

THE EFFECTS OF AI-WASHING ON CONSUMER'S TRUST, ETHICS AND PURCHASE INTENTION

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Abstract: As artificial intelligence becomes a dominant signifier of innovation in marketing, the practice of AI washing as the strategic exaggeration or fabrication of AI capabilities in marketing communications has emerged as a critical ethical concern. This article reports study results examining AI washing perception and its consequences for consumer trust, perceived brand ethicality, purchase intention, and word-of-mouth (WOM) intention. Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed with a survey sample of 854 consumers to establish predictive relationships. Drawing on the Trust-Action Model, Ethical Decision-Making Theory, and Consumer Information Processing Theory, the findings shows that AI washing severely and significantly damages all four consumer outcomes. Crucially, a serial mediation pathway Perceived Brand Ethicality-Brand-Trust-Behavioral Intentions was supported in the study, confirming that deception functions primarily as a moral failure before translating into eroded trust and suppressed behavior. Moderation analyses revealed a competence-based susceptibility gradient: technological literacy and prior AI experience amplified these negative effects, whereas age did not. Convergent cross-study effect sizes confirm robust findings with important implications for marketing practice, consumer protection, and AI governance.

Keywords: AI washing, consumer trust, perceived brand ethicality, behavioral intentions, technological literacy

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Introduction

Artificial intelligence (AI) has significantly transformed contemporary marketing by facilitating personalized, data-driven consumer engagement (Yazdani & Darbani, 2023; Das, 2025). As the strategic importance of AI increases, the “AI-powered” designation has become synonymous with innovation and competitiveness, prompting organizations to adopt or appear to align with AI trends (Jain et al., 2025; Gorjanc, 2025). Nevertheless, escalating ethical concerns, including transparency, bias, and privacy, have heightened consumer skepticism about AI-related claims (Mohanna, 2024; Yadav, 2024). The need to balance technological signaling with ethical accountability renders the credibility of AI claims a critical concern.

Within this context, AI washing has emerged as a significant concern. AI washing refers to the exaggeration or misrepresentation of AI capabilities, resulting in a discrepancy between organizational claims and actual deliverables (Elhajjar & Itani, 2025). In contrast to greenwashing, AI washing presents distinct risks due to the inherent complexity of AI systems. Consumers frequently lack the technical expertise required to assess such claims, which contributes to information asymmetry and potential misunderstandings (Elhajjar et al., 2025). These dynamics may result in reputational, privacy, financial, and algorithmic harms in a rapidly evolving, insufficiently regulated environment.

Despite increasing relevance, research on AI washing remains limited. Current studies typically rely on broad greenwashing frameworks or address general AI ethics, frequently neglecting specific behavioral outcomes such as consumer trust, purchase intention, and word of mouth, as well as the psychological mechanisms that drive these responses.

This study examines the impact of AI washing on consumer behavior, with particular emphasis on perceived brand ethicality as a central mechanism. It posits that ethical evaluations mediate the relationship between AI washing and outcomes such as trust, purchase intention, and word of mouth. Drawing on the Trust-Action Model and Ethical Decision-Making Theory, the research addresses (RQ1) the influence of AI washing on consumer responses, (RQ2) the role of ethical perceptions in shaping behavior, and (RQ3) the moderating effects of demographics and experience. Empirical evidence demonstrates that misleading AI claims erode trust and weaken consumer-brand relationships, underscoring the necessity of ethical transparency.

1. Literature Review

1.1 Influence of AI on Consumer Behavior and Consumer Trust

Artificial intelligence has transformed marketing by enabling personalized, data-driven consumer interactions (He & Zhang, 2023; Das, 2025). These developments underscore the centrality of trust in consumer engagement with AI-enabled systems (Yazdani & Darbani, 2023). The Trust-Action Model identifies trust as a primary determinant of behavioral intentions (Yazdani & Darbani, 2023; Gorjanc, 2025), while Ethical Decision-Making Theory elucidates the influence of ethical perceptions on consumer actions. Collectively, these frameworks indicate that trust serves as both a prerequisite and an outcome of AI-driven interactions. Transparency is therefore essential, especially in addressing concerns regarding data privacy and ethical practices (Ozturkcan & Bozdog, 2025).

1.2 Ethical Concerns in AI Marketing

Ethical concerns play a significant role in shaping consumer responses to AI. The inherent opacity of AI systems restricts consumer understanding and diminishes trust (Janz et al., 2025), while challenges such as data privacy and algorithmic bias further heighten skepticism (Goncalves et al., 2024; Yadav, 2024). Empirical evidence indicates that clearer communication regarding AI processes enhances consumer acceptance (Freeman et al., 2024). Ethical Decision-Making Theory (Stahl, 2021; Janz et al., 2025) conceptualizes this as a sequential process in which individuals identify ethical issues, form judgments, and subsequently modify their behavior.

