

Empirical Validation of an Ethical Branding Heuristics Index (EBHI) for AI Marketing

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Abstract

The proliferation of artificial intelligence in marketing practices has intensified consumer concerns regarding ethical implications, yet no validated instrument exists to systematically measure consumer perceptions of AI ethics in branding contexts. This study develops and empirically validates an Ethical Branding Heuristics Index (EBHI) through a mixed-methods approach combining exploratory factor analysis, confirmatory factor analysis, and multiple regression modeling across three industry sectors (technology, retail, and financial services). Data from 1,247 consumers revealed a five-factor structure encompassing Transparency Perception ($\alpha = .89$), Algorithmic Fairness Concern ($\alpha = .86$), Data Privacy Assurance ($\alpha = .91$), Human Agency Preservation ($\alpha = .84$), and Outcome Accountability ($\alpha = .87$). Cross-industry validation demonstrated strong predictive validity for brand trust ($R^2 = .67$), purchase intention ($R^2 = .54$), and brand advocacy ($R^2 = .61$). The EBHI provides marketing practitioners and researchers with a psychometrically robust tool for assessing and predicting consumer ethical perceptions in AI-enabled branding contexts, contributing to the emerging field of algorithmic marketing ethics.

Keywords: - Artificial Intelligence Marketing, Ethical Branding, Consumer Perception, Scale Development, Heuristic Processing

I. INTRODUCTION

The integration of artificial intelligence technologies in marketing practices has fundamentally transformed consumer-brand interactions, introducing unprecedented capabilities for personalization, prediction, and automation (Davenport et al., 2020; Dwivedi et al., 2021). However, this technological advancement has simultaneously generated substantial consumer apprehension regarding the ethical implications of AI-driven marketing strategies. Recent industry reports indicate that 70% of consumers have very little or no trust in companies to use AI responsibly, while 72% believe AI-based content generators could spread false or misleading information (IAPP, 2024; Gartner, 2024).

Despite extensive theoretical discourse on AI ethics in marketing, empirical research lacks validated instruments capable of systematically measuring consumer perceptions of ethical AI branding practices. Consumer decision-making regarding AI-enabled brands increasingly relies on heuristic processing mechanisms that simplify complex ethical evaluations into manageable cognitive shortcuts (Tversky & Kahneman, 1974). These heuristics, while efficient, may not accurately reflect the nuanced ethical considerations inherent in AI marketing applications.

This research addresses this critical gap by developing and empirically validating an Ethical Branding Heuristics Index (EBHI) designed to capture consumer perceptions of AI ethics in marketing contexts. The study's significance lies in providing marketing practitioners and researchers with a psychometrically robust instrument for assessing ethical perceptions, predicting consumer responses, and informing ethical AI marketing strategy development.

The research questions guiding this investigation are:

- What are the underlying factor dimensions of consumer ethical heuristics regarding AI-enabled branding?
- Does the EBHI demonstrate adequate psychometric properties across diverse industry contexts?

- What is the predictive validity of the EBHI for key consumer outcome variables?

II. LITERATURE REVIEW

2.1. Theoretical Foundations of AI Ethics in Marketing

The theoretical foundation for understanding AI ethics in marketing emerges from the convergence of technology acceptance theory (Davis, 1989), ethical decision-making frameworks (Rest, 1986), and consumer trust mechanisms (McKnight et al., 2002). Recent empirical research has identified several key ethical concerns in AI marketing contexts, with transparency emerging as a fundamental requirement for consumer acceptance (Dwivedi et al., 2021).

Studies have demonstrated that transparency and explainability are crucial for building public confidence in AI systems (MIT Sloan Management Review, 2024). The lack of transparency in AI decision-making processes can significantly erode consumer trust, as consumers infer that AI shares information with larger audiences and increases their sense of exploitation (Lefkeli et al., 2024). This finding has particular relevance for marketing applications where personal data collection and automated decision-making are prevalent.

2.2. Consumer Trust and AI Marketing Ethics

Consumer trust represents a central mediating mechanism linking ethical perceptions to behavioral outcomes in AI marketing contexts. The 2024 KPMG Generative AI Consumer Trust Survey found that 74% of consumers trust organizations that increasingly use generative AI in their day-to-day operations, but this trust is conditional on responsible and ethical use (KPMG, 2024). Key factors influencing consumer trust include regular internal audits for bias and fairness (86%), collaboration with regulatory bodies (85%), third-party review of AI oversight (84%), and human oversight in critical decision-making areas (82%).

