



REVIEW

A Systematic Literature Review on the Impact of Generative AI in Digital Marketing: Advancements, Opportunities, and Challenges

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ABSTRACT: Generative Artificial Intelligence (AI) is reshaping digital marketing by creating automated content, personalizing campaigns, and offering new ways to engage consumers. This systematic review examines research on generative AI, highlighting both its technological progress and the ethical, technical, and organizational hurdles that could limit its use. We used a PRISMA-based method to search major databases (ACM Digital Library, IEEE Xplore, and Scopus) for peer-reviewed studies published from 2018 to 2025. Our findings reveal major gains in text creation, image generation, and multimodal campaigns, which can lower costs and spark creative thinking. Still, data privacy, bias in models, and laws around compliance show the need for clear and responsible adoption. By bringing in ideas from Innovation Diffusion Theory and the Technology Acceptance Model, this review shows how organizational culture and perceived value interact with ethical frameworks to shape how generative AI tools take hold. We provide insights for marketers who want to apply generative AI in a responsible way and set a path for future research aimed at protecting consumer trust.

KEYWORDS: Generative AI; digital marketing; content generation; personalization; ethical AI; technology adoption; innovation diffusion theory; transformer models

1 Introduction

Generative Artificial Intelligence (AI) has rapidly emerged as a transformative force in digital marketing, driving advancements in content creation, personalized campaigns, and consumer engagement [1,2]. As marketers strive to adapt to the increasing digital competition and evolving consumer behavior, generative AI offers innovative tools for creating, personalizing, and disseminating content on an unprecedented scale [3,4]. This technology, underpinned by advancements in deep learning architectures such as transformers [5], Generative Adversarial Networks (GANs) [6], and diffusion models [7], is redefining digital marketing strategies by shifting from predictive analytics to creative applications.

The digital marketing landscape has undergone a significant transformation over the last decade, transitioning from basic banner ads and email campaigns to sophisticated, data-driven strategies across platforms such as social media, search engines, and mobile applications [8,9]. This shift has been accompanied by a

massive increase in user data generation, including click histories and social media interactions, enabling marketers to leverage intelligent, automated tools for impactful campaigns. Generative AI now empowers brands to design marketing assets such as text, images, and videos, automating processes like customer support and personalized messaging while reducing costs and accelerating campaign development [10,11]. For example, language models such as GPT are capable of crafting email headlines tailored to individual user preferences, while GANs can generate new product images to support market testing [12]. Generative AI not only analyzes consumer data but actively shapes brand interactions and consumer influence. Its ability to adapt content to specific demographics, languages, or cultural contexts within moments enables dynamic, real-time marketing campaigns that align with rapidly changing online discourse [13,14].

Generative AI stands apart within the broader field of artificial intelligence due to its ability to create new content that is not directly extracted from training data [15,16]. Unlike predictive analytics, which focuses on forecasting outcomes based on historical data, or rule-based systems that rely on explicitly coded instructions, generative AI autonomously constructs patterns and features from data, enabling novel content creation [17]. In digital marketing, this includes applications such as language generation, image synthesis, and multimodal systems that seamlessly integrate text, sound, and visuals into cohesive campaigns.

Despite the rapid adoption of generative AI, much of the existing literature on AI in marketing remains fragmented and focused on predictive models like recommendation systems or churn analysis [18–20]. Comprehensive empirical studies on generative AI's applications, encompassing text, image, and video creation, are scarce. Additionally, ethical and practical considerations such as data privacy, content bias, and accountability are often underexplored in the context of regulatory frameworks like GDPR or the AI Act in the European Union. Addressing these challenges is critical to realizing the potential of generative AI for responsible and sustainable deployment. To better understand the state of the art, a comparative analysis of existing survey papers is summarized in Table 1. This table reviews notable works on generative AI in digital marketing and related fields, evaluating their scope, contributions, and limitations. It highlights the areas of focus and identifies gaps, providing a roadmap for future exploration.

Table 1: Review of existing survey papers on Generative AI in digital marketing and related domains.

Ref.	Year	Systematic Review	Technological Advancements	Results Analysis	Ethical Concern	Challenges & Future Work	Contribution	Limitations
[21]	2025	×	✓	×	✓	✓	This research offers a comprehensive review of AI models in digital marketing, identifying key challenges and opportunities. It provides unique insights through a qualitative descriptive approach, enhancing understanding of AI's role in personalization, automation, and strategy development while emphasizing the ethical and organizational factors influencing adoption.	The study's main limitations include a lack of empirical evidence on AI's real-world marketing impact and insufficient exploration of ethical and regulatory challenges. Additionally, conversational AI's difficulty with complex language nuances may affect user interactions, highlighting areas requiring deeper investigation for practical and responsible implementation.

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Table 1 (continued)

Ref.	Year	Systematic Review	Technological Advancements	Results Analysis	Ethical Concern	Challenges & Future Work	Contribution	Limitations
[22]	2025	×	✓	×	×	✓	This research highlights the significant potential of digital marketing in B2B businesses and identifies key opportunities and challenges. It proposes practical recommendations such as using ChatBots, analytical tools, and regulatory assessments to improve customer engagement, ensure compliance, and strengthen marketing effectiveness within the B2B landscape.	The study is limited by time and budget constraints, which prevented site visits and stakeholder interviews at B2B companies. These omissions may have restricted the depth of insights and real-world validation and could limit the practical applicability and comprehensiveness of the findings.
[23]	2024	×	✓	×	×	✓	This study explores ChatGPT's role in marketing, highlighting its ability to enhance personalization, improve customer experience, and boost ROI. It also examines theoretical frameworks, future research avenues, and ethical considerations in AI adoption for marketing.	This study is not a systematic review and lacks a results-based analysis. It is confined to marketing, limiting generalizability. Theoretical frameworks may not apply across contexts, and practical challenges, ethical concerns, and unintended consequences of ChatGPT adoption are insufficiently addressed.
[24]	2023	×	✓	×	×	×	This paper explores the implications of generative AI in marketing, addressing ethical concerns, its impact on marketing strategies, and the need for cross-disciplinary collaboration to leverage AI technologies like ChatGPT and Stable Diffusion effectively.	This paper lacks empirical data to support its claims, focuses on the negative aspects of generative AI, and provides a limited analysis of dark marketing and adaptation strategies for organizations, potentially offering an imbalanced view of the technology's impact.

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Table 1 (continued)

Ref.	Year	Systematic Review	Technological Advancements	Results Analysis	Ethical Concern	Challenges & Future Work	Contribution	Limitations
[25]	2023	×	✓	×	×	×	This paper offers a comprehensive bibliometric analysis of 211 references, identifies key AI trends in digital marketing, suggests future research directions, and provides practical insights for businesses aiming to enhance their digital marketing strategies using AI.	This study's scope is limited by the literature reviewed, which may exclude recent advancements in Generative AI. Potential biases in source selection and the rapid evolution of AI technologies may also affect the long-term relevance and reliability of the findings.
Ours	–	✓	✓	✓	✓	✓	This study provides a comprehensive and systematic review of generative AI applications in digital marketing, integrating technological advancements, ethical concerns, and real-world use cases. It also proposes actionable insights and a roadmap for future interdisciplinary research to enhance the responsible adoption of generative AI.	This study may face limitations in generalizability due to the dynamic and rapidly evolving nature of generative AI technologies.

This review aims to bridge these gaps by synthesizing current research, examining the transformative potential of generative AI, and exploring the challenges associated with its adoption. It evaluates real-world applications, highlights opportunities for personalized and adaptive content generation, and discusses ethical concerns and regulatory issues. By integrating theoretical models such as the Innovation Diffusion Theory and the Technology Acceptance Model with contemporary ethical frameworks, the review provides a holistic understanding of the intersection between technology, organizational culture, and societal implications. Through this comprehensive analysis, the review seeks to empower marketing practitioners and researchers with the insights needed for responsible innovation and strategic implementation in the dynamic realm of digital marketing.

In particular, this review contributes to the field by offering a structured synthesis of existing literature, highlighting underexplored areas in the practical deployment of generative AI, and proposing a multidisciplinary framework to guide future research and practice. By aligning theoretical insights with empirical case studies, the paper not only identifies prevailing trends but also underscores the implications for ethical governance and strategic decision-making. These contributions are framed around several key research questions, as summarized in the [Table 2](#).

Table 2: Summary of research questions addressed in this review.

