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Developing a Consumer Trust Model for Reducing Privacy Concerns in AI-Personalised Digital Marketing

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Abstract **Original Research Article**

Privacy concerns accompany AI-personalised digital marketing, and the studies reviewed here say little about how trust can be built so that these concerns decline. This study develops and tests a consumer trust model in which perceived transparency, perceived control and perceived relevance are antecedents of consumer trust, trust is related to privacy concerns, and trust and privacy concerns are related to behavioural intention. A cross-sectional online survey of 412 adult consumers recruited through a panel measured the six constructs with 26 items, and the paths were estimated by regression-based path analysis on standardised construct scores with 5,000 bootstrap resamples. The measurement model met conventional reliability and validity thresholds. Transparency (β = .19), control (β = .22) and relevance (β = .32) were positively related to trust, explaining 28% of its variance. Trust was negatively related to privacy concerns (β = −.52, R^2 = .27), and behavioural intention was negatively related to privacy concerns (β = −.26) and positively related to trust (β = .23; R^2 = .18). Trust carried indirect effects from each antecedent to privacy concerns and from itself to intention through concerns, and all eight hypotheses were supported. The results are consistent with trust as the link between features of personalisation practice and lower privacy concerns, with relevance the antecedent most strongly related to trust, although the cross-sectional design limits causal interpretation.

Keywords: AI personalisation; consumer trust; privacy concerns; digital marketing; behavioural intention.

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Introduction

Artificial intelligence has become part of the routine machinery of digital marketing, in which machine learning models infer preferences from browsing, purchase and interaction data and use those inferences to select the advertisements, offers and recommendations that each consumer sees (Davenport et al., 2020; Huang & Rust, 2021).

Applications extend into customer relationship management (Saura et al., 2021b), business-to-business customer journeys (Rusthollkarhu et al., 2022), retail models that blur physical and digital channels (Jocevski, 2020) and the maintenance of customer relationships (Roy et al., 2025), and the use of AI in marketing has been related to the performance of small and medium enterprises in an emerging economy (Abrokwah-Larbi & Awuku-Larbi, 2023). Personalisation of this kind depends on continuous data collection, so that its commercial value and its privacy cost arise from the same activity, particularly where predictive models are

used to anticipate what individual consumers will want (Saura et al., 2026).

The tension between the benefits of personalisation and the data it requires has been described as a personalisation-privacy paradox, in which consumers value tailored content while objecting to the information gathering that makes it possible (Cloarec, 2020; Zeng et al., 2021). Recent work frames the issue as an ethical problem for AI-based marketing and as a new form of data privacy paradox (Saura et al., 2024), and a review of digital technologies and privacy sets out directions for further research on the topic (Scarpi et al., 2022), as the studies in Table 1 indicate.

Table 1: *Documented Privacy Problems in AI-Personalised Marketing and Related Settings*

Study	Context	Documented concern
Cloarec (2020)	Attention economy	Personalisation-privacy paradox examined within competition for consumer attention
Zeng et al. (2021)	Personalised services	Paradox treated as dynamic, with self-disclosure changing across two stages
Saura et al. (2021a)	Digital markets	User privacy questions raised by user-generated data and data-driven innovation
Scarpi et al. (2022)	Digital technologies	Privacy as a research direction across digital technologies
Saura et al. (2024)	AI-based digital marketing	Ethical assessment of a new data privacy paradox
Wang et al. (2024)	Recommender systems	Paradox bearing on the acceptance of recommendations
Suryati & Parulian (2026)	Systematic review	Privacy paradox in AI-driven personalisation, with trust, engagement and purchase behaviour

Note. Entries describe the focus of each study as stated in the source.

Studies that connect personalisation to consumer response have mostly treated trust as a determinant of purchase intention or loyalty (An & Ngo, 2025; Istianingsih et al., 2026; Jesus et al., 2026), whereas research on the paradox has concentrated on describing the trade-off between benefit and concern (Cloarec, 2020; Wang et al., 2024). Among the sources reviewed here, trust is seldom placed as the mechanism through which features of personalisation practice, such as transparency, user control and relevance, reduce privacy concerns and thereby bear on behavioural intention within a single tested model, which leaves open how trust can be built in a way that lowers concern.

The present study therefore develops and tests a consumer trust model for reducing privacy concerns in AI-personalised digital marketing, and it pursues four objectives: to estimate the effects of perceived transparency, perceived control and perceived relevance on consumer trust; to estimate the effect of trust on privacy concerns; to estimate the effects of privacy concerns and trust on behavioural intention toward AI-personalised marketing; and to test whether trust carries the influence of the three antecedents to privacy concerns. The objectives

translate into four research questions: how each antecedent relates to trust, whether trust is associated with lower privacy concerns, how trust and concerns jointly relate to behavioural intention, and whether trust transmits the antecedent effects to concerns.

The model contributes to research by placing trust between the observable features of personalisation practice and privacy concerns, which turns a descriptive paradox into a set of testable paths, and it contributes to practice by indicating which features carry the largest association with trust and therefore deserve priority when platforms redesign data disclosures, consent interfaces and personalisation logic. The model may also inform policy discussion where privacy concerns respond to organisational conduct that consumers can observe and not only to the technical properties of data processing.

