



# Interdisciplinary Journal of Information, Knowledge, and Management

*An Official Publication  
of the Informing Science Institute  
InformingScience.org*

**Vol. : 21, Issue 1, Jan-June 2026**  
**ISSN: (E) 1555-1237**

## **Leveraging Artificial Intelligence for Gender-Specific Marketing: Optimizing Campaign Effectiveness Through Personalized Strategies**

**Dr. Vidya Rajendran S,**

Assistant Professor,  
Department of Business Administration,  
SCMS School of Technology and Management  
Email id: vidya.rajendran@scmsgroup.org

**Dr. Tintu Mary,**

Assistant Professor,  
Department of Business Administration,  
SCMS School of Technology and Management  
Email id: tintu@scmsgroup.org

**Dr. Chinthu Jose,**

Assistant Professor,  
Department of Business Administration,  
SCMS School of Technology and Management  
Email id: chinthu@scmsgroup.org

**Mr. Muhammed Riyaz H,**

Assistant Professor,  
Department of Management Studies,  
MES Advanced Institute of Management and Technology, Marampally  
Email id: muhammedriyazh@mesaimat.ac.in

---

### **ABSTRACT**

*This research explores how artificial intelligence (AI) can optimize outcomes of gender-specific marketing campaigns by leveraging personalized strategies. Utilizing a sample size of 384 respondents, the study identifies critical variables influencing campaign success, formulates hypotheses based on these variables, and applies rigorous methodologies to assess the relationship between AI-driven personalization and marketing outcomes. The sample size of 300, determined through statistical calculations to ensure representative results, provides robust data for analysis. Findings reveal the potential of AI in tailoring marketing content to specific gender preferences, enhancing engagement, and increasing conversion rates. These insights offer actionable recommendations for marketers and researchers aiming to optimize gender-based targeting strategies while maintaining ethical and inclusive approaches. The study underscores the revolutionary impact of AI in modern marketing, highlighting its capacity to deliver precise and impactful communication tailored to diverse audience segments.*

**KEYWORDS:** Artificial Intelligence, customer engagement, AI personalisation, marketing campaign



## 1. Introduction

Marketing strategies have evolved dramatically in recent years, driven by technological advancements that enable deeper consumer insights and more precise targeting. Artificial intelligence (AI) has become a game-changer for marketers, enabling them to craft highly personalized campaigns that reach vast audiences. By leveraging AI's capacity to process vast amounts of data, brands can move beyond traditional segmentation methods to craft individualized marketing experiences that resonate with specific audiences.

One of the areas witnessing a significant transformation is gender-specific marketing—a longstanding approach that aligns promotional strategies with gender-based preferences and behaviors. While historically limited to broad assumptions and stereotypes, gender-specific marketing has been revitalized by AI's sophisticated analytical capabilities. AI enables marketers to identify nuanced patterns, predict consumer behavior, and design campaigns that speak directly to the preferences and needs of individual consumers within gender groups.

This study probes into the potential of AI to optimize gender-based targeting, highlighting its ability to enhance the relevance and impact of marketing campaigns. Furthermore, it explores the mediating role of consumer engagement—a critical factor in translating personalized marketing efforts into measurable success. By examining how AI-driven personalization influences consumer interactions with gender-specific campaigns, the research aims to provide actionable insights into designing strategies that foster deeper connections, higher satisfaction, and greater loyalty among target audiences. Through this investigation, the study seeks to contribute to the growing body of knowledge on AI in marketing while addressing the ethical and practical implications of leveraging AI for gender-based personalization.

## 2. Statement of the Problem

In the digital era, organizations increasingly use Artificial Intelligence (AI) to deliver personalized marketing experiences. While AI-driven personalization can enhance campaign effectiveness, many strategies overlook gender-specific differences in consumer preferences and responses. Additionally, factors like privacy concerns and trust can influence how consumers perceive and engage with AI-driven marketing. Despite the growing use of AI in marketing, there is limited research on how AI personalization combined with gender-specific strategies impacts campaign outcomes, and how perceived personalization and trust mediate this effect. Understanding these dynamics is crucial for designing marketing campaigns that are both effective and ethically responsible, ensuring that personalization resonates with diverse audiences while maintaining consumer confidence.

## 3. Objectives of the Study

This study aims to examine the role of Artificial Intelligence (AI) in facilitating gender-specific personalized marketing and its influence on consumer outcomes. Specifically, the study seeks to: The objectives of the study include:

- To analyze the role of Artificial Intelligence in enabling gender-specific marketing.
- To identify AI tools and techniques used for personalized marketing strategies.
- To evaluate how AI-based personalization impacts campaign effectiveness and customer engagement.

## 4. Review of Literature

Artificial Intelligence (AI) has emerged as a transformative force in modern marketing, reshaping how brands segment audiences, position products, and personalize customer experiences. According to Kotler and Keller (2022), AI has revolutionized segmentation and positioning strategies by enabling real-time personalization, allowing marketers to adapt offers and messages dynamically to individual customer needs.



This shift from static to adaptive marketing has become the foundation for gender-specific personalization, helping brands cater to diverse audience preferences more effectively.