SN.	Research Question	Addressed in
RQ1	What are the recent advancements in generative AI applications (e.g., text generation, image synthesis, multimodal campaigns) for digital marketing?	Section 3 , and Table 1
RQ2	How are real-world use cases utilizing generative AI to develop cost-effective, scalable, and personalized marketing strategies?	Section 4.4
RQ3	What are the critical ethical challenges (e.g., data privacy, model bias, regulatory compliance) in generative AI adoption for marketing?	Sections 5 and 5.3
RQ4	How do theoretical models like Innovation Diffusion Theory and Technology Acceptance Model explain organizational adoption of generative AI tools?	Sections 3 and 4
RQ5	What are the current gaps in literature, and how can future interdisciplinary research address these for responsible innovation in digital marketing?	Sections 5 and 6

The rest of the paper is organized as follows: [Section 2](#) details the systematic review methodology. [Section 3](#) addresses the background and theoretical underpinnings. [Section 4](#) explores current findings and trends. [Section 5](#) provides a critical discussion of the results, and [Section 6](#) concludes the paper.

2 Methodology

This section outlines the systematic literature review (SLR) methodology adopted to explore and synthesize the existing research on generative AI in digital marketing. Our goal was to ensure both transparency and replicability in the study selection and analysis process. Following common SLR guidelines (PRISMA as present in [Fig. 1](#)), we detail each phase: from designing search strategies to screening, quality assessment, and data extraction.

2.1 Research Design

We employed a methodical approach to capture a comprehensive set of academic and gray literature addressing *generative AI* within the *digital marketing* context. The research design covered three major phases:

1. Planning the Review: Identification of research questions, keywords, and databases to be searched.
2. Conducting the Review: Systematic searching, screening of studies against inclusion/exclusion criteria, and quality appraisal.
3. Reporting the Review: Data extraction, synthesis of key themes, and presentation of findings in subsequent sections.

In addition, we acknowledge that ChatGPT was used solely for writing refinement and language polishing. Its role was limited to improving readability and grammar without influencing the research design, analysis, or interpretation. All AI-assisted text was thoroughly reviewed and revised manually by the authors to ensure accuracy and appropriateness.

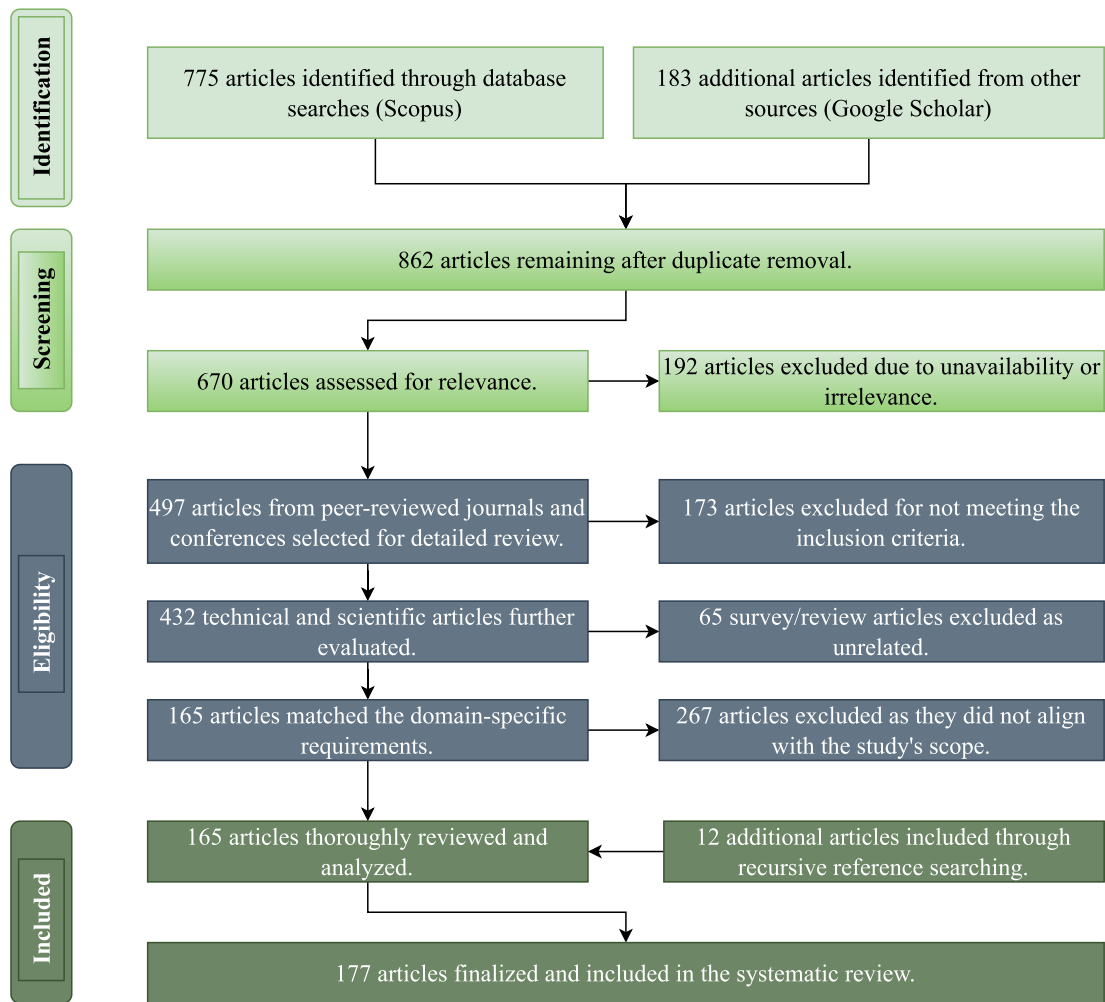


Figure 1: PRISMA-based flow diagram illustrating the study selection and screening process.

Our main research questions (RQs), as stated in the Introduction, focused on:

- **RQ1:** What is the current state of generative AI applications in digital marketing?
- **RQ2:** What opportunities and benefits does generative AI present to digital marketers?
- **RQ3:** What key challenges, limitations, and ethical considerations arise when deploying generative AI in marketing contexts?

2.2 Search Strategy

2.2.1 Databases and Sources Consulted

To capture both computer science and marketing perspectives, we searched major academic databases and scholarly platforms, including:

- ACM Digital Library
- IEEE Xplore
- Scopus
- Google Scholar (for potential gray literature or conference proceedings not indexed in the above repositories).

We augmented these sources by inspecting relevant journals and conference proceedings (e.g., *AI, Corporate Social Responsibility, and Marketing in Modern Organizations*, *ACM Computing Surveys*, *International Journal of Information Management*, *IEEE Transactions on Knowledge and Data Engineering*, among others) that frequently feature articles on AI-driven marketing innovations.

2.2.2 Search Terms and Query Formulation

Building on the research objectives, we developed a query string combining synonyms and Boolean operators. Core search terms included:

“Generative AI” OR “Generative Adversarial Network” OR “GPT” OR “Diffusion Models” OR “Transformers” AND “Digital Marketing” OR “Advertising” OR “Marketing Automation” OR “Personalized Marketing” OR “Marketing Campaigns”

We also employed wildcard operators (where supported) to capture variations (e.g., *advert** for *advertise*, *advertisement*, or *advertising*). To ensure the coverage of closely related works, we iteratively refined these queries by scanning initial results and incorporating additional keywords such as *marketing analytics*, *marketing content generation*, and *chatbot* references.

2.3 Screening and Eligibility Criteria

We adopted a multi-stage screening process to filter out irrelevant, duplicate, or low-quality studies.

2.3.1 Initial Screening

1. Title and Abstract Review: We assessed titles and abstracts against the core theme of “generative AI in digital marketing”. Papers focusing solely on *predictive analytics*, *sales forecasting*, or *general AI* without generative components were excluded at this stage.
2. Removal of Duplicates: Studies retrieved from multiple databases were consolidated using reference management tools (e.g., Zotero, Mendeley), and duplicates were eliminated.

2.3.2 Full-Text Evaluation

For studies surviving the initial screening, we downloaded the full texts and applied the following inclusion and exclusion criteria:

Inclusion Criteria

- Studies (journal articles, conference papers, book chapters) explicitly addressing generative AI models (e.g., Transformer-based models, GANs, VAEs, diffusion) in a digital marketing or advertising context.
- Works discussing empirical or conceptual insights on applications, opportunities, or challenges of generative AI in marketing.
- Publications in English, from peer-reviewed or credible sources (including gray literature if it met quality standards).
- Studies published from 2019 onward, reflecting the emergence of key generative technologies.

