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Research Article

A Systematic Review of Artificial Intelligence Applications in Marketing

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Abstract: AI has evolved from a futuristic idea to a key component of contemporary marketing strategy. The various uses of AI in the marketing industry are reviewed in this paper in a methodical manner. Consumer behaviour analysis, personalised customer experience, content creation, and predictive analytics are the four main functional areas into which we divide AI applications. According to recent research on five-star hotel reviews in India, sentiment analysis and machine learning are given particular attention in the hospitality sector. The review's conclusion highlights current research gaps and suggests a future research agenda that focusses on ethical issues and the collaborative interface between humans and AI.

Keywords: Artificial Intelligence; Marketing; Consumer Behaviour Analysis; Predictive Analytics; Sentiment Analysis.

INTRODUCTION

The digital revolution has produced an unprecedented volume of consumer data, commonly referred to as Big Data. For marketers, the challenge has shifted from data acquisition to data interpretation. Artificial Intelligence (AI) provides the computational power and algorithmic sophistication necessary to extract actionable insights from these vast datasets.

AI in marketing is defined as the use of technology to automate decisions based on data collection, data analysis, and additional observations of audience or economic trends that may impact marketing efforts. This review aims to systematically map the current landscape of AI applications and evaluate their impact on marketing efficiency and effectiveness.

LITERATURE REVIEW:

Artificial Intelligence and Sentiment Analysis in Marketing

1. Evolution of Sentiment Analysis in Marketing

The academic discourse on sentiment analysis (SA) has transitioned from binary classification (positive/negative) to complex emotional and aspect-based modeling. **Stuart et al. (2017)** initially highlighted how online reviews act as a digital "Word-of-Mouth" (e-WOM), significantly impacting consumer purchase intentions. This foundation was expanded by **Duarte and Silva (2019)** in the "Feels Like Home" case study, which demonstrated that customer sentiment is a more reliable predictor of return visits than traditional quantitative satisfaction scores.

2. Methodological Advancements in Opinion Mining

The literature reveals a clear trajectory in the tools used to extract meaning from consumer text:

- **Machine Learning (SVM & PSO): Sanwal and Kukreja (2019)** proposed a design approach for opinion mining using Support Vector Machines (SVM) combined with Particle Swarm Optimization (PSO). Their research suggests that optimizing hyperparameters in SVM leads to higher accuracy in categorizing hotel reviews compared to standard lexicon-based methods.
- **Deep Learning (LSTM):** To address the temporal nature of language, **Priyantina (2019)** utilized Long Short-Term Memory (LSTM) networks. This research found that deep learning excels at understanding context and long-term dependencies in lengthy hotel reviews, which traditional models often miss.
- **Hybrid Models:** Recent studies by **Kumar, Pal, and Mehta (2024)** emphasize the integration of qualitative sentiment with quantitative attribute ratings (Cleanliness, Service, Value). They argue that while ratings provide a baseline, the sentiment hidden in text provides the "diagnostic" power needed for management intervention.

3. Aspect-Based Sentiment Analysis (ABSA)

Current research increasingly focuses on *what* the consumer is talking about, rather than just *how* they feel.

Topic Modeling (LDA): Priyantina (2019) and **Rybakov & Malafeev** have explored Latent Dirichlet Allocation (LDA) to automatically discover topics within hotel reviews. This allows marketers to see if negative sentiment is clustered around specific attributes like "wifi quality" or "breakfast variety."

Attribute Impact: The study by **Kumar et al. (2024)** specifically analyzed five-star hotels across eight Indian cities (Delhi, Mumbai, Bangalore, etc.). Their findings indicate a significant correlation between specific attribute sentiments—particularly service and cleanliness—and the final "Overall Rating" provided by the user on platforms

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like TripAdvisor.

4. The Indian Hospitality Context

The Indian market presents unique linguistic and cultural nuances in online reviews. **Sharad et al. (2018)** noted that Indian consumers often provide "mixed" reviews where high praise for staff is tempered by criticism of infrastructure.

Geographic Diversity: Kumar et al. (2024) filled a gap in the literature by conducting a multi-city analysis, showing that consumer expectations in business hubs like Gurugram differ slightly from leisure-oriented locations like Jaipur.
Information Overload: As noted in the primary study, the sheer volume of reviews on TripAdvisor creates "patience fatigue" among travelers. This justifies the need for AI-driven summarization tools that can distill thousands of reviews into actionable sentiment scores for prospective guests.