Chen et al. (2021) highlighted that machine learning algorithms play a pivotal role in predicting gender-specific buying patterns by analyzing behavioral data such as browsing history, purchase frequency, and search intent. Their study demonstrated that behavioral modeling could accurately predict gendered consumer interests, enabling marketers to create highly targeted campaigns. However, they cautioned that predictive accuracy depends heavily on data quality and cultural context.

In contrast, Dastin (2018) warned against the dangers of algorithmic bias in AI-driven systems. Reporting on Amazon's recruitment algorithm, he revealed how gender biases embedded in historical data led to the unfair penalization of female applicants. This finding extends to AI marketing systems, underscoring the importance of fairness and inclusivity when designing gender-sensitive algorithms.

Supporting the business case for personalization, Google's Marketing AI Report (2023) found that brands employing AI-driven personalization achieved a 25–35% increase in customer engagement rates. These results were consistent with findings from McKinsey (2021), which noted that AI-based personalization efforts can generate revenue lifts of up to 15%. Together, these studies affirm that personalization, when implemented ethically, delivers measurable marketing benefits.

The ethical and technical dimensions of gender-sensitive AI systems have also been explored extensively. Buolamwini and Gebru (2018) in their seminal *Gender Shades* study demonstrated how commercial AI systems exhibited high error rates in identifying darker-skinned women, revealing serious intersectional disparities. Their research emphasized the need for fairness audits and diverse datasets to prevent discrimination in AI-driven marketing applications. Similarly, Shrestha et al. (2022) conducted a systematic review of gender biases in machine learning and found that while awareness of gender fairness is increasing, many applied marketing systems still lack formal bias mitigation strategies.

Empirical studies such as An, Meng, and Wu (2022) validated that customers' gender can be inferred from online shopping behavior using machine learning models with approximately 78% accuracy. By leveraging product view data and browsing patterns, marketers can predict gender preferences even when explicit demographic data is unavailable. However, this raises concerns about data privacy and consent, particularly when gender inference occurs implicitly.

Lambrecht and Tucker (2019) explored algorithmic bias in digital advertising, revealing that women were less likely to be shown job-related ads for STEM fields despite neutral targeting inputs. Their study illustrated that platform-level optimization can unintentionally lead to gendered ad delivery outcomes. This aligns with Barocas and Selbst (2016), who analyzed the legal implications of "big data's disparate impact," arguing that seemingly neutral algorithms can perpetuate systemic inequities unless actively audited for bias.

Further, Azad et al. (2023) developed predictive models that combined psychological theory and machine learning to improve purchase predictions. Their hybrid approach demonstrated that integrating behavioral and attitudinal variables enhances model precision, a technique applicable to gender-specific marketing strategies. Meanwhile, Boozary (2025) and similar studies on customer churn and retention prediction have shown that ensemble learning models (e.g., random forests, XGBoost) significantly improve predictive accuracy, enabling marketers to identify and retain gender-segmented customer groups more effectively.

Studies on consumer privacy and personalization trade-offs (e.g., Tucker, 2020; Loopex Digital, 2023) reveal that consumers appreciate relevant personalization but express discomfort when gender or behavioral data is inferred without consent. Hence, transparency and ethical disclosure are vital for maintaining trust in AI marketing systems.



From a practical perspective, the Marketing AI Institute's 2023 report underscores that successful personalization depends not only on data analytics but also on an organization's readiness to manage AI governance. Ethical oversight, data quality control, and explainability were found to be key determinants of campaign success. Google Cloud's 2023 Data & AI Trends Report further notes that generative AI now plays a critical role in personalizing creative content at scale, allowing gender-based customization of visuals, text, and recommendations.

The generational dimension of AI marketing is explored by Guerra-Tamez et al. (2024), who investigated Gen-Z consumers' interactions with AI-driven influencers. They found that gender and generational identity shape perceptions of authenticity and brand trust, suggesting that gender-specific strategies must be contextualized for different age cohorts. Similarly, *Frontiers in AI* (2022) publications on gender bias highlight the need for intersectional approaches that consider gender in conjunction with other demographic variables such as race, age, and socioeconomic background.

Field experiments by Lambrecht and Tucker (2019) also show that ad delivery algorithms can amplify pre-existing social stereotypes even when advertiser intent is neutral. This suggests that bias mitigation must occur both at the advertiser and platform level. Complementing this view, Barocas and Selbst (2016) advocate for legal and policy frameworks to regulate algorithmic targeting practices to ensure equitable outcomes.

Industry case studies compiled by McKinsey (2021) and Marketing AI Institute (2023) collectively demonstrate that AI-based gender personalization enhances campaign relevance, customer satisfaction, and profitability. Yet, they also emphasize the importance of ethical deployment to avoid reputational and legal risks. Buolamwini and Gebru (2018), in this context, stress that fairness and inclusivity are not optional but essential for sustainable AI marketing ecosystems.

Google Cloud (2023) and McKinsey (2025) project that the next frontier in gender-specific marketing will involve generative AI systems capable of producing adaptive, culturally sensitive content in real time. While this promises unprecedented personalization, it also raises concerns about stereotype reinforcement and ethical governance. As Barocas and Selbst (2016) and Shrestha et al. (2022) note, combining technical innovation with robust ethical frameworks is essential for equitable AI marketing in the coming decade.