Exclusion Criteria

- Studies focusing exclusively on *predictive* or *discriminative* AI (e.g., churn prediction, anomaly detection) without discussing generative outputs.
- Publications that addressed *marketing analytics* but lacked any generative AI component or methodology.
- Non-scholarly pieces such as blog posts, editorial opinions, or incomplete papers without peer review.

- Duplicate or *significantly overlapping* works (e.g., extended versions of the same conference paper) were counted only once.

2.4 Quality Assessment

We further evaluated eligible studies to ensure methodological rigor and relevance:

1. (QA1) Clarity of Research Aims: Did the study clearly define its research objectives regarding generative AI and marketing?
2. (QA2) Methodological Soundness: For empirical studies, were the data collection and analysis methods adequately described? For conceptual works, did the authors provide coherent frameworks or theoretical grounding?
3. (QA3) Relevance to Generative AI: Did the paper discuss generative models beyond mere mention, providing insights into deployment, performance, or strategic application?
4. (QA4) Marketing Focus: Did the study explicitly link AI methodologies to marketing objectives (e.g., personalization, brand communication, user engagement)?

Studies scoring low on multiple QA criteria were excluded or flagged for limited inclusion in the thematic discussion. Throughout this process, conflicts or uncertainties were resolved through consensus between at least two authors.

2.5 Data Extraction and Synthesis

Each included paper was carefully examined to extract pertinent information:

- Bibliographic Details: Author names, year of publication, source venue (journal, conference, book chapter), and geographical focus (if specified).
- AI Technique(s) Employed: Type of generative model (GAN, Transformer, VAE, diffusion model), training approach, and data domain (text, image, multimodal).
- Marketing Application: Context of usage—advertising, social media content generation, email campaigns, SEO optimization, or more specialized domains like AR/VR marketing.
- Outcomes and Metrics: Reported improvements, quantitative measures (e.g., click-through rate, time-to-market), and qualitative insights (e.g., brand perception, user acceptance).
- Identified Challenges and Ethical Considerations: Issues related to bias, privacy, transparency, or regulatory constraints.

We adopted a *thematic analysis* approach to categorize findings into broader clusters (e.g., *content generation, personalization, ethics and regulation*), matching the research questions stated earlier. The emergent themes guided the presentation of results in [Section 4](#). Where relevant, numeric metrics (e.g., effect sizes, success rates, or engagement metrics) were noted and compared across studies to offer quantitative context.

3 Background and Theoretical Foundations

In this section, we provide a comprehensive overview of the foundational concepts and theoretical underpinnings that inform the use of generative AI in digital marketing. Specifically, we explore the historical progression of generative AI technologies, discuss the principal domains of digital marketing, and map the relevant theoretical frameworks that guide these emerging tools' adoption and ethical considerations.

3.1 Generative AI Overview

Generative AI refers to a subset of artificial intelligence techniques designed to create new, synthetic content across various modalities, such as text, images, and videos, by learning patterns and features from

training data [26,27]. These systems rely on sophisticated algorithms, such as deep learning, transformers, and diffusion models, to generate outputs that are often indistinguishable from human-created content.

Over the years, generative AI has become indispensable in industries where creativity, automation, and personalization intersect. Its transformative potential lies in its ability to augment human capabilities, reduce operational overhead, and open new avenues for innovation in content creation and user engagement [28,29]. For instance, generative AI enables advancements in content generation for movies and music, synthetic data creation for training machine learning models, and the development of immersive virtual reality experiences.

The applications of generative AI span multiple domains, including automating customer support interactions using chatbots, generating hyper-personalized marketing campaigns tailored to individual consumer preferences, and advancing medical imaging analysis [30,31]. By leveraging vast amounts of structured and unstructured data, generative AI empowers industries to achieve better efficiency and impactful outcomes.

Historically, generative AI has evolved from foundational statistical models, such as autoregressive methods and probabilistic programming, to more advanced neural network-based approaches like transformers and diffusion models. The introduction of transformer architectures has significantly accelerated progress, enabling more accurate and versatile content creation. Fig. 2 provides an overview of key developments in generative AI, depicting popular models, their developers, publication years, and applications.

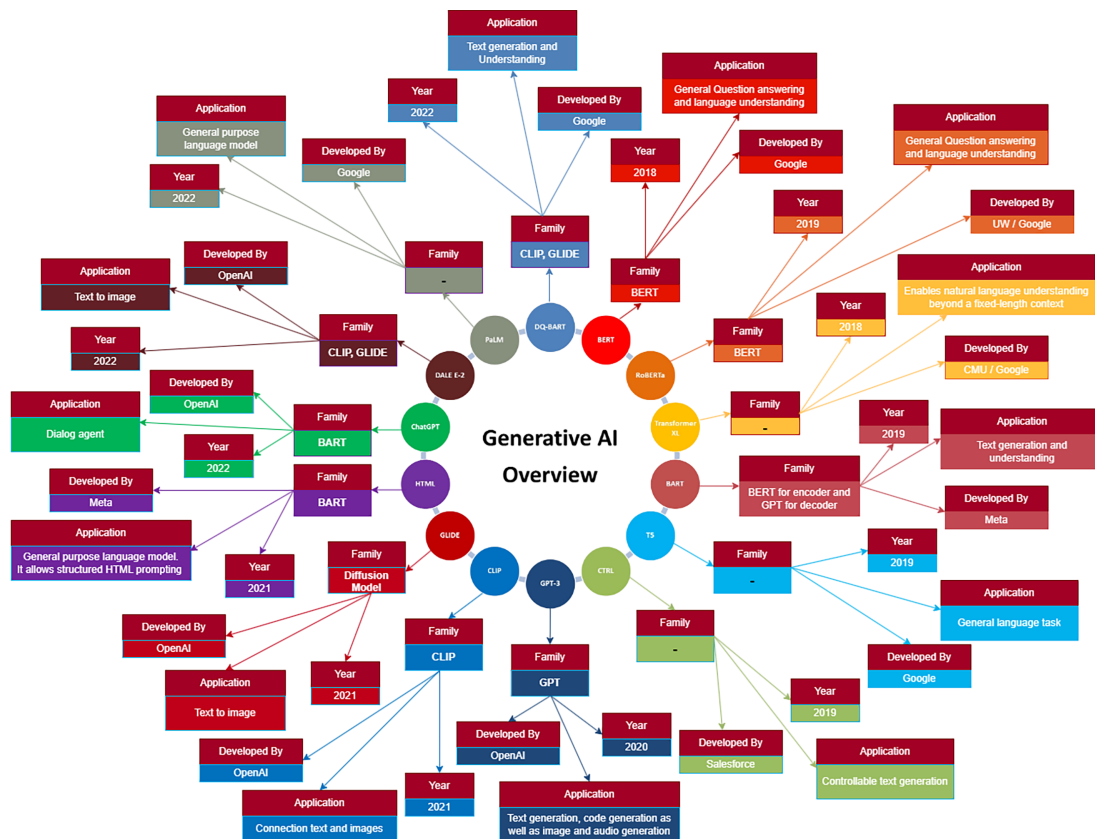


Figure 2: Overview of Generative AI developments and their key milestones. The visualization highlights various generative AI systems, their developers, publication years, and applications, showing the diverse use cases and continuous innovation in this field.

3.1.1 Historical Evolution

The trajectory of generative AI can be traced back to early language models and statistical approaches, which laid the groundwork for many modern techniques [32]. Initially, n-gram models and Markov chains were employed to model sequences of words or characters, enabling primitive text generation. These early methods, while rudimentary, showcased the potential for machines to produce human-like text through probabilistic assumptions [33,34]. As shown in Fig. 3, this early phase marked the beginning of a gradual evolution toward more advanced generative methods.

