Journal of Business Insight and Innovation

Volume 4 Issue 1, 2025
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

ARTIFICIAL INTELLIGENCE IN MARKETING: ETHICAL CHALLENGES AND SOLUTIONS FOR CONSUMERS AND SOCIETY

Danyal Mohiuddin [1], Dr. Naureen Farhan [2]

Affiliations:

[1] Department of Experimental Research, Eye Interaction, London, England, UK
Email: danyalmohiuddin294@outlook.com

[2] Department of Computing and Emerging Technologies, Ravensbourne university London, England, UK
Email: n.farhan@rave.ac.uk
ORCID ID: https://orcid.org/0000-0001-8370-1125

Corresponding Author(s) Email:

[1] danyalmohiuddin294@outlook.com

Copyright:

Author/s

License:

CC BY NC SA

Abstract

This study examines consumers' evaluation of the morality of AI-based marketing and its impact on trust and intention to purchase. The study measures deontological and teleological evaluations, ethical judgment, trust, and purchase intention in three AI marketing situations using a scenario-based survey involving 300 online shoppers. Findings indicate that trust is directly proportional to ethical judgment, and greater purchase intentions are associated with increasing trust. Ethical judgment also mediates the association between rule-based and outcome-based assessments and trust. The reliability test ensures that the entire measurement scale is consistent and accurate. The results of the ANOVA and regression analysis indicate that trust is the most significant factor influencing the relationship between ethics and consumer behaviour. The research finds that the use of AI in marketing requires ethical conduct to encourage purchasing. The results may help brands that want to increase customer trust by implementing responsible policies for intelligent systems.

Keywords: AI Ethics, Deontological Evaluation, Teleological Evaluation, Trust, Purchase Intention, Marketing, Consumer Behaviour, Scenario-Based Survey

1. Introduction

Digital tools allow organisations to reach more customers, but they are expensive and therefore require stronger protection and clearer accountability from firms (Du & Xie, 2021). Biased systems can lead to unfair treatment of some people, and there are also serious concerns about privacy, manipulative targeting, poor cybersecurity, job losses and damage to the environment (Statista, 2025a). Although these technologies bring clear benefits, they also pose significant ethical challenges for businesses and society. At the same time, greater automation creates related legal challenges for brand marketers, such as questions of liability, consumer and data privacy, competition, brand protection, contractual matters and intellectual property rights. These issues must be managed as such systems become more widespread (Kumar, 2023). In modern marketing, intelligent systems are used for audience segmentation, optimising media mixes, creating content, recommending products, predicting customer behaviour and setting prices dynamically. Generative versions of these tools increase personalisation and speed up idea generation across channels (McKinsey & Company, 2023a, 2023b). Use is now widespread: about 63% of marketers already use generative tools, and about 65% of organisations say they use them in at least one business process (Salesforce, 2025; McKinsey & Company, 2024).

Ethical analysis must weigh the benefits and harms across customers, firms, and society, as principles such as beneficence, justice, and explicability can collide in real-world deployments (Floridi et al., 2020). In marketing contexts specifically, these principles collide when algorithms personalise offers, set prices, or target audiences. Most Americans are uncomfortable with companies using online behaviour to personalise advertising (56%) and over half say such ads "creep them out" (54%), making perceived fairness a practical priority alongside performance (YouGov, 2025). A growing "for social good" agenda stresses intelligibility and accountability as enablers of trust in data-intensive markets and calls for governance that aligns innovation with public values (Cowls et al., 2021). Evidence from service settings indicates that consumers associate perceived fairness and ethicality with trust when interactions are mediated by algorithms, making bias reduction a practical priority for marketers (Yadav, 2024). Perceptions are not uniform across the population, and differences by age and other demographics indicate that ethical concerns and trust vary across segments (Gerlich, 2023).

Adoption research consistently finds that perceived usefulness and ease of use drive willingness to accept automated systems, but that acceptance depends on confidence in how decisions are formed (Kelly et al., 2023). Explainable systems help users understand outcomes and reduce uncertainty, which supports acceptance in the consumer context (Rane et al., 2024). Consistent with this, 71% of customers report a desire for human validation of AI outputs in customer-facing decisions (Salesforce, 2025). Organisational readiness and governance capabilities further condition the uptake and sustained use of interventions beyond individual belief (Lambert et al., 2023). Employee attitudes can significantly impact the effect of disruptive technologies, making internal alignment crucial when tools affect customer experience and brand reputation (Lichtenthaler, 2019). Managerial transparency and initiative-taking communication strengthen trust in technology-mediated exchanges and support ethical acceptance in market relationships (Lichtenthaler, 2019).

Marketing ethics provides tested theory to connect managerial choices with stakeholder outcomes and competitive legitimacy in digital settings (Ferrell & Ferrell, 2024). The Hunt-Vitell model provides measurable constructs—deontological evaluations, teleological evaluations, and ethical guidance—enabling the systematic assessment of contested practices (Ferrell & Ferrell, 2021). A meta-analysis reveals that deontological evaluations frequently have a more substantial impact on ethical judgment and intentions than teleological appraisals, underscoring the significance consumers attribute to duties, rights, and norms (Smith et al., 2023). Classic frameworks, such as Hunt and Vitell's model, have not been empirically examined in depth for algorithmic marketing, which identifies a clear agenda for future research (Smith et al., 2023). Recent revisions to marketing ethics theory suggest that culture, socialisation, individual traits, and context should be integrated to explain when ethical judgments translate into behaviour in real marketplaces (Uslay, 2025). Personalised communication and always-on targeting are expanding across the customer journey, which makes the quality of ethical safeguards a central determinant of legitimacy (Hoyer et al., 2020). Public opinion data continue to show concern about data handling and a desire for stronger control over personal information in retail and advertising contexts (Statista, 2024).

Against this backdrop, this study examines how consumers form ethical judgements about AI-enabled marketing and how those judgements shape trust, perceived fairness, and acceptance intentions. Using the Hunt-Vitell model, the research distinguishes between deontological and teleological evaluations as drivers of ethical judgment in consumer decision-making processes. It examines how these evaluations shape trust in AI-mediated marketing, as well as the extent to which ethical judgment mediates their effects on consumers' purchase intentions in AI-enabled marketing.