Literature Review

AI Personalisation in Digital Marketing

AI personalisation in digital marketing rests on models that learn consumer preferences from behavioural data and apply them to select content, offers and timing for each individual, an application that Davenport et al. (2020) treat as part of the wider change that AI is bringing to marketing. Huang and Rust (2021) arrange AI applications in a strategic framework running from marketing research and strategy to action, and later conceptual work extends the discussion to the influence of AI on consumer preferences and decisions (Sifat, 2025) and to predictive personalisation informed by digital cognition (Saura et al., 2026). The same logic reaches relationship management, where AI-capable tools are used to sustain customer relationships (Roy et al., 2025), and settings in which the content itself is produced by AI, including virtual influencers (Khalfallah & Keller, 2026) and AI systems that can serve as social companions (Chaturvedi et al., 2023).

Consumer responses to AI-generated marketing material depend on judgements that reach beyond the quality of the content. Authenticity and moral disgust shape reactions to marketing communications authored by AI (Kirk & Givi, 2025), perceived humanness and trust shape responses to AI-generated luxury advertising (Jung et al., 2025), and anthropomorphic attributes and social presence foster trust and continued use of generative AI chatbots (Li et al., 2026). These studies differ in product category, in the form of AI output and in whether the outcome is attitude, purchase or continued use, yet trust appears in several of them as a construct that carries consumer response, which makes trust a reasonable construct to place at the centre of a model of AI-personalised marketing.

Privacy Concerns and the Personalisation-Privacy Paradox

The personalisation-privacy paradox describes the coexistence of consumer appreciation for tailored content and reluctance to supply the data on which tailoring depends. Cloarec (2020) situates the paradox in the attention economy, whereas Zeng et al. (2021) treat it as dynamic and examine the role of self-disclosure across two stages. Wang et al. (2024) approach the tension from a privacy calculus perspective and apply it to recommender systems, and their framing differs from the other two in treating the paradox as open to resolution through the weighing of benefits against risks.

Broader assessments place the paradox within questions of data governance and ethics. Saura et al. (2021a) set out a research agenda on user privacy in digital markets that starts from user-generated data and data-driven innovation, Saura et al. (2024) assess whether AI-based digital marketing is ethical in light of a new data privacy paradox, and Scarpi et al. (2022) review digital technologies and privacy and identify directions for further research. A systematic review of AI-driven personalisation likewise connects the paradox with trust, engagement and purchase behaviour (Suryati & Parulian, 2026). Technical work on recommendation systems also incorporates trust, as in the trust-based federated learning approach to the cold start problem proposed by Wahab et al. (2022), although technical design does not by itself settle how consumers perceive data practices.

These studies describe the paradox, offer a calculus for explaining it and raise ethical questions about it, but they say little about the conditions under which

consumers' concerns would decline in practice, a question that depends on what consumers believe about the organisation collecting the data and therefore on trust.

Consumer Trust and Its Antecedents

Trust appears in research on AI in marketing as an antecedent, a mediator or an outcome, depending on the study. Dang and Li (2025) examine the antecedents and consequences of trust in AI together with cultural dynamics, and Wu et al. (2024) connect social trust and perceived algorithmic equity to users' intention to interact with algorithmic recommendation systems. In consumer studies, trust accompanies relevance and usefulness in explaining purchase intention for AI-powered personalised advertising in Vietnam (An & Ngo, 2025), e-trust is combined with hyper-personalisation and customer experience to explain e-loyalty in Indonesian e-commerce in a study that uses PLS-SEM (Istianingsih et al., 2026), and trust is examined with benefits and perceived threats in explaining attitudes toward AI (Iršič & Gjergjek, 2025).

Other studies relate trust to the source and manner of AI involvement. Jesus et al. (2026) relate AI-driven customer interaction, social media engagement and sustainability messaging to consumer trust and purchase intention, Israfilzade (2025) compares AI-generated and human-created advertising in terms of consumer trust and purchase intent, and Kailani et al. (2026) examine AI-driven marketing communication in terms of attitudes and purchase intentions among social media users in Romania (Table 2).

Table 2: *Studies Bearing Most Directly on the Proposed Model*

Study	Context	Constructs examined	Relation to the proposed model
Cloarec (2020)	Attention economy	Personalisation-privacy paradox	Frames the tension that privacy concerns represent
Zeng et al. (2021)	Personalised services	Self-disclosure across two stages of the paradox	Shows that disclosure is treated as dynamic
Wang et al. (2024)	Recommender systems	Privacy calculus, recommendation acceptance	Supplies the cost-benefit logic linking concern to acceptance
Saura et al. (2024)	AI-based digital marketing	Data privacy paradox, ethical assessment	Positions concerns as an ethical matter of marketing practice
An & Ngo (2025)	Digital advertising, Vietnam	Trust, relevance, usefulness, purchase intention	Joins relevance and trust in one account of intention
Istianingsih et al. (2026)	E-commerce, Indonesia	Hyper-personalisation, customer experience, e-trust, e-loyalty	Includes trust in a PLS-SEM model of AI personalisation
Iršič & Gjergjek (2025)	Attitudes toward AI	Benefits, trust, perceived threats	Combines benefits and trust, with threats as moderator

Study	Context	Constructs examined	Relation to the proposed model
Israfilzade (2025)	Advertising content	AI-generated and human-created advertising, trust, purchase intent	Places trust beside intention when comparing content sources
Kailani et al. (2026)	Social media users, Romania	AI-driven marketing communication, attitudes, purchase intentions	Supplies an intention outcome comparable to the model
Dang & Li (2025)	Trust in AI, cultural settings	Antecedents and consequences of trust	Organises the trust antecedents on which the model draws
Wu et al. (2024)	Algorithmic recommendation	Social trust, algorithmic equity, interaction intention	Links trust to intention to interact with recommendations
Suryati & Parulian (2026)	Systematic review	Personalisation, privacy paradox, trust, engagement, purchase behaviour	Summarises links among the model constructs

Note. Entries describe the focus of each study as stated in the source.

