

AI PERSONALISATION WITHOUT THE GUESSWORK: HOW TRANSPARENCY AND CONSUMER CONTROL SHAPE TRUST AND PURCHASE INTENTION IN ONLINE RETAIL

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Abstract

AI-enabled personalisation is increasingly shaping online retail, offering consumers relevant recommendations while raising concerns about privacy and transparency. This study examines the relationships among AI personalisation, algorithmic transparency, perceived consumer control, privacy concern, consumer trust, and purchase intention. Drawing on the Stimulus–Organism–Response perspective and privacy-calculus reasoning, consumer trust is proposed as a key mechanism linking AI-enabled marketing practices with purchase intention. A quantitative research design is demonstrated using a dataset of 400 online shoppers and 24 Likert-scale items. Data were analysed using reliability analysis, KMO and Bartlett’s tests, exploratory factor analysis, correlation, multiple regression, mediation, and moderation analysis. The results indicate positive associations of AI personalisation, transparency, and perceived control with consumer trust, while privacy concern is negatively associated with trust. Consumer trust is positively associated with purchase intention and mediates the relationship between AI personalisation and purchase intention. The study provides a framework for understanding the usefulness–privacy tension in AI-mediated marketing and offers implications for digital marketers.

Keywords: AI personalisation; algorithmic transparency; consumer trust; privacy concern; perceived consumer control; purchase intention; online retail.

1. Introduction

Personalisation has been a long-standing aspiration of marketers. The basic promise is straightforward: if a firm knows something about a consumer's interests, it can make the next message, recommendation or offer more relevant. Artificial intelligence has substantially expanded what “knowing” can mean in a digital environment. Recommendation engines can combine browsing behaviour, previous purchases, product similarity, contextual signals and other data points in milliseconds. From the consumer's side, this may reduce search effort. From the marketer's side, it creates an opportunity to move from broad segmentation towards highly individualised communication.

The difficulty is that relevance and intrusiveness can exist in the same experience. A recommendation that appears at the right moment may be welcomed because it removes effort. A similar recommendation can feel uncomfortable when it seems to reveal more about the consumer than the consumer knowingly disclosed. Earlier research on personalisation has therefore described a tension between the benefits of relevance and the costs of privacy concerns. Aguirre et al. (2015), for example, showed that personalisation can create a paradox: greater personalisation does not automatically produce better consumer responses when consumers become

concerned about the information practices behind it. More recent work on artificial intelligence adds another layer. AI is not simply another communication channel; it changes the consumer's perception of how decisions are made, who is making them and whether the system is acting in the consumer's interest (Puntoni et al., 2021).

Trust becomes particularly important in this setting. Online purchasing already involves uncertainty because consumers cannot physically inspect products or interact face-to-face with a seller. Gefen et al. (2003) demonstrated that trust is a central component of online shopping intention. AI-mediated recommendations add uncertainty of a different kind: consumers may not know why a particular product appeared, whether the ranking reflects their interests or commercial priorities, and how much personal information shaped the recommendation. Transparency and perceived control may therefore act as signals that make the system easier to understand and less threatening.

At the same time, transparency should not be treated as a universally beneficial switch. Disclosing that an algorithm uses browsing history may reassure one consumer and alarm another. Acquisti et al. (2020) note that privacy decisions are shaped by a complicated interaction between individuals, information environments and contextual cues. Dinev and Hart (2006) similarly conceptualised privacy decisions as a calculus in which perceived benefits and risks are weighed against one another. This suggests that privacy concern may change the way consumers interpret the same personalisation practice.

The present study addresses this issue by bringing four marketing variables—AI personalisation, algorithmic transparency, perceived control and privacy concern—into one model with consumer trust and purchase intention. Rather than assuming that personalisation directly produces purchase intention, the model treats trust as the psychological bridge between the marketing stimulus and the behavioural intention. This is consistent with the Stimulus–Organism–Response logic, in which external environmental cues affect an internal state that subsequently influences a response.