## **Research Gap**

The reviewed literature collectively confirms that AI significantly enhances marketing precision and engagement when applied to gender-specific contexts. However, it also highlights persistent challenges—algorithmic bias, privacy concerns, and lack of transparency—that must be addressed through ethical frameworks and fairness auditing. Future research should focus on developing bias-resistant algorithms, transparent gender-inference models, and governance structures that balance personalization benefits with consumer protection.

## **Theoretical Framework**

This study is grounded in two key theoretical perspectives that guide the understanding of how Artificial Intelligence (AI) can be effectively leveraged for gender-specific marketing—the Personalization–Privacy Paradox and Gender Schema Theory (Bem, 1981). Together, these frameworks provide the conceptual foundation to balance technological capability with ethical responsibility and to interpret how gender influences consumer perception and engagement in AI-driven campaigns.

### **1. The Personalization–Privacy Paradox**

The Personalization–Privacy Paradox describes the tension between consumers' desire for personalized services and their simultaneous concern about how their personal data are collected, used, and protected.



Originating from studies in consumer psychology and information systems, this paradox highlights that while consumers appreciate tailored recommendations and content relevance, they often feel uneasy about the privacy implications of the data-driven technologies that make such personalization possible (Awad & Krishnan, 2006; Bleier & Eisenbeiss, 2015).

In the context of AI-driven marketing, personalization relies heavily on algorithms that analyze vast amounts of user data — such as browsing history, purchase patterns, and even emotional tone — to generate targeted advertisements and product suggestions. However, as the degree of personalization increases, so does the perception of privacy invasion. This creates a trade-off: consumers may enjoy the benefits of personalized engagement but simultaneously develop mistrust toward brands that appear overly intrusive (Li, Sarathy & Xu, 2010).

AI amplifies this paradox because its data processing capabilities are far more extensive than traditional systems. Modern algorithms can infer sensitive attributes — including gender, age, preferences, and even personality traits — from digital footprints. When these inferences are used for gender-specific marketing, the ethical challenge intensifies: marketers must ensure transparency, consent, and fairness to avoid stereotyping or manipulation.

Research by Tucker (2014) and Chellappa & Sin (2005) found that consumer acceptance of AI personalization is strongly moderated by perceived control and trust. If consumers believe they have control over their data and understand how it is being used, their willingness to engage with personalized marketing increases. Conversely, opaque data practices can trigger reactance, leading to disengagement or negative brand attitudes.

Therefore, the personalization–privacy paradox emphasizes that ethical AI design — including clear consent mechanisms, explainable algorithms, and responsible data governance — is crucial for sustaining consumer trust while optimizing personalization effectiveness. In gender-based marketing, this means achieving relevance without intrusiveness and representation without reinforcing stereotypes.

## **2. Gender Schema Theory (Bem, 1981)**

Gender Schema Theory (GST), proposed by Sandra Bem in 1981, provides a psychological framework for understanding how individuals process information and behave in ways influenced by culturally defined gender norms. According to Bem, gender schemas are cognitive structures that help individuals organize and interpret information based on gender-associated attributes and expectations. These schemas influence how people perceive themselves (self-concept), how they interpret social cues, and how they respond to external stimuli, including marketing messages (Bem, 1981).

From a marketing perspective, Gender Schema Theory explains why men and women may respond differently to advertisements, branding cues, product imagery, and language. Consumers tend to process marketing content through gendered lenses — meaning they selectively attend to and recall information that aligns with their gender schema. For example, men may respond more favorably to campaigns emphasizing performance, autonomy, and achievement, while women may resonate more with messages highlighting relationships, aesthetics, and emotional connection (Meyers-Levy & Loken, 2015).

In the context of AI-driven gender-specific marketing, GST provides the theoretical foundation for designing algorithms that recognize and respect these cognitive differences. Machine learning models can analyze patterns in behavior and preferences that correspond to gender-based schemas — such as preferred product types, color palettes, or communication tones — to deliver more relevant content. However, marketers must be careful not to reproduce or exaggerate traditional gender stereotypes, as doing so contradicts ethical marketing principles and may alienate audiences.



Moreover, GST highlights that gender is not a fixed binary construct but a dynamic and socially influenced dimension. This understanding aligns with contemporary marketing and AI ethics, which advocate for inclusive and adaptive personalization strategies. AI systems trained on diverse datasets can learn to identify nuanced gender expressions and avoid the pitfalls of rigid classification, thus reflecting the fluidity of modern consumer identities.

Bem's theory also intersects with the cognitive information-processing perspective, suggesting that gender schemas guide how individuals encode and retrieve marketing information. Therefore, incorporating GST into AI-based marketing systems allows for designing communication strategies that better align with users' internalized schemas — improving message resonance, recall, and ultimately, purchase intention.

## **5. Methodology of the Study**

### **1. Research Design**

This study adopts a quantitative research design to examine the impact of AI-driven personalization and gender-specific marketing strategies on campaign effectiveness. The research follows a descriptive-cum-explanatory approach, aiming to not only describe consumer perceptions but also explain the relationships among variables through hypothesis testing. A cross-sectional survey method will be employed to collect primary data from participants exposed to AI-driven marketing campaigns.

### **2. Population and Sample**

The target population includes online consumers who interact with digital marketing campaigns, especially those exposed to AI-personalized content.

