recommender systems has long recognized that accuracy is central but insufficient. Technical evaluations have consequently broadened to include coverage, novelty, diversity, and serendipity (Ge *et al*., 2010; Herlocker *et al*., 2004; Kotkov *et al*., 2016) [9, 13, 16]. Consumer research likewise shows that perceived accuracy and novelty are meaningful evaluations of personalized recommender systems and can shape satisfaction and purchase-related responses

(Choi *et al*., 2017) [3]. Still, three issues remain insufficiently integrated. First, accuracy and novelty are often treated as system performance endpoints rather than as distinct cues that initiate consumer judgment. Second, research frequently emphasizes either utilitarian benefits or trust, leaving unclear whether these mechanisms operate in parallel and with similar strength. Third, a statistically significant recommendation effect can easily be overstated if explanatory power, effect size, and alternative bootstrap intervals are not considered together.

This study addresses these issues by examining a focused process model. Recommendation accuracy (RAC) and recommendation novelty (NOV) are modeled as external stimuli. Perceived value (PV) and trust (TRU) represent internal cognitive evaluations, and online purchase intention (PI) is the response. This structure follows the stimulus–organism–response (S–O–R) framework and preserves the original premise that recommendation quality affects purchase intention through value and trust. The study asks: (1) Do accuracy and novelty each enhance perceived value and trust? (2) Do perceived value and trust promote purchase intention? Moreover, (3) which indirect mechanism receives more robust empirical support?

The study makes three contributions. It first separates "fit" from "discovery," showing how accuracy and novelty can be analyzed as complementary rather than interchangeable properties of AI recommendations. It then places perceived value and trust in the same model, enabling a direct comparison of two cognitively plausible routes to purchase intention. Finally, it reports the model's weak and strong evidence. All six direct hypotheses meet conventional significance tests. However, the indirect results and low coefficients of determination reveal an asymmetric and bounded process: perceived value carries the effects of both recommendation cues more reliably than trust. At the same time, much of purchase intention remains outside the model. This more calibrated interpretation is theoretically useful and managerially realistic.

2. Theoretical Background and Hypotheses

2.1 The stimulus–organism–response perspective

The S–O–R framework proposes that environmental stimuli influence internal organism states, which subsequently shape approach or avoidance responses (Mehrabian & Russell, 1974) [18]. In online retailing, interface and information cues constitute the environment through which consumers experience the retailer, while cognitive and affective assessments mediate behavioral reactions (Eroglu *et al*., 2001) [7]. The framework is particularly suitable for AI-enabled commerce because consumers rarely observe the algorithm directly. They encounter its outputs and infer the system's usefulness, competence, and intentions from those outputs.

In the present model, perceived recommendation accuracy and novelty are the stimuli. Accuracy captures the extent to which recommended products match a consumer's preferences, needs, active search, and aesthetic expectations. Novelty captures the extent to which recommendations facilitate discovery by presenting unique, surprising, and previously unconsidered products. These properties are related but not redundant. An accurate list can be obvious and repetitive, whereas a novel list can be irrelevant. Effective personalization must balance the exploitation of known preferences with the exploration of potentially valuable alternatives.

Perceived value and trust are modeled as organism states. Perceived value is the consumer's overall assessment of what is gained relative to the time, effort, and other sacrifices involved (Sweeney & Soutar, 2001; Zeithaml, 1988) [25, 30]. Trust concerns willingness to rely on the recommendation system and platform based on beliefs about competence, integrity, security, and responsible conduct (McKnight *et al*., 2002; Wang & Benbasat, 2005) [17, 27]. Purchase intention represents an approach response: a consumer's stated likelihood and willingness to purchase products presented through the AI recommendation process. Similar applications of S–O–R show that technology-related stimuli can affect online purchase responses through perceived value and other internal evaluations (Yin & Qiu, 2021) [29].