The three antecedents in the proposed model were chosen because they correspond to recurring themes in the studies of Table 2: openness about data use, consumer agency over data, and the benefit that personalisation delivers. Each can be perceived by consumers without technical knowledge of the underlying algorithms, and each can be altered by a platform through disclosure design, settings and the quality of its personalisation logic, which makes the resulting model useful for decisions about platform practice.

Theoretical Foundation

The model rests on the privacy calculus perspective, which Wang et al. (2024) apply to recommender systems and which holds that consumers compare the benefits of personalisation with the privacy costs of supplying data, and on the trust perspective drawn from the reviews and empirical studies discussed above (Dang & Li, 2025; Wu et al., 2024), which holds that favourable beliefs about an organisation's conduct shape how consumers respond to uncertainty about it. In the present model relevance represents the benefit, privacy concerns represent the cost and behavioural intention is the resulting decision, while trust occupies the position between the observable features of practice, which are transparency and control, and consumers' concerns. The two perspectives are complementary because the calculus describes how costs and benefits are weighed, while the trust perspective helps to explain why perceived costs differ across organisations that offer similar benefits.

Hypothesis Development

Perceived transparency refers to the degree to which consumers believe that a platform makes clear which data it uses and why a given advertisement or recommendation appears. The ethics of AI-based digital marketing has been assessed in relation to a new data privacy paradox (Saura et al., 2024), and trust in algorithmic recommendation has been connected to algorithmic equity (Wu et al., 2024). Consumers who can see the reasoning behind

personalisation have less reason to suspect hidden uses of their data, which points to a positive association between transparency and trust and is consistent with the attention that Dang and Li (2025) give to antecedents of trust, so that perceived transparency is expected to be positively related to consumer trust (H1).

Perceived control concerns the extent to which consumers believe they can influence which data are collected and how they are used. The dynamic account of self-disclosure by Zeng et al. (2021) implies that willingness to disclose depends on how the exchange unfolds, and a review of digital technologies and privacy sets out directions for research on how consumers respond to data practices (Scarpi et al., 2022). Control reduces the exposure that consumers accept when they share data, and platforms that offer it signal that consumer interests are taken into account, so that perceived control is expected to be positively related to consumer trust (H2).

Perceived relevance is the degree to which personalised content matches a consumer's interests and needs, and it represents the benefit side of the exchange. Relevance appears together with trust and usefulness in an account of AI-powered personalised advertising and purchase intention (An & Ngo, 2025), and hyper-personalisation has been combined with e-trust in studies of e-commerce (Istianingsih et al., 2026). Accurate personalisation shows consumers that the platform understands them and acts on that understanding in their favour, so that perceived relevance is expected to be positively related to consumer trust (H3).

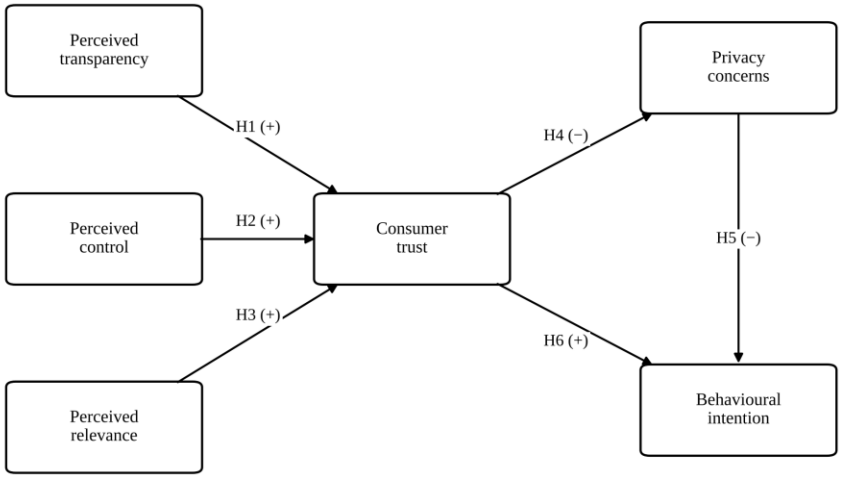
Privacy concerns are consumers' apprehension about how organisations collect, use and share their personal information, and they are the negative response that the paradox literature seeks to explain (Cloarec, 2020; Saura et al., 2024). A review of AI-driven personalisation places trust among the constructs that accompany the paradox, together with engagement and purchase behaviour (Suryati & Parulian, 2026). Where consumers believe that an organisation handles data honestly and in their interest, the perceived probability of misuse falls, and concerns about collection and sharing should fall with it, so that consumer trust is expected to be negatively related to privacy concerns (H4).

The privacy calculus perspective expects consumers to withhold acceptance when perceived privacy costs weigh heavily, and it has been applied to the acceptance of recommendations in recommender systems (Wang et al., 2024), while studies of AI-driven marketing communication on social media take behavioural intention as an outcome of interest (Kailani et al., 2026). Consumers who remain apprehensive about data use are therefore less likely to continue with, or act upon, personalised marketing, so that privacy concerns are expected to be negatively related to behavioural intention (H5).

