

Calibrated Explanation-Detail Transparency in AI Recommendation Explanations: Trust, Privacy Concern, and Purchase Intention in E-Commerce

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ABSTRACT

Artificial intelligence (AI)-based recommender systems increasingly provide explanations for product recommendations in e-commerce. Although such explanations can reduce algorithmic opacity and strengthen consumer trust, they can also make data collection, profiling, and personalization practices more salient. This study develops and tests a calibrated explanation-detail transparency model in which recommendation explanations serve as both competence signals and privacy-risk signals. We conducted a one-factor, three-level, between-subjects scenario experiment with 472 valid responses retained from 623 submissions. Participants were randomly assigned to low-, medium-, or high-detail explanation conditions for the same product scenario. The data were analyzed using regression, PROCESS serial mediation analysis, covariance-based structural equation modeling, alternative-model comparisons, robustness checks, and statistical power sensitivity analysis. Higher-detail explanation conditions were associated with greater perceived algorithm understandability and platform trust, providing evidence consistent with a positive trust-benefit mechanism. They were also associated with greater perceived data intrusiveness and information privacy concern, providing evidence consistent with a negative privacy-cost mechanism. Purchase intention exhibited an asymmetric concave pattern across the three discrete conditions and was highest in the medium-detail condition. These

findings support calibrated, layered, and privacy-sensitive explanation design in AI recommendation interfaces.

Keywords: AI recommendation, explanation-detail transparency, recommender systems, platform trust, information privacy concern, purchase intention, electronic commerce

1. INTRODUCTION

AI-based recommender systems are embedded in many e-commerce platforms. They reduce search costs, organize large product assortments, and transform consumer data into product recommendations that facilitate online product evaluation. As platforms increasingly provide user-facing explanations for these recommendations, transparency becomes more than a technical property of the underlying algorithm. This study examines transparency as explanation-detail transparency: an interface cue through which consumers interpret recommendation relevance, platform competence, data use, privacy risk, and purchase intentions [1, 2].

Prior research on recommender systems and explanation interfaces shows that explanations can improve users' understanding of recommendation logic, perceived system competence, trust, and acceptance [3-6]. Subsequent research on explainable AI (XAI) and consumer AI has emphasized interpretability, understandability, trust calibration, and user experience in algorithmic interfaces [7-13]. These issues are directly relevant to e-commerce, as recent IJECS studies have examined recommender-system applications and trust mechanisms in online and social commerce settings [14, 15]. A concise explanation can help consumers understand a product's relevance and reduce uncertainty during evaluation. However, the same explanation may reveal that the platform has collected, inferred, or integrated multiple types of behavioral data. Recommendation explanations therefore function as ambivalent design cues: they may signal algorithmic competence while simultaneously heightening the salience of personalization-related privacy risks, data intrusiveness, and privacy concern [16-28].

Two gaps remain in the e-commerce literature. First, transparency is often modeled as a linear antecedent of trust, acceptance, or decision quality, whereas fewer studies examine whether explanation-detail transparency can

simultaneously activate privacy concern and reduce purchase intention. Second, platform designers rarely choose between complete opacity and full disclosure. Instead, they must calibrate how much explanatory detail is useful during product evaluation and when additional detail becomes intrusive. This study addresses these gaps by proposing that a medium level of explanation-detail transparency may outperform both minimal and highly detailed explanations.

This study addresses three research questions. First, does explanation-detail transparency increase purchase intention through a trust-benefit path involving perceived algorithm understandability and platform trust? Second, does it reduce purchase intention through a privacy-cost path involving perceived data intrusiveness and information privacy concern? Third, does purchase intention exhibit a discrete concave pattern across low, medium, and high levels of recommendation-explanation detail?

This study makes four contributions to e-commerce research. First, it links AI recommendation-explanation design to consumer purchase intention through a dual-path model that integrates trust formation and privacy concern. Second, it distinguishes perceived algorithm understandability from platform trust and shows how interface-level explanation cues contribute to trust formation in recommender systems. Third, it differentiates perceived data intrusiveness from information privacy concern, thereby clarifying how privacy costs emerge when personalization cues become explicit. Fourth, it provides experimental evidence for calibrated explanation-detail transparency as a design principle for online retailing and AI-based personalization. By engaging directly with IJECS research on recommender systems, web-retailer trust, privacy concern, and social-commerce trust [14, 15, 29, 30], this study extends that literature by examining how explanation detail simultaneously shapes trust and privacy responses to AI-enabled product recommendations.

2. LITERATURE REVIEW AND HYPOTHESES

2.1. Explanation-Detail Transparency in AI Recommendation Interfaces

Explanation-detail transparency is defined as the degree of detail and specificity with which a recommendation interface communicates why a product is recommended and what information supports that recommendation.

In explainable recommender systems, explanations can facilitate user understanding, persuasion, trust calibration, and decision quality [3-10, 14]. In consumer-facing e-commerce, transparency is not treated as an abstract technical property or as disclosure of algorithmic code. Consumers generally do not observe the algorithm itself; instead, they evaluate the text, cues, and interface elements used to explain the recommendation.

This study conceptualizes explanation-detail transparency as a three-level design factor. A low-detail explanation provides only a basic recommendation statement. A medium-detail explanation provides a concise rationale based on behavior and preferences. A high-detail explanation describes data types, preferences, interactions, and usage scenarios in greater detail. This operationalization reflects a realistic e-commerce design dilemma: additional detail may clarify recommendation logic, but it may also make data tracking more salient. Accordingly, the manipulation represents recommendation-explanation detail, or explanation-detail calibration, in an interface context rather than a purely technical manipulation of algorithmic transparency. This framing is also consistent with IJECS research on recommender-system applications and consumer responses in e-commerce [14].

2.2. Trust-Benefit Path: Perceived Algorithm Understandability and Platform Trust

Perceived algorithm understandability reflects the extent to which users regard recommendation logic as comprehensible and interpretable. When an explanation clarifies the relationships among user behavior, preferences, and product attributes, it can reduce perceived algorithmic opacity and enable consumers to infer that the system is competent [5, 6, 9-13]. Greater explanation-detail transparency should therefore enhance perceived algorithm understandability.