2.2 Recommendation accuracy and perceived value

Recommendation accuracy is experienced as a reduction in the distance between what the consumer wants and what the platform displays. When suggested products closely match current needs and preferences, consumers need to inspect fewer irrelevant alternatives, expend less effort on reformulating searches, and face less uncertainty about where to look next. Accuracy, therefore, creates functional value through efficiency and decision support. This reasoning is consistent with the broader view of recommendation agents as technologies that improve decision quality and reduce information-processing costs (Xiao & Benbasat, 2007) [28].

Accuracy can also create experiential value. A recommendation that "gets it right" makes the interaction feel responsive rather than mechanical. Personalized systems have been evaluated in part through perceived accuracy, as it reflects how well the system understands the user (Choi *et al*., 2017) [3], while web personalization can alter information processing and decision outcomes (Tam & Ho, 2006) [26]. In value terms, the output makes the benefits of interacting with the platform more likely to exceed the required time and effort. Accordingly:

H1. Recommendation accuracy positively affects perceived value.

2.3 Recommendation novelty and perceived value

Novelty provides a different benefit. Consumers often enter digital marketplaces without complete knowledge of the available products or even of their own preferences. A recommendation can therefore be useful not only because it retrieves an expected option, but also because it reveals an attractive possibility that the consumer would not have found independently. Recommender-system research treats novelty and serendipity as important complements to accuracy, particularly when highly similar suggestions become predictable or narrow the user's exposure (Ge *et al*., 2010; Kotkov *et al*., 2016) [9, 16].

Novel recommendations can increase perceived value by broadening the consideration set, stimulating curiosity, and turning search into discovery. In the present study, novelty is not defined as difference for its own sake. Its indicators refer to unique, interesting, and surprising products that expand choice. This form of useful novelty adds informational and experiential benefits while reducing the

effort required to locate unfamiliar alternatives. Prior consumer-facing research also links perceived novelty in personalized recommendations to favorable evaluations and purchase-related outcomes (Choi *et al*., 2017) [3]. Thus:
H2. Recommendation novelty positively affects perceived value.

2.4 Recommendation accuracy and trust
Trust in digital environments develops through beliefs that the system can perform its task, behaves consistently, and does not expose the user to unacceptable vulnerability (McKnight *et al*., 2002) [17]. For a recommendation agent, output quality is a visible basis for those beliefs. Repeatedly relevant suggestions provide evidence that the system can interpret preferences and apply consumer data competently. They may also reduce the perception that recommendations are arbitrary or solely designed to promote unsuitable inventory.
Personalization can strengthen cognitive trust by demonstrating that the recommendation agent understands the individual and provides dependable assistance (Komiak & Benbasat, 2006) [15]. Similarly, research on online recommendation agents shows that trusting beliefs are consequential for adoption (Wang & Benbasat, 2005) [27]. Although accuracy does not, by itself, establish benevolence, privacy, or transparency, it provides performance evidence from which trust can begin to form. Hence:
H3. Recommendation accuracy positively affects trust.

2.5 Recommendation novelty and trust
The expected relationship between novelty and trust is less automatic. Unexpected recommendations may demonstrate that the system can identify useful options beyond the consumer's immediate search, signaling breadth and intelligence. When a surprising suggestion is still perceived as interesting and appropriate, it can serve as evidence of algorithmic competence. Discovery can also make the platform appear attentive to the consumer's longer-term interests rather than merely repeating prior choices.
At the same time, novelty can become disorienting if consumers do not understand why an item was shown. The trust effect, therefore, depends on novelty being experienced as meaningful rather than random. Explanation and transparency can help consumers interpret AI outputs and develop warranted confidence (Shin, 2021) [24]. Because the novelty construct used here emphasizes appealing discovery within a personalized recommendation context, a positive net association is expected:
H4. Recommendation novelty positively affects trust.

2.6 Perceived value and online purchase intention
Perceived value is a central basis for marketplace choice because consumers compare expected benefits with monetary and nonmonetary sacrifices (Zeithaml, 1988) [30]. In an AI recommendation context, those benefits include faster search, more effective decisions, practical relevance, and a shopping experience that feels worth the time invested. These benefits lower the friction between product exposure and purchase consideration.
Evidence from online commerce supports a positive relationship between perceived value and purchase intention (Bonsón Ponte *et al*., 2015; Yin & Qiu, 2021) [2, 29]. If AI recommendations make the decision process more efficient and worthwhile, consumers should be more willing to prioritize and purchase the recommended products. Therefore:
H5. Perceived value positively affects online purchase intention.