1.3 Demographic Variance in Consumers' AI Perception

Consumer responses to AI vary by demographic and experiential variables. Variations in knowledge and cognitive ability affect how individuals interpret AI-related claims (Kim et al., 2021). More experienced consumers are more inclined to scrutinize such claims, whereas less experienced consumers tend to rely on heuristic cues. Existing research emphasizes the importance of considering these differences, particularly in relation to fairness, ethics, and trust (Yadav, 2024; Chatterjee & Prabhakar, 2025).

1.4 AI Washing and the Knowledge Gap

AI washing, defined as the exaggeration or misrepresentation of AI capabilities, directly influences consumer perceptions and trust (Elhajjar & Itani, 2025). Despite its significance, three primary gaps persist: limited understanding of the mechanisms connecting AI washing to brand ethicality, inadequate exploration of moderating factors, and a scarcity of causal research designs. Addressing these gaps is critical for advancing scholarly understanding in this area.

1.5 The Theoretical Distinctiveness of AI Washing

AI washing differs from traditional forms of misrepresentation due to its pronounced opacity and limited verifiability. In contrast to greenwashing, where claims are often subject to external verification (Torelli et al., 2020; Siano et al., 2017), AI-related claims are challenging for consumers to assess due to concealed data and processes (Mittelstadt et al., 2016; Kim et al., 2021). This uncertainty prompts more cautious, skeptical consumer judgments (Mittelstadt et al., 2016; Floridi et al., 2018), which, in turn, diminish ethical evaluations and trust. As a result, consumers increasingly depend on prior knowledge and heuristics, and trust becomes more difficult to restore. These attributes establish AI washing as a unique and impactful form of technological misrepresentation.

2. Conceptual Framework

2.1 Theoretical Foundation

The theoretical foundation of this study integrates three complementary theories. Moral evaluation theory explains how consumers assess the ethics of AI washing, relationship trust theory illuminates the role of trust-based dynamics, and information processing theory addresses individual cognitive differences. Together, these theories dissect how consumers perceive and respond to AI washing in marketplace contexts.

The Trust-Action Model (hereafter mentioned as TAM) posits that cognitive evaluations shape consumer trust, which directly drives marketplace behaviours and supports the hypothesised direct effects (H1). This directly links cognitive judgments to behavioural intentions (Yazdani &

Darbani, 2023; Gorjanc, 2025). TAM's structure aligns with Morgan and Hunt's (1994) Commitment-Trust Theory, which positions trust and commitment as mediators in relationship marketing and sees brands as implicit promises. Violating these promises constitutes a moral breach (Bhargava & Bedi, 2022). Within this combined framework, AI washing is a rupture in the relational contract between firms and consumers.

H1a: AI washing perception is negatively associated with brand trust.

H1b: AI washing perception is negatively associated with perceived brand ethicality.

H1c: AI washing perception is negatively associated with purchase intention.

H1d: AI washing perception is negatively associated with WOM intention.

Ethical Decision-Making Theory delineates a sequential mediation pathway (H2): Consumers respond to ethical violations by first forming ethical judgments (perceived brand ethicality), which then influence trust formation (Janz et al., 2025; Stahl, 2021). Thus, the model specifies that ethical evaluation operates as the primary psychological filter through which AI washing influences trust.

H2a: The negative effect of AI washing perception on purchase intention is serially mediated by perceived brand ethicality and then brand trust.

H2b: The negative effect of AI washing perception on WOM intention is serially mediated by perceived brand ethicality and then brand trust.

Consumer Information Processing Theory underpins the moderating effects in H3. It explains that technological literacy, age, and prior AI experience affect consumers' ability to detect, interpret, and respond to deceptive AI claims. Specifically, technological literacy moderates how consumers scrutinise AI claims. Age moderate's cognitive flexibility and technology exposure. Prior AI experience moderates baseline familiarity and skepticism. These three are positioned as moderators within the information-processing mechanisms of our conceptual framework.

H3a: Technological literacy moderates the negative effect of AI washing perception on brand trust, strengthening the effect for consumers with high literacy.

H3b: Age moderates the negative effect of AI washing perception on purchase intention, with the effect potentially stronger among younger consumers.

H3c: Prior AI experience moderates the negative effect of AI washing perception on perceived brand ethicality, strengthening the effect for consumers with more extensive experience.