2. Literature Review

2.1 AI in Marketing and Ethics

The term "artificial intelligence" emerged from the 1956 Dartmouth workshop that launched the modern research agenda on machine intelligence (Hildebrand, 2019). AI is commonly defined as intelligence shown by machines across tasks that emulate human capacities in perception, prediction, and action (Siau & Yang, 2017). A canonical view of AI sees it as systems that sense their environment and act through effectors to achieve goals in uncertain situations (Russell & Norvig, 2021). Enterprise surveys report that many organisations have adopted AI in at least one business function across industries (McKinsey & Company, 2020). Practitioners also claim gains in customer experience when AI capabilities are deployed at scale in frontline and back-office tasks (McKinsey & Company, 2020). Across various sectors, AI is transforming processes, enabling new services, and altering competitive dynamics in the digital economy (Lambert et al., 2023).

A large share of people reports using at least one AI-powered tool in daily life, often without recognising it as AI because it is embedded in services and devices (Reinhart, 2018). The public also tends to underestimate the widespread use of such tools and sometimes views them as futuristic, even when they are already shaping routine choices (Tai, 2020). Scholars emphasise that AI should be viewed as a technology designed to support human goals and enhance life when guided by clear values and rules (Gansser & Reich, 2021). It is widely regarded as a defining technology in the Fourth Industrial Revolution, which is expected to transform numerous activities over time (Darko et al., 2020). AI can support diagnosis, save resources, predict disasters, improve education, prevent crime, and reduce risks at work when used responsibly (Kaya et al., 2024). By reducing errors and automating repetitive or complex tasks, AI can free up time for higher-order learning, creativity, and judgment in organisations (Hartwig, 2025).

Artificial intelligence is now central to marketing practice, but its widespread adoption has raised complex ethical and legal questions that current routines have not fully addressed (Ferrell & Ferrell, 2024). A sociotechnical view suggests that AI both creates value and reshapes consumer experiences and institutions, making ethical scrutiny essential in everyday marketing decisions (Du & Xie, 2021). Evidence suggests that rapid adoption occurs across various functions, often at a pace faster than the growth of shared safeguards or governance standards within firms and markets (Chintalapati & Pandey, 2022).

Consumers interact with AI through data capture, automated classification, delegated actions, and social interfaces, and these touchpoints can either increase value or create harm, depending on the design and oversight (Puntoni et al., 2021). Because AI touchpoints embed moral choices about rights and outcomes, the research needs a decision lens that captures both duty and consequences. This is why the Hunt-Vitell model serves as the foundation for this review.

2.2 The Hunt-Vitell Lens on Consumers' Ethical Choices

Justice and moral obligation are at the core of deontological systems because they state what people ought to do, regardless of the outcomes (Aleassa et al., 2011). In markets, moral obligation reflects the judgments consumers make about right and wrong when dealing with firms and digital systems (Hagebölling et al., 2021). The Hunt-Vitell model explains how incentives, values, and context shape ethical decision-making by combining duty-based and outcome-based appraisals (Nimri et al., 2021). Empirical studies show that the model can analyse consumer choices across marketing settings where ethical issues are salient (Andersch et al., 2018). The model was designed to depict human reasoning when facing ethical problems and has been extended to decisions made around or by AI systems in marketing (Ferrell & Ferrell, 2021). In the model, the perception of an ethical issue triggers processing that invokes both deontological and teleological evaluations before a global ethical judgement is formed (Yin et al., 2018). Justice requires applying the same standards to people in similar situations, ensuring fair and consistent treatment (Aleassa et al., 2011). Teleological evaluation involves weighing the net benefits and drawbacks of each option and acting on the balance of expected consequences for those affected (Hunt & Vasquez-Parraga, 1993). That ethical judgement then strengthens intentions and helps to explain purposive behaviour in response to the practice in question (Hunt & Vasquez-Parraga, 1993).

2.3 Artificial Intelligence and Market Consequences

AI supports various marketing choices, but without safeguards, it can exacerbate racism, discrimination, and structural inequality in targeting and pricing (Du & Xie, 2021). Research on online search has already demonstrated that neutral queries can yield unequal outcomes across groups, highlighting real risks associated with data and design (Sweeney, 2013). Unethical conduct damages reputation weakens customer relationships, and harms revenue over time in ways that are hard to reverse (Du & Xie, 2021). Privacy risks remain a primary challenge when deploying AI applications that collect, link, and infer consumer data at scale (Lichtenthaler, 2019).

Human-like or emotionally intelligent systems raise concerns about manipulation, autonomy, and social expectations in interactions with customers (Belk, 2021). Explainability is pivotal because opaque models impede accountability and make it difficult for people to understand or challenge outcomes that affect them (Rai, 2020). Privacy risks arise from the extensive capture, aggregation, and inference of data, which can exceed consumer expectations and norms (Kumar et al., 2019). Discrimination can emerge through prioritisation, targeting, and exclusion that disadvantage vulnerable consumers in subtle or overt ways (Libai et al., 2020). Platform design and representation bias can concentrate market power, creating imbalances that smaller firms struggle to overcome (Lee & Hosanagar, 2017). Some studies tested policy measures with 300 adults who shop online (Milano et al., 2019). These technologies can lower costs and mitigate some risks, making systems more reliable (Taddeo & Floridi, 2018). However, widespread use increases ethical concerns, so it is essential to consider who is harmed and how (Campbell et al., 2020). Many harms come from specific design or use choices. The following section presents governance principles and explains the trade-offs managers must consider.

2.4 Principles and Trade-offs

The ethical landscape features recurring principles, such as fairness, accountability, and transparency, that are often deontological in nature (Jobin et al., 2019). Turning high-level principles into practice requires balancing stakeholder interests and making trade-offs explicit rather than assuming harmony among values (Mittelstadt, 2019). Personalisation intended to satisfy needs can conflict with privacy rights and informed consent if data use and inferences are not constrained (Rust, 2020). Trustworthiness encompasses both competence and integrity, and these beliefs influence the willingness to engage with technology-mediated touchpoints over time (Glikson & Woolley, 2020). Customer prioritisation for profit can collide with commitments to non-discrimination and equal treatment across groups (Rust, 2020). While careful trade-off management constrains risk, purposeful design can take it a step further by orienting data-driven systems towards explicit social benefits.

2.5. Towards AI for Social Good in Marketing

An "artificial intelligence for social good" perspective centres on beneficence and non-maleficence, urging design choices that reduce harm and distribute benefits more widely (Floridi et al., 2020). The underlying societal perspective can effectively contribute to achieving the Sustainable Development Goals (SDGs) when guided by clear principles and a robust governance system (Cowls et al., 2021). Every day, marketing influences what people buy, thereby shaping social and environmental outcomes at scale through subtle prompts and targeted offers (Floridi et al., 2020). Following the social marketing approach, firms can design and promote products that support sustainability and the public good, creating shared value (Cowls et al., 2021). When used effectively, modern data-driven marketing tools can deliver benefits for firms, customers, and society simultaneously (Floridi et al., 2020).