Research has shown that Generation Z consumers, as digital natives, have heightened expectations for transparency and ethical conduct in AI interactions (Guerra-Tamez et al., 2024). Their attitudes toward AI, exposure to AI technologies, and perception of AI accuracy significantly enhance brand trust, which positively impacts purchasing decisions. This suggests that ethical considerations are particularly important for younger consumer segments who represent the future market for AI-enabled brands.

2.3. Heuristic Processing in Consumer Ethical Evaluation

Dual-process theories of cognition suggest that consumers employ both systematic and heuristic processing when evaluating complex ethical information (Chaiken & Trope, 1999). In AI marketing contexts, the technical complexity of algorithmic systems often overwhelms systematic processing capabilities, leading consumers to rely heavily on simplified heuristic judgments. Recent research indicates that consumers' trust in AI systems is regulated by their perceptions of transparency, fairness, accountability, and human oversight (Nature Humanities and Social Sciences Communications, 2024).

The development of validated measurement instruments for these perceptions is essential for advancing both theoretical understanding and practical implementation of ethical AI marketing practices. However, no empirical research has systematically examined how these heuristics operate specifically in AI marketing contexts or developed validated measures for their assessment.

III. METHODOLOGY

3.1. Research Design

This study employed a multi-phase mixed-methods approach to develop and validate the EBHI. Phase 1 involved qualitative exploration through focus groups and expert interviews to identify relevant ethical dimensions. Phase 2 utilized exploratory factor analysis (EFA) to determine the underlying factor structure. Phase 3 employed confirmatory factor analysis (CFA) to validate the factor structure across independent samples. Phase 4 conducted predictive validity testing through multiple regression analysis.

3.1.1. Phase 1: Qualitative Item Generation

- Participants: Eight focus groups (n = 64) were conducted with consumers aged 18-65 across three metropolitan areas. Additionally, 12 expert interviews were conducted with marketing practitioners, AI researchers, and consumer protection advocates.
- Procedure: Focus groups explored consumer perceptions of ethical issues in AI marketing through structured discussion protocols. Expert interviews utilized semi-structured interviews focusing on key ethical dimensions and measurement considerations. All sessions were recorded and transcribed for thematic analysis.
- Analysis: Thematic analysis following (Braun & Clarke, 2006) identified recurring ethical themes. Initial item generation produced 89 potential scale items across six preliminary dimensions: transparency, fairness, privacy, accountability, human agency, and beneficence.

3.1.2. Phase 2: Exploratory Factor Analysis

- Participants: An online survey was administered to 847 consumers recruited through a nationally representative panel. Demographic characteristics included 52% female, mean age 41.7 years (SD = 14.2), with representation across education and income levels.

- Measures: The 89 preliminary items were presented using 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). Participants evaluated items in the context of AI-enabled marketing scenarios across three industries (technology, retail, financial services).
- Analysis: EFA using principal axis factoring with oblique rotation (direct oblimin) was conducted to identify underlying factor dimensions. Item retention criteria included factor loadings $\geq .50$, communalities $\geq .40$, and absence of significant cross-loadings ($> .30$).

3.1.3. Phase 3: Confirmatory Factor Analysis

- Participants: A second independent sample of 400 consumers was recruited using identical demographic quotas to the EFA sample.
- Procedure: The refined item set from EFA was administered using identical procedures to Phase 2.
- Analysis: CFA using maximum likelihood estimation was conducted to confirm the factor structure. Model fit was evaluated using multiple criteria: $\chi^2/df < 3.0$, CFI $> .95$, TLI $> .95$, RMSEA $< .06$, SRMR $< .08$.

3.1.4. Phase 4: Predictive Validity Testing

- Participants: The CFA sample also completed criterion measures for predictive validity assessment.
- Criterion Measures:
 - Brand Trust Scale (7 items, $\alpha = .92$; Chaudhuri & Holbrook, 2001)
 - Purchase Intention Scale (4 items, $\alpha = .89$; Spears & Singh, 2004)
 - Brand Advocacy Scale (5 items, $\alpha = .91$; Zeithaml et al., 1996)
- Analysis: Multiple regression analysis examined the predictive validity of EBHI factors for criterion variables. Cross-industry analysis assessed generalizability across technology, retail, and financial services contexts.
- Ethical Considerations: This research was approved by the Institutional Review Board. All participants provided informed consent, and data collection procedures ensured anonymity and confidentiality. No deceptive practices were employed, and participants were debriefed regarding research purposes.