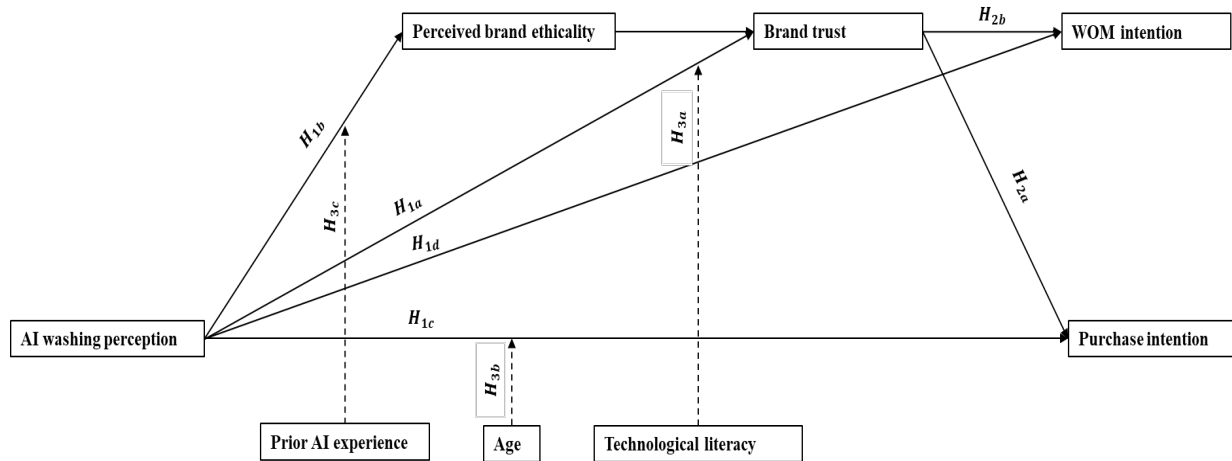


Figure 1. Conceptual model

Source: Author's own elaboration

Figure 1 presents the conceptual model of this study, illustrating the hypothesised direct effects, the serial mediation pathway via perceived brand ethicality and brand trust, and the moderating relationships among the specified variables.

2.2 Definition of Key Constructs

All constructs are measured using established definitions and validated scales. AI washing perception refers to consumers' views of exaggerated or misleading AI claims and is measured on a five-point Likert scale (Newell & Goldsmith, 2001). Brand trust captures confidence in a brand's reliability and integrity (Chaudhuri & Holbrook, 2001), while perceived brand ethicality reflects judgments of a firm's moral character (Singh et al., 2012); both use multi-item five-point scales.

Purchase intention and word-of-mouth (WOM) intention measure the likelihood of purchasing and recommending a brand, respectively, and are each assessed using single-item five-point scales (Dodds et al., 1991; Zeithaml et al., 1996). This approach is appropriate given the concreteness of these constructs (Bergkvist & Rossiter, 2009).

Technological literacy and prior AI experience are measured using multi-item scales capturing digital competence (Hargittai, 2005) and prior

interaction with AI (Venkatesh et al., 2003). Age is treated as a continuous variable, with additional demographics included as controls. All multi-item constructs are specified as reflective, ensuring reliability and construct validity.

3. Methods

3.1 Study Design

We used a quantitative, cross-sectional survey to test hypothesized relationships. The sample was large and drawn from real-world data. PLS-SEM was selected for its suitability for prediction-oriented research. It also handles complex models and non-normal data distributions (Hair et al., 2022; Risher & Hair, 2017).

3.2 Sample, Data Collection and Ethics

A pilot study with 37 participants assessed item discrimination, validity, and reliability. Two statistics professors, a postdoctoral fellow, and two independent doctoral researchers reviewed the items for clarity, relevance, and representativeness. Minor revisions followed. The web-based survey ran from February to August 2025 via Qualtrics. It was distributed through MTurk. Only participants with an approval rating of at least 95% were included. Respondents were US and UK residents aged 18 to 55, living in their respective countries for at least 5 years. Individuals in AI development or marketing were excluded to prevent bias. Demographic quotas ensured an approximate balance across age, gender, and education. This matched general population distributions. A reverse-coded attention checks detected careless responses, which were then removed. A post-hoc G*Power analysis confirmed statistical power for the final sample ($N = 854$). All participants received a digital information sheet, provided informed electronic consent, and had their data anonymised in accordance with GDPR.

3.3 Measures

All constructs used established scales adapted to the AI marketing context. They were measured on 5-point Likert scales (1 = Strongly Disagree, 5 = Strongly Agree). Behavioural intentions used a single item

(1 = Very Unlikely, 5 = Very Likely). AI Washing Perception was measured with a four-item scale adapted from Newell and Goldsmith (2001) and Siano et al. (2017). Reliability was pilot-tested ($\alpha = .89$). Brand Trust was measured using four items from Chaudhuri and Holbrook (2001). Perceived Brand Ethicality used three items adapted from Singh et al. (2012). Technological Literacy used a five-item scale from Hargittai (2005). Prior AI Experience was captured with a three-item scale, inspired by Venkatesh et al. (2003), and pilot-tested for reliability ($\alpha = .87$). Purchase Intention and WOM Intention were each operationalised using a single validated item (Dodds et al., 1991; Zeithaml et al., 1996). Single-item measures are appropriate for doubly concrete constructs that are both (a) concretely rather than abstractly conceived and (b) associated with a singular, unambiguous referent (Bergkvist & Rossiter, 2009). Purchase intention ('How likely are you to purchase from this brand?') and WOM intention ('How likely are you to recommend this brand to others?') satisfy both criteria: each refers to a specific, well-understood behaviour directed at a named object. Under these conditions, Diamantopoulos et al. (2012) demonstrate that single-item measures attain psychometric performance equivalent to multi-item scales, provided the item is precisely worded and pre-validated. Both items used in this study were adapted from established sources and pilot-tested ($n = 37$) prior to main data collection, confirming their discriminant and face validity.