2.7 Trust and online purchase intention
Online purchasing requires consumers to act under uncertainty. They cannot always verify how a recommendation was generated, whether personal information was handled appropriately, or whether the platform's incentives align with their own. Trust reduces the perceived vulnerability associated with relying on the platform and proceeding with a transaction. In e-commerce research, trust has repeatedly been linked to behavioral intention because it complements assessments of usefulness and reduces concerns about opportunism and risk (Gefen *et al*., 2003; Pavlou, 2003) [10, 20].
For AI recommendations, trust incorporates confidence that suggestions are reliable, personal information is secure, the algorithm is sufficiently objective and transparent, transactions are safe, and the platform uses AI responsibly. These beliefs should make consumers more willing to use recommended products as a basis for choice. Accordingly:
H6. Trust has a positive effect on online purchase intention.

2.8 The mediating roles of perceived value and trust
The S–O–R logic implies that system cues affect behavior through the consumer's internal evaluation of the encounter. Accuracy and novelty do not, by themselves, create purchase intention simply because they are technical properties. They matter when consumers translate them into a belief that the recommendation experience is beneficial or trustworthy. Perceived value should reflect the effects of accuracy because relevant recommendations reduce search and decision costs; it should also reflect the effect of novelty because useful discovery expands benefits. Trust should carry the effect of accuracy when good matches signal competence and dependability, and it should carry the effect of novelty when meaningful discovery signals intelligent and consumer-oriented assistance.
The four specific indirect effects make the original mediating premise explicit:
H7a. Recommendation accuracy has a positive indirect effect on online purchase intention through perceived value.
H7b. Recommendation novelty has a positive indirect effect on online purchase intention through perceived value.
H7c. Recommendation accuracy has a positive indirect effect on online purchase intention through trust.
H7d. Recommendation novelty has a positive indirect effect on online purchase intention through trust.

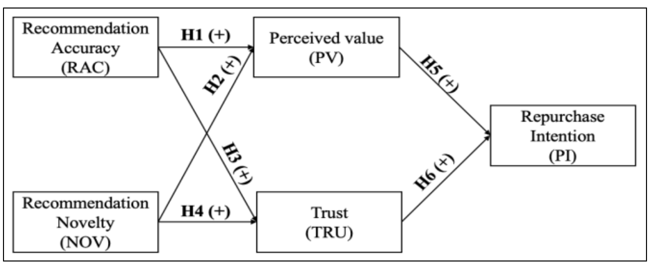

Fig 1: Conceptual research model

3. Methodology
3.1 Research design and sample
The study used a cross-sectional survey design to examine consumers' evaluations of AI-driven personalized recommendations on e-commerce platforms. The analytical dataset contained 493 complete response records across all 27 indicators, with no item-level missing values. Responses were captured on a five-point agreement scale ranging from 1 (strongly disagree) to 5 (strongly agree). The unit of analysis was the individual online shopper with prior experience of AI-generated product recommendations.
Data were collected in Vietnam between June and August 2026 through an online questionnaire. The instrument was distributed via consumer- and shopping-oriented social media communities (Facebook groups and Zalo) and university alum networks in major urban centers, principally Hanoi and Ho Chi Minh City. The study employed non-probability convenience sampling combined with a purposive eligibility screen. Respondents were eligible if they were at least 18 years old, resided in Vietnam, had made at least one purchase on an e-commerce platform (e.g., Shopee, TikTok Shop, Lazada, or Tiki) within the preceding six months, and had encountered AI-driven personalized product recommendations on those platforms. A screening question at the beginning of the questionnaire filtered out individuals without such experience. After removing incomplete submissions, duplicate entries, responses that failed an embedded attention check item, and questionnaires exhibiting invariant response patterns, 493 usable responses were retained for analysis.
The demographic profile of the sample is presented in Table 1. Respondents were predominantly young adults, with 34.1% aged 18–24 and 41.6% aged 25–34, a distribution consistent with the age structure of active online shoppers in Vietnam. Women constituted 55.0% of the sample and men 44.2%. The majority held a university qualification (55.0%) or a postgraduate qualification (13.2%). Online shopping was frequent: 43.4% of respondents purchased one to three times per week, and a further 12.4% shopped more than three times per week. Shopee was the most frequently reported primary platform (47.9%), followed by TikTok Shop (21.9%) and Lazada (18.7%).