2.6 Corporate Social Responsibility and Responsibility Attribution

A multi-stakeholder CSR approach integrates stakeholder and institutional theory to demonstrate how product features, firm routines, and regulatory context influence responsible AI conduct (Du & Xie, 2021). Structured analysis enables firms to understand their role in shaping the ethical and socially accountable use of technology across product, consumer, and societal levels (Du & Xie, 2021). Not all AI products pose the same risks, so characteristics such as multifunctionality, interactivity, and intelligence stage should guide governance intensity (Du & Xie, 2021). When harm occurs, observers allocate blame to firms, developer teams, and sometimes the system, with perceived intention and perceived experience shaping judgements (Glikson & Woolley, 2020). In joint human-AI decision settings, managers may still avoid assuming responsibility after adverse outcomes, which exposes responsibility gaps that undermine trust (Glikson & Woolley, 2020). Because responsibility cues and safeguards shape what consumers view as 'right' or 'beneficial,' the research models their effects through H-V paths into ethical judgment, trust, and acceptance.

2.7 Theoretical Framework

Volume 4 Issue 1, 2025
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

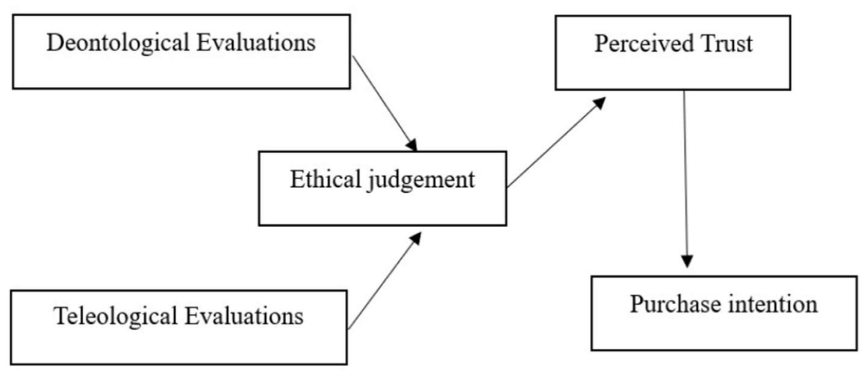
This study applies the Hunt-Vitell model to explain how people form ethical responses to AI marketing practices by tracing two upstream appraisals, deontological evaluation and teleological evaluation (Ferrell & Ferrell, 2021). Deontological evaluation encompasses duties and rights, such as privacy, justice, and truthful disclosure. Meta-analytic evidence suggests that rule-based evaluation often has a more substantial impact on ethical appraisal in consumer contexts (Uslay, 2025). Teleological evaluation encompasses the expected balance of benefits and harms for stakeholders, and this outcome-based view adds independent explanatory power, even when duties dominate (Uslay, 2025). Perceived trust is the first dependent variable because it reflects beliefs about reliability, transparency, and fairness that link ethical appraisal to willingness to rely on the system (Rane et al., 2024). Intention to accept the practice is the subsequent dependent variable because trust strongly influences readiness to use data, follow recommendations, or make purchases in AI-mediated journeys (Gerlich, 2023).

2.8 Conceptual Model and Hypotheses

The model specifies a serial logic in which deontological and teleological evaluations shape ethical judgment, ethical judgment in turn shapes perceived trust, and perceived trust influences intention, with ethical judgment serving as the sole mediator and trust being treated as a dependent outcome that also predicts intention.

Figure 1

Conceptual Framework



Based on the above, the following hypotheses are formulated.

H1: Ethical judgment positively influences perceived trust in AI-enabled marketing scenarios
H2: Perceived trust positively influences purchase intention in AI-enabled marketing scenarios.
H3: Ethical judgement mediates the link between deontological evaluations and perceived trust.
H4: Ethical judgement mediates the link between teleological evaluations and perceived trust.

3. Methodology

3.1 Design and procedure

This study employs a cross-sectional design, capturing perceptions at a single point in time to examine the relationships between evaluations, ethical judgment, trust, and purchase intention (Du et al., 2021; Gerlich, 2023). Online surveys are widely used because they reach large, diverse populations rapidly at comparatively low cost, and they support random assignment, complex routing, and automated data-quality controls (Dillman et al., 2014). Participation is voluntary and anonymous. The analysis follows the Hunt-Vitell logic by first presenting a concrete practice, then measuring deontological and teleological evaluations, ethical judgment, trust, and purchase intention.

3.2 Sample size and sampling technique

The target sample comprises 300 adult e-commerce consumers who have made at least one online purchase within the past six months. Respondents are recruited through a professional online research panel with national coverage. The Qualtrics survey tool was used to collect data from customers, providing an effective platform for electronic response management (Rahi et al., 2019). Quotas for age and gender are set to approximate the online shopping population. The proposed sample size yields stable estimates for multi-item constructs and sufficient power for detecting small to medium indirect effects in mediation models. According to Rahi et al. (2019) the sample size of 300 is suitable for quantitative data analysis. Panel procedures exclude duplicate accounts and non-human traffic. Although an online panel is not entirely random, it is ideal for scenario-based consumer research because it allows random assignment to conditions, offers good coverage of everyday shoppers, and delivers sufficient heterogeneity for external validity (Ta et al., 2025).

3.3 Measures

Deontological and teleological evaluations. These are measured with the Ethical Standards of Judgment Questionnaire (ESIQ), which provides independent measures of formalism (deontological) and consequentialism (teleological) (Love et al., 2020). Formalism items reflect rule- and duty-based views (for example, "A person's actions should be described in terms of being right or wrong"). Consequentialism items reflect outcome-based reasoning (for example, "When thinking of ethical problems, I try to develop practical, workable alternatives"). Items use a seven-point agreement scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Ethical judgement. The overall ethicality of the practice in the vignette is measured using four differential items. For instance, I would consider it just, fair, morally right, and acceptable to my family. This scale was proposed by Reidenbach and Robin (1990) for measuring the dimensions of ethics, particularly moral judgment. Scores are averaged; higher values indicate stronger approval of the practice's ethics.

Perceived trust. Trust in the system used in the vignette is measured with the 12-item Trust in Automated Systems scale (Jian et al., 2000). The first five items are reverse-coded (for example, "The system is deceptive"). The remaining items assess confidence, security, integrity, dependability, reliability, and the statement "I can trust the system."