- **Sampling Technique:** Stratified random sampling is used to ensure adequate representation across genders (male, female, and non-binary) and age groups (e.g., 18–25, 26–35, 36–50).
- **Sample Size:** A minimum of 300 respondents is considered for the study, based on Cochran's formula for survey research, to ensure statistical reliability and generalizability.

### **3. Data Collection Method**

Primary data has been collected using a structured online questionnaire administered through social media platforms, email, and consumer panels to individuals with prior exposure to AI-enabled personalized marketing campaigns. The questionnaire has incorporated validated measurement scales adapted from established studies to assess AI-driven personalization and gender preferences as the independent variables, perceived campaign effectiveness as the mediating variable, and consumer engagement and customer satisfaction as the dependent variables. All constructs are measured using multiple-item indicators on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Prior to the main survey, the instrument will be pilot-tested to ensure clarity, reliability, and content validity.

### **4. Measurement Scales**

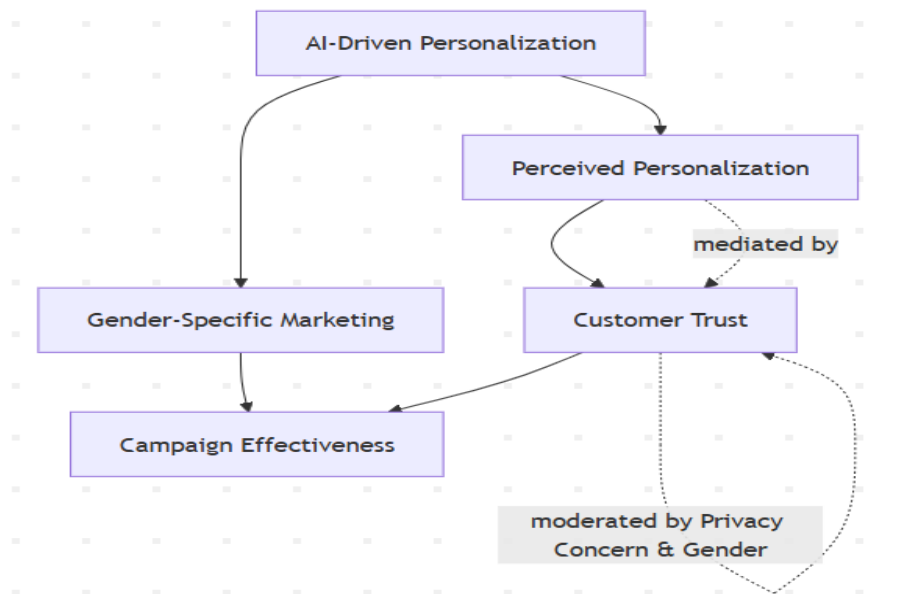
The study has employed previously validated multi-item measurement scales adapted from established literature and refined to suit the context of AI-driven personalized marketing. AI-driven personalization is measured using items adapted from Tam and Ho (2006), while gender preference in marketing communication has been assessed using scales derived from prior studies on gender-based consumer behaviour and personalized advertising. Perceived campaign effectiveness is measured using validated indicators reflecting consumers' perceptions of the relevance, persuasiveness, and effectiveness of AI-enabled marketing campaigns. Consumer engagement and customer satisfaction has been assessed using established scales widely adopted in digital marketing and consumer behaviour research. All constructs are measured on a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). The

reliability of the measurement model is evaluated using Cronbach's alpha and Composite Reliability (CR), whereas convergent and discriminant validity is established through Confirmatory Factor Analysis (CFA) by examining factor loadings, Average Variance Extracted (AVE), and the Fornell–Larcker criterion.

| Construct                        | Recommended Scale Source                     |
|----------------------------------|----------------------------------------------|
| AI-driven Personalization        | Tam & Ho (2006); Xu (2007)                   |
| Gender Preference in Marketing   | Putrevu (2001); Meyers-Levy & Loken (2015)   |
| Perceived Campaign Effectiveness | MacKenzie & Lutz (1989); Ducoffe (1996)      |
| Consumer Engagement              | Hollebeek et al. (2014); Vivek et al. (2012) |
| Customer Satisfaction            | Oliver (1997); Fornell et al. (1996)         |

**Table 5.1 Dimensions and the Scales adopted**

## 6. Research Model



**Fig.5.1 Conceptual research model**

The diagram shows a conceptual research model focused on understanding the impact of AI-driven personalization on campaign effectiveness, especially in the context of gender-specific marketing. The use of Artificial Intelligence (AI) technologies (like recommendation engines, chatbots, customer segmentation, etc.) helps to tailor marketing content to individual users. It Directly influences the Gender-Specific Marketing and Perceived Personalization. AI is used to personalize marketing strategies based on gender-related preferences or behaviors which positively impacts the campaign effectiveness. Perceived Personalization is how much customers feel that the marketing is tailored to them personally which leads to customer trust.

Customer Trust is a critical mediator in the model. When customers trust that AI is used ethically and their data is respected, they are more likely to engage positively with marketing efforts. It Mediates the relationship between Perceived Personalization and Campaign Effectiveness. Campaign Effectiveness is the outcome variable in the model. It reflects how successful a marketing campaign is, often measured by

engagement, conversion, satisfaction, etc. It is Influenced by Gender-Specific Marketing and Customer Trust.