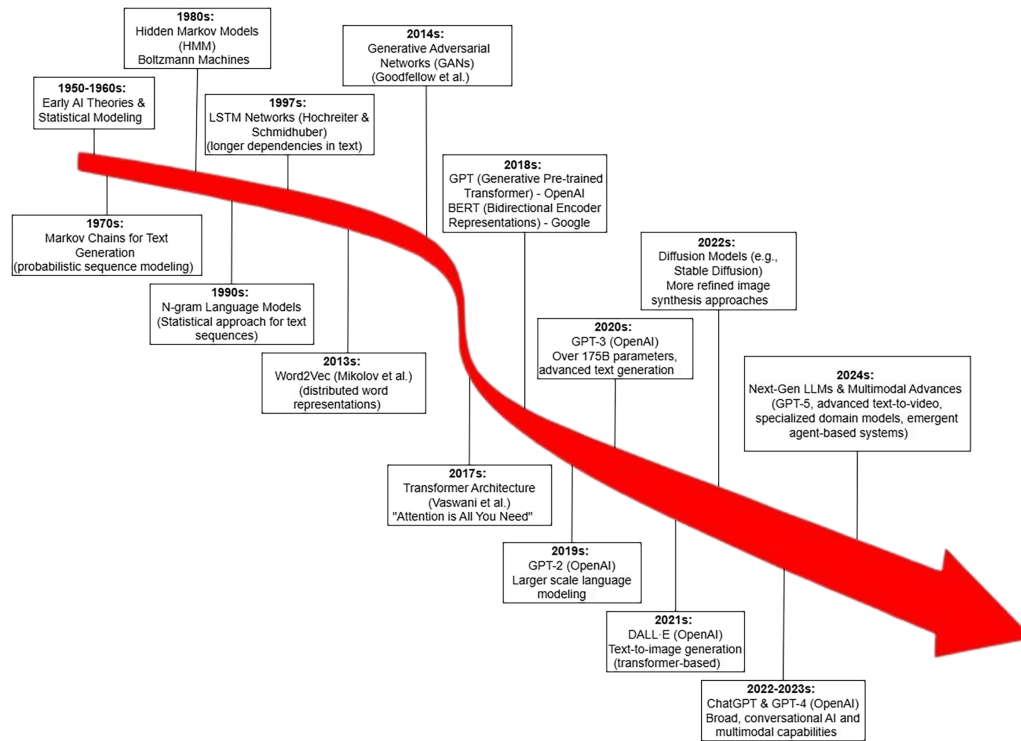


Figure 3: Evaluation of Generative AI from 1950 to 2024.

Subsequent breakthroughs in recurrent neural networks (RNNs) [35] and long short-term memory (LSTM) [36] networks extended the capabilities of language modeling by managing longer dependencies within text sequences. Researchers harnessed these architectures to generate more coherent and contextually relevant sentences, albeit with limitations in capturing extremely long-range dependencies or global context within larger documents [37].

A significant leap forward occurred with the emergence of transformer-based models, notably introduced by Vaswani [38] in the seminal paper "Attention is All You Need". Transformers replaced recurrence with a self-attention mechanism, vastly improving the capacity to process entire sequences in parallel and capture long-range relationships more effectively. This architectural advancement catalyzed the development of large-scale pre-trained language models (e.g., GPT, BERT) that demonstrated unprecedented fluency and versatility across a broad spectrum of language tasks.

In parallel, computer vision researchers pioneered generative adversarial networks (GANs), introduced by Goodfellow et al. [39], which enabled the generation of highly realistic images. GANs involve two networks, a generator and a discriminator, which are trained in opposition to each other, iteratively refining their performance through adversarial training [40]. More recently, diffusion models have emerged as a powerful

class of generative models for image synthesis, leveraging stochastic processes to incrementally refine noise into coherent images [41,42]. These advancements in text, image, and multimodal generation form the cornerstone of generative AI capabilities that are now being integrated into various marketing applications.

3.1.2 Fundamental Concepts

At the core of modern generative AI are two primary classes of models: generative and discriminative [43]. Although these models use similar advanced neural architectures, they serve different objectives and approaches to working with data. Generative models focus on understanding and replicating the underlying data distribution, while discriminative models aim to make predictions based on observed features [44].

Generative models [45] aim to model the joint probability distribution $p_{\theta}(\mathbf{x})$ of the observed data $\mathbf{x}$ and potentially some latent variables $\mathbf{z}$ [46]. In essence, they try to capture the underlying distribution of the data and can generate new data points that resemble the training data. These models are critical when the goal is to generate novel content, such as images, text, or music.

Discriminative models [47], on the other hand, focus on learning the conditional probability distribution $p_{\phi}(y | \mathbf{x})$, where y represents the label or class, and $\mathbf{x}$ represents the features of the data. They are used for tasks such as classification and regression, where the goal is to make accurate predictions given input data.

Generative Models: Generative models attempt to learn the joint probability distribution of the observed data and any latent variables that might influence it. This is typically achieved by modeling the data as a combination of factors, which may include complex dependencies between observed variables and latent factors. By learning the joint distribution, these models can generate new data points that are similar to the original dataset [48]. Common examples include Variational Autoencoders (VAEs), which encode data into a latent space and sample new instances with similar characteristics; Generative Adversarial Networks (GANs), which use adversarial training between a generator and discriminator to produce realistic outputs; Transformer-based language models, such as GPT and BERT variants, which generate coherent and contextually relevant text; and advanced neural network architectures that combine convolutional, recurrent, and attention mechanisms to generate high-fidelity images, audio, and multimodal content. Recent advancements in these models include diffusion models for improved image generation, fine-tuned large language models for domain-specific text generation, and multimodal generative models that integrate text, image, and audio to support creative and interactive applications in marketing, healthcare, and entertainment.

- **Variational Autoencoders (VAEs):** VAEs [49] are generative models that integrate deep learning with probabilistic modeling. They consist of an encoder that maps input data x into a latent space and a decoder that generates data from this latent representation. The encoder produces a latent distribution characterized by a mean and standard deviation, from which a latent vector is sampled. The decoder then reconstructs the original input from this vector. Training a VAE involves optimizing both the reconstruction quality and the regularization of the latent space to ensure meaningful and continuous representations.

Table 3: Summary of VAEs' role in digital marketing.

Ref.	Year	Dataset	Contribution	Limitation
[50]	2024	BlogCatalog, Flickr [51], and Enron	This paper proposes a dual VAE-GAN model for anomaly detection in attributed social networks, enhancing data encoding and detecting anomalies without labeled data. The model outperforms existing methods, achieving AUC scores of 0.8368, 0.8202, and 0.7118 on BlogCatalog, Flickr, and Enron datasets.	The proposed model faces challenges with low-dimensional datasets, as seen in Enron, and its performance is sensitive to data quality. Additionally, the complexity of integrating dual VAEs and GANs may complicate training and tuning, limiting its practical application in some real-world scenarios.
[52]	2018	CelebA [53], CelebA-HQ [54], LSUN BED ROOM [55]	This paper proposes the IntroVAE model, which synthesizes high-resolution images by combining VAEs and GANs into a single-stream architecture. It incorporates a self-evaluation mechanism for performance improvement and stable training. It successfully generates images with high quality and diversity, outperforming existing GANs in metrics like MS-SSIM and FID.	The IntroVAE model faces challenges in generating fine details, often resulting in blurriness due to the limitations of VAEs. Despite simplifying hybrid models, it does not achieve the image quality of GANs in high-resolution tasks, and its adaptability to other tasks may require further adjustments.
[56]	2018	CelebA	This paper enhances image quality in Variational Auto-Encoders (VAEs) using an adversarial learning framework with perceptual guidance, stabilizing training through error feedback. The approach generates high-resolution, diverse facial attributes and expressions, outperforming Boundary Equilibrium GANs (BEGAN). Quantitative improvements highlight its capability to produce realistic images with enhanced resolution and variety.	The model's reliance on a large dataset (360 k celebrity images) limits generalizability to smaller datasets. Training complexity due to hyper-parameter tuning challenges in practical deployment. Additionally, the model remains vulnerable to mode collapse, where generated outputs lack diversity, a common issue in GAN-based methods despite their designed improvements.

Fig. 4 illustrates the VAE process, showing the probabilistic encoder compressing the input image into a latent space and the decoder reconstructing the image from the sampled latent vector, highlighting the flow from input to latent representation and back to output. Table 3 summarizes various research works on VAEs, emphasizing their role in digital marketing and other applications.

- **Generative Adversarial Networks (GANs):** GANs, introduced by Goodfellow et al. [57], consist of two neural networks: a generator (G) and a discriminator (D). The generator produces synthetic data from random noise, while the discriminator classifies inputs as real or fake. The two networks engage in an adversarial process in which the generator aims to create data that is indistinguishable from real samples, and the discriminator tries to correctly identify real vs. generated data. Training alternates between updating the discriminator and the generator, with the goal of reaching a balance where the generator produces realistic outputs and the discriminator achieves approximately 50% accuracy on distinguishing real from fake data.