IV. RESULTS

4.1. Phase 1: Qualitative Results

Thematic analysis revealed five primary ethical dimensions consistently discussed across focus groups and expert interviews:

- Transparency Perception: Consumer desire for clear disclosure of AI involvement and decision-making processes
 - Algorithmic Fairness Concern: Apprehension regarding discriminatory or biased AI targeting
 - Data Privacy Assurance: Expectations for secure and appropriate data handling
 - Human Agency Preservation: Preference for maintaining human control and override capabilities
 - Outcome Accountability: Expectations for responsibility and recourse mechanisms
- Item refinement reduced the initial pool to 67 items distributed across these five dimensions.

4.2. Phase 2: Exploratory Factor Analysis Results

Initial EFA revealed a six-factor solution explaining 71.3% of total variance. However, the sixth factor contained only two items with marginal factor loadings, leading to a five-factor solution explaining 68.7% of variance. Item reduction based on statistical criteria yielded a final 25-item scale (5 items per factor).

4.2.1 Factor 1: Transparency Perception (Eigenvalue = 8.42, 33.7% variance)

- Items focused on AI disclosure, explainability, and communication clarity
- Example item: "This brand clearly explains when AI is used in their marketing"

4.2.2. Factor 2: Algorithmic Fairness Concern (Eigenvalue = 3.78, 15.1% variance)

- Items addressed discriminatory targeting and biased recommendations
- Example item: "I worry this brand's AI might treat some customers unfairly"

4.2.3. Factor 3: Data Privacy Assurance (Eigenvalue = 2.94, 11.8% variance)

- Items examined data security, consent, and usage transparency
- Example item: "This brand protects my personal data when using AI"

4.2.4. Factor 4: Human Agency Preservation (Eigenvalue = 2.31, 9.2% variance)

- Items focused on human control and override capabilities
- Example item: "I can easily opt-out of AI-powered marketing from this brand"

4.2.5. Factor 5: Outcome Accountability (Eigenvalue = 2.19, 8.8% variance)

- Items addressed responsibility and recourse mechanisms

- Example item: "This brand takes responsibility for their AI marketing decisions"

4.3. Phase 3: Confirmatory Factor Analysis Results

CFA results supported the five-factor structure with acceptable model fit: $\chi^2 = 487.23$, $df = 265$, $\chi^2/df = 1.84$, CFI = .967, TLI = .961, RMSEA = .046 (90% CI: .039-.053), SRMR = .052.

4.3.1. Internal Consistency Reliability:

- Transparency Perception: $\alpha = .89$, $\omega = .91$
- Algorithmic Fairness Concern: $\alpha = .86$, $\omega = .88$
- Data Privacy Assurance: $\alpha = .91$, $\omega = .92$
- Human Agency Preservation: $\alpha = .84$, $\omega = .86$
- Outcome Accountability: $\alpha = .87$, $\omega = .89$

4.3.2. Convergent and Discriminant Validity:

All factors demonstrated adequate convergent validity ($AVE > .50$) and discriminant validity ($\sqrt{AVE} > \text{inter-factor correlations}$). Factor correlations ranged from .23 to .67, indicating related but distinct constructs.

4.4. Phase 4: Predictive Validity Results

Multiple regression analysis demonstrated significant predictive validity for all criterion variables:

4.4.1. Brand Trust Prediction:

- $R^2 = .67$, $F(5, 394) = 159.8$, $p < .001$
- Significant predictors: Transparency ($\beta = .31$, $p < .001$), Data Privacy ($\beta = .28$, $p < .001$), Accountability ($\beta = .22$, $p < .001$)

4.4.2. Purchase Intention Prediction:

- $R^2 = .54$, $F(5, 394) = 93.6$, $p < .001$
- Significant predictors: Data Privacy ($\beta = .29$, $p < .001$), Transparency ($\beta = .25$, $p < .001$), Human Agency ($\beta = .18$, $p < .01$)

4.4.3. Brand Advocacy Prediction:

- $R^2 = .61$, $F(5, 394) = 123.4$, $p < .001$
- Significant predictors: Transparency ($\beta = .33$, $p < .001$), Accountability ($\beta = .26$, $p < .001$), Data Privacy ($\beta = .21$, $p < .001$)

4.4.4. Cross-Industry Validation

Multi-group CFA confirmed measurement invariance across technology, retail, and financial services industries ($\Delta CFI < .01$, $\Delta RMSEA < .015$). However, regression coefficients varied significantly across industries, with transparency showing stronger effects in technology contexts and privacy showing stronger effects in financial services.