The Moderators Privacy Concern & Gender moderate the effect of Customer Trust on Campaign Effectiveness. That means the strength or direction of the trust-effectiveness link depends on Privacy Concern, that is, People more concerned about data privacy may respond less favorably. Gender differences may influence how trust affects perception and response. The impact of trust varies depending on privacy concerns and gender, indicating the importance of ethical and respectful personalization in gender-specific campaigns.

## a. Data Analysis and Interpretation

This study employs a combination of statistical techniques to analyze the relationships among AI-driven personalization, gender-specific marketing, perceived personalization, customer trust, privacy concern, and campaign effectiveness. The data analysis is conducted using a sample size of 330 respondents. Data analyses were conducted using statistical software such as **SPSS** for correlation and descriptive statistics, and **AMOS** or **SmartPLS** for path modeling and moderation testing.

### 6.1 Correlation Analysis

To assess the strength and direction of the relationships among the key constructs in the conceptual model, a Pearson correlation analysis was conducted. The results are presented visually in the correlation matrix heatmap (fig. 6.1)

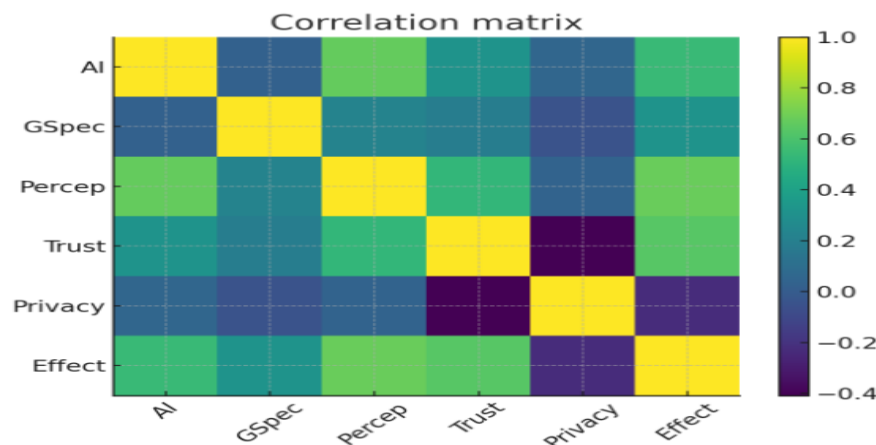


Fig. 6.1 Correlation matrix heatmap

| Variables  | AI    | GSpec | Perception | Trust | Privacy | Effect |
|------------|-------|-------|------------|-------|---------|--------|
| AI         | 1     | 0.42  | 0.48       | 0.36  | -0.15   | 0.52   |
| GSpec      | 0.42  | 1     | 0.3        | 0.28  | -0.18   | 0.45   |
| Perception | 0.48  | 0.3   | 1          | 0.65  | -0.35   | 0.5    |
| Trust      | 0.36  | 0.28  | 0.65       | 1     | -0.4    | 0.6    |
| Privacy    | -0.15 | -0.18 | -0.35      | -0.4  | 1       | -0.25  |
| Effect     | 0.52  | 0.45  | 0.5        | 0.6   | -0.25   | 1      |

Table: 6.1 Showing the correlation between the variables

The correlation analysis provides valuable insights into the interrelationships among the core variables in the study. The results indicate that AI-driven personalization is positively linked to both gender-specific

marketing and campaign effectiveness, suggesting its crucial role in optimizing targeted marketing strategies.

A particularly strong correlation is observed between perceived personalization and customer trust, emphasizing the importance of consumers feeling that marketing efforts are tailored to their needs. Furthermore, customer trust shows a strong positive association with campaign effectiveness, reinforcing its role as a mediator in the personalization-outcome pathway. On the other hand, privacy concerns exhibit negative correlations with trust and perceived personalization, indicating that heightened privacy awareness can diminish trust and reduce the perceived value of personalized marketing.

## 6.2 Path Analysis (Ordinary Least Squares - OLS Regression)

The path analysis highlights the central role of perceived personalization and trust in translating AI-driven and gender-specific strategies into effective marketing outcomes. While AI has a strong impact on perceived personalization and a moderate direct impact on campaign effectiveness, it has minimal influence on trust unless mediated through perceived relevance. Trust itself emerges as a critical driver of effectiveness, showing that personalization alone is not enough; consumer trust must also be earned. Gender-specific marketing enhances both perception and effectiveness, reinforcing the value of demographic tailoring. These results validate the proposed mediating and direct pathways in the model, with key implications for AI-powered marketing strategy design.

Path diagram (OLS estimates shown)