Variants like Wasserstein GAN (WGAN) [58] have been proposed to improve training stability and output quality by modifying the loss function. GANs have revolutionized generative modeling across

various applications, including image generation, super-resolution, and style transfer [59,60]. Fig. 5 illustrates the architecture of GANs, highlighting the interplay between the generator and the discriminator. Table 4 provides a detailed summary of these notable contributions, highlighting the datasets used, contributions made, and the challenges addressed in each study. This tabulated summary illustrates the growing versatility of GANs, while pointing out limitations such as the reliance on specific datasets, challenges with generalization, and the need for more diverse training data that remain open areas for further research.

Table 4: Summary of GANs research and applications.

Ref.	Year	Dataset	Contribution	Limitation
[61]	2024	Own Dataset	This paper introduces an automated ad creative generation method using GANs and reinforcement learning. It integrates landing page information, improving ad relevance. Empirical results show high-quality generated ads, achieving impressive ROUGE scores, with longer sequences enhancing performance and capturing expected ad formats.	This study relies heavily on quantitative metrics like ROUGE scores, which may not fully assess ad quality. Additionally, repetitive content emerged with certain sequence lengths, suggesting the need for model refinement to boost creativity and content diversity, and future work could improve the reward function for better ad format emphasis.
[62]	2024	E-Commerce Website Datasets	This paper introduces a novel GAN-VGG-based visual transformer model for generating advertising images, enhancing their quality, appeal, and interactivity. Achieving an AUC of over 0.7 on multiple datasets, the algorithm proves effective in real-world applications, boosting website operations through visually engaging advertisements that resonate with users.	The algorithm's generalization across diverse advertising domains is limited, with reduced effectiveness on varied datasets. It lacks multimodal integration, focusing solely on image generation while neglecting textual content. The inclusion of more diverse training data and a joint generative model incorporating text and images could significantly improve performance.
[63]	2024	Social Network Advertising Dataset	This paper introduces a generative augmentation framework using GANs, VAEs, and GMMs to enhance social network advertising data, improving machine learning classifier performance. It shows VAEs provide the greatest performance boost, with significant accuracy gains through data augmentation, offering insights for digital marketing practitioners.	The study is limited by its reliance on a single dataset, affecting the generalizability of the findings. Additionally, the analysis does not cover all possible classifiers and lacks an exploration of advanced data augmentation techniques on fairness and bias in predictions.
[64]	2021	Jingdong Dataset	The proposed M-GAN-XGBOOST model enhances sales prediction accuracy for online stores by combining LSTM, GAN, and XGBOOST. It adapts to real-time consumer behavior and improves prediction accuracy, achieving an RMSE of 11.9 and an MAE of 8.23, validated with the Jingdong dataset.	The model's performance is data-dependent, requiring high-quality, abundant input data. Its complex implementation, integrating LSTM, GAN, and XGBOOST, may challenge online retailers. Additionally, its generalizability to other e-commerce platforms or product categories needs further validation.

- Transformer-Based Language Models:** Transformer-based language models, such as GPT [65], have advanced natural language processing by using self-attention mechanisms to capture long-range dependencies and contextual relationships across entire sequences [66]. Unlike RNNs or LSTMs, transformers process sequences in parallel, improving training efficiency. GPT uses a decoder-only architecture for text generation, while the multi-head attention mechanism allows the model to capture multiple levels of abstraction [67]. Despite their effectiveness, transformers require large datasets and substantial computational resources [68,69].

Fig. 6 illustrates the transformer architecture, highlighting its self-attention layers and feed-forward networks that process sequences in parallel. Table 5 summarizes key studies and advancements in transformer-based models, highlighting the models used, contributions made, and their respective limitations. This table reflects the growing diversity of transformer applications across various NLP tasks, while emphasizing ongoing challenges related to model size, efficiency, and generalizability.

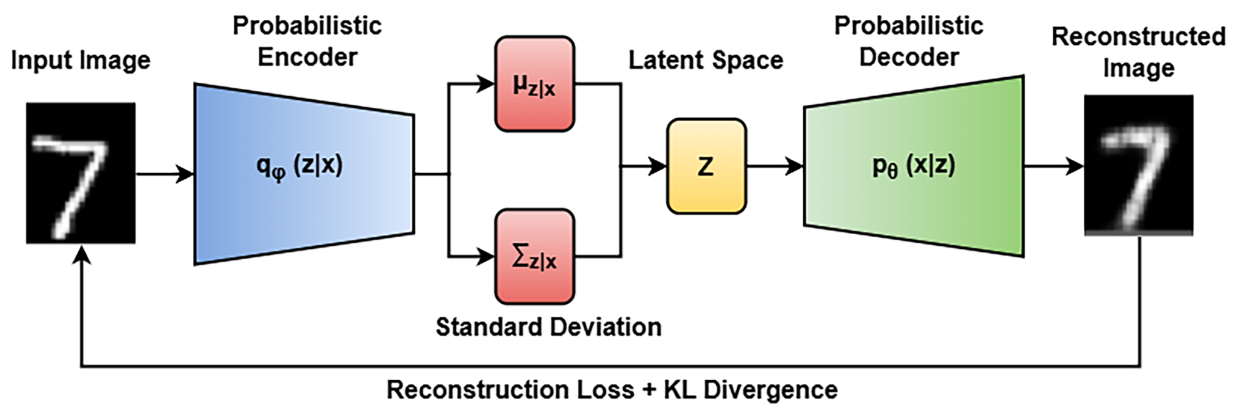


Figure 4: Architecture of VAE for image reconstruction.

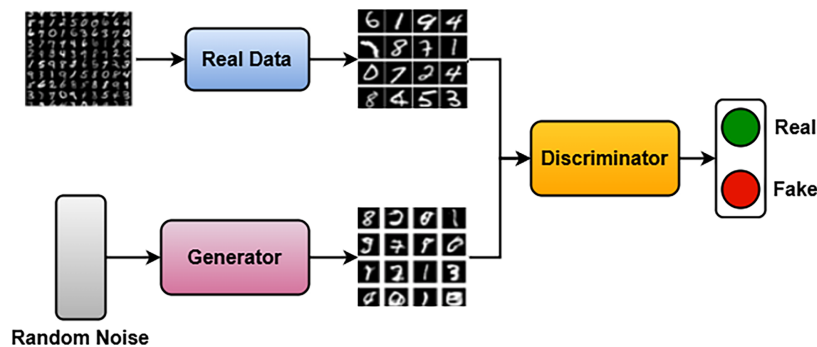


Figure 5: Architecture of GAN for image generation.

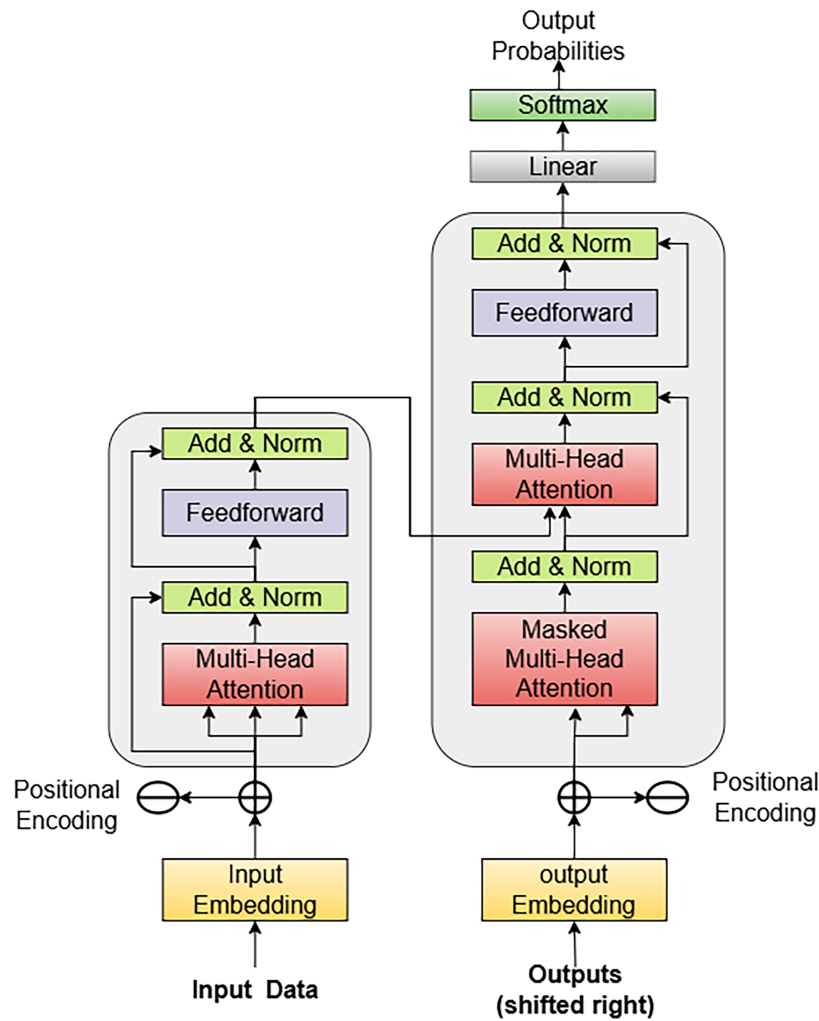


Figure 6: The architecture of a transformer model with multiple layers of attention and feed-forward networks.