Trust also bears on intention directly, because trust can lower the perceived risk of acting on a recommendation or accepting an advertisement, and trust has been examined alongside purchase intention for AI-generated and human-created advertising (Israfilzade, 2025), for AI-driven customer interaction and brand reputation (Jesus et al., 2026) and for AI-generated luxury advertising in which perceived humanness also matters (Jung et al., 2025), so that consumer trust is expected to be positively related to behavioural intention (H6).

The hypotheses above imply an indirect structure in which the three antecedents reach privacy concerns through trust and trust reaches intention partly through concerns. Treating trust as the connecting mechanism follows the cost-benefit logic of the calculus perspective and the trust accounts discussed earlier, and it can be tested through indirect effects (Figure 1). Consumer trust is therefore expected to mediate the negative effects of perceived transparency (H7a), perceived control (H7b) and perceived relevance (H7c) on privacy concerns, and privacy concerns are expected to mediate the positive effect of consumer trust on behavioural intention (H8).

Figure 1: *Proposed Consumer Trust Model*



Note. Signs in parentheses show the hypothesised direction of each direct path. H7a to H7c refer to the indirect effects of the three antecedents on privacy concerns through consumer trust, and H8 refers to the indirect effect of consumer trust on behavioural intention through privacy concerns.

Methodology

Research Design

The study follows a positivist, quantitative and cross-sectional design in which an online questionnaire measured six constructs and the paths among them were tested against the hypotheses stated above. A survey suits the aim because the constructs describe consumer perceptions and intentions that are not observable in platform records, and because the model requires the same respondents to report on antecedents, trust, concerns and intention.

Population, Sampling and Sample Size

The target population comprised adults aged 18 years or older who used social media or e-commerce platforms at least weekly and who reported having seen advertisements or recommendations that they believed had been tailored to them by automated systems during the previous three months. Respondents were recruited through an online research panel using non-probability quota sampling on age and gender, and data were collected over three weeks. The required sample size was determined by a power analysis for the regression with the largest number of predictors, which has three; detecting a small effect ($f^2 = .05$) at $\alpha = .05$ with power of .95 required 348 respondents, and the final sample of 412 gave a power of .98 for that effect.

Measurement

All constructs were measured with multi-item reflective scales on a five-point agreement scale from 1 (strongly disagree) to 5 (strongly agree). Items were written for this study from the conceptualisations used in the sources listed in Table 3, reviewed by three academics in marketing and information systems for clarity and content coverage, and pretested with 30 consumers, after which two items were reworded. Construct scores were computed as the mean of the items belonging to each construct.

Table 3: *Constructs, Items and Conceptual Basis*

Construct	Items	Conceptual basis
Perceived transparency (TRA)	1. The platform explains why a particular advertisement or recommendation was shown to me. 2. It is clear which personal data are used to tailor what I see. 3. The platform is open about how its algorithms select content for me. 4. Information about data use is easy to understand.	Saura et al. (2024); Scarpi et al. (2022)
Perceived control (PCO)	1. I can change the settings that determine how my data are used for personalisation. 2. I can easily switch off personalised advertising. 3. I can correct or delete data the platform holds about me. 4. I feel in charge of the information on which personalisation draws.	Zeng et al. (2021); Scarpi et al. (2022)
Perceived relevance (PRE)	1. The advertisements and recommendations shown to me match my interests. 2. Personalised content helps me find items I need. 3. The content I am shown fits my current needs. 4. Personalised offers save me time when I search.	An & Ngo (2025); Cloarec (2020)
Consumer trust (TRU)	1. I believe the platform handles my data honestly. 2. I trust the platform to use AI-based personalisation in my interest. 3. The platform keeps its promises about data use. 4. I consider the personalisation provided by the platform reliable. 5. The platform considers my interests when it personalises content.	Istianingsih et al. (2026); Dang & Li (2025)
Privacy concerns (PCN)	1. I am concerned about how much personal information AI-driven personalisation collects about me. 2. I worry that my data could be used for purposes I did not agree to. 3. I am uneasy when advertisements reveal how much the platform knows about me. 4. I fear that my data could be shared with third parties without my knowledge. 5. I worry about being profiled by automated systems.	Cloarec (2020); Saura et al. (2024)
Behavioural intention (BI)	1. I intend to keep using platforms that personalise content with AI. 2. I would act on personalised recommendations. 3. I am willing to share information to receive more tailored content. 4. I would recommend platforms with personalised features to others.	An & Ngo (2025); Kailani et al. (2026)

Note. All items were rated on a five-point agreement scale.

Data Collection and Ethics

Participants received information on the purpose of the study, gave informed consent on the first screen and could withdraw at any time before submission, and no names, contact details or device identifiers were stored. Two attention-check items and a completion-time criterion were embedded in the questionnaire. Of 451 respondents who started, 39 were excluded, 21 for failing an attention check and 18 for completing the questionnaire in less than one third of the median completion time, which left 412 complete responses and no missing values.