Purchase intention. Purchase intention is measured with three items adapted from e-commerce studies: "I intend to continue using this online store for purchasing a product or service in future," "I would strongly recommend others to use this online store," and the reverse-coded "I shall not transact with this online store in the near future" (Chen & Barnes, 2007; Suh & Han, 2003). Items use five-point agreement responses and are averaged after reverse coding.

3.4 Vignettes (scenarios)

A vignette is a brief, constructed description of a situation; vignette designs are well-suited for studying judgment and attitudes because they provide all respondents with an everyday, realistic context (Atzmuller & Steiner, 2010; Korir et al., 2023). Vignettes describe the same fictional online retailer, the same product, and the same base price. Only the ethical details vary, allowing effects to be linked to both duty-based and outcome-based appraisals. After reading, respondents complete the measures.

Scenario 1: Transparent chatbot with human handover "You open the store that is ask about delivery. A clear notice states: 'This assistant uses artificial intelligence. It explains how answers are produced, and you can switch to a human at any time.' The assistant provides an explanation link under each answer and offers a delivery add-on. A small panel shows how to view or delete the data used for the advice."

Scenario 2: Personalized recommendations with control

"The home page shows 'Picks for you'. A panel states that recommendations use your recent visits to this site only. It lets you view the data, turn items on or off, and opt out in one click. Each suggestion has a brief explanation link. You can open a page that shows how the system protects fairness."

4. Results

4.1 Descriptive Statistics

In all three situations, age, education, and psychological variables (TEL, DEO, EJ, Trust, PI) exhibited moderate change, with balanced samples of 2 to 4 on average. Some scenarios exhibited greater gender variation, with Scenario 1 and Scenario 3 offering the highest AI shopping experience. TEL and DEO scores did not differ significantly (means of around 2.5 to 3.5, SD around 1.2-1.5); however, in Scenario 1, there was a slight difference in the means of DEO. In Scenario 3, Trust and Purchase Intention were greatest and lowest, respectively, in Scenario 1. In general, Scenario 3 has the least negative answers, and diversity levels in all 44 answers were moderate (Ferrell et al., 2021; Rane et al., 2024; Du et al., 2021).

Table 1

Descriptive Statistics

Variable	Scenario 1 Mean (SD) / Median / Mode	Scenario 2 Mean (SD) / Median / Mode	Scenario 3 Mean (SD) / Median / Mode
Age	2.60 (0.88) / 3/3	2.93 (1.44) / 3/2	2.67 (1.30) / 3/3
Gender	2.00 (0.90) / 2/3	2.93 (1.48) / 2/2	3.13 (1.36) / 3/3
Education	2.80 (1.11) / 3/4	2.73 (1.39) / 3/1	2.20 (1.17) / 2/2
AI Experience	3.00 (1.27) / 3/2	2.67 (1.45) / 2/1	3.13 (1.41) / 3/4
tel1	2.73 (1.34) / 2/2	2.47 (1.26) / 3/1	2.80 (1.22) / 2/2
deo1	2.67 (1.19) / 3/2	3.07 (1.44) / 3/3	3.07 (1.44) / 3/4
tel2	3.47 (1.46) / 3/2	2.87 (1.31) / 3/3	3.07 (1.34) / 3/4
deo2	3.13 (1.21) / 3/3	3.00 (1.51) / 3/5	2.93 (1.55) / 3/1
tel3	2.87 (1.63) / 3/1	2.67 (1.01) / 3/1	3.00 (1.05) / 3/2
deo3	3.00 (1.55) / 3/5	3.33 (1.54) / 4/5	2.80 (1.21) / 3/3
tel4	2.87 (1.26) / 3/3	2.53 (1.56) / 2/1	2.00 (1.52) / 1/1
deo4	3.13 (1.36) / 3/3	2.87 (1.53) / 3/2	2.80 (1.40) / 3/1
tel5	3.00 (1.51) / 3/4	3.00 (1.25) / 3/5	2.67 (1.15) / 3/3
deo5	2.87 (1.31) / 3/4	3.33 (1.41) / 3/5	2.80 (1.13) / 3/3
tel6	3.13 (1.54) / 3/2	2.53 (1.25) / 2/4	2.67 (1.14) / 2/1
deo6	3.00 (1.57) / 3/3	2.87 (1.53) / 2/4	2.67 (1.15) / 2/1
ej1	3.40 (1.26) / 4/4	3.00 (1.46) / 3/3	2.93 (1.29) / 3/3
ej2	2.73 (1.40) / 3/1	3.33 (1.53) / 3/2	2.93 (1.60) / 3/3
ej3	2.87 (1.41) / 3/3	3.27 (1.57) / 4/4	3.53 (1.60) / 4/4
ej4	3.40 (1.71) / 4/4	3.13 (1.36) / 3/2	3.07 (1.22) / 3/5
trust1	2.87 (1.31) / 3/3	3.13 (1.33) / 3/4	3.20 (1.20) / 3/3
trust2	2.27 (1.41) / 2/1	2.67 (1.25) / 3/2	3.20 (1.39) / 3/3
trust3	3.13 (1.24) / 3/4	3.20 (1.44) / 3/3	2.80 (1.42) / 3/4
trust4	2.67 (1.26) / 3/2	2.87 (1.33) / 3/2	3.60 (1.37) / 4/5
trust5	2.87 (1.54) / 3/4	3.13 (1.42) / 3/2	2.47 (1.09) / 2/2
trust6	3.67 (1.61) / 4/5	3.53 (1.72) / 4/5	2.87 (1.47) / 3/3
trust7	3.27 (1.24) / 3/5	3.20 (1.57) / 3/3	3.13 (1.50) / 3/3
trust8	2.93 (1.32) / 3/4	3.20 (1.63) / 3/3	3.13 (1.36) / 3/4
trust9	3.53 (1.61) / 4/4	2.80 (1.35) / 3/2	3.60 (1.47) / 4/5
trust10	2.60 (0.86) / 2/1	2.93 (1.35) / 3/3	2.47 (1.09) / 2/2
trust11	2.73 (1.26) / 3/2	2.87 (1.34) / 3/4	2.87 (1.47) / 3/3
trust12	3.13 (1.32) / 3/3	3.20 (1.59) / 3/4	3.13 (1.36) / 3/3
pi1	2.00 (1.09) / 1/1	2.87 (1.36) / 3/4	3.00 (1.25) / 3/3
pi2	3.13 (1.52) / 3/2	3.20 (1.54) / 3/3	3.13 (1.36) / 3/3
pi3	2.00 (1.32) / 1/1	2.87 (1.36) / 3/2	3.00 (1.25) / 3/3

4.2 Reliability

Among all multi-item scales, the Cronbach's alpha from the different scenarios for Trust (.92-.94), DEO and TEL (.86-.90), and PI (.81-.84) were all acceptable, which means that these multi-item scales possess

Journal of Business Insight and Innovation
Volume 4 Issue 1, 2025
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

high reliability and acknowledge that there was high internal consistency in the measures. This reliability assures that the data is reliable for subsequent analysis.