Table 1: Demographic profile of respondents

Characteristic	Category	*n*	%
Gender	Female	271	55,0
	Male	222	45,0
Age (years)	18–24	168	34.1
	25–34	205	41.6
	35–44	87	17.6
	45 and above	33	6.7
Education	High school or lower	61	12.4
	College / vocational	96	19.5
	University (bachelor's)	271	55.0
	Postgraduate	65	13.2
Online shopping frequency	Less than once a month	42	8.5
	1–3 times per month	176	35.7
	1–3 times per week	214	43.4
	More than 3 times per week	61	12.4
Primary e-commerce platform	Shopee	236	47.9
	TikTok Shop	108	21.9
	Lazada	92	18.7
	Tiki	41	8.3
	Other	16	3.2

3.2 Measures
All five constructs were specified reflectively. Recommendation accuracy was measured using five items addressing preference fit, need recognition, search relevance, the proportion of useful suggestions, and alignment with personal taste. Recommendation novelty used five items concerning unique products, discovery, surprise, expanded choice, and serendipitous browsing. Perceived value was captured with six items reflecting search-time savings, decision efficiency, practical benefits, the benefit–effort trade-off, a more worthwhile shopping experience, and the benefit–time trade-off. Trust was assessed with six items covering consumers' genuine interest, information security, recommendation reliability, algorithmic objectivity and transparency, transaction safety, and responsible AI use. Online purchase intention was measured with five items concerning intention, likelihood, prioritization, willingness to spend, and future reliance on AI recommendations. All items were rated on a five-point agreement scale from 1 (strongly disagree) to 5 (strongly agree).
The measurement content was grounded in established research on recommender-system evaluations, perceived value, e-commerce trust, and purchase intention. Items for recommendation accuracy and novelty were adapted from Choi *et al*. (2017) [3], Xiao and Benbasat (2007) [28], Ge *et al*. (2010) [9], and Kotkov *et al*. (2016) [16]; perceived-value items from Sweeney and Soutar (2001) [25] and Zeithaml (1988) [30]; trust items from McKnight *et al*. (2002) [17] and Wang and Benbasat (2005) [27]; and purchase-intention items from Dodds *et al*. (1991) [6] and Choi *et al*. (2017) [3]. Rather than being quoted verbatim from any single source, all items were adapted to the specific context of AI-driven personalized recommendations on e-commerce platforms. Table 1 reports the full item wording, the questionnaire codes used in the analysis, the conceptual labels (RAC, NOV, PV, TRU, and PI), and the standardized indicator loadings obtained from the measurement model.