1.1 Research Problem

AI personalisation creates a practical dilemma for marketers. Consumers expect digital services to be relevant, but they do not necessarily want every aspect of their behaviour to become visible in the marketing system. If personalisation is experienced as useful, it can reduce search effort. If it is experienced as surveillance, the same mechanism may weaken trust. The research problem is therefore not simply whether AI personalisation works, but under what psychological conditions consumers remain comfortable enough to trust the platform and consider purchasing.

1.2 Research Gap

Three gaps motivate the present model. First, studies of personalisation and studies of AI-mediated consumer experiences have often developed in parallel, leaving room for integrated models that connect personalisation with trust and purchase intention. Second, transparency and consumer control are frequently discussed as ethical or governance principles, but they can also be understood as marketing signals that shape consumer evaluations. Third, privacy concern deserves treatment as a boundary condition rather than merely as a descriptive demographic characteristic. The proposed model therefore combines the usefulness side of personalisation with the risk side of privacy in a single consumer-behaviour framework.

1.3 Research Questions

RQ1: How is perceived AI personalisation associated with consumer trust in online retail?

RQ2: How are algorithmic transparency and perceived consumer control associated with consumer trust?

RQ3: What is the relationship between consumer trust and purchase intention?

RQ4: Does consumer trust mediate the relationship between AI personalisation and purchase intention?

RQ5: Does privacy concern alter the relationship between AI personalisation and consumer trust?

1.4 Research Objectives

1. To examine the relationship between AI personalisation and consumer trust.
2. To assess the influence of algorithmic transparency and perceived control on consumer trust.
3. To examine the relationship between consumer trust and purchase intention.
4. To test the mediating role of consumer trust between AI personalisation and purchase intention.
5. To examine privacy concern as a moderating condition in the personalisation–trust relationship.

2. Theoretical Foundation

2.1 Stimulus–Organism–Response Perspective

The Stimulus–Organism–Response (S-O-R) framework provides the organising logic for the model. In this study, AI personalisation, transparency and perceived control are treated as environmental or marketing stimuli. Consumer trust represents an internal evaluative state, while purchase intention represents the behavioural response. The framework is useful because it prevents the analysis from assuming that a marketing technology has a direct and automatic effect on behaviour. Instead, consumers interpret the technology first; the resulting psychological evaluation then influences intention.

2.2 Privacy Calculus Perspective

Privacy calculus theory adds the risk–benefit side of the argument. Consumers may accept information practices when the expected benefits appear worthwhile, but the balance changes when perceived privacy risk becomes salient. Dinev and Hart (2006) found that privacy concerns can inhibit online transactions while trust and perceived benefits can offset some of that resistance. In an AI personalisation context, privacy concern is therefore expected to weaken the favourable interpretation of personalisation.

2.3 Trust in Online Commerce

Trust is central because online purchasing involves uncertainty. Gefen et al. (2003) showed that trust complements technology-related beliefs in explaining online purchase intentions. In the present model, trust is not treated as an abstract attitude. It represents the consumer's willingness to rely on the platform's recommendations and believe that the system is reasonably dependable and acts in a manner consistent with the consumer's interests.

3. Literature Review and Hypotheses Development

3.1 AI Personalisation

AI personalisation refers here to the use of algorithmic systems to tailor product recommendations, promotional messages or shopping content to an individual consumer. Personalisation is not new, but AI increases the speed, scale and granularity with which it can be delivered. Puntoni et al. (2021) emphasise that AI can alter the consumer experience because people respond not only to outcomes but also to the nature of the technology involved. In practical terms, consumers may appreciate an AI system when it removes effort and provides useful recommendations, while reacting negatively when the technology feels invasive or difficult to understand.

Personalisation research also shows that relevance alone is not sufficient. Aguirre et al. (2015) demonstrated that personalisation can become less effective when consumers become aware of data collection practices. Bleier and Eisenbeiss (2015) similarly found that the effectiveness of personalised online advertising depends on contextual and consumer-related conditions. These findings suggest that personalisation should be understood as a conditional marketing resource rather than a guaranteed driver of positive responses.

H1: Perceived AI personalisation is positively associated with consumer trust.