5. Summary of Research Gaps

Despite the wealth of studies on SVM and LSTM, there remains a gap in understanding the *real-time* application of these models in a dynamic pricing environment. Most literature, including **Pal et al. (2022)**, focuses on retrospective analysis. Future research is needed to bridge the gap between sentiment extraction and automated, real-time service recovery strategies.

Synthesis Table of Key Literature

Author(s)	**Focus Area**	**Key Methodology**	**Finding**
Kumar et al. (2024)	Indian 5-Star Hotels	Regression & SA	Attribute sentiments directly influence overall TripAdvisor ratings.
Sanwal & Kukreja (2019)	Accuracy Optimization	SVM + PSO	Optimization algorithms significantly improve sentiment classification.
Priyantina (2019)	Context Awareness	LDA & LSTM	Deep learning provides better context for complex, multi-topic reviews.
Sharad et al. (2018)	General Sentiment	Basic ML	Identified the rising importance of e-WOM in the Indian hospitality sector.

METHODOLOGY

This review follows a structured selection process of academic literature and industry reports published between 2018 and 2024. Keywords utilized included "AI in Marketing," "Machine Learning," "Sentiment Analysis," "Predictive Analytics," and "Consumer Behavior."

3. Core Applications of AI in Marketing

3.1 Consumer Behavior and Sentiment Analysis

One of the most profound applications of AI is in understanding the "voice of the customer." Natural Language Processing (NLP) allows firms to analyze unstructured data from social media, blogs, and review sites.

Recent research (Kumar et al., 2024) highlights how sentiment analysis of online reviews for five-star hotels in India helps managers understand the impact of specific attribute ratings (service, cleanliness, location) on overall customer satisfaction. By employing techniques like Support Vector Machines (SVM) and Latent Dirichlet Allocation (LDA), marketers can pinpoint exactly which facilities drive positive sentiments.

3.2 Hyper-Personalization and Recommendation Engines

AI enables marketers to move beyond broad segmentation to "segments of one."

Recommendation Systems: Algorithms used by platforms like Netflix, Amazon, and Spotify analyze past behavior to predict future preferences.

Dynamic Pricing: AI models adjust prices in real-time based on demand, competition, and user profiles, maximizing both conversion rates and profit margins.

3.3 Content Generation and Creative AI

Generative AI (GenAI) has revolutionized the creative aspect of marketing:

Automated Copywriting: Tools can generate email subject lines, social media posts, and even long-form articles tailored to specific brand voices.

Visual Content: AI-driven image and video generation tools allow for rapid prototyping of advertisements and personalized visual messaging.

3.4 Predictive Analytics and Lead Scoring

Predictive modeling helps marketers anticipate future outcomes:

Churn Prediction: Identifying customers likely to leave a service allows firms to intervene with targeted retention offers.

Lead Scoring: In B2B marketing, AI ranks lead based on their likelihood to convert, allowing sales teams to prioritize high-value prospects.

4. Challenges and Ethical Considerations

- AI integration has several drawbacks despite its advantages:
  Data Privacy: The use of personal data raises serious questions about consumer trust and GDPR compliance. • Algorithmic Bias: AI results may reinforce stereotypes or exclude particular groups if training data is skewed.
- The "Black Box" Issue: Marketers may find it challenging to defend tactics to stakeholders due to the opaqueness of deep learning models' decision-making process.

DISCUSSION AND FUTURE DIRECTIONS

AI integration enhances human creativity rather than replaces it. Future studies should investigate "Augmented Intelligence," which combines the analytical speed of AI with the emotional intelligence of human marketers. The effects of AI on small and medium-sized businesses (SMEs), which might not have the resources of large corporations, also require more investigation.

CONCLUSION

The marketing funnel is being radically transformed by artificial intelligence, from initial awareness through sentiment analysis to post-purchase loyalty through tailored engagement. The ability to use AI to decipher customer sentiment is no longer a luxury but rather a strategic requirement for preserving a competitive edge in a digital-first economy, as the analysis of the hospitality industry shows.

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