Platform trust refers to consumers' belief that an e-commerce platform is competent, reliable, and capable of supporting confidence in transactions [31-33]. Trust is particularly important in digital commerce because consumers rely on platform-provided information but cannot fully inspect the matching logic underlying personalized recommendations. IJECS research on unfamiliar web retailers and social commerce likewise identifies trust as a central mechanism in e-commerce behavior [15, 29]. When consumers

understand why a recommendation has been generated, they are more likely to perceive the platform as competent and trustworthy. Trust, in turn, reduces uncertainty and supports purchase intention in online shopping contexts [31-41]. Accordingly, this study proposes a sequential trust-benefit path in which explanation-detail transparency increases perceived algorithm understandability, which strengthens platform trust and, in turn, increases purchase intention.

H1. Explanation-detail transparency positively affects perceived algorithm understandability.

H2. Perceived algorithm understandability is positively associated with platform trust.

H3. Platform trust is positively associated with purchase intention.

H4. Explanation-detail transparency has a positive sequential indirect association with purchase intention through perceived algorithm understandability and platform trust.

2.3. Privacy-Cost Path: Perceived Data Intrusiveness and Information Privacy Concern

Information privacy research indicates that consumers respond not only to whether data are collected but also to how data collection is framed, justified, disclosed, and made visible in service interactions [16-18, 25]. Perceived data intrusiveness refers to the immediate, interface-specific perception that a platform's data-collection, inference, or personalization practices have crossed a psychologically acceptable boundary. This construct is adapted from research on advertising intrusiveness and psychological reactance for the AI recommendation context [26, 27]. Even when data use is technically legitimate, highly detailed explanations can make consumers more aware that the platform has monitored browsing, interaction, and preference signals.

Information privacy concern is a broader evaluative judgment about whether personal information is collected excessively, used without sufficient user control, or disclosed in ways that consumers cannot anticipate [16-18]. Perceived data intrusiveness should therefore increase information privacy concern. In turn, privacy concern may reduce purchase intention because consumers may avoid platforms that appear to collect or infer excessive information [19-24, 28]. This argument is also consistent with recent IJECS

evidence that privacy concern shapes consumer behavior in e-commerce contexts [30]. Although perceived data intrusiveness and information privacy concern are related, they are conceptually distinct. Data intrusiveness is a proximal perception that the displayed recommendation is over-personalized, overly revealing, or boundary-crossing. Information privacy concern is a broader assessment of information collection, control, secondary use, and potential misuse. The model therefore treats the two constructs as sequential components of the privacy-cost path.

H5. Explanation-detail transparency positively affects perceived data intrusiveness.

H6. Perceived data intrusiveness is positively associated with information privacy concern.

H7. Information privacy concern is negatively associated with purchase intention.

H8. Explanation-detail transparency has a negative sequential indirect association with purchase intention through perceived data intrusiveness and information privacy concern.

2.4. Calibrated Explanation-Detail Transparency and the Discrete Concave Condition Pattern

The two paths imply that explanation-detail transparency can produce countervailing effects. Low detail provides insufficient information to support understanding and trust. Medium detail provides enough information to make the recommendation logic intelligible without making data tracking overly salient. High detail may further increase understandability, but it can also intensify perceived data intrusiveness and privacy concern. Together, these effects suggest that purchase intention should be highest under medium explanation-detail transparency.

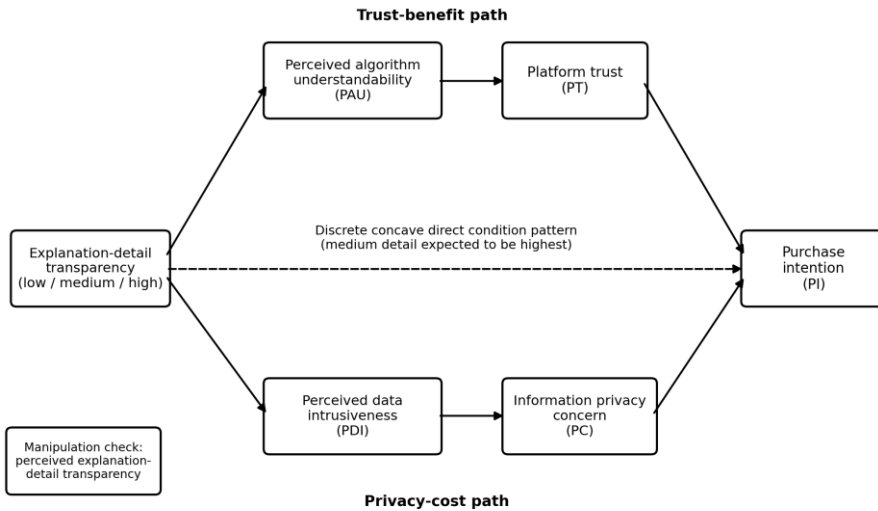
The concave-pattern argument is consistent with trust calibration: effective explanations should provide enough information to support appropriate reliance without introducing unnecessary risk salience or cognitive burden [9-13, 37]. Because the experiment includes three discrete levels of explanation detail, the empirical test is interpreted as evidence of a concave pattern across the manipulated conditions rather than proof of a fully continuous inverted-U relationship. The pattern is tested by coding explanation-detail transparency

as -1, 0, and 1 and entering a squared term. A significant negative quadratic coefficient indicates that expected purchase intention is higher in the medium-detail condition than in the low- and high-detail conditions.

H9. Explanation-detail transparency produces a discrete concave pattern in purchase intention across low-, medium-, and high-detail conditions, such that purchase intention is highest under medium explanation-detail transparency.

Figure 1 summarizes the proposed trust-benefit and privacy-cost paths and the hypothesized discrete concave pattern in the direct condition effect.

Figure 1. Conceptual model.



3. RESEARCH METHOD

3.1. Design and Experimental Stimuli

A one-factor, three-level, between-subjects online experiment was conducted. The independent variable was the level of explanation-detail transparency in an AI product-recommendation explanation: low, medium, or high. All participants evaluated the same e-commerce product scenario involving wireless Bluetooth earphones priced at CNY 199 and rated 4.7 out of 5. The recommendation explanation was the only interface element that varied across conditions. Table 1 presents the manipulation texts. The complete Chinese and English versions of the low-, medium-, and high-detail

experimental stimuli, together with their manipulated explanation-detail features, are provided in Supplementary File S1.

The manipulation reflects a practical interface-design choice. Moving from low to high detail increases both the amount and specificity of explanatory information, including behavioral, preference, interaction, and scenario cues. This feature is theoretically central to the privacy-cost mechanism because privacy concern is expected to arise as data-use cues become more explicit. The manipulation is therefore treated as calibrated explanation-detail transparency rather than as a purely technical manipulation of algorithmic transparency [9-13, 26-28].