3.2 Algorithmic Transparency

Algorithmic transparency concerns the extent to which consumers can understand that a recommendation is generated by an algorithm and can obtain a meaningful explanation of why a recommendation was shown. Transparency can reduce ambiguity. When a platform states that a product is recommended because the consumer previously viewed similar products, the recommendation becomes easier to interpret. Recent marketing research also suggests that transparency in AI-mediated communication can influence consumer responses, although the direction may depend on the design and context. Wang and Qiu (2024), for example, found positive effects of AI-technology transparency for digital endorsers.

H2: Perceived algorithmic transparency is positively associated with consumer trust.

3.3 Perceived Consumer Control

Control refers to the consumer's perception that they can influence personalisation settings, modify preferences, limit data use or otherwise exercise meaningful choice. Control is conceptually different from transparency. A platform can explain its recommendation system without giving consumers any practical choice. Conversely, a privacy setting may provide control without explaining why a particular recommendation appeared. Treating the two constructs separately allows the study to examine whether both informational clarity and agency matter for trust.

H3: Perceived consumer control over personalisation is positively associated with consumer trust.

3.4 Privacy Concern

Privacy concern is the degree to which consumers worry about the collection, use or potential misuse of personal information. It is particularly relevant to AI personalisation because the perceived usefulness of the system may itself be evidence that the platform knows a great deal about the user. Acquisti et al. (2020) describe privacy decision-making as a difficult balance between the desire for privacy and the practical benefits of participating in digital environments. Lefkeli et al. (2024) further show that consumers may react differently when information is shared with AI rather than a human, with privacy concern strengthening negative brand-trust effects in their experiments.

H4: Privacy concern is negatively associated with consumer trust.

3.5 Consumer Trust and Purchase Intention

Purchase intention represents a consumer's stated willingness to consider or make a purchase. Trust is expected to be a proximal antecedent because recommendations ask consumers to rely on information generated by a system they may not fully understand. Gefen et al. (2003) provide a strong foundation for this relationship in e-commerce. In AI-mediated environments, the logic remains relevant: a consumer may find a recommendation useful but still decline to act if the platform is not trusted.

H5: Consumer trust is positively associated with purchase intention.

3.6 Mediating Role of Consumer Trust

The model proposes that personalisation affects purchase intention partly through trust. This is a more cautious proposition than claiming that personalisation directly causes purchasing. A recommendation can be relevant without being persuasive. Trust provides the psychological mechanism that allows consumers to rely on the recommendation. Therefore, the positive effect of AI personalisation on purchase intention is expected to be transmitted, at least in part, through consumer trust.

H6: Consumer trust mediates the relationship between AI personalisation and purchase intention.

3.7 Moderating Role of Privacy Concern

The same level of personalisation may be interpreted differently by consumers with different levels of privacy concern. A consumer with low privacy concern may focus on convenience and relevance, whereas a highly privacy-concerned consumer may interpret personalised recommendations as evidence of extensive data collection. This creates a plausible interaction between personalisation and privacy concern. The expected positive relationship between personalisation and trust should therefore be weaker when privacy concern is high.

H7: Privacy concern negatively moderates the positive relationship between AI personalisation and consumer trust.

4. Conceptual Framework

The proposed model is presented below in simplified form:

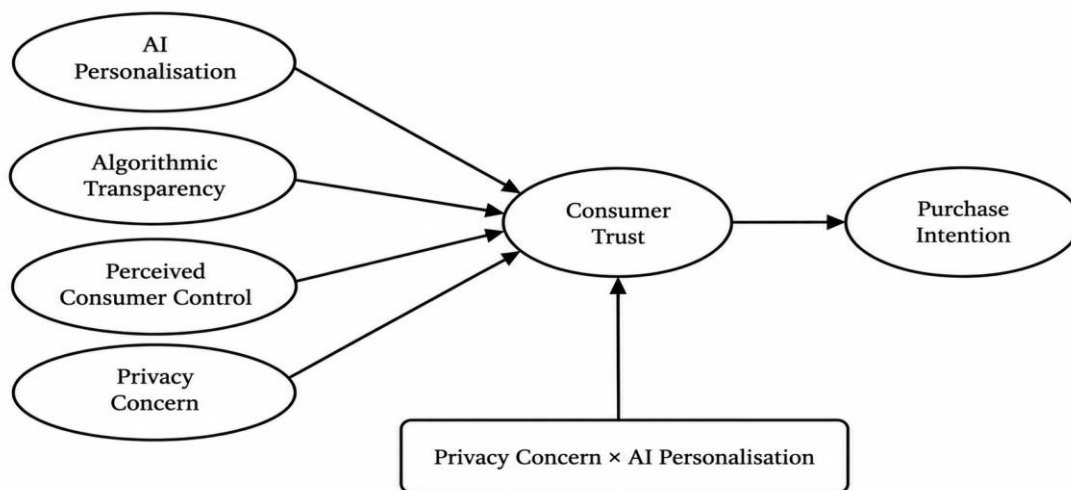


Fig 1: Proposed Model

5.1 Research Design

The study uses a quantitative, explanatory, cross-sectional design. The purpose is to demonstrate how measurable consumer perceptions can be translated into a statistical model.

5.2 Population and Sampling Design

The proposed population consists of adult online shoppers who have encountered algorithmic recommendations on e-commerce or digital retail platforms across the cities in Gujarat State. For the analysis, 400 respondents were surveyed across Gujarat. The sample was designed to resemble a digitally active consumer population rather than to reproduce the demographics of any particular city.

5.3 Measurement Instrument

A structured questionnaire was specified using a seven-point Likert response format, where 1 represented strongly disagree and 7 represented strongly agree. The wording was developed from established conceptualisations in the literature and adapted to the present context.

AI Personalisation (AIP)

AIP1: Recommendations are relevant to my interests.

AIP2: The platform personalises products in ways that are useful to me.

AIP3: Personalised recommendations reduce the effort I spend searching.

AIP4: The recommendations generally fit my shopping needs.

Algorithmic Transparency (TR)

TR1: The platform makes it reasonably clear why a product is recommended.

TR2: I can understand the main basis on which recommendations are generated.

TR3: The platform clearly communicates when recommendations are algorithmically generated.

TR4: The explanation behind a recommendation is understandable to me.

Perceived Consumer Control (PC)

PC1: I feel that I can control how recommendations are personalised for me.

PC2: I can change my personalisation preferences when I want.

PC3: I have meaningful choices about the use of my data for personalisation.

PC4: The platform gives me enough control over personalised recommendations.

Privacy Concern (PCT)

PCT1: I worry about how much personal information is used for personalisation.

PCT2: I am concerned that my shopping data could be used in ways I did not expect.

PCT3: Personalised recommendations sometimes make me feel that my privacy is at risk.

PCT4: I am concerned about excessive data collection for personalised marketing.

Consumer Trust (TRUST)

CT1: I trust this type of platform to provide reliable recommendations.

CT2: I believe the platform generally has my interests in mind when recommending products.

CT3: I feel confident relying on the platform's personalised recommendations.

CT4: I consider the platform trustworthy when it uses my data for recommendations.

Purchase Intention (PI)

PI1: I would consider purchasing a product recommended by the platform.

PI2: I am likely to buy products that are recommended in a relevant way.

PI3: Personalised recommendations increase my willingness to purchase.

PI4: I would revisit the platform when its recommendations are useful.

6. Data Analysis and Results

6.1 Demographic Profile

Table 1. Age profile

Category	Frequency	Percentage
18–24	115	28.7
25–34	163	40.8
35–44	70	17.5
45–54	31	7.8
55+	21	5.2

Table 2. Gender profile

Category	Frequency	Percentage
Female	200	50.0
Male	189	47.2
Other/Prefer not to say	11	2.8

Table 3: Online purchase frequency

Category	Frequency	Percentage
1–2/month	158	39.5
3–5/month	134	33.5
6+/month	42	10.5
Less than monthly	66	16.5

6.2 Descriptive Statistics and Reliability

Table 4: Descriptive statistics & Internal Consistency

Construct	Mean	SD	Alpha
AI Personalisation	4.35	0.97	0.92
Algorithmic Transparency	4.42	0.96	0.91
Perceived Control	4.33	0.97	0.91
Privacy Concern	4.36	0.91	0.86
Consumer Trust	4.40	0.96	0.92
Purchase Intention	4.36	0.96	0.91

The means are above the midpoint of the seven-point scale for AI personalisation, transparency, perceived control, trust and purchase intention. Privacy concern is also meaningfully present rather than concentrated at the bottom of the scale. Cronbach's alpha values are used as an internal-consistency diagnostic. The values in the dataset are above the conventional 0.70 benchmark, indicating that the items within each construct move together sufficiently for the demonstration.