3.4 Analytical Procedure

PLS-SEM was run in SmartPLS-4 (Cheah et al., 2024) using a two-step procedure (Ringle et al., 2020; Wong, 2013). Harman's single-factor test addressed potential common-method bias. Principal Component Analysis (Table 1) showed that the first component accounted for 44.4% of the variance, which is below the 50% threshold. The measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity. The structural model used non-parametric bootstrapped path coefficients with 5,000 subsamples (Chin, 1998). R^2 , Cohen's F^2 , and the Stone-Geisser Q^2 statistic (Geisser, 1975; Stone, 1974) were also reported.

Table 1
Principal component analysis

Indicator	Component 1 Loading	Uniqueness	Remarks
ai_wash_1	-0.842	0.290	Cross-construct
ai_wash_2	-0.857	0.265	Cross-construct
ai_wash_3	-0.847	0.283	Cross-construct
ai_wash_4	-0.851	0.277	Cross-construct
trust_1	0.816	0.333	Cross-construct
trust_2	0.837	0.299	Cross-construct
trust_3	0.815	0.336	Cross-construct
trust_4	0.825	0.319	Cross-construct
ethicality_1	0.790	0.376	Cross-construct
ethicality_2	0.795	0.368	Cross-construct
ethicality_3	0.791	0.374	Cross-construct
purchase_intent	0.923	0.148	Cross-construct
wom_intent	0.953	0.091	Cross-construct
tech_lit_1 to tech_lit_5	< 0.10	0.984–0.989	Unique to construct
AI_exp_1 to AI_exp_3	< 0.10	0.990–0.995	Unique to construct
Component Summary	SS Loadings: 9.33	% of Variance: 44.4%	Cumulative %: 44.4%

Source: Authors' primary data. Web-based survey administered via Qualtrics (N = 854, February–August 2025). Principal Component Analysis conducted in SPSS to implement Harman's (1976) single-factor test for common method bias assessment. No rotation applied.

The results of Harman's single-factor test (*Table 3*) confirmed that common method bias was not a concern, as the first component variance was 44.4%, below the 50% threshold. No rotation was applied. Technological literacy was measured using a five-item self-reported scale assessing participants' familiarity, confidence, and proficiency with digital technologies. Prior AI experience was captured through a single item that asked respondents whether they had prior exposure to using or interacting with AI tools. Both sets of items loaded uniquely onto their respective constructs (uniqueness > 0.98), demonstrating that these moderators are orthogonal to the core nomological network.

4. Results

4.1 Demographic Characteristics

The final sample comprised 854 participants. Ages ranged from 18 to 55 years ($M = 38.4$, $SD = 11.5$, $Mdn = 38$). Gender was balanced: 54.0% male, 44.0% female, and 2.0% other. Most held a graduate degree (52.6%), followed by post-graduate (28.2%) and high school (19.2%). Significant Shapiro-Wilk results ($p < .001$ for all variables) support the use of PLS-SEM as a distribution-free method.

Table 2
Respondent's demographic profile

Statistic	Age	Gender	Education
N	854	854	854
Missing	0	0	0
Mean	38.4	1.48	2.09
Median	38	1	2
Standard Deviation	11.5	0.538	0.683
Minimum	18	1	1
Maximum	55	3	3
Shapiro–Wilk W	0.986	0.685	0.801
Shapiro–Wilk p	< .001	< .001	< .001
<i>Gender Frequencies</i>		%Percent of total	Cumulative
%			
1 = Male (Counts)	461	54.0%	54.0%
2 = Female (Counts)	376	44.0%	98.0%
3 = Other (Counts)	17	2.0%	100.0%
<i>Education Frequencies</i>		%Percent of total	Cumulative %
1 = High School (Counts)	164	19.2%	19.2%
2 = Graduate (Counts)	449	52.6%	71.8%
3 = Post-Graduate (Counts)	241	28.2%	100.0%

Source: Authors' primary data. Web-based survey administered via Qualtrics (N = 854, February–August 2025). Gender and education are reported as frequency distributions; age is reported as a continuous variable. Shapiro–Wilk statistics confirm non-normal distributions, supporting the use of PLS-SEM.

4.2 Measurement Model Assessment

The reflective measurement model was assessed following established PLS-SEM guidelines (Hair et al., 2019; Hair & Alamer, 2022; Henseler et al., 2015). All indicator outer loadings exceeded 0.708, ranging from 0.841 to 0.944. All Variance Inflation Factor (VIF) values were below 5.0, with a maximum of 3.745. Composite reliability ranged from 0.898 to 0.969. Average Variance Extracted (AVE) ranged from 0.719 to 0.887, both exceeding the 0.50 benchmark (Fornell & Larcker, 1981). All Heterotrait-Monotrait (HTMT) ratios were below 0.85, confirming adequate discriminant validity. Full reliability and validity statistics are reported in *Table 3*. *Figure 2* presents the measurement model with standardized loadings.