Table 1. Experimental manipulation of recommendation explanation-detail transparency.

Condition	Recommendation explanation displayed to participants	Transparency logic
Low detail	This product is recommended for you.	Minimal explanation; no explicit data-use or preference rationale.
Medium detail	Based on your recent relevant platform behavior and product preferences, this product is recommended for you.	Concise data-use and preference rationale.
High detail	Based on the audio products you recently viewed, your attention to long battery life and high-definition sound quality, and your interactions on similar product pages, the system determines that these earphones match your commuting, exercise, and study scenarios; therefore, it recommends this product to you.	Detailed behavioral, preference, interaction, and scenario rationale.

3.2. Sample, Screening, and Randomization Checks

The raw survey-platform export contained 623 submissions. A prespecified screening procedure retained only eligible, high-quality responses. Respondents were required to provide consent, be at least 18 years old, report recent online shopping or browsing experience, pass the attention check, correctly recall the product and price information, exceed the minimum completion-time threshold, and submit complete responses without straight-lining. The final analytic sample comprised 472 valid responses: 157 in the low-detail condition, 158 in the medium-detail condition, and 157 in the high-detail condition. Screening was completed before hypothesis testing and was not modified to improve the results.

Randomization balance was assessed in the retained sample. Most demographic, shopping-experience, and control variables did not differ significantly across the three explanation-detail transparency conditions. The only significant baseline difference concerned prior purchases made because of platform recommendations ($p = .005$). To reduce the likelihood that this imbalance affected the substantive conclusions, the robustness analyses controlled for product attractiveness, price fairness, page design, product involvement, online shopping experience, recommendation-use frequency, and prior purchase due to a platform recommendation. The core conclusions remained unchanged after these controls were included.

Table 2. Sample screening and data-quality procedure.

Step	Screening stage	Rule	N before screening	Excluded n	Retained N
1	Raw survey submissions	Original survey-platform export	623	0	623
2	Consent check	Excluded non-consenting respondents	623	12	611
3	Age eligibility	Excluded respondents below 18 years old	611	18	593
4	Recent online-shopping/browsing experience	Excluded respondents without recent experience	593	24	569
5	Attention check	Excluded failed attention-check responses	569	20	549
6	Product recall	Excluded incorrect product recall	549	8	541
7	Price recall	Excluded incorrect price recall	541	10	531
8	Completion time	Excluded completion time < 180 seconds	531	31	500

Step	Screening stage	Rule	N before screening	Excluded n	Retained N
9	Completeness	Excluded incomplete or key-missing cases	500	20	480
10	Response quality	Excluded straight-lining/zero-variance cases	480	8	472
11	Final analytic sample	Included in SPSS, PROCESS, AMOS, and SmartPLS analyses	472	0	472

Table 3. Participant profile of the valid sample (N = 472).

Variable	Category	n	%
Gender	Female	244	51.7
Gender	Male	215	45.6
Gender	Prefer not to disclose	8	1.7
Gender	Other	5	1.1
Age	18-24	155	32.8
Age	25-34	187	39.6
Age	35-44	85	18.0
Age	45-54	34	7.2
Age	55 or above	11	2.3
Education	High school or below	45	9.5
Education	Junior college	99	21.0
Education	Bachelor's degree	217	46.0
Education	Master's degree	98	20.8
Education	Doctoral degree or above	13	2.8
Monthly disposable income	CNY 3,000 or below	83	17.6
Monthly disposable income	CNY 3,001-6,000	137	29.0
Monthly disposable income	CNY 6,001-9,000	119	25.2
Monthly disposable income	CNY 9,001-12,000	67	14.2
Monthly disposable income	CNY 12,001 or above	42	8.9
Monthly disposable income	Prefer not to disclose	24	5.1
Average online shopping frequency	Almost every day	51	10.8
Average online shopping frequency	Several times per week	136	28.8
Average online shopping frequency	Once per week	108	22.9

Variable	Category	n	%
Average online shopping frequency	Several times per month	133	28.2
Average online shopping frequency	Once per month or less	44	9.3
Recommendation-use frequency	Often	109	23.1
Recommendation-use frequency	Sometimes	227	48.1
Recommendation-use frequency	Rarely	88	18.6
Recommendation-use frequency	Almost never	41	8.7
Recommendation-use frequency	Not sure	7	1.5
Purchased due to platform recommendation	Yes	269	57.0
Purchased due to platform recommendation	No	132	28.0
Purchased due to platform recommendation	Not sure	71	15.0

Table 4. Randomization balance checks across explanation-detail transparency conditions.

Variable	Test statistic	p	Assessment
Gender	$\chi^2 = 9.256$, df = 6	.160	Balanced
Age	$\chi^2 = 5.112$, df = 8	.746	Balanced
Education	$\chi^2 = 4.018$, df = 8	.856	Balanced
Occupation	$\chi^2 = 9.131$, df = 12	.692	Balanced
Monthly disposable income	$\chi^2 = 5.740$, df = 10	.837	Balanced
Average online shopping frequency	$\chi^2 = 9.332$, df = 8	.315	Balanced
Recommendation-use frequency	$\chi^2 = 10.404$, df = 8	.238	Balanced
Purchased due to platform recommendation	$\chi^2 = 14.771$, df = 4	.005	Imbalanced; included in robustness checks
Product attractiveness	F = 0.100, df = 2, 469	.905	Balanced
Price fairness	F = 0.060, df = 2, 469	.941	Balanced
Page design	F = 0.074, df = 2, 469	.929	Balanced
Product involvement	F = 0.104, df = 2, 469	.902	Balanced

3.3. Measures

All focal constructs were measured using 7-point Likert-type scales ranging from 1 = strongly disagree to 7 = strongly agree. The items were adapted from established scales and prior research on explanation transparency, recommender-system evaluation, e-commerce trust, privacy concern, perceived data intrusiveness, purchase intention, and consumer evaluation. The manipulation-check and perceived-algorithm-understandability items drew on research on transparency and explanation interfaces [5, 6, 9, 13, 42]. Platform-trust items were adapted from e-commerce trust measures [31-33], and perceived-data-intrusiveness items were adapted from measures of advertising intrusiveness and psychological reactance [26, 27]. Information-privacy-concern items drew on established privacy-concern scales [16, 17]. Purchase-intention and control-variable items were adapted from validated measures of e-commerce behavior, online purchase intention, consumer value, price fairness, website quality, and product involvement [33, 36-48]. The questionnaire was administered in Chinese, and the finalized Chinese questionnaire was treated as the source version for international reporting. An English version was then prepared, and the Chinese and English texts were compared item by item to verify construct meaning, item referents, response anchors, and terminology. For transparency and content-validity assessment, the complete bilingual wording of the experimental stimuli, manipulation-check items, focal construct measures, and four multi-item control measures is provided in Supplementary File S1. The supplement also reports the source references, contextual adaptations, item-retention status, and analytical role of every disclosed item. All items for the five focal structural constructs were retained; no focal structural measurement items were deleted. The structural model includes perceived algorithm understandability, platform trust, perceived data intrusiveness, information privacy concern, and purchase intention. Perceived explanation-detail transparency served only as the manipulation check and was not included in the structural model.