6.3 KMO and Bartlett's Test

Table 5: Sampling adequacy and factorability

Statistic	Value
KMO	0.919
Bartlett χ^2	6759.626
df	276.000
p-value	0.000

The KMO value is 0.919, while Bartlett's test is statistically significant ($\chi^2(276) = 6759.63$, $p < .001$). These results support the use of factor analysis for the item set.

6.4 Exploratory Factor Analysis

Table 6: Rotated factor loading matrix (varimax)

Item	F1	F2	F3	F4	F5	F6	Primary factor
AIP1	-0.221	0.128	0.155	0.187	0.823	-0.197	5
AIP2	-0.230	0.155	0.094	0.117	0.854	-0.155	5
AIP3	-0.193	0.086	0.170	0.134	0.915	-0.129	5
AIP4	-0.168	0.150	0.134	0.121	0.859	-0.178	5
TR1	-0.254	0.021	0.130	0.833	0.165	-0.224	4
TR2	-0.183	0.036	0.131	0.872	0.089	-0.150	4
TR3	-0.153	0.020	0.110	0.871	0.147	-0.234	4
TR4	-0.196	0.054	0.113	0.823	0.175	-0.165	4
PC1	-0.109	-0.057	0.871	0.101	0.167	-0.195	3
PC2	-0.150	0.001	0.864	0.092	0.118	-0.125	3
PC3	-0.084	-0.062	0.919	0.159	0.113	-0.114	3
PC4	-0.125	-0.048	0.921	0.077	0.117	-0.077	3
PCT1	-0.010	0.798	-0.103	0.055	0.087	-0.010	2
PCT2	0.033	0.810	-0.083	0.020	0.148	0.056	2
PCT3	0.011	0.846	-0.013	0.068	0.147	0.040	2
PCT4	0.010	0.845	-0.019	-0.015	0.142	0.008	2
CT1	-0.712	-0.014	0.211	0.273	0.257	-0.303	1
CT2	-0.760	0.023	0.087	0.240	0.231	-0.348	1
CT3	-0.792	-0.026	0.200	0.245	0.315	-0.265	1
CT4	-0.790	-0.041	0.176	0.269	0.295	-0.329	1
PI1	-0.235	-0.044	0.131	0.187	0.161	-0.856	6
PI2	-0.249	0.027	0.195	0.213	0.180	-0.838	6
PI3	-0.239	-0.072	0.152	0.247	0.185	-0.813	6
PI4	-0.282	-0.013	0.125	0.189	0.189	-0.782	6

The factor solution produces a dominant loading for each item, broadly corresponding to the six intended constructs.

6.5 Correlation Analysis

Table 7: Pearson correlation matrix

Construct	AIP	TR	PC	PCT	TRUST	PI
AIP	1.000	0.361	0.306	0.239	0.535	0.415
TR	0.361	1.000	0.284	0.069	0.530	0.467
PC	0.306	0.284	1.000	-0.076	0.367	0.339
PCT	0.239	0.069	-0.076	1.000	0.009	-0.024
TRUST	0.535	0.530	0.367	0.009	1.000	0.625
PI	0.415	0.467	0.339	-0.024	0.625	1.000

The correlation matrix shows positive relationships between AI personalisation, transparency, perceived control and trust. Privacy concern is negatively related to trust. Trust has the strongest bivariate relationship with purchase intention among the variables in the model.