Table 3
Reliability and convergent validity

Construct / Indicator	λ	VIF	α	CR	AVE
<i>AI Washing Perception</i>			0.957	0.969	0.887
ai_wash_1	0.942	1.066			
ai_wash_2	0.944	1.173			
ai_wash_3	0.941	1.038			
ai_wash_4	0.939	2.874			
<i>Brand Trust</i>			0.935	0.953	0.836
trust_1	0.910	1.375			
trust_2	0.920	3.745			
trust_3	0.909	2.349			
trust_4	0.918	1.681			
<i>Perceived Brand Ethicality</i>			0.909	0.943	0.846
ethicality_1	0.919	2.022			
ethicality_2	0.916	1.887			
ethicality_3	0.924	1.179			
<i>Technological Literacy</i>			0.903	0.928	0.719
tech_lit_1	0.841	2.380			
tech_lit_2	0.852	2.331			
tech_lit_3	0.852	2.368			
tech_lit_4	0.853	2.426			
tech_lit_5	0.843	2.219			
<i>Prior AI Experience</i>			0.829	0.898	0.745
AI_exp_1	0.878	2.002			
AI_exp_2	0.857	1.941			
AI_exp_3	0.855	1.782			

Source: Authors' primary data. Measurement model estimated in SmartPLS-4 (Cheah et al., 2024). λ = standardised outer loading; VIF = Variance Inflation Factor; α = Cronbach's alpha; CR = composite reliability; AVE = Average Variance Extracted. All loadings > 0.708; AVE > 0.50 (Fornell & Larcker, 1981); all VIF < 5.0.

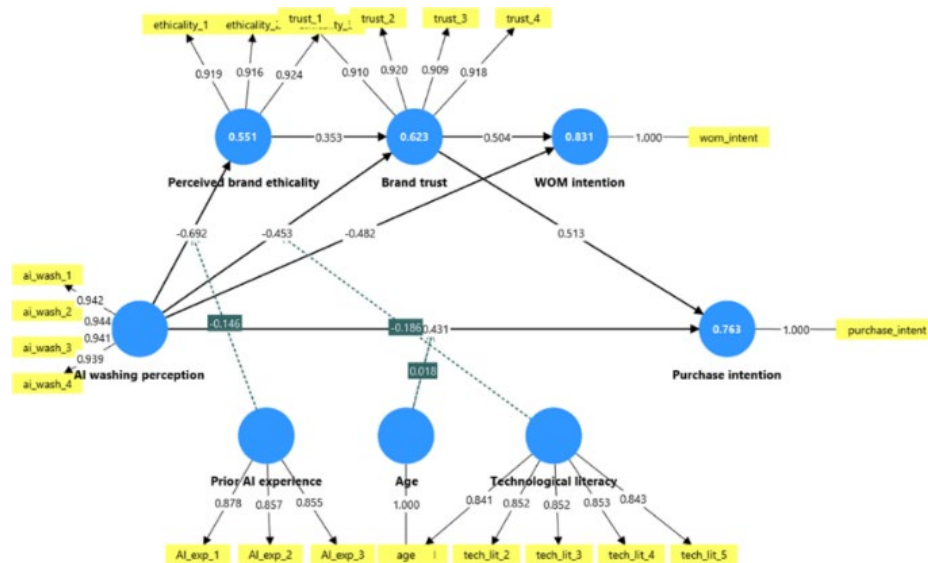


Figure 2. Measurement model

Table 4

Discriminant validity- Heterotrait-Monotrait (HTMT) ratio

	AWP	Age	BT	PBE	PAE	PI	TL	WOMI	PAI x AWP	Age x AWP
AWP										
Age	0.023									
BT	0.75	0.026								
PBE	0.748	0.054	0.726							
PAE	0.038	0.03	0.014	0.263						
PI	0.813	0.014	0.847	0.843	0.034					
TL	0.035	0.036	0.21	0.039	0.037	0.036				
WOMI	0.858	0.023	0.875	0.875	0.041	0.013	0.016			
PAI x AWP	0.007	0.014	0.009	0.15	0.022	0.009	0.017	0.008		
Age x AWP	0.03	0.009	0.015	0.019	0.037	0.03	0.037	0.004	0.017	
TL x AWP	0.021	0.019	0.178	0.038	0.02	0.012	0.036	0.001	0.058	0.018

Source: Authors' primary data. Discriminant validity assessed via the Heterotrait-Monotrait (HTMT) ratio in SmartPLS-4 (Henseler et al., 2015). All HTMT values below the 0.85 threshold, confirming adequate discriminant validity. AWP = AI Washing Perception; BT = Brand Trust; PBE = Perceived Brand Ethicality; PAE = Prior AI Experience; PI = Purchase Intention; TL = Technological Literacy; WOMI = WOM Intention.