Information privacy concern was modeled as a first-order construct with six items, and purchase intention was specified as the final behavioral outcome.

Table 5. Construct and variable mapping.

Code	Construct	Role	Operationalization
EXPLAIN	Explanation-detail transparency	Experimental factor	Low detail = -1, medium detail = 0, high detail = 1
EXPLAIN2	Squared explanation-detail term	Discrete concave direct effect	EXPLAIN $\times$ EXPLAIN
MC	Perceived explanation-detail transparency	Manipulation check	Four items; not included in SEM
PAU	Perceived algorithm understandability	Trust-benefit mediator 1	Four items
PT	Platform trust	Trust-benefit mediator 2	Six items
PDI	Perceived data intrusiveness	Privacy-cost mediator 1	Four items
PC	Information privacy concern	Privacy-cost mediator 2	Six items; first-order construct
PI	Purchase intention	Dependent variable	Four items; final focal outcome
Controls	CA, PF, PD, INV, experience variables	Robustness checks	Product attractiveness, price fairness, page design, product involvement, online shopping experience, recommendation-use frequency, and prior purchase due to a platform recommendation

3.4. Analytic Strategy

Analyses were conducted using SPSS 26, PROCESS 4.2, AMOS 29, SmartPLS 4.1.0.9, and G*Power 3.1.9.7. SPSS was used for data screening, descriptive statistics, randomization checks, reliability analysis, manipulation checks, correlations, hierarchical regression, and robustness analyses. PROCESS 4.2 Model 6, with 5,000 bootstrap samples and HC3 robust standard errors, was used to test the two theoretically specified serial-mediation paths [49, 50]. AMOS was used for confirmatory factor analysis (CFA), common-method-bias diagnostics, structural equation modeling (SEM), alternative-model comparisons, and supplementary path-level bootstrap diagnostics, following established guidance on SEM and measurement validity [51-56]. SmartPLS was used to obtain supplementary heterotrait-monotrait ratio (HTMT) evidence of discriminant validity, particularly for perceived data intrusiveness and information privacy concern

[57]. G*Power was used to conduct a sensitivity analysis for the three-group design [58, 59].

The discrete concave pattern was tested by coding explanation-detail transparency as -1, 0, and 1 and entering the squared term. A significant negative coefficient for EXPLAIN2 indicates that expected purchase intention is higher in the medium-detail condition than in the low- and high-detail conditions. Because the independent variable has three ordered experimental levels and the direct relationship is nonlinear, supplementary mediation analyses included EXPLAIN2 and the control variables. The core serial-mediation conclusions remained unchanged. The experimental manipulation supports causal inference regarding the effect of the explanation-detail condition. However, because the mediators and outcome were measured in the same questionnaire wave, the sequential mediation results are interpreted as theory-driven evidence consistent with the proposed trust-benefit and privacy-cost mechanisms rather than as definitive proof of temporally ordered psychological processes.

3.5. Ethics, Consent, and Data Protection

Under the institutional requirements applicable at the time of data collection, formal ethics review was not required for this anonymous, low-risk, noninterventive, scenario-based online survey of adult participants. The study did not involve clinical procedures, vulnerable groups, real purchases, financial transactions, access to participants' actual browsing histories, or the collection of identifiable personal information. Before participation, all respondents received an informed-consent statement explaining the academic purpose of the study, voluntary participation, anonymity, aggregate reporting, and their right to withdraw without penalty. Survey-platform operational metadata were used solely for data-quality screening and were removed from the de-identified analytic dataset.

Eligibility was limited to adults with recent online shopping or browsing experience. All results are reported in aggregate.

4. RESULTS

4.1. Manipulation Check

The manipulation check confirmed that participants perceived the three recommendation explanations as intended. Perceived explanation-detail transparency increased monotonically across the low-, medium-, and high-detail conditions. The groups were nearly equal in size, with 157, 158, and 157 valid respondents, respectively.

Table 6. Manipulation check for perceived explanation-detail transparency.

Group/test	EXPLAIN code	N	Statistic or mean	SD or p value	Assessment
Low detail	-1	157	2.748	0.776	a
Medium detail	0	158	4.877	0.798	b
High detail	1	157	5.854	0.709	c
ANOVA	--	472	$F(2,469)=681.516$	$p < .001, \eta^2 = .744$	Manipulation successful
Levene test	--	472	$F = 0.724$	$p = .485$	Homogeneity of variance supported
Tukey HSD	--	472	Low < Medium < High	all $p < .001$	All pairwise differences significant

4.2. Reliability, Validity, and Common Method Bias

All multi-item measures demonstrated acceptable to excellent reliability under conventional measurement-quality criteria [52, 55, 56]. The five-factor CFA measurement model fit the data well, and all standardized loadings for the five structural-model constructs were acceptable. Composite reliability and average variance extracted met conventional thresholds [51, 52, 55]. The highest HTMT value was .764 for perceived data intrusiveness and information privacy concern, which was below the conservative threshold of .85 [57]. The two constructs were therefore related but empirically distinguishable.

Common method bias was assessed using Harman's single-factor test and a comparison with a single-factor CFA model [53]. The first unrotated factor explained 37.111% of the variance and did not dominate the factor solution. The single-factor CFA model also fit the data substantially worse than the theoretical five-factor model. Together, these diagnostics indicate that common method bias is unlikely to account for the principal findings.

Table 7. Reliability and convergent validity.