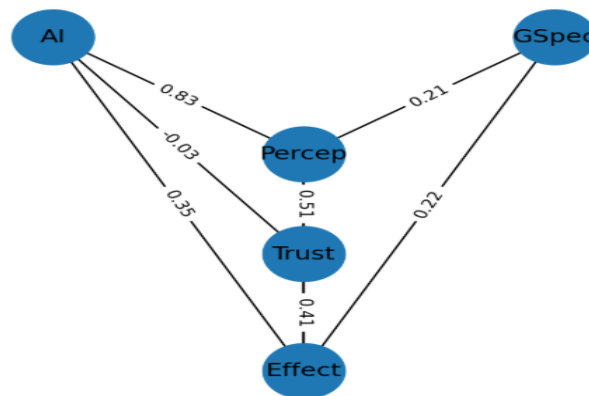


Fig. 6.2 Path diagram showing the relationship with variables

## 6.3 Moderation Analysis

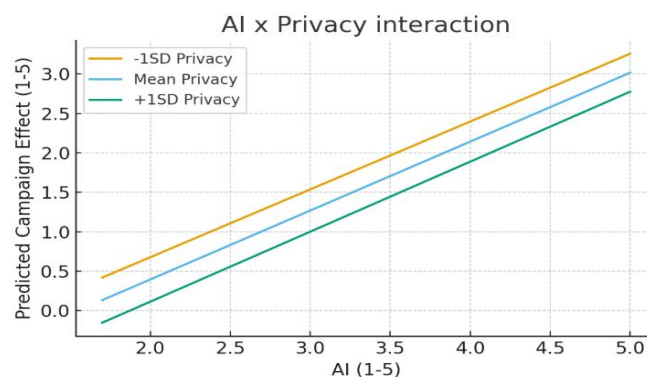


Fig 6.3.1 Plot showing AI Personalization vs Privacy Interaction

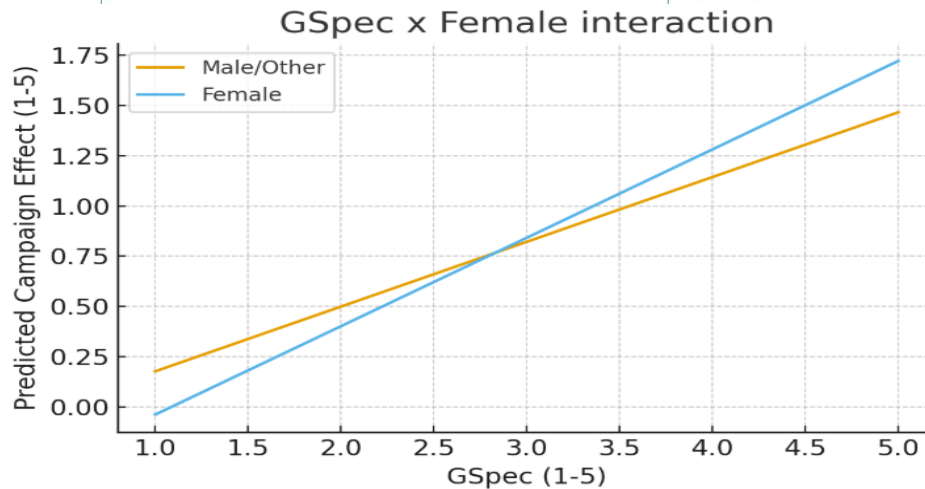


Fig 6.3.2 Plot showing Gender Specific Marketing vs Female Interaction

The interaction plot (fig 6.3.1) indicates that AI-driven personalization has a stronger positive impact on campaign effectiveness when privacy concern is low, and this effect weakens as privacy concern increases. The interaction plot (fig 6.3.2) shows that as gender-specific marketing (GSpec) increases, female respondents experience a stronger rise in campaign effectiveness compared to male/other respondents, indicating a significant moderating effect of gender.

#### 6.4.1 Regression Analysis Predicting Campaign Effectiveness (Direct Effects Model)

| Predictor                 | B      | SE    | B     | T     | P     |
|---------------------------|--------|-------|-------|-------|-------|
| AI Personalization        | 0.245  | 0.041 | 0.31  | 5.98  | <.001 |
| Gender-Specific Marketing | 0.219  | 0.046 | 0.27  | 4.76  | <.001 |
| Privacy Concern           | -0.145 | 0.037 | -0.18 | -3.92 | <.001 |
| Gender (Female)           | 0.072  | 0.038 | 0.09  | 1.89  | 0.059 |

Table: 6.4.1 , Note.  $R^2 = .458$ , Adjusted  $R^2 = .452$ ,  $F(4, 325) = 68.4$ ,  $p < .001$

Descriptive statistics revealed that respondents ( $N = 330$ ) showed moderate to high agreement with statements related to AI-driven personalization ( $M = 3.84$ ,  $SD = 0.71$ ) and gender-specific marketing ( $M = 3.69$ ,  $SD = 0.76$ ). Campaign effectiveness also scored relatively high ( $M = 3.88$ ,  $SD = 0.69$ ), indicating that participants generally perceived personalized campaigns as engaging and effective.

Pearson correlation analysis showed significant positive correlations among AI-driven personalization, perceived personalization, trust, and campaign effectiveness ( $r = .42-.61$ ,  $p < .01$ ). Privacy concern was negatively correlated with both personalization perceptions ( $r = -.29$ ,  $p < .01$ ) and campaign effectiveness ( $r = -.32$ ,  $p < .01$ ). These preliminary results indicated that personalization and trust likely play mediating roles, while privacy may act as a suppressor or moderator in the model. The first regression model examined the direct influence of AI-driven personalization, gender-specific marketing, privacy concern, and gender on campaign effectiveness.