Tables 4 and 5 show discriminant validity analysis with the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larcker test results. HTMT assesses whether two constructs are distinct, while the Fornell-Larcker test compares the variance within a construct to the variance shared with other constructs.

All HTMT values are below 0.85 (Henseler et al., 2015), confirming adequate discriminant validity.

Table 5
Discriminant validity- Fornell-Larcker

	AWP	Age	BT	PBE	PAE	PI	TL	WOMI
AWP	0.942							
Age	-0.022	1						
BT	-0.709	0.025	0.914					
PBE	-0.698	0.052	0.669	0.92				
PAE	0.029	-0.03	-0.011	-0.229	0.863			
PI	-0.795	0.014	0.819	0.804	-0.031	1		
TL	0.032	-0.03	-0.194	-0.036	-0.015	-0.034	0.848	
WOMI	-0.839	0.023	0.846	0.834	-0.037	0.946	-0.015	1

Source: Authors' primary data. Fornell-Larcker criterion assessed in SmartPLS-4. Diagonal elements represent the square root of AVE for each construct; off-diagonal elements are inter-construct correlations. Discriminant validity is confirmed when diagonal values exceed corresponding off-diagonal values in the same row and column. Abbreviations as per Table 4.

4.3 Structural Model and Hypotheses Test

Figure 3 shows the measurement model for Study 1, displaying standardized outer loadings for reflective indicators and R² values for endogenous latent variables estimated via SmartPLS-4.

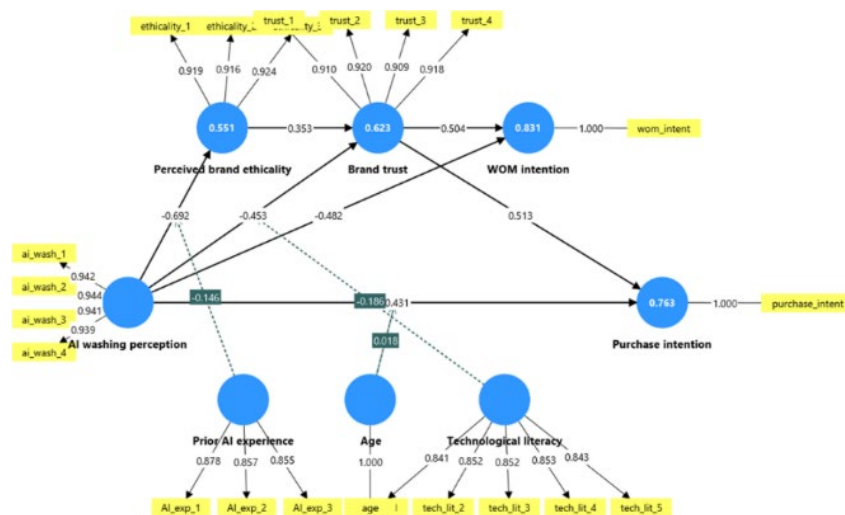


Figure 3. Measurement model

Source: Authors' primary data. Structural model estimated in SmartPLS-4 (Cheah et al., 2024) with 5,000 bootstrap subsamples. Standardised path coefficients (β) are displayed on paths; R² values are shown inside endogenous constructs. Significance: *** $p < .001$; n.s. = not significant.

Table 6 presents all hypothesis testing results. AI washing perception exerted strong, significant negative direct effects on all four outcome variables (H1a-H1d, all $p < .001$), with the largest path coefficient observed for perceived brand ethicality (beta = -0.692), confirming it as the most sensitive consumer outcome consistent with Ethical Decision-Making Theory. The serial mediation analyses confirmed H2a and H2b: the indirect effects of AI washing on purchase intention (beta = -0.126, 95% CI [-0.153, -0.099]) and WOM intention (beta = -0.123, 95% CI [-0.149, -0.097]) were both significant ($p < .001$), operating through the chain of reduced ethicality perception followed by eroded brand trust. The total effect on purchase intention (beta = -0.789) substantially exceeded the direct effect (beta = -0.431), indicating that mediated pathways account for a majority of AI washing's commercial harm.

Table 6
Summary of Hypothesis Testing Results

Hypothesis	Path	β	t	p	Outcome
<i>H1: Direct Effects</i>					
H1a	AI Washing Perception → Brand Trust	-0.453	15.886	<.001	Supported
H1b	AI Washing Perception → Perceived Brand Ethicality	-0.692	48.423	<.001	Supported
H1c	AI Washing Perception → Purchase Intention	-0.431	16.460	<.001	Supported
H1d	AI Washing Perception → WOM Intention	-0.482	22.079	<.001	Supported
<i>H2: Mediation Effects (Specific Indirect Effects)</i>					
H2a	AI Washing → PBE → Brand Trust → Purchase Intention	-0.126	9.299	<.001	Supported
H2b	AI Washing → PBE → Brand Trust → WOM Intention	-0.123	9.451	<.001	Supported
<i>H3: Moderation Effects</i>					
H3a	Tech. Literacy × AI Washing → Brand Trust	-0.186	9.012	<.001	Supported
H3b	Age × AI Washing → Purchase Intention	0.018	1.196	.116	Not Supported
H3c	Prior AI Exp. × AI Washing → Perceived Brand Ethicality	-0.146	7.189	<.001	Supported

Source: Authors' primary data. Structural model estimated in SmartPLS-4 (Cheah et al., 2024) using 5,000 bootstrap subsamples (Chin, 1998). β = standardised path coefficient; t = bootstrap t-statistic; p = two-tailed p-value. H3b was not supported ($p = .116$). All remaining hypotheses supported at $p < .001$.