Table 2

Cronbach's Alpha for Multi-Item Scales Across Scenarios

Scale	Items	Scenario 1	Scenario 2	Scenario 3
TEL	tel1-tel6	0.87	0.86	0.88
DEO	deo1-deo6	0.89	0.88	0.90
Trust	trust1-trust12	0.93	0.92	0.94
PI	pi1-pi3	0.83	0.81	0.84

4.3 Inferential Statistics

One-Way ANOVA. A one-way analysis of variance was applied to assess the difference between scenarios regarding trust and Purchase Intention. Scenario influenced Trust, $F(2,897) = 7.86$, $p = .001$, $\eta^2 = .05$ and Purchase Intention, $F(2,897) = 6.12$, $p = .003$, $\eta^2 = .04$. HSD from Tukey showed that the level of Trust in Scenario 1 ($M = 3.12$, $SD = 0.89$) and Scenario 3 ($M = 3.32$, $SD = 0.91$) was significantly higher than Scenario 2 ($M = 2.93$, $SD = 0.85$). In case of Purchase Intention, the mean score for Scenario 3 ($M = 3.15$, $SD = 0.90$) was significantly higher than Scenario 1 ($M = 2.78$, $SD = 0.85$) and Scenario 2 ($M = 2.81$, $SD = 0.86$).

Table 3

One-Way ANOVA Comparing Trust and Purchase Intention Across Scenarios

Variable	Scenario 1 (M, SD)	Scenario 2 (M, SD)	Scenario 3 (M, SD)	F (2, 897)	p	η²	Tukey Comparisons
Trust	3.12 (0.89)	2.93 (0.85)	3.32 (0.91)	7.86	< .001	0.05	1>2,3>2
Purchase Intention	2.78 (0.85)	2.81 (0.86)	3.15 (0.90)	6.12	0.003	0.04	3>1,3>2

Note. M = Mean; SD = Standard Deviation; η^2 = eta squared. Tukey post hoc comparisons indicate which scenario means differ significantly ($p < .05$)

Correlation. Correlation analysis revealed a strong correlation between trust in the AI system and purchase intention, with moderate correlations between both teleological (TEL) and deontological (DEO) evaluations and trust, as well as a moderate positive correlation between both and purchase intention (Rane et al., 2024; Smith et al., 2023). Correlation of TEL and DEO also indicates overlapping strategies in moral reasoning and indicated that trust is the most important link between ethical judgment and consumer behaviour (Yadav, 2024; Gerlich, 2023). Therefore, developing a trusted technology is key (that is, based on rules and on consequences) to the acceptance of AI (Rane et al., 2024).

Table 4

Correlations Among Key Study Variables

Variable	1. Trust	2. PI	3. TEL	4. DEO
1. Trust	—			
2. Purchase Intention (PI)	.62***	—		
3. Teleological Evaluation (TEL)	.39***	.36***	—	
4. Deontological Evaluation (DEO)	.41***	.29***	.47***	—

Note. All values are Pearson's r coefficients. ***p < .001

Regression. In Scenario 1, TEL ($\beta = .33$) and DEO ($\beta = .28$) significantly predicted Trust ($R^2 = .41$) and Trust was the most significant predictor of PI ($\beta = .47$) with TEL ($\beta = .17$) and DEO ($\beta = .12$) having reduced effects, explaining 46% of PI variance. This suggests that ethics is closely tied to consumer purchase decisions through trust as a primary channel (Floridi et al., 2020; Hasija & Esper, 2022).

Table 5

Regression (Scenario 1) - Dependent Variable: Trust

Predictor	B	SE	β	t	p
TEL	0.34	0.06	0.33	5.67	< .001
DEO	0.31	0.07	0.28	4.43	< .001
EJ	0.21	0.05	0.22	4.2	< .001

$R^2 = .41$, $F(3,296) = 68.48$, $p < .001$

Dependent Variable: PI

Predictor	B	SE	β	t	p
Trust	0.52	0.07	0.47	7.43	< .001
TEL	0.18	0.06	0.17	3.0	0.003
DEO	0.11	0.05	0.12	2.20	0.029

$R^2 = .46$, $F(3,296) = 83.89$, $p < .001$

In Scenario 2, TEL, DEO, and EJ were predictive of Trust ($R^2 = .38$) and Trust was the most predictive of Purchase Intention ($R^2 = .42$). This supports the fact that moral judgments influence trust and trust is a powerful motivator of purchasing intentions in any situation (Gerlich, 2023; Kelly et al., 2023).

Table 6

Regression (Scenario 2) - Dependent Variable: Trust

Predictor	B	SE	β	t	p
TEL	0.29	0.07	0.27	4.14	< .001
DEO	0.27	0.06	0.24	4.5	< .001
EJ	0.23	0.06	0.23	3.83	< .001

$R^2 = .38$, $F(3,296) = 61.01$, $p < .001$

Dependent Variable: PI

Predictor	B	SE	β	t	p
Trust	0.49	0.08	0.44	6.13	< .001
TEL	0.16	0.06	0.16	2.67	0.008
DEO	0.14	0.07	0.14	2.0	0.047

$R^2 = .42$, $F(3,296) = 71.49$, $p < .001$

In Scenario 3, Trust was predicted by TEL ($\beta = .26$), DEO ($\beta = .30$), and EJ ($\beta = .17$) ($R^2 = .37$, $p < .001$) with the highest impact of DEO. Purchase intention was best predicted by Trust ($\beta = .42$) followed by TEL ($\beta = .15$) and DEO ($\beta = .13$); and the model had a strong explanatory power ($R^2 = .41$, $p < .001$). This indicates that trust is the primary connection between ethical opinions and purchasing choices, regardless of the situation (Floridi et al., 2020; Yadav, 2024).