Table 5: Summary of transformer-based recent work.

Ref.	Year	Dataset	Contribution	Limitation
[70]	2024	COCO [71], YFCC100M [72], Fashion-MNIST [73], ImageNet [74]	This paper introduces the Transformer-cGANs model, integrating Transformers with GANs for enhanced advertising image generation. Extensive experiments on datasets like COCO, YFCC100M, and ImageNet show superior performance, achieving high PSNR and SSIM scores. The model demonstrates robustness, adaptability, and high-quality outputs, validated by metrics like FID, IS, and MIoU.	The Transformer-cGANs model faces limitations such as high computational demand, and restricting real-time marketing applications. It requires improved hyperparameter tuning for optimal performance and involves complex implementation due to Transformer integration, posing challenges for broader accessibility. These issues highlight areas for refinement to improve usability and efficiency in practical scenarios.

(Continued)

Table 5 (continued)

Ref.	Year	Dataset	Contribution	Limitation
[75]	2024	TargetingVis Dataset [76]	This study integrates Vision Transformer (ViT) and Graph Neural Networks (GNN) with GANs to analyze advertising effectiveness, improving predictive accuracy and feature quality. It enables comprehensive ad content analysis by transforming data into high-dimensional representations and addresses research gaps, offering valuable insights for optimizing digital marketing strategies.	The paper identifies data constraints, methodological singularities, and a lack of attention to temporal changes as key limitations affecting generalization and relevance. Additionally, it highlights insufficient privacy protection in prior studies, emphasizing the need for better approaches to ensure robust, adaptive, and ethical methods in advertising effectiveness research.
[77]	2024	Women's Clothing E Commerce Reviews dataset [78]	This paper benchmarks CNN, RNN, and Bi-LSTM for sentiment analysis in e-commerce, emphasizing RoBERTa's superiority. Advanced embeddings like BERT, FastText, and Word2Vec enhance model performance. Ensemble models outperform solo models. Simplified class structures improve predictions, providing insights for practical applications in consumer sentiment analysis.	The used dataset lacks thorough screening for spam or fraudulent reviews, potentially affecting prediction accuracy. The study focuses solely on English reviews, limiting its applicability in multilingual settings. Additionally, findings based on American English may not generalize to other dialects or languages, reducing the global relevance for diverse e-commerce platforms.
[79]	2023	Online Retail DataSet [80]	This paper presents a novel transformer-based model for predicting the next purchase day (NPD) in e-commerce, outperforming traditional methods like ARIMA, XGBoost, and LSTM by 6.15% in RMSE. The model adapts to various time series patterns and handles non-stationary data more effectively, improving accuracy.	The self-attention mechanism's permutation-invariance in transformers may negatively affect the order of values in time series applications. Additionally, challenges arise for long-time series forecasting, where linear models sometimes outperform transformers, and external regressors cannot be used effectively due to dataset limitations.

Table 6 presents a comparative analysis of prominent generative techniques, highlighting their strengths, weaknesses, typical applications, and critical insights, which complements the discussion on transformers and other generative models.

Table 6: Comparative analysis of generative AI models.

Model	Key Strengths	Key Weaknesses	Typical Applications	Critical Insight
GANs	High-quality image generation, realistic outputs	Training instability, mode collapse, difficult to evaluate	Image synthesis, data augmentation, super-resolution	Excels in realism but can be unstable; requires careful architecture tuning.

(Continued)

Table 6 (continued)

Model	Key Strengths	Key Weaknesses	Typical Applications	Critical Insight
VAEs	Probabilistic modeling, latent space interpretability	Blurry outputs compared to GANs, lower visual fidelity	Representation learning, anomaly detection, generative modeling	Better for structured latent space and interpretability; output quality trades off realism.
Diffusion Models	Strong mode coverage, high-quality outputs, stable training	Computationally expensive, slow sampling	Image generation, molecular design	Offers a balance of stability and output diversity but at a computational cost.
Transformers	Handles long-range dependencies, scalable, versatile	Data-hungry, high memory consumption	Text-to-image generation, language modeling, multimodal tasks	Flexible and powerful for cross-domain tasks; performance depends heavily on dataset size.

Discriminative Models: Discriminative models are a class of machine learning models designed to learn the conditional relationship between input features and target outputs, such as class labels or regression values [81]. Unlike generative models, which model the joint distribution of inputs and outputs, discriminative models focus on directly predicting outcomes or distinguishing between classes [82]. They assign a score to each possible output and normalize these scores to estimate the likelihood of each outcome.

In practice, discriminative models are widely applied across domains and frequently complement generative models by serving as evaluative tools. For example, in **GANs**, the discriminator is a discriminative model that assesses whether generated samples are realistic, guiding the generator to produce outputs aligned with the target distribution. In **digital marketing**, discriminative models help rank, filter, or classify generated content based on quality, engagement potential, or alignment with brand objectives [83].

These models have found extensive applications in marketing, excelling in tasks such as ranking content, predicting customer interactions, and enabling data-driven personalization. Nallapati [84] highlights the use of Support Vector Machines (SVMs) in Information Retrieval, demonstrating improvements in feature learning and ranking performance. Haider et al. [85] propose a discriminative clustering framework for market segmentation, showing better interpretability and adaptability to temporal patterns. An et al. [86] integrate discriminative models with generative features for citation classification, achieving notable improvements in predictive performance. Collectively, these studies underscore the potential of discriminative models in enhancing marketing strategies, content targeting, and personalized recommendations.

Neural Network Architectures: Beyond generative or discriminative objectives, models can be implemented using various neural network architectures, each suited to different marketing tasks such as text generation, time-series analysis, or social network exploration.

Feedforward Networks (FFN): FFN [87] are the simplest neural architectures, consisting of layers that apply linear transformations followed by nonlinear activations. These networks are widely used for regression, basic classification, and transformations in marketing pipelines, such as predicting user responses to campaigns.

Recurrent Architectures: It's including RNNs, LSTMs, and GRUs [88,89], are specialized for sequence-related tasks. They maintain a hidden state over time, enabling the analysis of user behavior sequences or generating sequential marketing content like emails or social media posts. LSTMs and GRUs incorporate gating mechanisms to handle long sequences and mitigate gradient issues.

Attention-Based Transformers: Attention-based transformers leverage multi-head self-attention mechanisms to capture both short- and long-range dependencies more efficiently than RNNs. Transformers process entire sequences in parallel, generating coherent, contextually rich content, making them highly effective for tasks like ad copy generation, product descriptions, and marketing chatbots.

Graph Neural Networks (GNNs): GNNs [90–92] are designed for graph-structured data, representing entities and their relationships (e.g., users in a social network). GNNs are useful for analyzing social interactions, identifying influential users, and recommending personalized marketing strategies, though they are less commonly used for direct content generation.

Image Synthesis: Image synthesis involves generating new images by learning the distribution of visual data using computational models. In marketing, it enables scalable creation of visual content, such as product mockups, personalized ads, and virtual try-on experiences [93,94].