Data Analysis

The analysis began with a measurement stage that examined internal consistency with Cronbach's alpha and composite reliability, convergent validity with item loadings from a single-component solution and average variance extracted, and discriminant validity with the heterotrait-monotrait ratio, using the conventional cut-offs of .70 for reliability and loadings, .50 for average variance extracted and .85 for the ratio, together with a single-factor test for common method variance and variance inflation factors for collinearity. A structural stage followed in which the recursive model was estimated by ordinary least squares regressions on standardised construct scores, with standard errors and 95% percentile intervals obtained from 5,000 bootstrap resamples, effect sizes expressed as f^2 and R^2, and indirect effects computed as products of path coefficients with their own bootstrap intervals. A hypothesis was treated as supported when the coefficient had the predicted sign and a two-tailed p-value below .05. All computations were run in Python with NumPy and SciPy.

Results

Respondent Profile and Descriptive Statistics

The final sample of 412 respondents included 230 women (55.8%), 174 men (42.2%) and 8 respondents who identified as non-binary or preferred not to state their gender (1.9%). The largest age group was 25 to 34 years (n = 144, 35.0%), followed by 35 to 44 years (n = 97, 23.5%), 45 to 54 years (n = 71, 17.2%), 18 to 24 years (n = 67, 16.3%) and 55 years or older (n = 33, 8.0%). A bachelor's degree was the highest qualification of 193 respondents (46.8%), 97 held a postgraduate degree (23.5%), 82 a diploma or college certificate (19.9%) and 40 secondary education or less (9.7%). Daily time on social media or e-commerce platforms was 2 to 4 hours for 157 respondents (38.1%), 5 to 7 hours for 125 (30.3%), under 2 hours for 67 (16.3%) and 8 hours or more for 63 (15.3%).

Privacy concerns had the highest mean construct score on the five-point scale (M = 3.66, SD = 0.80), followed by perceived relevance (M = 3.59, SD = 0.78), behavioural intention (M = 3.41, SD = 0.85), perceived transparency (M = 3.34, SD = 0.82), consumer trust (M = 3.25, SD = 0.83) and perceived control (M = 3.17, SD = 0.83; Table 4).

Measurement Model

All constructs met the reliability and convergent validity cut-offs (Table 4). Cronbach's alpha ranged from .84 to .88, composite reliability from .89 to .92, average variance extracted from .66 to .73, and item loadings from .78 to .88. The highest heterotrait-monotrait ratio was .59, observed between consumer trust and privacy concerns, and no ratio exceeded .85. The first unrotated factor accounted for 29.4% of the variance across all 26 items, and the variance inflation factors were 1.14 to 1.15 for the three antecedents of trust and 1.37 for trust and privacy concerns as predictors of behavioural intention.

Table 4: *Descriptive Statistics, Reliability and Convergent Validity of the Constructs*

Construct	Items	*M*	*SD*	Loadings	α	CR	AVE
Perceived transparency	4	3.34	0.82	.82–.86	.86	.90	.70
Perceived control	4	3.17	0.83	.81–.84	.85	.90	.69
Perceived relevance	4	3.59	0.78	.78–.85	.84	.89	.68
Consumer trust	5	3.25	0.83	.79–.84	.87	.91	.66
Privacy concerns	5	3.66	0.80	.79–.85	.87	.91	.66
Behavioural intention	4	3.41	0.85	.84–.88	.88	.92	.73

Note. M and *SD* refer to construct scores on the five-point scale. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted. Loadings are item loadings from a single-component solution.

Structural Model and Hypothesis Tests

Perceived transparency (β = .19, 95% CI [.10, .28], $p < .001$), perceived control (β = .22, 95% CI [.14, .30], $p < .001$) and perceived relevance (β = .32, 95% CI [.23, .40], $p < .001$) were each positively related to consumer trust, and together they accounted for 28% of its variance (Table 5, Figure 2). Consumer trust was negatively related to privacy concerns (β = −.52, 95% CI [−.58, −.45], $p < .001$), with $R^2 = .27$ for concerns. Privacy concerns were negatively related (β = −.26, 95% CI [−.36, −.17], $p < .001$) and consumer trust positively related (β = .23, 95% CI [.13, .32], $p < .001$) to behavioural intention, with $R^2 = .18$.

Effect sizes (f^2) were .04 for transparency, .06 for control and .12 for relevance in the equation for trust, .37 for the path from trust to privacy concerns, and .05 for trust and .06 for privacy concerns in the equation for behavioural intention. The indirect effects of transparency (−.10, 95% CI [−.15, −.05]), control (−.11, 95% CI [−.16, −.07]) and relevance (−.16, 95% CI [−.22, −.11]) on privacy concerns through trust were all negative and their bootstrap intervals excluded zero, and the indirect effect of trust on behavioural intention through privacy concerns was positive (.14, 95% CI [.08, .19]). The total effect of trust on behavioural intention was .36.