Construct	Items	CFA loading range	Cronbach's α	CR	AVE	Rating
MC	4	--	.979	--	--	Manipulation check only
PAU	4	0.924-0.935	.961	.961	.861	Excellent
PT	6	0.842-0.869	.943	.943	.735	Excellent
PDI	4	0.932-0.944	.967	.967	.880	Excellent
PC	6	0.853-0.892	.949	.950	.758	Excellent
PI	4	0.787-0.814	.876	.876	.639	Good

Note. For MC, corrected item-total correlations ranged from .946 to .949. MC was used only as the manipulation check and was not included in the CFA. CFA fit: $\chi^2/\text{df} = 1.099$, GFI = .957, AGFI = .946, NFI = .977, IFI = .998, TLI = .998, CFI = .998, RMR = .039, and RMSEA = .014. CR = composite reliability; AVE = average variance extracted.

Table 8. Common method bias and discriminant-validity diagnostics.

Diagnostic	Key result	Criterion	Assessment
Harman single-factor test	KMO = .946; Bartlett $\chi^2(276) = 11444.053$, $p < .001$; first unrotated factor = 37.111%	No single factor should dominate	No single factor dominated
Theoretical five-factor CFA	$\chi^2/\text{df} = 1.099$; CFI = .998; RMSEA = .014	Good fit	Supported measurement model
Single-factor CFA	$\chi^2/\text{df} = 27.634$; CFI = .411; RMSEA = .238	Poor fit	Substantially worse than five-factor model
HTMT discriminant validity	Highest HTMT = .764 for PDI-PC	Below .85	PDI and PC are distinguishable

4.3. Descriptive Statistics and Correlations

Table 9 presents descriptive statistics and correlations for the core model variables. The correlation pattern was broadly consistent with the proposed dual-path model: explanation-detail transparency was positively associated with perceived algorithm understandability and perceived data intrusiveness; platform trust was positively associated with purchase intention; and information privacy concern was negatively associated with purchase intention.

Table 9. Descriptive statistics and correlations.

No.	Variable	M	SD	1	2	3	4	5	6	7
1	EXPLAIN	0.000	0.816	1						
2	EXPLAIN2	0.665	0.472	.000	1					
3	PAU	4.635	1.193	.659**	-.277**	1				
4	PT	4.659	1.017	.231**	-.454**	.532**	1			
5	PDI	4.086	1.284	.719**	.072	.463**	.078	1		
6	PC	4.055	1.233	.580**	.041	.335**	.042	.732**	1	
7	PI	4.646	1.076	.162**	-.432**	.390**	.549**	-.020	-.153**	1

Note. EXPLAIN was coded -1 = low detail, 0 = medium detail, 1 = high detail. EXPLAIN2 is the squared term. ** $p < .01$.

4.4. Discrete Concave Direct Pattern of Explanation-Detail Transparency

Hierarchical regression supported the hypothesized concave pattern across the three discrete explanation-detail transparency conditions. After the control variables were entered, the linear term was positive and significant, whereas the squared term was negative and significant. The squared term added substantial explanatory power, and variance inflation factor (VIF) values were close to 1, indicating that multicollinearity was not a concern. As shown in Figure 2, the observed group means exhibited an asymmetric concave pattern: purchase intention was highest in the medium-detail condition ($M = 5.301$), lower in the high-detail condition ($M = 4.530$), and lowest in the low-detail condition ($M = 4.104$). Because the manipulation includes three ordered experimental levels, this result is interpreted as a discrete concave condition pattern rather than as an unrestricted continuous nonlinear curve.

Figure 2. Purchase intention means across explanation-detail transparency conditions.

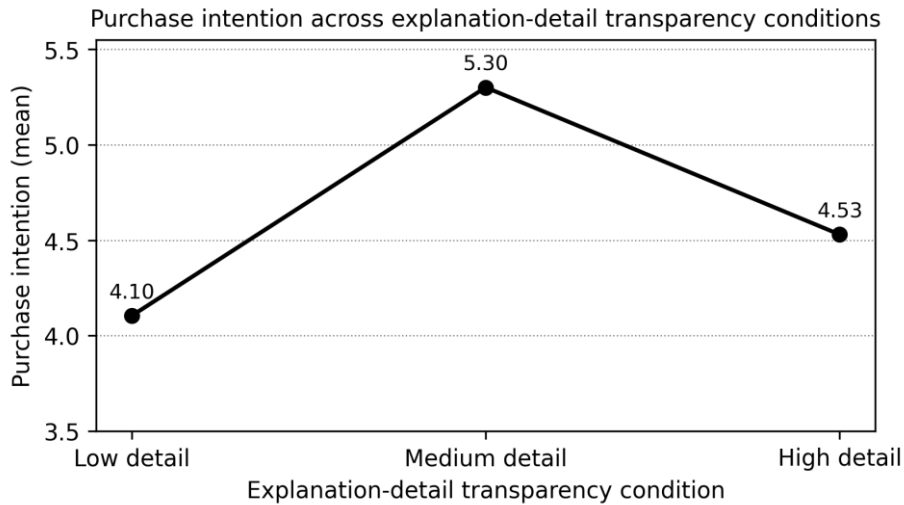


Table 10. Hierarchical regression test of the discrete concave direct pattern.

Model	Variables entered	Key coefficient or model fit	Incremental model fit	Conclusion
M1 controls	CA, PF, PD, INV	$R^2 = .118$; adjusted $R^2 = .110$	$F(4,467)=15.618$, $p < .001$	Baseline controls significant as a block
M2 linear explanation-detail term	Add EXPLAIN	$B = .209$, $\beta = .159$, $p < .001$	$\Delta R^2 = .025$	Linear trend positive
M3 quadratic term	Add EXPLAIN2	$B = -.962$, $\beta = -.422$, $t = -11.050$, $p < .001$	$\Delta R^2 = .178$; final $R^2 = .321$	Concave pattern supported
Diagnostics	Final model	VIF values approximately 1; Durbin-Watson = 2.002	--	No evidence of problematic multicollinearity or autocorrelation

4.5. Serial-Mediation Results

The PROCESS 4.2 Model 6 results were consistent with both theoretically specified serial-mediation mechanisms [49, 50]. Along the trust-benefit path, higher explanation-detail conditions were associated with greater perceived algorithm understandability; perceived algorithm understandability was positively associated with platform trust, which was positively associated with purchase intention. The estimated full sequential indirect effect of explanation-detail transparency on purchase intention through perceived

algorithm understandability and platform trust was positive and significant. These associations are interpreted as evidence consistent with the proposed mechanism rather than as proof of a temporally ordered causal sequence.

