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Consumer Trust in AI-Generated Recommendations: Role of Transparency and Perceived Control

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Abstract
Algorithmic recommenders now mediate much of what consumers see, buy and watch, yet acceptance depends less on accuracy than on whether the system can be understood and influenced. This study examines how transparency, perceived control, recommendation accuracy and privacy concern shape consumer trust in AI-generated recommendations, and whether trust predicts willingness to follow them. Data were collected from 140 respondents using a structured questionnaire on a five-point Likert scale and analysed in IBM SPSS Statistics (Version 27) through reliability analysis, descriptive statistics, Pearson correlation, regression and an independent samples t-test. The model explained 63.9 per cent of the variance in trust. Transparency was the strongest predictor, followed by perceived control and accuracy, while privacy concern exerted a significant negative influence. Trust strongly predicted willingness to act on recommendations, indicating that interpretability and user agency underpin algorithmic acceptance.

Keywords: consumer trust, AI recommendations, transparency, perceived control, explainability, algorithm aversion

1. Introduction

1.1 Background of the Study

Recommendation systems have become the default interface between consumers and large assortments. Streaming catalogues, marketplaces, news feeds and financial platforms infer preference from behavioural traces and present a narrowed set of options. This shifts the consumer's experience from searching to receiving, making artificial intelligence a participant in choice rather than a background utility (Puntoni et al., 2021), and reconfigures the customer journey itself (Davenport et al., 2020). Whether consumers accept what these systems suggest remains an open question, since evidence on algorithmic reliance is strikingly mixed (Jussupow et al., 2020).

1.2 Transparency and Perceived Control as Design Levers

Two design properties recur in explanations of algorithmic acceptance. Transparency concerns the visibility of how a recommendation was produced, and has been advanced as the route from black-box to glass-box systems (Rai, 2020). Perceived control concerns the consumer's ability to influence output by adjusting inputs, correcting mistakes or overriding suggestions. The two are distinct but linked, since consumers can rarely control a process they cannot observe. Both bear on consumer autonomy in markets curated by machines (André et al., 2018), making their relative contribution to trust a managerial as well as theoretical question.

1.3 Objectives and Significance of the Study

The study pursues three objectives: to examine the relationship between transparency, perceived control, recommendation accuracy, privacy concern and consumer trust in AI-generated recommendations; to determine which of these factors most strongly influences trust; and to test whether trust predicts willingness to act on recommendations. Its significance is twofold. Conceptually, it brings transparency and control into a single model rather than treating them separately, allowing their relative weight to be compared. Practically, it informs platform design choices, since publishing explanations, building preference controls and improving model precision impose very different costs and, as the findings suggest, deliver very different returns.

2. Review of Literature

2.1 Consumer Trust in Algorithmic Recommendations

Early experimental work established that consumers penalise algorithms disproportionately for visible error, abandoning a statistically superior model after seeing it fail (Dietvorst et al., 2015). Later studies complicated this. Logg et al. (2019) documented algorithm appreciation, with people often weighting algorithmic advice above human advice on estimation tasks. Castelo et al. (2019) showed reliance to be task-dependent, falling sharply for subjective tasks thought to require human judgement, while Longoni et al. (2019) traced medical resistance to a belief that algorithms ignore individual uniqueness. Reviews confirm that trust in AI is shaped by transparency, reliability and representational cues rather than performance alone (Glikson & Woolley, 2020), and that public perceptions of automated decision-making remain cautious (Araujo et al., 2020). Recent evidence links resistance to underlying psychological attitudes rather than to specific tool features (De Freitas et al., 2023).

2.2 Transparency and Explainability

A second stream tests transparency directly. Kizilcec (2016) found the relationship non-monotonic: moderate explanation raised trust in an algorithmic interface, whereas excessive disclosure reduced it, indicating an optimum rather than a maximum. Shin and Park (2019) showed that fairness, accountability and transparency operate jointly as algorithmic affordances, and Shin (2021) found that explainability and causability influence trust through perceived understanding. Lee (2018) reported that reactions depend on whether the task is seen as requiring human skill, with opacity amplifying negative responses. Sundar (2020) framed these effects within machine agency, arguing that interface cues signalling how a system operates shape attributions of trustworthiness. Transparency thus functions less as information provision than as a signal of accountability.