Table 2: Measurement items and standardized indicator loadings

Code	Construct	Item wording	Loading
RAC1	Recommendation Accuracy	The products recommended by AI on the e-commerce platform are usually highly relevant to my personal preferences.	.800
RAC2		I feel that AI product recommendations understand my actual shopping needs quite well.	.781
RAC3		The AI system usually suggests items that I genuinely need or am looking for.	.760
RAC4		A high proportion of the recommended products are useful to me.	.782
RAC5		The recommended product lists rarely deviate from my tastes and preferences.	.745
NOV1	Recommendation Novelty	The AI system often introduces unique products that I had not previously considered.	.734
NOV2		AI recommendations give me a genuinely new product-discovery experience.	.754
NOV3		I often find interesting and surprising products through AI recommendations.	.794
NOV4		Personalized recommendations broaden my choices to include novel products.	.756
NOV5		Recommendation algorithms make browsing the e-commerce platform feel like an enjoyable process of unexpected discovery.	.750
PV1	Perceived Value	AI-personalized recommendations save me considerable time when searching for products.	.782
PV2		Using AI recommendations helps me make shopping decisions more quickly and effectively.	.730
PV3		I receive practical benefits from products recommended specifically for me.	.736
PV4		Overall, the benefits provided by the AI recommendation system exceed the effort I invest.	.749
PV5		AI-enabled features make my shopping experience more worthwhile.	.751
PV6		The benefits I gain from interacting with personalized recommendations exceed the time I spend.	.730
TRU1	Trust	I trust that the AI system makes recommendations with consumers' genuine interests in mind.	.750
TRU2		I feel confident that my personal information is secure when I interact with the AI recommendation system.	.794
TRU3		The AI-generated product recommendations on this e-commerce platform are reliable.	.724
TRU4		I trust the objectivity and transparency of the product-recommendation algorithm.	.794
TRU5		I feel safe conducting transactions based on these personalized recommendations.	.775
TRU6		I firmly trust that the e-commerce platform uses AI responsibly toward its users.	.676
PI1	Online Purchase Intention	I intend to purchase products recommended by the AI system in the near future.	.779
PI2		I am highly likely to order products shown in AI-personalized recommendations.	.744
PI3		When shopping online, I prioritize products recommended by AI.	.776
PI4		I am willing to spend money on products included in the recommendation list personalized for me.	.784
PI5		In the near future, I will use AI recommendations as a basis for my purchase decisions.	.745

3.3 Analytical Procedure

The model was estimated with partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4 (Ringle *et al.*, 2024) [23]. PLS-SEM was appropriate for estimating the simultaneous measurement and structural relationships and for evaluating specific indirect effects in a prediction-oriented model (Hair *et al.*, 2019; Nitzl *et al.*, 2016) [11, 19]. The algorithm used the path-weighting scheme, standardized data, a stop criterion of 10^{-7}, and a maximum of 3,000 iterations.

The analysis followed a two-stage assessment. For the reflective measurement model, indicator loadings, Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE) were examined. Discriminant validity was assessed with the heterotrait–monotrait ratio (HTMT) and checked against the Fornell–Larcker criterion (Fornell & Larcker, 1981; Henseler *et al.*, 2015). Variance inflation factors (VIFs) were inspected for collinearity. For the structural model, standardized path coefficients, R^2, adjusted R^2, and f^2 effect sizes were evaluated. As rough benchmarks, f^2 values of .02, .15, and .35 indicate small, medium, and large effects, respectively (Cohen, 1988) [4].

Statistical inference used 5,000 bootstrap samples, a fixed random seed, two-tailed tests, a 5% significance level, and percentile confidence intervals. Bias-corrected 95% intervals from the supplied output were also examined as a sensitivity check. A direct or indirect effect was treated as robust when its test and interval estimates converged. Where the percentile and bias-corrected results differed, the discrepancy is reported rather than resolved in favor of the more favorable result. Because the design is cross-sectional and observational, "effect" refers to an estimated directional association within the specified model, not proof of temporal causality.

4. Results

4.1 Descriptive results and measurement model

The construct-level means ranged from 3.578 to 3.790 on the five-point response scale. These descriptive scores are unweighted respondent-level item averages, whereas the PLS-SEM estimates use latent-variable composites. As shown in Table 1, Cronbach's alpha ranged from .816 to .851, rho_A from .826 to .864, and composite reliability from .871 to .887. All AVE values exceeded .50. Indicator loadings ranged from .676 to .800 and were statistically significant. One trust indicator (TRU6, responsible AI use) loaded at .676, below the commonly preferred .708 level. It was retained because it represented a substantively important aspect of trust, and the construct continued to meet reliability and convergent validity criteria (Hair *et al.*, 2019) [11].