Moderation analysis revealed a competence-based susceptibility gradient. Technological literacy significantly strengthened the negative relationship between AI washing perception and brand trust (H3a: $\beta = -0.186$, $p < .001$, $f^2 = .087$). Prior AI experience intensified the negative effect of AI washing on perceived brand ethicality (H3c: $\beta = -0.146$, $p < .001$, $f^2 = .044$). Contrary to expectations, age did not moderate the AI washing-purchase intention relationship (H3b: $\beta = .018$, $p = .116$), suggesting that scepticism toward misleading AI claims is broadly distributed across age groups, likely due to widespread media coverage of AI-related controversies. These results are summarized in *Tables 6 and 7*.

Table 7
Model Explanatory Power (R^2), Effect Sizes (f^2), and Predictive Relevance (Q^2)

Endogenous Construct / Path	R^2	Q^2	f^2	t	p
<i>Perceived Brand Ethicality</i>	0.551	0.547			
AI Washing Perception → Perceived Brand Ethicality			1.066	12.508	< .001
Prior AI Experience → Perceived Brand Ethicality			0.094	4.044	< .001
Prior AI Exp. × AI Washing → Perceived Brand Ethicality			0.044	3.474	< .001
<i>Brand Trust</i>	0.623	0.547			
AI Washing Perception → Brand Trust			0.278	6.578	< .001
Perceived Brand Ethicality → Brand Trust			0.169	5.361	< .001
Technological Literacy → Brand Trust			0.079	3.614	< .001
Tech. Literacy × AI Washing → Brand Trust			0.087	4.380	< .001
<i>Purchase Intention</i>	0.763	0.610			
AI Washing Perception → Purchase Intention			0.390	6.573	< .001
Brand Trust → Purchase Intention			0.552	9.612	< .001
Age → Purchase Intention			0.000	0.169	.433
Age × AI Washing → Purchase Intention			0.001	0.527	.299
<i>WOM Intention</i>	0.831	0.682			
AI Washing Perception → WOM Intention			0.682	8.791	< .001
Brand Trust → WOM Intention			0.748	9.673	< .001

Source: Authors' primary data. Model performance indices estimated in SmartPLS-4. R^2 = coefficient of determination (proportion of endogenous construct variance explained); Q^2 = Stone-Geisser predictive relevance (Stone, 1974; Geisser, 1975), with $Q^2 > 0$ indicating predictive relevance; f^2 = Cohen's (2013) effect size for individual paths, with $f^2 \geq 0.02$ (small), ≥ 0.15 (medium), ≥ 0.35 (large).

5. Discussion

Study 1 offers robust empirical evidence regarding the behavioral consequences of AI washing, situating these effects within a theoretically grounded nomological network. The results are interpreted in relation to the research questions and established theoretical frameworks.

5.1 Findings: Answering the Research Questions

RQ1. AI washing has strong, consistent negative effects across all measured consumer outcomes. PLS-SEM analysis reveals significant reductions in perceived brand ethicality ($\beta = -.692$), brand trust ($\beta = -.453$), purchase intention ($\beta = -.431$), and word-of-mouth (WOM) intention ($\beta = -.482$), all $p < .001$. The most pronounced effect occurs for perceived brand ethicality, suggesting that consumers initially respond at the level of moral evaluation. This finding aligns with Ethical Decision-Making Theory (Stahl, 2021; Janz et al., 2025), which posits that ethical judgment precedes behavioral responses.

RQ2. The serial mediation model posits a sequential mechanism in which perceived brand ethicality influences brand trust, which, in turn, affects behavioral intentions. Both indirect effects are significant for purchase intention ($\beta = -.126$) and WOM intention ($\beta = -.123$). The total effect on purchase intention ($\beta = -.789$) substantially exceeds the direct effect, indicating that the majority of the behavioral impact is mediated by ethical evaluation and trust. This finding identifies perceived brand ethicality as the primary psychological filter in the effects of AI washing.

RQ3. Moderation analysis reveals a competence-based pattern. Technological literacy amplifies the negative effect of AI washing on brand trust ($\beta = -.186$), and prior AI experience intensifies its effect on perceived brand ethicality ($\beta = -.146$), both $p < .001$. Conversely, age does not exhibit a significant moderating effect ($\beta = .018$, $p = .116$). These results suggest that susceptibility to AI washing is determined by knowledge and experience rather than demographic characteristics, challenging age-based assumptions in Consumer Information Processing Theory.