2.3 Perceived Control, Accuracy and Privacy

The third stream concerns agency and its limits. Dietvorst et al. (2018) showed that allowing users to modify an algorithm's output, even slightly, substantially increased willingness to use it, establishing control as a remedy for aversion. André et al. (2018) situated this within debates on consumer autonomy, warning that personalised systems may narrow choice while appearing to serve it. Accuracy matters but is not decisive: Yin et al. (2019) found stated model accuracy influences trust, though observed performance moderates the effect. Privacy works in the opposite direction, since recommendation quality rests on data collection consumers may resent, with measurable effects on customer and firm outcomes (Martin et al., 2017). These strands motivate a

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model in which transparency and control drive trust, accuracy supports it and privacy concern erodes it.

3. Research Methodology

The study follows a descriptive and analytical design based on primary data. The target population comprised adult internet users who regularly encounter AI-generated recommendations on e-commerce, streaming, social media or financial platforms. A sample of 140 respondents was obtained through purposive sampling supplemented by referral, with data collected between December 2024 and March 2025 through an online questionnaire.

The instrument had two sections. Section A recorded demographic details and platform usage. Section B contained twenty-six statements measuring six constructs, namely transparency, perceived control, recommendation accuracy, privacy concern, consumer trust and willingness to follow recommendations, adapted from validated scales (Kizilcec, 2016; Shin, 2021; Glikson & Woolley, 2020) and rated from 1 (strongly disagree) to 5 (strongly agree). Two academic experts reviewed content validity, and a pilot study of 20 respondents preceded full deployment; pilot responses were excluded from the final dataset.

Analysis was performed in IBM SPSS Statistics (Version 27) using Cronbach's alpha for internal consistency, descriptive statistics, Pearson correlation, multiple regression estimating the joint effect of the four antecedents on trust, simple regression testing the effect of trust on willingness to follow recommendations, and an independent samples t-test comparing experienced and less experienced users. Normality, linearity, homoscedasticity and multicollinearity assumptions were verified, with all variance inflation factors below 2.0. Significance was assessed at the five per cent level.

4. Results and Discussion

Table 1 profiles the 140 respondents. The sample skews young and well educated, and three-quarters encounter algorithmic recommendations at least weekly, indicating routine exposure.

Table 1: Profile of Respondents (n = 140)

Variable	Category	Frequency	Percentage
Gender	Male	74	52.9
	Female	66	47.1
Age (years)	18–25	42	30.0
	26–35	49	35.0
	36–45	28	20.0
	Above 45	21	15.0
Education	Undergraduate	56	40.0
	Postgraduate	63	45.0
	Other	21	15.0
Occupation	Student	35	25.0
	Salaried employee	56	40.0
	Self-employed	28	20.0
	Other	21	15.0
Main platform	E-commerce	56	40.0
	Streaming services	42	30.0
	Social media	28	20.0
	Financial and others	14	10.0
Exposure frequency	Daily	49	35.0
	Weekly	56	40.0
	Occasionally	35	25.0
Experience with AI tools	Two years or more	82	58.6
	Less than two years	58	41.4

Source: Primary data analysed through SPSS.

Table 2 reports construct means, standard deviations and reliability coefficients, with all alpha values above the 0.70 threshold. Privacy concern records the highest mean (3.96) and perceived control the lowest (3.41), indicating that respondents worry about data use while feeling little ability to influence what is recommended to them.

Table 2: Descriptive Statistics and Reliability of Constructs

Construct	Items	Mean	SD	Cronbach's α
Transparency	5	3.54	0.76	0.831
Perceived control	4	3.41	0.82	0.807
Recommendation accuracy	4	3.87	0.68	0.794
Privacy concern	4	3.96	0.73	0.818
Consumer trust	5	3.62	0.71	0.856
Willingness to follow	4	3.58	0.74	0.842

n = 140. Overall scale reliability = 0.874.