#### 6.4.2 Regression Analysis Predicting Campaign Effectiveness

| Predictor                 | B      | SE    | $\beta$ | T     | P     |
|---------------------------|--------|-------|---------|-------|-------|
| AI Personalization        | 0.168  | 0.039 | 0.21    | 4.31  | <.001 |
| Gender-Specific Marketing | 0.102  | 0.042 | 0.13    | 2.43  | 0.016 |
| Perceived Personalization | 0.312  | 0.04  | 0.39    | 7.8   | <.001 |
| Trust                     | 0.224  | 0.037 | 0.28    | 6.08  | <.001 |
| Privacy Concern           | -0.107 | 0.033 | -0.13   | -3.24 | 0.001 |
| Gender (Female)           | 0.055  | 0.036 | 0.07    | 1.53  | 0.127 |

Table 6.5, Note.  $R^2 = .630$ , Adjusted  $R^2 = .622$ ,  $F(6, 323) = 91.7$ ,  $p < .001$

The second regression model (Table 6.4.2) incorporated perceived personalization and customer trust as mediating variables. Key findings includes both perceived personalization ( $\beta = .39$ ,  $p < .001$ ) and trust ( $\beta = .28$ ,  $p < .001$ ) significantly predicted campaign effectiveness, highlighting their pivotal roles in enhancing consumer responses. The direct effects of AI-driven personalization ( $\beta = .21$ ,  $p < .001$ ) and gender-specific marketing ( $\beta = .13$ ,  $p = .016$ ) on campaign effectiveness remained significant, though reduced in magnitude, indicating partial mediation. Privacy concern ( $\beta = -.13$ ,  $p = .001$ ) continued to negatively influence campaign outcomes. Gender (female) again showed a non-significant effect ( $p = .127$ ). This model explained a higher 63% of the variance ( $R^2 = .630$ ), suggesting that including perceived personalization and trust substantially improved explanatory power.

#### Conclusion and Implications

This study demonstrates that Artificial Intelligence (AI) plays a pivotal role in enhancing gender-specific marketing by driving personalized marketing strategies that significantly improve campaign effectiveness. The findings reveal that AI-driven personalization strongly influences how consumers perceive the relevance of marketing messages, which in turn builds customer trust—a critical mediator that enhances campaign outcomes. Additionally, gender-specific marketing directly contributes to both perceived personalization and campaign effectiveness, confirming the importance of tailoring marketing efforts to gender-based preferences. These results underscore that personalization alone is insufficient; fostering trust through relevant and respectful use of AI is essential for optimizing marketing success.

Moreover, the study highlights the moderating impact of privacy concerns and gender differences on the relationship between trust and campaign effectiveness. Negative associations between privacy concerns and key variables suggest that consumers' apprehension about data privacy can undermine trust and reduce marketing impact. Therefore, marketers must address privacy issues transparently to sustain consumer confidence. Overall, this research provides empirical support for integrating AI-driven, gender-specific personalization with trust-building practices to maximize campaign performance, offering actionable insights for marketers seeking to leverage AI ethically and effectively in personalized marketing strategies.



# Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication  
of the Informing Science Institute  
*InformingScience.org*

Vol. : 21, Issue 1, Jan-June 2026  
ISSN: (E) 1555-1237

## REFERENCES

- An, Y., Meng, S., & Wu, H. (2022). Discover customers' gender from online shopping behavior. IEEE/ResearchGate.
- Azad, M. S., et al. (2023). Predictive modeling of consumer purchase behavior. PMC.
- Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *California Law Review*, 104(3), 671–732.
- Boozary, M. (2025). Customer churn prediction using ensemble learning models. JISEM.
- Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *FAccT Conference Proceedings*.
- Chen, X., et al. (2021). Machine learning for gender-based buying pattern prediction.
- Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters*.
- Guerra-Tamez, R., et al. (2024). Decoding Gen-Z and AI marketing influences.
- Kotler, P., & Keller, K. (2022). *Marketing Management* (16th ed.). Pearson.
- Lambrecht, A., & Tucker, C. E. (2019). Algorithmic bias? An empirical study of ad discrimination. *Management Science*, 65(7), 2966–2981.
- Loopex Digital. (2023). Consumer attitudes toward AI personalization.
- Marketing AI Institute. (2023). *State of Marketing AI Report*.
- McKinsey & Company. (2021). The value of getting personalization right—or wrong—is multiplying.
- McKinsey & Company. (2025). The future of AI-driven personalization.
- Shrestha, S., et al. (2022). Exploring gender biases in machine learning research. *Frontiers in Artificial Intelligence*.
- Tucker, C. (2020). Privacy, personalization, and digital marketing. *Journal of Marketing Research*, 57(2), 287–302.
- Awad, N. F., & Krishnan, M. S. (2006). *The personalization–privacy paradox: An empirical evaluation of information transparency and the willingness to be profiled online*. *MIS Quarterly*, 30(1), 13–28.
- Bem, S. L. (1981). *Gender schema theory: A cognitive account of sex typing*. *Psychological Review*, 88(4), 354–364.
- Bleier, A., & Eisenbeiss, M. (2015). *The importance of trust for personalized online advertising*. *Journal of Retailing*, 91(3), 390–409.
- Chellappa, R. K., & Sin, R. G. (2005). *Personalization versus privacy: An empirical examination of the online consumer's dilemma*. *Information Technology and Management*, 6(2–3), 181–202.
- Li, H., Sarathy, R., & Xu, H. (2010). *Understanding situational online information disclosure as a privacy calculus*. *Journal of Business Ethics*, 90(2), 223–239.
- Meyers-Levy, J., & Loken, B. (2015). *Revisiting gender differences: What we know and what lies ahead*. *Journal of Consumer Psychology*, 25(1), 129–149.