Along the privacy-cost path, higher explanation-detail conditions were associated with greater perceived data intrusiveness; perceived data intrusiveness was positively associated with information privacy concern, which was negatively associated with purchase intention. The estimated full sequential indirect effect of explanation-detail transparency on purchase intention through perceived data intrusiveness and information privacy concern was negative and significant. These associations are likewise interpreted as mechanism-consistent evidence. Because EXPLAIN2 captured the nonlinear direct component, the robustness models included EXPLAIN2 and the control variables; the key chain estimates remained significant and in the expected directions.

Table 11. PROCESS serial-mediation results.

Mechanism	Path	Estimate	Significance or CI	Conclusion
Trust-benefit chain	EXPLAIN → PAU	B = .9603	p < .001	Supported
Trust-benefit chain	PAU → PT	B = .5349	p < .001	Supported
Trust-benefit chain	PT → PI	B = .4604	p < .001	Supported
Trust-benefit chain	EXPLAIN → PAU → PT → PI	Indirect effect = .2365; BootSE = .0326	95% CI [.1765, .3048]	Supported
Privacy-cost chain	EXPLAIN → PDI	B = 1.1322	p < .001	Supported
Privacy-cost chain	PDI → PC	B = .6165	p < .001	Supported
Privacy-cost chain	PC → PI	B = -.2919	p < .001	Supported
Privacy-cost chain	EXPLAIN → PDI → PC → PI	Indirect effect = -.2038; BootSE = .0424	95% CI [-.2910, -.1259]	Supported

Note. PROCESS 4.2 Model 6 used 5,000 bootstrap samples, 95% confidence intervals, HC3 robust standard errors, and control variables [49, 50]. Estimates are unstandardized. Supplementary models that included EXPLAIN2 yielded the same substantive mediation conclusions.

4.6. SEM, Bootstrap Diagnostics, and Alternative Models

The AMOS structural model demonstrated acceptable-to-good fit and supported all core structural paths. The model explained 44.7% of the variance in perceived algorithm understandability, 30.6% in platform trust, 53.8% in perceived data intrusiveness, 58.5% in information privacy concern, and 41.3% in purchase intention. Although the RMR was comparatively high, the remaining fit indices consistently indicated acceptable-to-good model fit under conventional SEM guidelines [54, 55]. The RMR was therefore interpreted cautiously rather than used as the sole basis for rejecting the model.

Table 12. SEM model fit and structural paths.

Result type/path	Estimate	Interpretation
Model fit	$\chi^2 = 482.130$; $df = 292$; $\chi^2/df = 1.651$; GFI = .929; AGFI = .914; NFI = .961; IFI = .984; TLI = .982; CFI = .984; RMR = .119; RMSEA = .037; AIC = 600.130	Overall acceptable-to-good fit
EXPLAIN $\rightarrow$ PAU	$\beta = .668$; $p < .001$	Trust-benefit path start supported
PAU $\rightarrow$ PT	$\beta = .553$; $p < .001$	Trust-benefit path middle supported
PT $\rightarrow$ PI	$\beta = .471$; $p < .001$	Trust-benefit outcome path supported
EXPLAIN $\rightarrow$ PDI	$\beta = .733$; $p < .001$	Privacy-cost path start supported
PDI $\rightarrow$ PC	$\beta = .765$; $p < .001$	Privacy-cost path middle supported
PC $\rightarrow$ PI	$\beta = -.356$; $p < .001$	Privacy-cost outcome path supported
EXPLAIN $\rightarrow$ PI	$\beta = .278$; $p < .001$	Positive linear direct component
EXPLAIN2 $\rightarrow$ PI	$\beta = -.266$; $p < .001$	Concave direct component supported
R ²	PAU = .447; PT = .306; PDI = .538; PC = .585; PI = .413	Moderate-to-strong explanatory power

The AMOS bootstrap diagnostics provided supplementary path-level evidence for both theoretically specified mechanisms. Across 5,000 bias-corrected bootstrap samples, the confidence interval for each of the six component paths excluded zero: EXPLAIN $\rightarrow$ PAU, PAU $\rightarrow$ PT, PT $\rightarrow$ PI, EXPLAIN $\rightarrow$ PDI, PDI $\rightarrow$ PC, and PC $\rightarrow$ PI. These results are interpreted as path-level robustness evidence. The complete sequential indirect effects were tested primarily using PROCESS 4.2 Model 6, which provides dedicated bootstrap confidence intervals for each complete serial indirect effect.

Table 13. AMOS bootstrap path-level diagnostics.

Path	β	BC 95% CI	p	Interpretation
EXPLAIN → PAU	.668	[.617, .713]	.001	Trust-benefit start supported
PAU → PT	.553	[.475, .617]	.001	Trust-benefit middle supported
PT → PI	.471	[.377, .559]	< .001	Trust-benefit outcome supported
EXPLAIN → PDI	.733	[.691, .770]	< .001	Privacy-cost start supported
PDI → PC	.765	[.725, .800]	< .001	Privacy-cost middle supported
PC → PI	-.356	[-.451, -.260]	< .001	Privacy-cost outcome supported

Note. AMOS estimates are standardized and are based on 5,000 bias-corrected bootstrap samples. This table reports confidence intervals for the component paths from the supplementary AMOS analysis. The PROCESS 4.2 Model 6 results in Table 11 provide the primary tests of the complete sequential indirect effects of EXPLAIN on PI.

Alternative-model comparisons were conducted to determine whether the retained theoretical model offered mechanism-level explanatory value beyond simpler specifications. The models were not treated as interchangeable tests of the same question. The direct-effect-only model included the same experimental condition variables and purchase-intention outcome and showed excellent global fit; however, it omitted the latent trust-benefit and privacy-cost constructs and therefore summarized only condition mean differences. It could not address the study's central mechanism questions. The trust-only and privacy-only models each included a single mediator chain and therefore omitted the competing mechanism central to the personalization-paradox and trust-calibration logic. The reverse-path alternative fit the data substantially worse than the theoretical model, reducing concern that the proposed directionality was arbitrary. Accordingly, the theoretical model was retained on the basis of its purpose, construct coverage, directionality, and supported mechanism evidence rather than global fit statistics alone. Because the specifications differ in their observed-variable sets, latent structures, and degrees of freedom, they are neither nested nor directly comparable on a like-for-like basis. Their fit indices are therefore interpreted in relation to each model's theoretical purpose rather than used for mechanical ranking.

Table 14. Alternative model comparison.