Table 3 presents the correlation matrix. Transparency, perceived control and accuracy correlate positively with trust, while privacy concern correlates negatively. Transparency shows the strongest association with trust (r = .668) and trust correlates most strongly with willingness to follow recommendations (r = .703). Inter-predictor correlations remain moderate, indicating no multicollinearity threat.

Table 3: Pearson Correlation Matrix

Variable	1	2	3	4	5	6
1. Transparency	1					
2. Perceived control	.562**	1				
3. Accuracy	.487**	.453**	1			
4. Privacy concern	–.341**	–.386**	–.268**	1		
5. Consumer trust	.668**	.631**	.545**	–.412**	1	
6. Willingness to follow	.597**	.589**	.521**	–.377**	.703**	1

**Correlation is significant at the 0.01 level (2-tailed). n = 140.

Table 4 summarises the regression of consumer trust on the four antecedents. The model is significant, $F(4, 135) = 59.74$, $p < .001$, with R^2 of .639 and adjusted R^2 of .628, explaining about 64 per cent of the variance in trust.

Table 4: Multiple Regression Results (Dependent Variable: Consumer Trust)

Predictor	B	SE	β	t	Sig.	VIF
(Constant)	1.128	0.312	—	3.615	.000	—
Transparency	0.305	0.069	.327	4.420	.000	1.66
Perceived control	0.252	0.064	.291	3.963	.000	1.59
Recommendation accuracy	0.223	0.075	.214	2.976	.003	1.48
Privacy concern	–0.159	0.066	–.163	–2.412	.017	1.35

$R^2 = .639$; Adjusted $R^2 = .628$; $F(4, 135) = 59.74$, $p < .001$; n = 140.

Transparency is the dominant predictor ($\beta = .327$, $p < .001$), followed by perceived control ($\beta = .291$, $p < .001$) and accuracy ($\beta = .214$, $p = .003$), while privacy concern reduces trust ($\beta = –.163$, $p = .017$). That accuracy ranks third is notable, suggesting that a precise but unexplained recommender earns less trust than a slightly weaker system whose logic is visible and adjustable. The pattern aligns with Kizilcec (2016) and Shin (2021) on explanation effects and with Dietvorst et al. (2018) on the restorative power of user control. A simple regression confirmed that trust predicts willingness to follow recommendations, $\beta = .703$, $R^2 = .494$, $F(1, 138) = 134.71$, $p < .001$.

Table 5 reports the independent samples t-test comparing users with two or more years of experience against less experienced users. Experienced users rate transparency, control and trust significantly higher, consistent with the view that familiarity builds calibrated rather than blind confidence.

Table 5: Independent Samples t-Test by Experience with AI Recommendations

Construct	Experienced	Less experienced	t (138)	Sig.
Transparency	3.71	3.30	3.24	.001
Perceived control	3.58	3.17	2.98	.003
Consumer trust	3.78	3.39	3.31	.001

Values are group means. Experienced n = 82; less experienced n = 58. Equal variances assumed; Levene's test non-significant.

5. Conclusion

This study examined the determinants of consumer trust in AI-generated recommendations among 140 respondents. Trust rests primarily on transparency and perceived control rather than on predictive accuracy, and privacy concern measurably erodes it. Trust in turn strongly predicts willingness to act on recommendations, making it the pivotal construct between system design and consumer behaviour. Platforms should therefore offer concise explanations of why an item was suggested, provide accessible controls that let consumers correct or override inferences, state data practices plainly, and resist the assumption that model precision alone will secure acceptance.

Certain limitations apply. Purposive sampling of 140 respondents restricts generalisability, self-reported perceptions may diverge from observed behaviour, and the cross-sectional design prevents causal inference. The study also treats recommendations generically rather than distinguishing between product, content and financial contexts, where stakes differ considerably. Future research could employ experimental manipulation of explanation depth to test the non-monotonic effect reported by Kizilcec (2016), compare high-stakes and low-stakes domains, and apply structural equation modelling to examine trust as a mediator between system attributes and behavioural outcomes.

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