Generative Adversarial Networks are among the most prominent techniques for image synthesis. GANs consist of a generator that creates synthetic images and a discriminator that evaluates their realism. Variants like StyleGAN [95] and BigGAN allow fine-grained control over attributes such as shape, color, and structure, supporting applications like virtual clothing simulations, promotional graphics, and digital avatar customization. Diffusion models [96], such as Imagen and Stable Diffusion [97], progressively convert noise into high-fidelity images, providing improved realism and diversity compared to GANs. In marketing, these models reduce content production costs, shorten design cycles, and enable the generation of visuals tailored to different customer segments or campaigns [98].

Multimodal Approaches: Multimodal approaches integrate data from multiple sources, such as text, images, video, and audio, to build systems that reason across modalities. In marketing, such systems enhance personalization, product discovery, and coherent content generation [99,100].

Transformer-based models are commonly used in multimodal learning. For instance, CLIP [101] jointly embeds textual and visual information into a shared semantic space, aligning text and image representations. Generative models like DALL-E and Imagen [102,103] extend this approach by creating images from textual prompts, typically using an encoder to process text and a decoder (based on diffusion or vector quantization) to synthesize images. Applications include aligning advertisements with consumer preferences, automatically generating campaign materials from brand stories, and enabling semantic product search using both text and images [104]. While multimodal models pose challenges in aligning and fusing diverse data types, they enhance context-aware, adaptive, and engaging user experiences in modern marketing systems.

Choice of Model and Architecture: The selection of an appropriate model type and architecture is a critical step in designing AI-driven strategies for digital marketing. This decision depends on multiple interrelated factors that affect the model's suitability for specific tasks, its performance, and how well it can be deployed in practical settings.

One key factor is the target modality, which defines the type of data the model processes. This may include text, images, audio, or multimodal formats that combine several data types. For example, a model

tailored for text input will differ significantly in structure and purpose compared to one intended for image generation or audio synthesis. Another important consideration is the marketing objective. Goals such as personalized recommendations, ad copy generation at scale, audience segmentation, or visual content creation require specific model capabilities. Choosing the right model ensures that the system is efficient and aligned with the desired output.

The characteristics of big data, including volume, velocity, and veracity, play a central role in selecting appropriate generative models. Volume refers to the vast amount of consumer data available, which can improve learning but also requires significant computational resources. Velocity concerns the rapid flow and processing demand of data, especially in dynamic marketing environments where near real-time output may be required. Veracity refers to the reliability and noise level in the data, which affects the consistency and quality of the generated results. These aspects introduce critical trade-offs when selecting among models such as GANs, VAEs, and diffusion models.

GANs are typically used when fast generation of realistic visual content is required. However, they may require more careful training due to potential instability and issues like mode collapse. VAEs are more stable and computationally efficient, making them a good option when moderate image quality is acceptable. Diffusion models provide high-fidelity outputs with strong controllability, but they are computationally intensive and time-consuming, which may limit their usability in time-sensitive or energy-constrained environments.

Selecting among these models involves evaluating trade-offs across several dimensions, including training and inference time, cost of deployment, performance accuracy, and energy consumption. These trade-offs should be carefully assessed depending on the digital marketing use case and operational constraints. [Table 7](#) outlines these considerations in a structured way.

Table 7: Factors influencing the choice of model and architecture.

Factor	Description	Relevance to Digital Marketing
Target Modality	Refers to the type of data the model will handle, such as text, images, audio, or multimodal data combining different formats	Text models support ad copy generation, image models enable visual campaigns, and multimodal models drive interactive or immersive experiences
Marketing Objective	Refers to the end goal of the model, such as recommendations, segmentation, or content generation	Discriminative models are well-suited for audience classification, while generative models are used for producing new content like ads or visuals
Computational Constraints	Refers to limits in training resources, inference speed, and model complexity	Heavier models may not be viable in real-time use while lightweight alternatives can support on-device or low-latency applications
Big Data Characteristics	Involves the volume, velocity, and veracity of consumer data used for training and deployment	High-volume data can enhance learning but increases resource demand. High-velocity data needs faster models. High-veracity data leads to more reliable outputs

(Continued)

Table 7 (continued)

Factor	Description	Relevance to Digital Marketing
Model Trade-offs	Covers the balance between cost, time, energy, and performance across model types like GANs, VAEs, and diffusion models	GANs are fast and realistic but require tuning. VAEs are efficient and stable with moderate output quality. Diffusion models produce superior visuals but are computationally expensive

A generative approach is most appropriate when new content creation is required. This includes tasks such as designing creative ad copy or generating product visuals. A discriminative approach is more effective for classification and forecasting tasks such as audience segmentation or predicting user behavior. For image generation in marketing, GANs are preferred for their fast and realistic outputs. VAEs offer a balance of speed and stability with lower resource use. Diffusion models are ideal when the highest visual quality is needed, but may not be feasible for time-sensitive tasks due to high energy and computation demands.

For tasks that combine text and image understanding, such as producing branded visuals from product descriptions or retrieving marketing images based on text prompts, multimodal models like CLIP and DALL·E are highly effective. These models align visual and textual information, enabling cohesive content generation and retrieval strategies.

A clear understanding of these trade-offs, along with the influence of big data properties, is essential for building AI solutions that are not only technically sound but also practical and scalable in digital marketing contexts.

3.2 Digital Marketing Landscape

Digital marketing encompasses a wide array of channels and strategies that businesses utilize to reach their target audiences online [105,106]. These include content marketing, email campaigns, search engine optimization (SEO), social media engagement, and paid advertising, among others. Each of these components plays a critical role in shaping a brand's digital presence and influencing consumer behavior.

To present a more unified understanding of how these components interrelate within a comprehensive digital strategy, Fig. 7 provides a schematic representation of the digital marketing landscape. At the center of this framework lies the concept of "Digital Strategy", which integrates three essential pillars: content, data, and analytics. Surrounding this hub are key domains, including Mobile, Social, Ads, SEO, Website, Conversation Marketing, Email, and CRM. Each domain contributes uniquely to the overarching strategy. For example, Mobile and Social enhance accessibility and engagement; Ads and SEO drive discoverability; Website design and optimization support conversion goals; while Email and CRM aid in lead nurturing and customer retention.

This visual structure emphasizes the interconnected nature of modern digital efforts, showing how each element must operate in alignment with others to produce coherent and effective marketing outcomes. The integration of these elements supports data-driven decision-making and user-centric design, both of which are critical for sustained success in today's competitive digital environment.

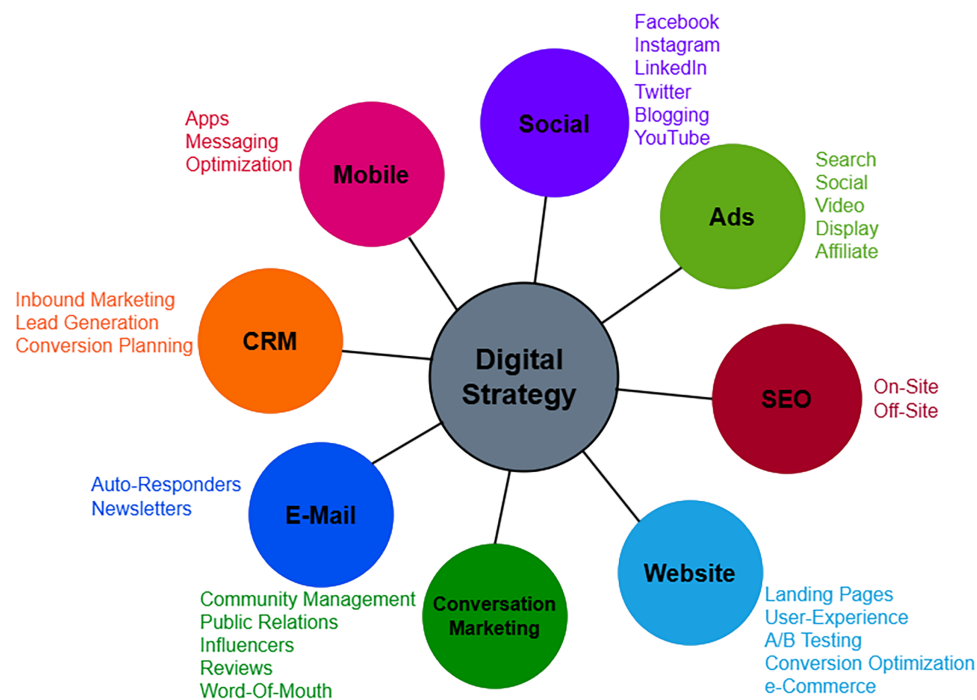


Figure 7: A schematic diagram illustrating the integrated components of a modern digital marketing strategy.