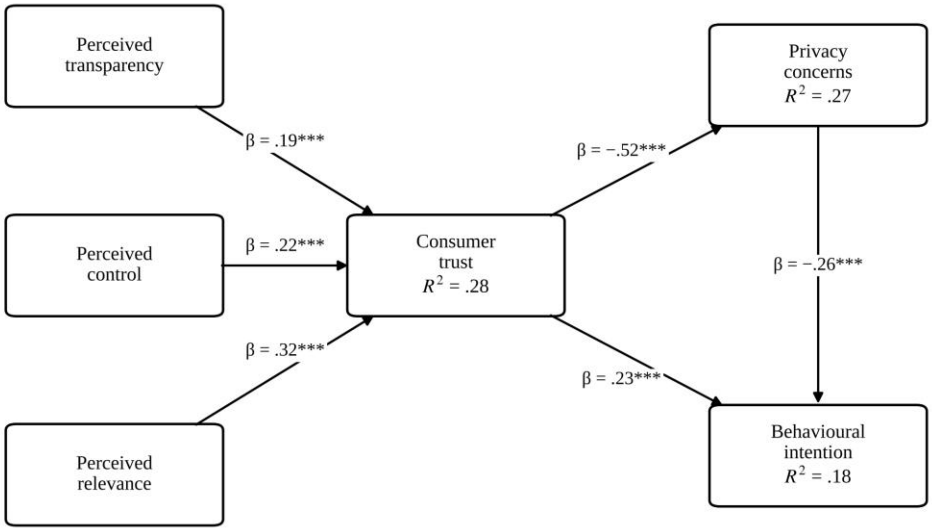
Table 5: *Hypothesis Tests for Direct and Indirect Effects*

Hypothesis	Path	β or indirect effect	95% CI	*t*	*p*	f^2	Decision
H1	TRA → TRU	.19	[.10, .28]	4.20	< .001	.04	Supported
H2	PCO → TRU	.22	[.14, .30]	5.14	< .001	.06	Supported
H3	PRE → TRU	.32	[.23, .40]	7.41	< .001	.12	Supported
H4	TRU → PCN	−.52	[−.58, −.45]	−14.86	< .001	.37	Supported
H5	PCN → BI	−.26	[−.36, −.17]	−5.31	< .001	.06	Supported
H6	TRU → BI	.23	[.13, .32]	4.71	< .001	.05	Supported
H7a	TRA → TRU → PCN	−.10	[−.15, −.05]	−3.98	< .001	–	Supported

Hypothesis	Path	β or indirect effect	95% CI	*t*	*p*	f^2	Decision
H7b	PCO → TRU → PCN	−.11	[−.16, −.07]	−4.92	< .001	–	Supported
H7c	PRE → TRU → PCN	−.16	[−.22, −.11]	−6.36	< .001	–	Supported
H8	TRU → PCN → BI	.14	[.08, .19]	4.89	< .001	–	Supported

Note. TRA = perceived transparency; PCO = perceived control; PRE = perceived relevance; TRU = consumer trust; PCN = privacy concerns; BI = behavioural intention. Confidence intervals are 95% percentile intervals from 5,000 bootstrap resamples, and *p*-values are two-tailed. For indirect effects, *t* is the estimate divided by its bootstrap standard error.

Figure 2: *Estimated Consumer Trust Model*



Note. Values on the arrows are standardised path coefficients, and three asterisks indicate $p < .001$. R^2 values are shown within the endogenous constructs.

Discussion

All eight hypotheses were supported in the sample, and the estimates place trust between the antecedents and privacy concerns as the model specified. The three antecedents explained a little more than a quarter of the variance in trust, trust explained a similar share of the variance in privacy concerns, and trust and concerns together explained 18% of the variance in behavioural intention, so the model accounts for a moderate part of each outcome and leaves room for other determinants.

Perceived relevance had the largest association with trust (β = .32), which is compatible with accounts that treat relevance as part of the route from AI personalisation to purchase intention alongside trust and usefulness (An & Ngo, 2025) and with the inclusion of e-trust in models of hyper-personalisation (Istianingsih et al., 2026). One

reading is that consumers infer good faith from accurate personalisation, since content that fits their needs signals that the platform uses data in a way that benefits them. The same result also fits the privacy calculus view, in which the benefit of personalisation offsets perceived cost, although the data cannot separate an inference of good faith from a simple weighing of benefits because both would yield a positive association.

Control and transparency had smaller associations with trust, and their effect sizes were .06 and .04, which indicates that disclosure and settings influence trust without carrying it alone. The result sits alongside the ethical questions that Saura et al. (2024) raise about data practices in AI-based marketing and the continuing research attention to privacy in digital technologies (Scarpi et al., 2022). A plausible explanation is that many consumers do not read or use disclosure and control interfaces in detail, so that their perception of these features reflects general impressions of the platform and not specific tools, and because the survey measured perceptions it cannot show which interface designs produce them.

The path from trust to privacy concerns was the strongest in the model ($\beta = -.52$, $f^2 = .37$), and the effect size is large by conventional benchmarks. The magnitude is notable against accounts that describe the paradox mainly as a trade-off between benefit and concern (Cloarec, 2020; Wang et al., 2024), since the concern reported in this sample varied closely with trust in the platform. The result also fits the connection between trust and the paradox noted in the systematic review by Suryati and Parulian (2026), and it suggests that part of the paradox reflects differences in how far consumers trust the organisation and not only differences in how much they value personalisation. The cross-sectional design leaves the direction of the association open, because consumers who are already concerned may also report lower trust.

Behavioural intention was related to both trust and concerns, with a positive direct association for trust ($\beta = .23$) and a negative association for concerns ($\beta = -.26$), and the indirect path through concerns (.14) made up about 38% of the total effect of trust (.36). Trust was related to intention directly, in line with studies that place trust beside purchase intention for AI-generated and human-created advertising (Israfilzade, 2025) and for AI-driven brand interaction (Jesus et al., 2026), and indirectly through lower concern, which follows the calculus logic that Wang et al. (2024) apply to the acceptance of recommendations.