Model	Specification	χ^2/df	CFI	RMSEA	Interpretation
M1	Theoretical main model: trust-benefit + privacy-cost + concave direct effect	1.651	.984	.037	Retained as final theoretical mechanism model
M2	Direct effects only: EXPLAIN and EXPLAIN2 $\rightarrow$ PI	1.204	.998	.021	Parsimonious support for direct effects, but no mechanism evidence
M3	Trust-benefit path only	2.450	.977	.055	Acceptable fit, but omits the privacy-cost mechanism
M4	Privacy-cost path only	1.232	.997	.022	Good fit, but omits the trust-benefit mechanism
M5	Reverse-path alternative model	3.511	.939	.073	Weaker fit; does not replace theoretical model

4.7. Robustness Checks and Statistical Power

Robustness checks addressed randomization imbalance, potential control-variable confounding, nonlinear specification, and discriminant validity. To maintain readability, the hypothesis tests in Sections 4.4-4.6 are presented as the primary analyses, whereas the additional regression, PROCESS 4.2, AMOS-control, AMOS path-level bootstrap, SmartPLS HTMT, and G*Power results are treated as supplementary robustness evidence. The concave direct pattern remained significant after product attractiveness, price fairness, page design, and product involvement were entered as controls. The PROCESS 4.2 mediation results remained stable when the nonlinear term and the same controls were included; an extended check additionally controlled for online shopping experience, recommendation-use frequency, and prior purchase due to a platform recommendation. AMOS models that included controls preserved the direction and significance of the core structural paths, and the supplementary AMOS bootstrap diagnostics showed that all six component-path confidence intervals excluded zero. The SmartPLS analysis showed that all HTMT values were below .85, with the highest value observed for PDI and PC (.764) [57]. The sensitivity analysis followed established guidance on statistical power [58, 59].

Table 15. Robustness and power summary.

Check	Key result	Conclusion
Regression with controls	EXPLAIN → PI: $B = .213$, $\beta = .162$, $p < .001$; EXPLAIN2 → PI: $B = -.958$, $\beta = -.421$, $p < .001$	Concave direct effect remained robust
PROCESS trust path with controls	EXPLAIN → PAU → PT → PI: effect = .237, 95% CI [.178, .302]	Trust-benefit chain remained robust
PROCESS privacy path with controls and EXPLAIN2	EXPLAIN → PDI → PC → PI: effect = -.207, 95% CI [-.282, -.134]; EXPLAIN2 → PI: $B = -.936$, $p < .001$	Privacy-cost chain and nonlinear term remained robust
Extended controls, including prior recommendation-driven purchase	EXPLAIN2 → PI: $\beta = -.424$, $p < .001$; trust-benefit chain effect = .2345, 95% CI [.1720, .3025]; privacy-cost chain effect = -.2074, 95% CI [-.2935, -.1276]	Core conclusions remained robust after controlling for prior purchase due to a platform recommendation
HTMT discriminant validity	Highest HTMT = .764 for PDI-PC; all values < .85	Discriminant validity supported
G*Power sensitivity analysis	$N = 472$, $\alpha = .05$, power = .80, three groups; detectable $f = .143$	The sample was adequate to detect small group differences

4.8. Hypothesis Summary

Table 16. Hypothesis-testing summary.

Hypothesis	Expected effect	Main evidence	Conclusion
H1	EXPLAIN → PAU (+)	SEM $\beta = .668$; PROCESS $B = .9603$	Supported
H2	PAU → PT (+)	SEM $\beta = .553$; PROCESS $B = .5349$	Supported
H3	PT → PI (+)	SEM $\beta = .471$; PROCESS $B = .4604$	Supported
H4	EXPLAIN → PAU → PT → PI (+)	PROCESS effect = .2365; 95% CI [.1765, .3048]	Supported
H5	EXPLAIN → PDI (+)	SEM $\beta = .733$; PROCESS $B = 1.1322$	Supported
H6	PDI → PC (+)	SEM $\beta = .765$; PROCESS $B = .6165$	Supported
H7	PC → PI (-)	SEM $\beta = -.356$; PROCESS $B = -.2919$	Supported
H8	EXPLAIN → PDI → PC → PI (-)	PROCESS effect = -.2038; 95% CI [-.2910, -.1259]	Supported
H9	Concave direct effect on PI	Regression $\beta = -.422$; SEM $\beta = -.266$	Supported
Supplementary analysis	AMOS path-level bootstrap	Six component-path BC 95% CIs excluded zero	Path-level robustness supported

Note. AMOS bootstrap path-level results are supplementary robustness evidence. Complete trust-benefit and privacy-cost serial indirect effects are evaluated primarily with PROCESS 4.2 Model 6.

5. DISCUSSION

The findings indicate that explanation-detail transparency in AI recommendation interfaces has both benefits and costs for e-commerce system design. On the benefit side, greater explanation detail was associated with higher perceived algorithm understandability and platform trust, and the trust-path estimates were consistent with stronger purchase intention. On the cost side, greater detail made data use more visible and was associated with higher perceived data intrusiveness and information privacy concern, while privacy concern was negatively associated with purchase intention. Taken together, the results are consistent with the interpretation that recommendation explanations operate as both competence signals and privacy-risk signals, which helps account for why the most detailed interface is not necessarily the most effective in terms of purchase intention.

The concave condition pattern has a central implication for interface design. The medium-detail condition showed the highest purchase intention. This pattern is consistent with the interpretation that medium detail provided sufficient rationale for consumers to understand the recommendation without overemphasizing the breadth of data tracking. The pattern was asymmetric: the high-detail condition still outperformed the low-detail condition but performed worse than the medium-detail condition. The managerial implication is therefore not that transparency should be avoided, but that explanation detail should be calibrated.

The study also clarifies the distinction between perceived data intrusiveness and information privacy concern. Their correlation and HTMT value indicate that the constructs are related, whereas the discriminant-validity results show that they are empirically distinct. This finding is consistent with the proposed privacy-cost sequence: a highly detailed explanation may make data use feel intrusive, and that perception was associated with broader privacy concern and lower purchase intention.

From an e-commerce management perspective, AI recommendation explanations should be designed as calibrated rather than maximal disclosure. Platforms should make the reasons for a recommendation visible, concrete, and easy for consumers to understand, while avoiding excessive lists of behavioral traces or highly granular inferred scenarios in the default interface. Additional information can be made available through expandable 'Why am

I seeing this?' links, privacy dashboards, layered notices, data-control options, and user-adjustable explanation-depth settings. Such a layered design can preserve the trust benefits of transparency while mitigating its privacy costs.