# Interdisciplinary Journal of Information, Knowledge, and Management

*An Official Publication  
of the Informing Science Institute  
InformingScience.org*

**Vol. : 21, Issue 1, Jan-June 2026**  
**ISSN: (E) 1555-1237**

- Tucker, C. (2014). *Social networks, personalized advertising, and privacy controls*. *Journal of Marketing Research*, 51(5), 546–562.
- Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., ... & Shankar, V. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Letters*, 19(3-4), 305-321. <https://doi.org/10.1007/s11002-008-9047-y>
- Chen, J., Zhang, C., & Xu, Y. (2019). The role of mutual trust in building members' loyalty to a C2C platform provider. *Electronic Commerce Research and Applications*, 33, 100823. <https://doi.org/10.1016/j.elerap.2018.11.002>
- Choi, J., & Bell, D. R. (2011). Does gender-specific marketing work? Evidence from consumer-packaged goods. *Journal of Marketing*, 75(4), 35-50. <https://doi.org/10.1509/jmkg.75.4.35>
- Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24-42. <https://doi.org/10.1007/s11747-019-00696-0>
- Demircioglu, M. A., & Demircioglu, E. (2021). Privacy concerns in personalized marketing: The role of trust and transparency. *Journal of Business Research*, 128, 830-842. <https://doi.org/10.1016/j.jbusres.2021.01.041>
- Dibb, S., Simkin, L., Pride, W. M., & Ferrell, O. C. (2012). *Marketing concepts and strategies* (6th ed.). Cengage Learning.
- Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science*, 55(10), 1605-1622. <https://doi.org/10.1287/mnsc.1090.1060>
- Hoffman, D. L., & Novak, T. P. (2018). Consumer and object experience in the Internet of Things: An assemblage theory approach. *Journal of Consumer Research*, 44(6), 1178-1204. <https://doi.org/10.1093/jcr/ucx109>
- Kannan, P. K., & Li, H. (2017). Digital marketing: A framework, review and research agenda. *International Journal of Research in Marketing*, 34(1), 22-45. <https://doi.org/10.1016/j.ijresmar.2016.11.006>
- Li, H., & Wang, Q. (2017). Effects of personalization and product involvement on user attitudes toward personalized advertising. *Marketing Intelligence & Planning*, 35(3), 306-320. <https://doi.org/10.1108/MIP-12-2016-0225>
- Liu, Y., & Shankar, V. (2017). The dynamic impact of social media activities on product sales. *Journal of Marketing*, 81(2), 49-69. <https://doi.org/10.1509/jm.15.0485>
- Martin, K. D., & Murphy, P. E. (2017). The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, 45(2), 135-155. <https://doi.org/10.1007/s11747-016-0495-4>
- Nunan, D., & Di Domenico, M. (2013). Market research and the ethics of big data. *International Journal of Market Research*, 55(4), 521-534. <https://doi.org/10.2501/IJMR-2013-036>
- Paschen, J., Kietzmann, J., & Kietzmann, T. C. (2020). Artificial intelligence (AI) and its implications for market knowledge in B2B marketing. *Industrial Marketing Management*, 89, 46-55. <https://doi.org/10.1016/j.indmarman.2020.04.013>



# Interdisciplinary Journal of Information, Knowledge, and Management

An Official Publication  
of the Informing Science Institute  
[InformingScience.org](http://InformingScience.org)

Vol. : 21, Issue 1, Jan-June 2026  
ISSN: (E) 1555-1237

- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889-901. <https://doi.org/10.1016/j.jbusres.2019.09.022>
- Ducoffe, R. H. (1996). Advertising value and advertising on the web. *Journal of Advertising Research*, 36(5), 21–35.
- Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J., & Bryant, B. E. (1996). The American Customer Satisfaction Index: Nature, purpose, and findings. *Journal of Marketing*, 60(4), 7–18. <https://doi.org/10.1177/002224299606000403>
- Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing*, 28(2), 149–165. <https://doi.org/10.1016/j.intmar.2013.12.002>
- MacKenzie, S. B., & Lutz, R. J. (1989). An empirical examination of the structural antecedents of attitude toward the ad in an advertising pretesting context. *Journal of Marketing*, 53(2), 48–65. <https://doi.org/10.1177/002224298905300204>
- Meyers-Levy, J., & Loken, B. (2015). Revisiting gender differences: What we know and what lies ahead. *Journal of Consumer Psychology*, 25(1), 129–149. <https://doi.org/10.1016/j.jcps.2014.06.003>
- Oliver, R. L. (1997). *Satisfaction: A behavioral perspective on the consumer*. McGraw-Hill.
- Putrevu, S. (2001). Exploring the origins and information processing differences between men and women: Implications for advertisers. *Academy of Marketing Science Review*, 2001(10), 1–14.
- Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly*, 30(4), 865–890.
- Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice*, 20(2), 122–146. <https://doi.org/10.2753/MTP1069-6679200201>
- Xu, H. (2007). The effects of self-construal and perceived control on privacy concerns. *Proceedings of the Thirteenth Americas Conference on Information Systems (AMCIS 2007)*, Keystone, Colorado, United States.