5.2 Theoretical Contributions

This study advances the literature in three primary ways. First, it establishes a clear causal mechanism linking AI washing to consumer

behavior by integrating the Trust-Action Model (Yazdani & Darbani, 2023; Gorjanc, 2025) with Ethical Decision-Making Theory. The findings indicate that moral evaluation precedes trust erosion and drives behavioral decline, with mediation accounting for the majority of the total effect ($\beta = -.789$ compared to a direct effect of $-.431$).

Second, it validates AI washing perception as a reliable and psychometrically sound consumer-level construct, enabling its use in future empirical research. Third, the findings refine Consumer Information Processing Theory by demonstrating that competence-based factors, such as technological literacy and AI experience, rather than age, determine susceptibility to AI washing. This shifts the explanatory focus from demographic. The findings indicate that AI washing causes substantial commercial harm by diminishing ethical perceptions, trust, and behavioral intentions. Ethical perception emerges as the primary driver of consumer response, positioning claim accuracy as a strategic imperative rather than merely a compliance requirement.

5.3 Managerial contributions

The findings show that AI washing generates substantial commercial harm by weakening ethical perceptions, trust, and behavioural intentions. Ethical perception emerges as a primary driver of consumer response, making claim accuracy a strategic necessity rather than a compliance issue. The moderation results further indicate that highly knowledgeable consumers are most sensitive to AI washing. This is particularly important as these consumers often represent early adopters and influential market segments, meaning misleading claims risk disproportionate strategic damage. For policymakers, the magnitude and consistency of effects support stronger regulatory oversight of AI-related marketing claims. This includes clearer disclosure standards, verification mechanisms, and investment in AI literacy to improve consumer detection of misleading practices.

5. Conclusion

6.1 Summary of Key Findings

Analysis of a large-scale PLS-SEM dataset ($N = 854$) demonstrates that AI washing significantly and negatively impacts perceived brand

ethicality, trust, purchase intention, and WOM intention. Effect sizes are substantial across all outcomes ($\beta = -.431$ to $-.692$), with strong explanatory power (R^2 up to .831).

The serial mediation model confirms that ethical evaluation and trust sequentially transmit the effects of AI washing on behavioral intentions. Significant indirect effects and a total effect that exceeds the direct effect confirm mediation as the primary mechanism.

Moderation analysis demonstrates that technological literacy and prior AI experience amplify negative responses to AI washing, while age has no significant effect. This reinforces the importance of competence over demographic factors.

6.2 Theoretical and Practical Implications

The study integrates trust and ethical decision-making theories to explain the effects of AI washing, validates a consumer-level measurement construct, and advances Consumer Information Processing Theory by introducing competence-based moderation. The findings demonstrate that accurate AI communication is essential for maintaining ethical perception and trust. Policymakers are encouraged to develop enforceable standards for AI claims and support consumer AI literacy as a systemic safeguard against deceptive marketing.

6.3 Limitations and Future Research

Four boundary conditions of this study merit acknowledgement. First, the cross-sectional design precludes definitive causal inference regarding the temporal ordering and persistence of AI-washing effects. Although the scenario-based stimulus was structured to approximate experimental conditions by presenting a concrete, controlled instance of AI-washing claims, this approach does not substitute for experimental manipulation with random assignment. Longitudinal panel designs are necessary to examine how AI-washing perceptions decay or intensify over time, and how trust may be repaired following corrective disclosure. Second, the use of single-item measures for purchase intention and WOM intention, while psychometrically justified for doubly concrete constructs (Bergkvist & Rossiter, 2009; Diamantopoulos et al., 2012), represents a methodological trade-off. Future replications should employ multi-item operationalisation. For example, adapted from Zeithaml et al. (1996) to permit full-scale confirmatory factor

analysis and to assess whether effect magnitudes are sensitive to measurement format. Third, the sample is restricted to adult consumers in the United States and the United Kingdom. Although demographic quotas ensured approximate population representativeness within these contexts, the findings may not generalise to markets with different levels of AI familiarity, regulatory environments, or cultural orientations toward institutional trust. Cross-cultural replication studies, particularly in high-growth AI adoption markets in Southeast Asia and the Gulf Cooperation Council region, are warranted. Fourth, this study treats AI washing as a unidimensional phenomenon at the level of the marketing communication practice. The model does not differentiate consumer responses by product or service category. For instance, whether AI-washing claims embedded in a software application, a consumer electronics device, or a healthcare service elicit equivalently severe ethical and trust responses. Product category is a theoretically plausible moderator: the stakes of AI opacity are likely highest in high-involvement, health-adjacent, or financially consequential domains where the consequences of misinformation are acute. Future research should systematically vary category types to test whether the effects identified here are context-invariant, or whether category risk amplifies the moral judgment process.

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