Table 3: Descriptive statistics, reliability, and convergent validity

Construct	Mean	SD	Cronbach's alpha	CR	AVE	Outer loadings
RAC	3.578	.914	.833	.882	.599	.745–.800
NOV	3.740	.888	.816	.871	.574	.734–.794
PV	3.755	.864	.842	.883	.557	.730–.782
TRU	3.628	.917	.851	.887	.567	.676–.794
PI	3.790	.760	.825	.876	.587	.744–.784

Discriminant validity was satisfactory. HTMT values ranged from .143 to .254, well below conservative thresholds. In the Fornell–Larcker check, the square root of AVE for each construct (.747–.774) exceeded its correlations with the remaining constructs. The very low HTMT values also indicate that accuracy, novelty, value, trust, and purchase intention were empirically distinct in this sample.

Table 2: Heterotrait–monotrait ratio matrix

Construct	RAC	NOV	PV	TRU	PI
RAC					
NOV	.197				
PV	.252	.236			
TRU	.156	.153	.254		
PI	.239	.218	.206	.143	

Outer VIF values ranged from 1.528 to 1.892, and inner VIF values ranged from 1.028 to 1.048. These results did not indicate problematic collinearity in either the measurement or structural model.

4.2 Structural model and direct hypotheses

Table 3 reports the direct paths. Recommendation accuracy was positively related to perceived value (β = .183, t = 4.231, p < .001), supporting H1. Recommendation novelty was also positively related to perceived value (β = .176, t = 3.829, p < .001), supporting H2. The two coefficients were close in magnitude, suggesting that relevance and discovery made comparably small contributions to value.

Accuracy was positively associated with trust (β = .125, t = 2.776, p = .006), supporting H3, and novelty was positively associated with trust (β = .117, t = 2.409, p = .016), supporting H4. Perceived value had a positive relationship with purchase intention (β = .159, t = 3.826, p < .001), supporting H5. Trust was positively related to purchase intention under the prespecified percentile-bootstrap test (β = .092, t = 2.087, p = .037; 95% percentile CI [.008, .180]), providing qualified support for H6. However, the bias-corrected interval for this path included zero [−.010, .168]. H6 should therefore be read as a weak, interval-sensitive result rather than firm evidence.

Table 3: Direct structural relationships

Hypothesis	β	t	p	Percentile 95% CI	Bias-corrected 95% CI	f²	Decision
H1:RAC → PV	.183	4.231	< .001	[.102, .274]	[.086, .259]	.035	Supported
H2:NOV → PV	.176	3.829	< .001	[.092, .272]	[.079, .257]	.033	Supported
H3:RAC→TRU	.125	2.776	.006	[.038, .216]	[.017, .201]	.016	Supported
H4:NOV→TRU	.117	2.409	.016	[.023, .217]	[.004, .201]	.014	Supported
H5: PV → PI	.159	3.826	< .001	[.082, .247]	[.067, .229]	.025	Supported
H6: TRU → PI	.092	2.087	.037	[.008, .180]	[−.010, .168]	.008	Qualified

4.3 Explanatory power and model diagnostics

The model explained 7.5% of the variance in perceived value, 3.4% in trust, and 4.0% in purchase intention (Table 4). The corresponding adjusted values were 7.2%, 3.0%, and 3.6%. These values are low, indicating that the model captures a narrow recommendation-quality mechanism rather than a comprehensive account of consumer purchasing. Effect sizes were likewise small or negligible: the largest was accuracy → perceived value (f^2 = .035), while all three paths involving trust as an immediate antecedent or outcome (RAC → TRU = .016, NOV → TRU = .014, TRU → PI = .008) fell below the .02 threshold.

Table 4: Explanatory power of endogenous constructs

Endogenous construct	R²	Adjusted R²	Interpretation
Perceived value	.075	.072	Low
Trust	.034	.030	Low
Online purchase intention	.040	.036	Low

Note. Interpretations are deliberately conservative. The model focuses on recommendation-quality mechanisms and omits many established determinants of purchase intention.

The standardized root mean square residual (SRMR) was .049 for the saturated model and .064 for the estimated model. Both values were below .08, although global fit indices are secondary in composite-based PLS-SEM. The estimated model's normed fit index was .873. Predictive relevance (Q^2) and out-of-sample prediction statistics were not present in the supplied outputs and are therefore not reported.