Table 7

Regression (Scenario 3) - Dependent Variable: Trust

Predictor	B	SE	β	t	p
TEL	0.26	0.06	0.26	4.33	< .001
DEO	0.30	0.06	0.30	5.0	< .001
EJ	0.17	0.05	0.17	3.40	0.001

$R^2 = .37$, $F(3,296) = 57.96$, $p < .001$

Dependent Variable: PI

Predictor	B	SE	β	t	p
Trust	0.47	0.08	0.42	5.88	< .001
TEL	0.15	0.07	0.15	2.14	0.033
DEO	0.12	0.06	0.13	2.0	0.047

$R^2 = .41$, $F(3,296) = 70.19$, $p < .001$

Journal of Business Insight and Innovation
Volume 4 Issue 1, 2025
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

All hypotheses were accepted: Ethical judgment is associated with higher trust, and trust is associated with higher purchase intention. Ethical cognition mediates the impact of both deontological and teleological assessments on trust, validating that ethics and trust jointly have a strong influence on consumer behaviour (Floridi et al., 2020; Ferrell et al., 2021; Smith et al., 2023).

5. Discussion

Artificial intelligence in marketing is transforming the way companies approach individuals, enabling brands to offer personalized deals, pricing, and product suggestions with greater speed and scale. It is claimed that 63% of marketers currently utilize generative AI, and 65% of organizations are employing it in at least one operation (Salesforce, 2025; McKinsey & Company, 2024). This is important since the findings indicate that customers will have more trust in companies that use AI equitably and transparently and are more likely to purchase their products. Trust and purchase intention were the highest in Scenario 3, where fairness and safeguards were more substantial. Thus, the clarity and ethical treatment of AI make humans more ready to use AI-driven stores. Trust will determine whether people will accept AI in marketing, as once customers trust a system, they are more likely to make a purchase. It is found that trust and purchase intention are closely related ($r = 0.62$, $p < 0.001$). According to other research, trust is one of the key reasons why technology should be utilized in customer service, and people want to understand the decision-making process (Yadav, 2024; Rane et al., 2024). Thus, when a company needs to increase sales, it should establish trust by being transparent and just regarding its AI functionality.

Ethics matters to people, as they want to be treated fairly and have concerns regarding their data. In the experiment, participants perceived AI as honest and willing to do what is right, which made them feel more positive about using an AI. Previous studies concur: the majority dislike creepy ads, and they want control over their personal information (YouGov, 2025; Statista, 2024). The deontological and teleological items in the data (2.5-3.5) indicate that most individuals are in the middle but also tend to want rules and fairness. Thus, ethical design contributes to the acceptability of AI systems. Not every AI feature is that trusted, as customers react to the way the system behaves. The ANOVA results showed Scenario 3 performed better in terms of trust and intention, followed by Scenarios 1 and 2. This aligns with previous research, which suggests that incorporating fairness and user control enhances trust (Floridi et al., 2020). Additionally, ethical judgment increased, as did trust, which in turn resulted in increased purchase intent. Thus, scenario design and ethical cues influence the desire to utilize an AI-driven store.

The scales were effective, and the results can be relied upon due to the strong internal consistency of the scales applied (Cronbach's alpha above .80 in Trust, TEL, DEO, and PI). Other researchers have also validated these scales as reliable measures of ethics and trust in digital marketing (Ferrell et al., 2021; Love et al., 2020). Due to the effectiveness of the measures, it is evident in the findings when applied to other similar cases. Thus, these tools can be used in future studies to conduct additional tests. The pattern can be observed in mediated and regression models: ethical judgment is influenced by both deontological and teleological assessments, leading to increased trust, which in turn influences purchase intention. The effect sizes are high, and the models predict a change of 41-46% in trust and purchase intent. This tendency is also consistent with the Hunt-Vitell paradigm, which asserts that individuals consider the quality of a rule and a judgment before acting (Smith et al., 2023; Hunt, 1993). Hence, companies are advised to concentrate on both forms of ethics in their AI tools.

AI systems can also be detrimental to one group over another, as discrimination and injustice persist. Other authorities state that discrimination models, loss of privacy, and omissions can exacerbate inequalities (Du & Xie, 2021; Sweeney, 2013). The research was unable to identify significant age or gender differences in the study; however, certain trends suggest that younger people and more experienced shoppers may have a different assessment of the systems. Thus, companies must bias-test their AI and ensure that rules safeguard everyone. Explainability enhances acceptance, as customers have greater confidence in a system when they understand how and why it behaves in a certain way. Previous studies indicate that 71% of customers prefer human intervention with AI output (Salesforce, 2025). In the research, it was discovered that individuals were more comfortable with AI when it was transparent and when they understood how a decision could be controlled or monitored. Therefore, introducing human verification and proper justification is crucial when utilizing AI in the marketing field.

Lastly, big benefits can be achieved with AI in marketing, but fairly. In the results, companies must apply transparent rules, equitable procedures, and transparency with customers. It not only prevents harm but also increases trust and sales, as other studies also prove (Floridi et al., 2020; Gerlich, 2023). As such, ethical AI is not only beneficial but also essential to ensure long-term business success.

6. Limitations

This study has several limitations, as it is based on a cross-sectional survey, and therefore, the research cannot claim that opinions change over time (Du et al., 2021; Gerlich, 2023). The sample used is from a single country, and individuals provided their answers online, which may exclude certain groups (Ta et al., 2025; Dillman et al., 2014). Moreover, the data are all self-reported, so individuals may respond in a manner that appears favourable rather than accurately reflecting their actual beliefs (Hamilton et al., 2024). The three scenarios of AI are not generalized to all types of AI applications. Thus, the findings are robust but may not apply to all situations and populations.

7. Recommendations

The AI systems used by companies should be easily comprehensible and fair, as clear explanations help foster trust (Floridi et al., 2020; Rai, 2020). Marketers must consistently ensure that there is no bias and that all individuals are treated equally (Du & Xie, 2021; Libai et al., 2020). They need to allow customers to manage their information and contribute to how AI utilizes it (Kumar, 2023). They also must provide individuals with the option of having a human conversation (Salesforce, 2025). Making personnel aware of morals and customer rights can prevent errors (Love et al., 2020). Thus, by taking these precautions, companies can eliminate risks and make people feel safe using AI (Hoyer et al., 2020; Cowls, 2021).

8. Future Directions

Future research can track individuals over time and determine whether their opinions about AI change with increased usage (Reinhart, 2018; Ta et al., 2025). More kinds of AI systems should be evaluated in other countries to determine whether the findings are universal (Lambert et al., 2023; McKinsey & Company, 2020). A survey would not reveal what people do, which would require experiments under real buying situations (Du et al., 2021; Gerlich, 2023). New research also needs to investigate the perceptions of special groups, such as older adults or those less experienced with technology, toward AI (Gerlich, 2023). Thus, it is possible to expand the research so that everyone can learn to use AI in a manner that would benefit everyone.