The results suggest that the privacy calculus and trust perspectives can be combined in one structure in which trust sits between observable features of practice and the cost side of the calculus. The model gives the personalisation-privacy paradox a mechanism that can be tested, since relevance was related to trust while trust was related to lower concern, which suggests that raising the quality of personalisation and reducing concern need not conflict when trust is present. The support for this mechanism is correlational, and alternative orderings of the constructs, such as concerns leading to lower trust, would need to be examined with longitudinal or experimental designs.

The relative sizes of the coefficients suggest an order of priority for platforms, since improving the fit of personalisation was associated with the largest difference in trust, while explanations of why content is shown and accessible controls over data were associated with smaller but consistent differences and relate to the ethical questions that Saura et al. (2024) raise for AI-based marketing. Where content is produced or delivered by AI, attention to perceived authenticity and humanness (Kirk & Givi, 2025; Jung et al., 2025) and to the credibility of virtual influencers (Khalfallah & Keller, 2026) is also relevant to trust, and technical designs that incorporate trust into recommendation, such as the federated approach of Wahab et al. (2022), may complement communication measures.

The close variation of concerns with trust suggests that rules requiring plain explanations of data use and workable consumer controls act on determinants of concern that consumers can observe, which would be of interest to regulators and consumer organisations, although the effect sizes imply that such rules alone would leave most of the variance in trust unexplained.

The conclusions drawn from the model are qualified by several limitations, the first being that the cross-sectional design prevents causal inference, while all variables were self-reported by the same respondents, so that common method bias cannot be excluded even though the single-factor test did not indicate a dominant factor. The non-probability panel sample limits generalisation to the wider population of online consumers, and the survey did not distinguish between platforms or between types of AI personalisation. Construct scores were computed as item means and the model was estimated with regression-based path analysis, which does not correct for measurement error as latent variable modelling does, and behavioural intention was measured in place of observed behaviour.

Conclusion

This study developed and tested a consumer trust model in which perceived transparency, perceived control and perceived relevance are positively related to consumer trust, trust is associated with lower privacy concerns, and trust and concerns jointly relate to behavioural intention toward AI-personalised digital marketing. Based on responses from 412 adult online consumers, all eight hypotheses were supported: the three antecedents were positively related to trust (R^2 = .28), trust was negatively related to privacy concerns ($\beta = -.52$), and both trust and concerns were related to intention (R^2 = .18), with indirect effects consistent with trust carrying the influence of the antecedents to concerns. Relevance had the largest association with trust, which indicates that the perceived fit of personalisation is the feature most closely related to trust, while transparency and control played smaller but consistent roles.

The conclusions are limited by the cross-sectional, self-reported design and the non-probability sample. Future research could test the model with longitudinal or experimental designs, compare platforms and forms of AI content, add behavioural data to measures of intention, and examine whether the paths differ across cultural settings, which Dang and Li (2025) identify as relevant to trust in AI.

References

Abrokwah-Larbi, K., & Awuku-Larbi, Y. (2023). The impact of artificial intelligence in marketing on the performance of business organizations: Evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies*, *16*(4), 1090–1117. https://doi.org/10.1108/JEEE-07-2022-0207

An, G. K., & Ngo, T. T. A. (2025). AI-powered personalized advertising and purchase intention in Vietnam's digital landscape: The role of trust, relevance, and usefulness. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(3), Article 100580. https://doi.org/10.1016/j.joitmc.2025.100580

Chaturvedi, R., Verma, S., Das, R., & Dwivedi, Y. K. (2023). Social companionship with artificial intelligence: Recent trends and future avenues. *Technological Forecasting and Social Change*, *193*, Article 122634. https://doi.org/10.1016/j.techfore.2023.122634

Cloarec, J. (2020). The personalization–privacy paradox in the attention economy. *Technological Forecasting and Social Change*, *161*, Article 120299. https://doi.org/10.1016/j.techfore.2020.120299

Dang, Q., & Li, G. (2025). Unveiling trust in AI: The interplay of antecedents, consequences, and cultural dynamics. *AI & Society*, *41*(2), 669–692. https://doi.org/10.1007/s00146-025-02477-6

Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of*

Marketing Science, *49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Iršič, M., & Gjergjek, T. (2025). The influence of benefits and trust on consumers' attitudes towards artificial intelligence: The moderating role of threats. *Organizacija*, *58*(2), 138–157. https://doi.org/10.2478/orga-2025-0009

Israfilzade, K. (2025). AI-generated versus human-created advertising: Effects on consumer trust and purchase intent. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *20*(4), 1301–1337. https://doi.org/10.24136/eq.4038

Istianingsih, N., Masnun, A., Zulkifli, Rianto, & Zakiah, T. (2026). An integrating AI-driven hyper-personalization, customer experience, and e-trust to explain e-loyalty in Indonesian e-commerce: A PLS-SEM study. *Qubahan Academic Journal*, *6*(2), 355–365. https://doi.org/10.48161/qaj.v6n2a2328

Jesus, J. B., Besario, M. R. A., Bueno, N. L. E., Bonghanoy, C. L., Navaja, R. I., Basilisco, G. L., Sumilhig, J. M., & Ople-Alviola, C. (2026). Brand reputation in the age of AI: Impact of AI-driven customer interaction, social media engagement, and sustainability messaging on consumer trust and purchase intention. *International Review of Management and Marketing*, *16*(1), 161–169. https://doi.org/10.32479/irmm.21424