4.4 Indirect Effects

The specific indirect effects reveal a clear difference between the two proposed mechanisms. Accuracy had a positive indirect association with purchase intention through perceived value (β = .029, p = .008; percentile 95% CI [.012, .055]; bias-corrected CI [.010, .051]), supporting H7a. Novelty also had a positive indirect association through perceived value (β = .028, p = .011; percentile CI [.012, .055]; bias-corrected CI [.009, .050]), supporting H7b.

By contrast, the accuracy → trust → purchase-intention indirect effect was not significant by its two-tailed test (β = .011, p = .138), and its bias-corrected interval included zero. H7c was not supported. The novelty → trust → purchase-intention effect was also nonsignificant (β = .011, p = .161), with both inferential approaches providing no stable evidence; H7d was not supported. The total indirect effects of accuracy (β = .041, p = .001) and novelty (β = .039, p = .003) were significant because each combined a reliable value pathway with a much weaker trust pathway.

Table 5: Specific indirect effects

Hyp	Indirect path	β	t	p	Percentile 95% CI	Bias-corrected 95% CI	Decision
H7a	RAC → PV → PI	.029	2.645	.008	[.012, .055]	[.010, .051]	Supported
H7b	NOV → PV → PI	.028	2.540	.011	[.012, .055]	[.009, .050]	Supported
H7c	RAC → TRU → PI	.011	1.484	.138	[.000, .030]	[−.001, .028]	Not supported
H7d	NOV → TRU → PI	.011	1.402	.161	[−.000, .030]	[−.001, .028]	Not supported

The structural specification did not include direct paths from accuracy or novelty to purchase intention. The results, therefore, establish the significance or nonsignificance of the specified indirect effects but do not justify labeling the relationships as "full" or "partial" mediation. Such labels would require estimating the omitted direct paths in an explicitly compared model.

5. Discussion

The results tell a more differentiated story than a simple claim that "better AI recommendations increase purchase intention." Accuracy and novelty both matter, but they matter primarily because they improve how worthwhile the recommendation experience feels. Their effects on perceived value were similar in magnitude, and both value-based indirect effects were stable across percentile and bias-corrected bootstrap intervals. Consumers appear to value an AI system for two complementary reasons: it reduces wasted effort by presenting relevant products, and it creates discovery benefits by presenting appealing options that would otherwise remain outside the consideration set.

This joint result is important because accuracy and novelty can be framed as competing goals. Optimizing solely for similarity to prior behavior can yield familiar yet monotonous recommendations, whereas maximizing novelty can diminish relevance. At the perceptual level examined here, however, both qualities contributed positively to value. The implication is not that any unusual item adds value, but that useful novelty, surprising options that still make sense in the consumer's shopping context, can complement accurate preference matching. This interpretation is consistent with work that extends recommender evaluation beyond accuracy to encompass serendipity and discovery (Ge *et al*., 2010; Kotkov *et al*., 2016) [9, 16].

Both recommendation cues also predicted trust, although these relationships were smaller. Accurate outputs may demonstrate technical competence and consistency; novel but meaningful outputs may signal a broader understanding of the consumer. This finding extends research in which personalization and recommendation quality provide bases for trusting beliefs (Komiak & Benbasat, 2006; Wang & Benbasat, 2005) [15, 27]. However, the downstream role of trust was fragile. Trust predicted purchase intention under the conventional percentile-bootstrap criterion. However, the bias-corrected confidence interval crossed zero, and neither trust-based specific indirect effect was significant by the two-tailed test.

That pattern does not make trust irrelevant. Trust may function as a threshold or enabling condition rather than a strong incremental motivator in this sample. Consumers may require a minimally acceptable level of confidence before considering an AI recommendation. However, once that threshold is met, concrete benefits such as relevance, efficiency, and discovery may do more to move intention. Trust may also compete with unmodeled determinants, including price, product quality, brand familiarity, delivery terms, social proof, perceived risk, and current need. The low R^2 for purchase intention is consistent with that interpretation.