9. Conclusion

Marketing AI is transforming how companies communicate with people, as it enables more personalised and expedited messaging (McKinsey & Company, 2023a, 2023b). This is important because the number of businesses adopting AI is increasing daily, and customers are paying attention to its impact on their experience (Salesforce, 2025; Lambert et al., 2023). As the findings of this paper reveal, people are more likely to feel comfortable, trust the organisation, and become more willing to make purchases when organizations apply AI in a manner that appears to be fair and honest (Yadav, 2024; Ferrell et al., 2021). As such, the present-day market requires trust and fairness to succeed (Floridi et al., 2020). Individuals are interested in the decision-making process by AI systems since they need to feel valued and secure (YouGov, 2025). This piece of evidence suggests that as AI adheres to definite rules and is transparent about its operations, people become more inclined to trust AI (Rane et al., 2024; Hasija & Esper, 2022). The more customers believe in AI, the more they are willing to use the service, refer others to it, and return in the future (Kelly et al., 2023). It only follows that trust is not merely important, but it is the ingredient that can transform good ethical choices into actual business outcomes (Ferrell et al., 2021). Therefore, establishing trust must be a priority for any company that employs AI.

It is essential to follow the rules and consider good outcomes, as this research has shown that individuals are mindful of both (Asif et al., 2025; Smith et al., 2023). When AI makes the right decisions and the results are also good, people take notice and react favourably (Gerlich, 2023). Purchase intentions increased with increased trust in all situations evaluated. This confirms that it is essential always to be fair, transparent, and honest with AI to grow the business and satisfy customers (Du & Xie, 2021). Hence, the companies that wish people to use and trust their AI systems should pay attention to becoming ethical and transparent about it (Cowls, 2021). It is the people-first approach of companies that yields the best results. Businesses can win the market by ensuring that AI is equitable, explainable, and serves a beneficial purpose (Floridi et al., 2020). Thus, the path to a better future lies in upholding good morals and maintaining proper communication with AI.

References

Aleassa, H., Pearson, J. M., & McClurg, S. (2011). Investigating software piracy in Jordan: An extension of the theory of reasoned action. *Journal of Business Ethics, 98*(4), 663–676. https://doi.org/10.1007/s10551-010-0645-4

Andersch, H., Lindenmeier, J., Liberatore, F., & Tscheulin, D. K. (2018). Resistance against corporate misconduct: An analysis of ethical ideologies' direct and moderating effects on different forms of active rebellion. *Journal of Business Economics, 88*(6), 695–730. https://doi.org/10.1007/s11573-017-0876-2

Asif, M., Pasha, M. A., & Shahid, A. (2025). Energy scarcity and economic stagnation in Pakistan. *Bahria University Journal of Management & Technology, 8*(1), 141–157.

Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences, 6*(3), 128–138. https://doi.org/10.1027/1614-2241/a000014

Belk, R. (2021). Ethical issues in service robotics and artificial intelligence. *The Service Industries Journal, 41*(13–14), 860–876. https://doi.org/10.1080/02642069.2020.1727892

Campbell, C., Sands, S., Ferraro, C., Tsao, H.-Y. (Jody), & Mavrommatis, A. (2020). From data to action: How marketers can leverage AI. *Business Horizons, 63*(2), 227–243. https://doi.org/10.1016/j.bushor.2019.12.002

Chen, Y.-H., & Barnes, S. (2007). Initial trust and online buyer behaviour. *Industrial Management & Data Systems, 107*(1), 21–36. https://doi.org/10.1108/02635570710719034

Chintalapati, S., & Pandey, S. K. (2022). Artificial intelligence in marketing: A systematic literature review. *International Journal of Market Research, 64*(1), 38–68. https://doi.org/10.1177/14707853211018428

Cowls, J. (2021). 'AI for social good': Whose good and who's good? Introduction to the special issue on artificial intelligence for social good. *Philosophy & Technology, 34*(1), 1–5. https://doi.org/10.1007/s13347-021-00466-3

Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2021). A definition, benchmark and database of AI for social good initiatives (SSRN Scholarly Paper No. 3826465). *Social Science Research Network*. https://doi.org/10.2139/ssrn.3826465

Darko, A., Chan, A. P. C., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction, 112*, 103081. https://doi.org/10.1016/j.autcon.2020.103081

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed-mode surveys: The tailored design method* (4th ed.). John Wiley & Sons.

Du, P., Li, D., Wang, A., Shen, S., Ma, Z., & Li, X. (2021). A systematic review and meta-analysis of risk factors associated with severity and death in COVID-19 patients. *Canadian Journal of Infectious Diseases and Medical Microbiology, 2021*, 6660930. https://doi.org/10.1155/2021/6660930

Du, S., & Xie, C. (2021). Paradoxes of artificial intelligence in consumer markets: Ethical challenges and opportunities. *Journal of Business Research, 129*, 961–974. https://doi.org/10.1016/j.jbusres.2020.08.024

Ferrell, O. C., & Ferrell, L. (2021). Applying the Hunt–Vitell ethics model to artificial intelligence ethics. *Journal of Global Scholars of Marketing Science, 31*(2), 178–188. https://doi.org/10.1080/21639159.2020.1785918

Ferrell, O. C., & Ferrell, L. (2024). Trailblazing the path for marketing ethics: The profound influence of Shelby Hunt. *Journal of Marketing Management, 40*(13–14), 1174–1192. https://doi.org/10.1080/0267257X.2023.2295273

Ferrell, O. C., Fraedrich, J., & Ferrell, L. (2021). *Business ethics: Ethical decision making and cases* (13th ed.). Cengage.