Jocevski, M. (2020). Blurring the lines between physical and digital: Business model innovation in retailing. *California Management Review*, *62*(3), 94–117. https://doi.org/10.1177/0008125620916244

Jung, T., Koghut, M., Lee, E., & Kwon, O. (2025). Artificial creativity in luxury advertising: How trust and perceived humanness drive consumer response to AI-generated content. *Journal of Retailing and Consumer Services*, *87*, Article 104403. https://doi.org/10.1016/j.jretconser.2025.104403

Kailani, C., Alniacik, U., Barbu, A. M., Ionescu, F. T., & Ploeșteanu, M. G. (2026). How AI-driven marketing communication shapes consumer attitudes and purchase intentions: Evidence from social media users in Romania. *Journal of Theoretical and Applied Electronic Commerce Research*, *21*(8), 281–302. https://doi.org/10.3390/jtaer21080281

Khalfallah, D., & Keller, V. (2026). Virtual influencer-brand collaborations: A multiple-case study of strategic design and the credibility-engagement paradox. *Cogent Business & Management*, *13*(1), Article 2653916. https://doi.org/10.1080/23311975.2026.2653916

Kirk, C. P., & Givi, J. (2025). The AI-authorship effect: Understanding authenticity, moral disgust, and consumer responses to AI-generated marketing communications. *Journal of Business Research*, *186*, Article 114984. https://doi.org/10.1016/j.jbusres.2024.114984

Li, J., Wei, J., Pang, H., & Xie, Y. (2026). Unpacking how anthropomorphic attribute and social presence foster consumer trust and continued use of Gen-AI chatbots: An integration of AIDUA and Cognitive Appraisal Theory. *Journal of Theoretical and Applied Electronic Commerce Research*, *21*(5), Article 135. https://doi.org/10.3390/jtaer21050135

Roy, S. K., Tehrani, A. N., Pandit, A., Apostolidis, C., & Ray, S. (2025). AI-capable relationship marketing: Shaping the future of customer relationships. *Journal of Business Research*, *192*, Article 115309. https://doi.org/10.1016/j.jbusres.2025.115309

Rustholllkarhu, S., Toukola, S., Aarikka-Stenroos, L., & Mahlamäki, T. (2022). Managing B2B customer journeys in digital era: Four management activities with artificial intelligence-empowered tools. *Industrial Marketing Management*, *104*, 241–257. https://doi.org/10.1016/j.indmarman.2022.0

4.014

Saura, J. R., Ratten, V., & Jeremic, V. (2026). Digital cognition in predictive marketing personalization: A conceptual framework. *Psychology & Marketing*, *43*(5), 1228–1260. https://doi.org/10.1002/mar.70109

Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2021a). From user-generated data to data-driven innovation: A research agenda to understand user privacy in digital markets. *International Journal of Information Management*, *60*, Article 102331. https://doi.org/10.1016/j.ijinfomgt.2021.102331

Saura, J. R., Ribeiro-Soriano, D., & Palacios-Marqués, D. (2021b). Setting B2B digital marketing in artificial intelligence-based CRMs: A review and directions for future research. *Industrial Marketing Management*, *98*, 161–178. https://doi.org/10.1016/j.indmarman.2021.08.006

Saura, J. R., Škare, V., & Ozretić Došen, Đ. (2024). Is AI-based digital marketing ethical? Assessing a new data privacy paradox. *Journal of Innovation & Knowledge*, *9*(4), Article 100597. https://doi.org/10.1016/j.jik.2024.100597

Scarpi, D., Pizzi, G., & Matta, S. (2022). Digital technologies and privacy: State of the art and research directions. *Psychology & Marketing*, *39*(9), 1687–1697. https://doi.org/10.1002/mar.21692

Sifat, A. I. (2025). The algorithmic consumer: A conceptual investigation of AI's influence on consumer preferences and decisions. *Asian Management and Business Review*, *5*(2), 471–486. https://doi.org/10.20885/AMBR.vol5.iss2.art14

Suryati, L., & Parulian, E. (2026). AI-driven marketing personalization and the consumer privacy paradox: A systematic literature review of trust, engagement, and purchase behavior. *Golden Ratio of Data in Summary*, *6*(3), 826–842. https://doi.org/10.52970/grdis.v6i3.2517

Wahab, O. A., Rjoub, G., Bentahar, J., & Cohen, R. (2022). Federated against the cold: A trust-based federated learning approach to counter the cold start problem in recommendation systems. *Information Sciences*, *601*, 189–204. https://doi.org/10.1016/j.ins.2022.04.027

Wang, Y., Zhu, J., Liu, R., & Jiang, Y. (2024). Enhancing recommendation acceptance: Resolving the personalization–privacy paradox in recommender systems: A privacy calculus perspective. *International Journal of Information Management*, *76*, Article 102755. https://doi.org/10.1016/j.ijinfomgt.2024.102755

Wu, W., Huang, Y., & Qian, L. (2024). Social trust and algorithmic equity: The societal perspectives of users' intention to interact with algorithm recommendation systems. *Decision Support Systems*, *178*, Article 114115. https://doi.org/10.1016/j.dss.2023.114115

Zeng, F., Ye, Q., Li, J., & Yang, Z. (2021). Does self-disclosure matter? A dynamic two-stage perspective for the personalization-privacy paradox. *Journal of Business Research*, *124*, 667–675. https://doi.org/10.1016/j.jbusres.2020.02.006