The modest explanatory power deserves emphasis. Accuracy and novelty explained 7.5% of perceived value and 3.4% of trust; perceived value and trust explained 4.0% of purchase intention. These percentages do not negate statistically reliable paths, but they constrain their substantive interpretation. AI recommendation quality is one input to a purchase decision, not the dominant cause of the decision. By reporting this boundary directly, the study avoids equating small, precisely estimated associations with large behavioral leverage.

6. Theoretical Implications

First, the study advances consumer-oriented recommender research by treating accuracy and novelty as distinct stimuli within one process model. Accuracy represents successful preference exploitation; novelty represents valuable exploration. Their similar relationships with perceived value indicate that consumers can derive benefit from both reduced search friction and expanded discovery. This clarifies why a technically accurate recommender may still underperform experientially if it repeatedly presents obvious alternatives.

Second, the study compares perceived value and trust as parallel cognitive responses rather than treating either as a universal explanation. The results favor an asymmetric dual-mechanism account. Recommendation quality can strengthen both evaluations, but only perceived value consistently transmits accuracy and novelty to purchase intention. Theoretically, this means that an upstream predictor of trust need not generate a statistically dependable trust-based indirect effect; the strength of the second-stage path matters.

Third, the findings place an empirical boundary around the S–O–R account used here. The framework organizes the sequence from recommendation cues to internal judgments and purchase responses, but the low explained variance indicates that these stimuli and organismic states are not exhaustive. A more complete S–O–R model may need to incorporate emotional responses (e.g., enjoyment or irritation), perceived intrusiveness, privacy risk, product involvement, and situational need alongside value and trust.

Finally, the study illustrates the importance of inference transparency in PLS-SEM. A dichotomous reading of $p < .05$ would treat all six direct paths as equally supported. Considering effect sizes and alternative confidence intervals yields a more informative conclusion: the value pathway is small but stable, whereas the trust-to-intention relationship is weak and sensitive to the choice of confidence interval. This distinction matters for cumulative theory building.

7. Managerial Implications

For e-commerce managers, the priority should be to make recommendations demonstrably worthwhile. Improving matching quality remains important, but it should be assessed in consumer terms: fewer irrelevant products, shorter search time, and faster movement toward a defensible choice. Platform teams should complement relevance metrics with measures of decision efficiency and perceived usefulness rather than relying only on click-through rate.

Novelty should be introduced with relevance guardrails. A useful operational approach is to reserve part of the recommendation slate for exploratory items while ensuring that each item has an intelligible connection to the consumer's context. Novelty can then expand choice without appearing random. Teams can test the exploration share, category distance, and explanation format, using incremental conversion, saved items, downstream satisfaction, and longer-term assortment engagement as outcomes.

Trust-building remains necessary, but the results suggest that trust communication alone may not materially increase purchase intention. Explanations such as "recommended because…," preference controls, data-use notices, and accessible privacy settings can help consumers interpret the system and reduce uncertainty. Those features should be coupled with tangible value: reliable product information, competitive offers, return assurances, and recommendations that genuinely save effort. Transparency is most credible when the recommended outcome is also useful.

Managers should also distinguish diagnostic goals. If users rate accuracy and novelty highly but perceive little value, the interface may be failing to translate recommendation quality into time savings or decision support. If value is high but trust is low, privacy, transparency, platform reputation, or transaction safeguards may be the constraint. If both are high but purchase intention remains low, managers should investigate price, availability, brand preference, product involvement, and current demand rather than continuing to tune the algorithm alone.

8. Conclusion

AI-driven recommendations create consumer value through both fit and discovery. In this sample, recommendation accuracy and novelty each strengthened perceived value and trust, but perceived value was the more dependable bridge to online purchase intention. Trust showed a positive yet fragile direct relationship and did not carry either recommendation cue to intention under conservative mediation tests. The effects were small, and the model explained only a limited share of purchase intention, underscoring that recommendation quality works within a wider commercial and psychological context. The central implication is therefore precise: design AI recommendations to be relevant and pleasantly exploratory, translate those qualities into visible consumer benefit, and treat trust as a necessary foundation whose behavioral influence should be demonstrated rather than assumed.

9. References

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