V. DISCUSSION

5.1. Theoretical Implications

The empirical validation of the EBHI makes several important theoretical contributions to understanding consumer perceptions of AI ethics in marketing contexts. First, the five-factor structure provides empirical support for multidimensional conceptualization of AI marketing ethics, moving beyond unidimensional trust measures commonly employed in previous research. The distinct factors suggest that consumers employ sophisticated heuristic processing to evaluate different ethical dimensions rather than relying on global ethical judgments.

The strong predictive validity of transparency and data privacy factors aligns with recent industry findings showing that consumers expect clear disclosure of AI usage and robust data protection measures (KPMG, 2024; MIT Sloan Management Review, 2024). However, the significant role of human agency preservation represents a novel theoretical contribution, suggesting that consumers value perceived control over AI interactions beyond traditional privacy concerns.

The differential factor loadings across industries support contingency theories of consumer ethical evaluation, indicating that industry context moderates the relative importance of ethical dimensions. Technology companies face greater transparency expectations, while financial services companies encounter heightened privacy concerns, reflecting industry-specific ethical norms and regulatory environments.

5.2. Practical Implications

The EBHI provides marketing practitioners with a validated tool for assessing and improving ethical perceptions of AI-enabled branding strategies. The scale enables systematic measurement of consumer ethical concerns, facilitating data-driven ethical decision-making in AI marketing implementation. Practitioners can utilize the EBHI to benchmark ethical perceptions against competitors, identify areas for ethical improvement, and predict consumer responses to AI marketing initiatives.

The predictive validity results offer specific guidance for ethical AI marketing strategy development. The strong relationship between transparency and brand outcomes suggests that clear AI disclosure and explainability should be prioritized in marketing communications. The significant role of data privacy assurance indicates that robust privacy protection and transparent data usage policies are essential for maintaining consumer trust.

The human agency preservation factor suggests that providing meaningful opt-out mechanisms and human override capabilities can significantly enhance ethical perceptions. This finding challenges purely automated approaches to AI marketing and supports hybrid human-AI systems that preserve consumer autonomy.

5.3. Limitations and Future Research

Several limitations constrain the generalizability of these findings. First, the sample was limited to English-speaking consumers in the United States, potentially limiting cross-cultural applicability. Future research should validate the EBHI across diverse cultural contexts to assess its universal applicability.

Second, the study focused on three industry sectors, and validation across additional industries would strengthen generalizability claims. Different industries may reveal unique ethical dimensions not captured in the current five-factor structure.

Third, the cross-sectional design prevents causal inferences regarding the relationship between ethical perceptions and consumer outcomes. Longitudinal research could examine how ethical perceptions evolve over time and influence long-term brand relationships.

Future research opportunities include investigating individual difference moderators of the ethical perception-outcome relationships. Additionally, experimental research could examine how specific AI marketing practices influence EBHI scores, providing causal evidence for ethical marketing strategy effectiveness.

VI. CONCLUSION

This research successfully developed and validated the Ethical Branding Heuristics Index (EBHI), providing the marketing discipline with its first psychometrically robust instrument for measuring consumer perceptions of AI ethics in branding contexts. The five-factor structure encompassing transparency perception, algorithmic fairness concern, data privacy assurance, human agency preservation, and outcome accountability offers both theoretical insight and practical utility for understanding consumer ethical evaluation of AI-enabled marketing.

The strong predictive validity of the EBHI for brand trust, purchase intention, and brand advocacy demonstrates its practical value for marketing practitioners seeking to implement ethical AI strategies. The cross-industry validation confirms the scale's broad applicability while highlighting important contextual variations in ethical priorities.

As AI technologies continue to proliferate in marketing applications, the EBHI provides a standardized approach for measuring and managing consumer ethical concerns. This measurement capability is essential for advancing both theoretical understanding and practical implementation of ethical AI marketing practices. The scale's development represents a crucial step toward establishing evidence-based standards for ethical AI marketing that protect consumer interests while enabling innovative marketing applications.

Future research utilizing the EBHI can advance understanding of ethical AI marketing through systematic measurement and comparison across diverse contexts. The scale's validation establishes a foundation for continued theoretical development and practical improvement in the rapidly evolving domain of AI-enabled marketing ethics.

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