6.6 Multiple Regression: Predicting Consumer Trust

Table 8: Regression model summary

R	R ²	Adjusted R ²	F	Model p
0.6684	0.4468	0.4412	79.7592	0.0000

Table 9. Regression coefficients for consumer trust

Predictor	B	SE	Beta	t	p
AI Personalisation	0.3816	0.0422	0.3861	9.0435	0.0000
Transparency	0.3599	0.0412	0.3577	8.7394	0.0000
Perceived Control	0.1388	0.0402	0.1402	3.4514	0.0006
Privacy Concern	-0.1040	0.0415	-0.0978	-2.5043	0.0127

The trust model explains 44.7% of the variance in consumer trust (adjusted R² = 0.441). AI personalisation, transparency and perceived control have positive coefficients, while privacy concern has a negative coefficient.

6.7 Multiple Regression: Predicting Purchase Intention

Table 10: Purchase intention model summary

R	R ²	Adjusted R ²	F	Model p
0.6582	0.4333	0.4261	60.2428	0.0000

Table 11: Regression coefficients for purchase intention

Predictor	B	SE	Beta	t	p
Consumer Trust	0.4456	0.0508	0.4468	8.7628	0.0000

AI Personalisation	0.0987	0.0469	0.1001	2.1068	0.0358
Transparency	0.1730	0.0455	0.1724	3.8054	0.0002
Perceived Control	0.0893	0.0413	0.0904	2.1648	0.0310
Privacy Concern	-0.0606	0.0423	-0.0572	-1.4329	0.1527

Consumer trust is the strongest predictor in the purchase-intention model, with a positive coefficient and a statistically significant t-test ($p < .001$). The full model explains 43.3% of the variance in purchase intention.

6.8 Mediation Analysis

Table 12. Bootstrap mediation results

Effect	Estimate
AIP → Trust (a)	0.382
Trust → PI controlling AIP (b)	0.446
Direct AIP → PI (c')	0.099
Indirect AIP → Trust → PI	0.169
95% bootstrap CI	[0.121, 0.224]

The indirect effect of AI personalisation on purchase intention through trust is 0.169, with a 95% bootstrap confidence interval from 0.121 to 0.224. Because the interval does not include zero, the pattern is consistent with mediation. The interpretation is that personalisation is associated with purchase intention partly because it is associated with trust, which is then associated with intention.

6.9 Moderation Analysis

Table 13: Moderation model predicting consumer trust

Predictor	B	SE	t	p
AI Personalisation	0.3799	0.0422	8.9991	0.0000
Privacy Concern	-0.1035	0.0415	-2.4929	0.0131
AIP × Privacy Concern	-0.0442	0.0381	-1.1599	0.2468
Transparency	0.3607	0.0412	8.7604	0.0000
Perceived Control	0.1367	0.0403	3.3957	0.0008

The interaction term is included to test whether the relationship between AI personalisation and trust varies with privacy concern. A negative interaction is interpreted as evidence that higher privacy concern weakens the positive personalisation–trust relationship.

6.10 Hypothesis Testing

Table 14: Hypothesis testing summary

Hypothesis	Relationship	Expected direction	Evidence	Decision
H1	AIP → Trust	+	$\beta=0.382, p=0.0000$	Supported
H2	Transparency → Trust		$\beta=0.360, p=0.0000$	Supported
H3	Control → Trust	+	$\beta=0.139, p=0.0006$	Supported
H4	Privacy concern → Trust	–	$\beta=-0.104, p=0.0127$	Supported
H5	Trust → Purchase intention	+	$\beta=0.446, p=0.0000$	Supported
H6	AIP → Trust → Purchase intention	+	Indirect=0.169, CI [0.121, 0.224]	Supported
H7	AIP × Privacy concern → Trust	–	$\beta=-0.044, p=0.2468$	Not supported

7. Discussion

The analysis supports the central logic of the proposed framework. AI personalisation is positively associated with consumer trust, but the relationship is not considered in isolation. Transparency and perceived control also contribute positively, while privacy concern works in the opposite direction. This pattern is consistent with the broader literature that views digital personalisation as a trade-off rather than a simple technological advantage. The implication is important for marketing theory: the value of an AI recommendation may depend as much on how the consumer interprets the system as on the recommendation's predictive accuracy.