6. THEORETICAL CONTRIBUTIONS

First, this study extends research on explainable recommender systems by showing that recommendation explanations are not merely cognitive aids that make algorithmic matching easier to understand. They also serve as privacy-risk signals by revealing how consumers interpret a platform's use of personal data. This dual-signal logic helps reconcile research that emphasizes the benefits of transparency with privacy research that highlights the costs of personalization.

Second, the study contributes to e-commerce trust research by identifying perceived algorithm understandability as an antecedent of platform trust in AI recommendation contexts. Trust is therefore shaped not only by platform reputation, vendor safeguards, transaction security, or sanctions but also by the intelligibility of algorithmic product matching in the recommendation interface.

Third, the study contributes to research on privacy and the personalization paradox by distinguishing perceived data intrusiveness from information privacy concern. This distinction clarifies how privacy costs may unfold. Consumers may first perceive an explanation as revealing excessive detail about data use, after which this sense of intrusiveness may develop into broader concern about information collection and control.

Fourth, the study advances a calibrated explanation-detail transparency perspective for e-commerce theory and system design. Rather than treating transparency as a unidirectional benefit or a simple disclosure obligation, the study identifies a discrete concave design logic in this experimental context. Here, the medium-detail condition was associated with the highest purchase intention, suggesting that moderate explanation detail may offer a favorable balance between trust benefits and privacy costs.

7. PRACTICAL IMPLICATIONS

For e-commerce managers, the results suggest that recommendation explanations should be concise, relevant, and easy to understand. An effective

default explanation should answer a consumer's basic question, 'Why is this product recommended to me?' without implying that the platform has developed an exhaustive profile of the consumer.

Platforms should avoid default explanations that enumerate excessive behavioral records, inferred preferences, or life scenarios. Such wording may increase transparency in a literal sense while simultaneously triggering perceptions of data intrusiveness. A layered design is preferable: platforms can display a medium-detail explanation by default, provide an expandable 'Why am I seeing this?' explanation for users who want more information, link the explanation to a privacy dashboard, offer data-control options such as enabling or disabling specific signals, and allow users to adjust explanation depth.

AI governance teams should evaluate recommendation explanations using both trust and privacy metrics. A/B tests that measure only click-through or conversion outcomes may overlook privacy concern and longer-term trust calibration. Interface reviews should therefore assess whether an explanation functions as a competence signal without becoming a privacy-risk signal. The measures used in this study, which draw on validated scales of e-commerce trust, privacy concern, intrusiveness, purchase intention, and website evaluation [16, 17, 26, 27, 31-48], provide a useful diagnostic set for determining whether explanations are informative without being intrusive.

8. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, it used a scenario-based experiment involving a single product category and price point. The evidence should therefore be interpreted within this product, scenario, and cultural and platform context. Future research should examine whether the calibrated explanation-detail pattern holds for high-involvement products, services, financial recommendations, health-related recommendations, and other privacy-sensitive services. Second, the dependent variable was purchase intention rather than actual purchase behavior. Although purchase intention is appropriate for a scenario experiment, the findings should not be generalized to actual conversion effects. Future studies could combine experimental manipulations with clickstream data, add-to-cart behavior, subscription renewal, actual purchases, conversion outcomes, or field A/B tests.

Third, the sample comprised online consumers with recent shopping or browsing experience in a specific cultural and platform context. Cross-cultural research could examine whether privacy sensitivity, trust formation, and preferences for explanation detail vary across markets. Fourth, the study used three discrete levels of explanation detail. Future research could examine richer formats, including visual explanations, counterfactual explanations, natural-language explanations generated by large language models, and user-controlled layered explanations.

Fifth, the manipulation represents realistic explanation-detail calibration rather than a pure manipulation of technical transparency. The high-detail condition necessarily made behavioral and preference cues more explicit. Although this feature is central to the privacy-cost mechanism, it may also have introduced perceptions of data salience or creepiness. Future studies should manipulate explanation amount, data-type specificity, personalization depth, and tone independently to identify which design features most strongly activate privacy concern.

Sixth, because the mediators and outcome were measured in the same questionnaire wave, the sequential mediation paths should be interpreted as theory-driven mechanism tests rather than as definitive evidence of temporally ordered psychological processes. Longitudinal or multistage experimental designs could strengthen causal inference regarding the progression from understandability to trust and from data intrusiveness to privacy concern and purchase intention.

Finally, although formal ethics review was not required under the institutional requirements applicable at the time of data collection, future studies should prospectively document the applicable ethics-review or exemption status and report it clearly.

9. CONCLUSIONS

This study indicates that explanation-detail transparency in AI recommendations is associated with both trust benefits and privacy costs in e-commerce. Greater explanation detail was associated with higher perceived algorithm understandability and platform trust, and the trust-path estimates were consistent with stronger purchase intention. At the same time, greater detail was associated with higher perceived data intrusiveness and

information privacy concern, while privacy concern was negatively associated with purchase intention. The coexistence of these mechanism-consistent patterns helps account for the asymmetric discrete concave condition pattern observed in the experiment: the medium-detail condition produced the most favorable purchase intention. The findings support calibrated explanation-detail transparency as a design principle for human-centered AI recommendation systems. E-commerce platforms should not equate transparency with maximum disclosure; instead, they should provide explanations that are understandable, relevant, and sensitive to privacy concerns.

10. DECLARATIONS

10.1. Funding

This research received no external funding.

10.2. Institutional Review Board Statement

Under the institutional requirements applicable at the time of data collection, formal ethics review was not required for this anonymous, low-risk, noninterventional, scenario-based online survey of adult participants. The study did not involve clinical procedures, vulnerable groups, real purchases, financial transactions, access to participants' actual browsing histories, or the collection of identifiable personal information. Informed consent was obtained before participation, and the procedure incorporated voluntary participation, anonymity, aggregate reporting, and data minimization.

10.3. Informed Consent Statement

Informed consent was obtained from all participants before they began the questionnaire. Participants were informed of the study's academic purpose, the anonymous and aggregate use of their responses, the voluntary nature of participation, and their right to withdraw without penalty.

10.4. Data Availability Statement

The de-identified analytic dataset and study materials may be made available as supplementary materials or obtained from the authors upon reasonable request. Raw survey-platform exports are not publicly available because they may contain operational metadata that are unnecessary for replication.

10.5. Conflicts of Interest

The authors declare no conflicts of interest.

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