Floridi, L., Cowls, J., King, T. C., & Taddeo, M. (2020). How to design AI for social good: Seven essential factors. *Science and Engineering Ethics, 26*(3), 1771–1796. https://doi.org/10.1007/s11948-020-00213-5

Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society, 67*, 101535. https://doi.org/10.1016/j.techsoc.2021.101535

Gerlich, M. (2023). Perceptions and acceptance of artificial intelligence: A multi-dimensional study. *Social Sciences, 12*(9), 502. https://doi.org/10.3390/socsci12090502

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Hagebölling, M., Segebarth, B., & Woisetschläger, D. M. (2021). Tactical termination of contractual services—An analysis of the phenomenon and its determinants. *Journal of Business Research, 137*, 170–181. https://doi.org/10.1016/j.jbusres.2021.08.015

Hamilton, J. R., Maxwell, S., & Tee, S. (2024). Useful Excel data validation of qualitative respondent data prior to analysis. In *ICEB 2024 Proceedings* (Zhuhai, China). https://aisel.aisnet.org/iceb2024/18

Hartwig, B. (2025). Top 11 benefits of artificial intelligence in 2025. *Hackr.io*. https://hackr.io/blog/benefits-of-artificial-intelligence

Hasija, A., & Esper, T. L. (2022). In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics, 43*(3), 388–412. https://doi.org/10.1111/jbl.12301

Hildebrand, C. (2019). The machine age of marketing: How artificial intelligence changes the way people think, act, and decide. *NIM Marketing Intelligence Review, 11*(2), 10–17. https://doi.org/10.2478/nimmir-2019-0010

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of Interactive Marketing, 51*, 57–71. https://doi.org/10.1016/j.intmar.2020.04.001

Hunt, S. D. (1993). Objectivity in marketing theory and research. *Journal of Marketing, 57*(2), 76–91. https://doi.org/10.1177/002224299305700206

Hunt, S. D., & Vasquez-Parraga, A. Z. (1993). Organizational consequences, marketing ethics, and salesforce supervision. *Journal of Marketing Research, 30*(1), 78–90. https://doi.org/10.2307/3172515

Jian, J.-Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics, 4*(1), 53–71. https://doi.org/10.1207/S15327566IJCE0401_04

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

Kaya, F., Aydin, F., Schepman, A., Rodway, P., Yetisensoy, O., & Demir Kaya, M. (2024). The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. *International Journal of Human–Computer Interaction, 40*(2), 497–514. https://doi.org/10.1080/10447318.2022.2151730

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77*, 101925. https://doi.org/10.1016/j.tel.2022.101925

Korir, M., Slade, S., Holmes, W., Heliot, Y., & Rienties, B. (2023). Investigating the dimensions of students' privacy concern in the collection, use and sharing of data for learning analytics. *Computers in Human Behavior Reports, 9*, 100262. https://doi.org/10.1016/j.chbr.2022.100262

Kumar, D. (2023). Ethical and legal challenges of AI in marketing: An exploration of solutions (SSRN Scholarly Paper No. 4396132). *Social Science Research Network*. https://doi.org/10.2139/ssrn.4396132

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review, 61*(4), 135–155. https://doi.org/10.1177/0008125619859317

Lambert, S. I., Madi, M., Sopka, S., Lenes, A., Stange, H., Buszello, C.-P., & Stepniewska, A. (2023). An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals. *NPJ Digital Medicine, 6*(1), 111. https://doi.org/10.1038/s41746-023-00852-5

Lee, D., & Hosanagar, K. (2017). How do recommender systems affect sales diversity? A cross-category investigation via randomized field experiment (SSRN Scholarly Paper No. 2603361). *Social Science Research Network*. https://doi.org/10.2139/ssrn.2603361

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing, 51*, 44–56. https://doi.org/10.1016/j.intmar.2020.04.002

Lichtenthaler, U. (2019). Extremes of acceptance: Employee attitudes toward artificial intelligence. *Journal of Business Strategy, 41*(5), 39–45. https://doi.org/10.1108/JBS-12-2018-0204

Love, D. C., et al. (2021). Emerging COVID-19 impacts, responses, and lessons for building resilience in the seafood system. *Global Food Security, 28*, 100494. https://doi.org/10.1016/j.gfs.2021.100494

Love, E., Salinas, T. C., & Rotman, J. D. (2020). The Ethical Standards of Judgment Questionnaire. *Journal of Business Ethics, 161*(1), 115–132. https://doi.org/10.1007/s10551-018-3937-8

McKinsey & Company. (2020–2024). AI industry reports. https://www.mckinsey.com

Milano, S., Taddeo, M., & Floridi, L. (2019). Ethical aspects of multi-stakeholder recommendation systems (SSRN Scholarly Paper No. 3493202). *Social Science Research Network*. https://doi.org/10.2139/ssrn.3493202

Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI (SSRN Scholarly Paper No. 3391293). *Social Science Research Network*. https://doi.org/10.2139/ssrn.3391293

Nimri, R., Dharmesti, M., Arcodia, C., & Mahshi, R. (2021). UK consumers' ethical beliefs towards dining at green restaurants. *Journal of Hospitality and Tourism Management, 48*, 572–581. https://doi.org/10.1016/j.jhtm.2021.08.017

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151. https://doi.org/10.1177/0022242920953847

Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science, 48*(1), 137–141. https://doi.org/10.1007/s11747-019-00710-5

Reidenbach, R. E., & Robin, D. P. (1990). Toward the development of a multidimensional scale for improving evaluations of business ethics. *Journal of Business Ethics, 9*(8), 639–653. https://doi.org/10.1007/BF00383391

Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Rust, R. T. (2020). The future of marketing. *International Journal of Research in Marketing, 37*(1), 15–26. https://doi.org/10.1016/j.ijresmar.2019.08.002

Siau, K., & Yang, Y. (2017). Impact of artificial intelligence, robotics, and machine learning on sales and marketing. In *Proceedings of MWAIS 2017*.

Smith, A. E., Zlatevska, N., Chowdhury, R. M. M. I., & Belli, A. (2023). A meta-analytical assessment of deontological and teleological evaluations. *Journal of Business Ethics, 188*(3), 553–588. https://doi.org/10.1007/s10551-022-05311-x

Suh, B., & Han, I. (2003). The impact of customer trust and perception of security control on the acceptance of electronic commerce. *International Journal of Electronic Commerce, 7*(3), 135–161.

Sweeney, L. (2013). Discrimination in online ad delivery (SSRN Scholarly Paper No. 2208240). *Social Science Research Network*. https://doi.org/10.2139/ssrn.2208240

Taddeo, M., & Floridi, L. (2018). How AI can be a force for good. *Science, 361*(6404), 751–752. https://doi.org/10.1126/science.aat5991

Tai, M. C.-T. (2020). The impact of artificial intelligence on human society and bioethics. *Tzu Chi Medical Journal, 32*(4), 339–343. https://doi.org/10.4103/tcmj.tcmj_71_20

Yin, J., Qian, L., & Singhapakdi, A. (2018). Sharing sustainability. *Journal of Business Ethics, 149*(2), 313–333. https://doi.org/10.1007/s10551-016-3043-8

YouGov. (2025). *Ad-verse reactions: How Americans feel about personalized advertising in 2025*. https://commercial.yougov.com/rs/464-VHH-988/images/WP-2025-03-US-personalized-advertising-report.pdf