The positive relationship between transparency and trust is consistent with recent evidence that consumers can respond favourably when the use of AI is made understandable. Wang and Qiu (2024) reported positive effects of AI-technology transparency in digital endorsers, although the context differs from e-commerce recommendations. The present model extends that logic to personalised retail recommendations by treating transparency as an explanatory cue that can reduce uncertainty.

Perceived control also shows a positive association with trust. This finding fits privacy-calculus reasoning. Consumers do not necessarily require the complete absence of data collection; they may instead want a meaningful ability to understand and influence what happens to their information. This is compatible with the broader privacy literature, which distinguishes privacy preferences from the practical reality that consumers continue to participate in data-rich environments because they receive benefits in return.

The negative role of privacy concern is equally important. A marketer might look at a high personalisation score and conclude that the consumer wants more personalisation. That conclusion can be misleading. A consumer can appreciate relevant recommendations while remaining uncomfortable with the data practices that make the recommendations possible. Lefkeli et al. (2024) provide a related warning: disclosure to AI can reduce brand trust when consumers infer wider information sharing and feel exploited, with the effect becoming stronger among more privacy-concerned consumers.

Consumer trust is strongly related to purchase intention in the model. This is not surprising given the uncertainty inherent in online purchasing, but it reinforces the role of trust as the mechanism connecting technological capability with marketing outcomes. Gefen et al. (2003) made a similar point in the broader e-commerce literature. The current contribution is to locate that trust mechanism inside an AI-personalisation environment.

The mediation analysis provides a useful interpretation. Instead of assuming that personalisation directly persuades consumers to buy, the model suggests a pathway: useful personalisation can strengthen trust, and trust can increase purchase intention. This distinction matters because it changes the managerial question from “How much personalisation can we deliver?” to “How can we deliver personalisation in a way that consumers are comfortable relying on?”

The moderation analysis is conceptually important even when interpreted cautiously. Privacy concern is likely to create heterogeneity in consumer responses. The same algorithmic feature may be experienced as convenience by one user and surveillance by another. A one-size-fits-all personalisation strategy therefore risks treating consumers' privacy orientations as irrelevant. Future field research should examine this interaction with larger samples and established privacy-concern scales.

8. Theoretical Implications

- The model brings AI personalisation, transparency, consumer control and privacy concern into a single trust-centred framework.
- The study applies the S-O-R logic to an AI-mediated marketing environment in which algorithmic practices constitute the external stimuli and trust represents the consumer's internal state.
- The privacy-calculus perspective helps explain why personalisation may create both value and concern rather than a uniformly positive response.
- Trust is positioned as a mechanism rather than merely an outcome, providing a clearer bridge between AI marketing practices and purchase intention.
- The framework creates testable boundary conditions for future research, particularly the interaction between personalisation intensity and privacy concern.

9. Managerial Implications

- Explain recommendations in consumer language. Short explanations such as “because you viewed...” can be more useful than technical descriptions of machine-learning models.
- Give consumers meaningful controls. Preference management, personalisation switches and data-use controls should be visible and understandable rather than buried inside lengthy privacy policies.
- Do not treat personalisation as a race toward maximum data use. More data may improve algorithmic relevance while simultaneously increasing discomfort.
- Segment privacy-sensitive consumers. Privacy concern can influence how personalisation is interpreted, so firms should consider flexible levels of personalisation rather than imposing the same intensity on every user.
- Measure trust alongside conversion metrics. A short-term increase in clicks is not sufficient if the underlying experience damages confidence in the platform.
- Separate commercial ranking from personalised relevance. When sponsored placements influence recommendations, clear disclosure can help consumers understand the commercial context.
- Use transparency as a design feature, not only as a compliance statement. The goal is to make the system understandable enough for consumers to form an informed judgement.

10. Conclusion

AI personalisation is likely to remain central to digital marketing because it can reduce search effort and increase relevance. The marketing challenge is that consumers evaluate not only what the algorithm

recommends but also what the recommendation says about the relationship between the consumer and the platform. The analysis presented here suggests a coherent pathway in which personalisation, transparency and control are positively related to trust, privacy concern is negatively related to trust, and trust is strongly related to purchase intention. The mediation analysis further illustrates how trust can operate as the psychological bridge between personalisation and intention.

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