3.2.1 Key Domains in Digital Marketing

Digital marketing includes various channels and tactics, each offering unique opportunities and challenges while often overlapping in practice:

- **Advertising.** Advertising involves strategies such as pay-per-click campaigns, display ads, sponsored listings, and affiliate marketing [107,108]. Generative AI enables automation in creating diverse ad creatives, headlines, and visuals, enhancing engagement and conversion rates [109]. Studies highlight both opportunities and challenges, including balancing efficiency and personalization [110], enhancing dynamic ads and personalized content like Netflix trailers [109], and trends in AI-driven advertising with ethical considerations and methodological limitations.
- **Social Media Marketing.** Platforms such as Facebook, Instagram, Twitter, LinkedIn, and TikTok are key for engagement [111,112]. Generative AI supports rapid content creation and real-time sentiment analysis [113]. Research highlights the influence of online word-of-mouth [114], GPT-4's role in content strategies [115], and adoption drivers like efficiency and scalability, alongside creativity limitations and risks [116].
- **Content Marketing.** Content includes blogs, infographics, e-books, articles, and videos [117]. Generative AI enhances both quality and volume, enabling personalized and dynamic content [118]. Studies show improvements in visual marketing [119], engagement [120], and support for SMEs in SEO and platform-specific strategies [121]. Benefits include streamlined production and consistent brand identity, with challenges in data quality and implementation.
- **Email Marketing.** Email marketing relies on personalization and strategic timing [122,123]. Generative AI enables hyper-personalized content, including tailored subject lines, body text, and product recommendations [124–126]. Studies demonstrate improvements in engagement and conversions, with challenges in demographic bias, dataset limitations, and broader applicability.

- **Search Engine Optimization.** SEO focuses on optimizing websites and content for search engines [127,128]. Generative AI assists in keyword selection, meta descriptions, article creation, and content optimization. Research highlights AI-driven methods for alt text generation [129], readability improvements, website analytics and branding [130], and voice search adaptation [131]. Challenges remain in scalability, data quality, and tool enhancement.

3.2.2 Traditional AI vs. Generative AI in Marketing Contexts

Historically, digital marketing has harnessed AI primarily through predictive analytics, rule-based systems, and recommendation engines [132,133]. These approaches excelled at analyzing historical data to forecast user behavior, such as predicting which users are most likely to click on an ad or buy a product, and were instrumental in personalizing marketing messages to specific segments.

Shift towards Content Creation and Personalization Generative AI marks a major paradigm shift by creating brand-new text, images, or videos rather than just analyzing or predicting [134]. For example, while a traditional AI system might determine the best time to send an email for optimal open rates, a generative model can also compose the email's subject line and body text to maximize relevancy and engagement [135]. This ability to automate creative tasks allows marketing teams to significantly scale their content strategies, producing a higher volume of material while maintaining consistent quality and personalization.

Opportunities and Challenges

Despite its obvious advantages, generative AI brings new considerations for marketing professionals:

- **Quality Control and Brand Consistency:** Large-scale automated content generation can lead to off-brand messaging or stylistic inconsistencies if not carefully supervised. Maintaining a brand's voice across ads, social posts, and emails requires a strategic balance of human curation and AI oversight [136].
- **Ethical and Authenticity Concerns:** As generative AI produces highly realistic content, consumers may become skeptical about the authenticity of brand interactions. Overuse of AI-generated communication risks eroding trust, particularly if it is not transparent [137,138]. Marketers must therefore disclose AI-driven aspects where appropriate and ensure all content adheres to ethical guidelines.
- **Regulatory and Legal Issues:** Intellectual property questions, deepfake regulations, and emerging data protection laws pose challenges. Marketers must stay compliant with local and international guidelines, particularly when AI-generated content resembles original copyrighted material or manipulates user perceptions [139,140].

By recognizing these potential pitfalls and establishing robust strategies to manage them, organizations can harness generative AI to deliver more engaging, personalized, and effective campaigns. While predictive and rule-based AI systems remain critical for analytics and user profiling, generative AI takes marketing a step further empowering teams to achieve unprecedented creativity and scale in digital campaigns.

3.3 Relevant Theoretical Frameworks

Generative AI adoption in digital marketing is not solely determined by technological capabilities; it is also influenced by organizational culture, perceived value, and ethical and social contexts [141]. This section highlights two major theoretical lenses, Innovation Diffusion Theory (IDT) [142] and the Technology Acceptance Model (TAM) [143], which offer insight into how novel technologies gain traction. Additionally, it addresses the ethical considerations that shape the responsible deployment of these technologies.

3.3.1 Innovation Diffusion Theory and Technology Acceptance Model

Innovation Diffusion Theory (IDT)

Rogers' Innovation Diffusion Theory offers a structured perspective on how individuals and organizations adopt new technologies [144]. The process is conceptualized through five sequential stages, each influenced by contextual factors such as organizational environment, leadership openness, and market demands. In the context of our review, these stages were consistently observed in marketing case studies, where organizations moved from initial awareness of generative AI tools to measurable business outcomes such as increased engagement rates and reduced campaign development costs. This demonstrates how IDT is not only theoretical but also directly applicable to real-world adoption patterns in digital marketing.

- **Knowledge:** This stage begins when individuals or teams become aware of a new technology, such as generative AI. At this point, they typically lack a detailed understanding of how the technology works or how it might be relevant to their tasks. The presence of a proactive organizational culture that encourages learning and staying updated with technological trends can accelerate the transition from simple awareness to deeper exploration.
- **Persuasion:** In this stage, individuals start forming opinions about the technology based on its perceived advantages and limitations. Internal discussions, expert opinions, case studies, and early experiments shape these perceptions. A supportive culture that fosters open dialogue and values innovation often enables employees to view new tools with optimism. Meanwhile, consumer behavior, such as increasing demand for faster, personalized digital experiences, can reinforce positive attitudes toward adopting new technologies.
- **Decision:** Here, a concrete choice is made to either adopt or reject the technology. This decision is often the result of cost-benefit analysis, feedback from colleagues or industry peers, and alignment with strategic goals. Organizational culture again plays a critical role. In highly hierarchical firms, decisions may depend on leadership endorsement. In flatter organizations, team consensus or pilot trial outcomes may drive the final verdict. External consumer trends may also exert pressure, compelling marketing teams to adopt generative AI tools to remain competitive.
- **Implementation:** At this point, the technology is integrated into the organization's existing workflows. Successful implementation may require re-training employees, adjusting work processes, or investing in supporting infrastructure. A flexible and adaptive organizational culture can significantly ease this transition. Implementation is more likely to succeed when early adopters within the firm champion the technology and share their experiences with others, reducing resistance and confusion.
- **Confirmation:** During this final phase, the organization evaluates the outcomes of adoption. If the results are satisfactory, such as increased efficiency or improved engagement rates, continued use is reinforced. If expectations are not met, the technology may be revised or discontinued. Open feedback channels, performance measurement tools, and alignment with customer feedback are essential at this stage. Consumer response, such as higher satisfaction or increased conversions, can validate the effectiveness of the adopted technology.

Rogers also outlines five key attributes that influence how quickly and widely a new technology is adopted:

- **Relative Advantage:** This refers to the degree to which generative AI is perceived as superior to current methods. If it clearly provides benefits such as cost savings, time efficiency, or improved content quality, organizations are more likely to pursue adoption. In cultures that prioritize performance and results, this factor is especially influential.

- **Compatibility:** Compatibility assesses how well the technology fits within the existing values, workflows, and systems of an organization. If generative AI integrates seamlessly with content management systems or marketing automation tools, adoption is more straightforward. When organizational norms support innovation and process evolution, compatibility is less of a barrier.
- **Complexity:** If the new technology is perceived as difficult to use or understand, adoption may be delayed. Simplicity in interface design and ease of training can counteract this issue. Organizations with a strong culture of continuous learning are better equipped to overcome perceived complexity.
- **Trialability:** This factor considers whether the technology can be tested on a limited scale before full deployment. Pilot campaigns using AI-generated content can help assess effectiveness without significant risk. An experimental culture within the organization allows teams to learn from trial runs and refine their strategies accordingly.
- **Observability:** This refers to how visible the benefits of the technology are to others in the organization. If results such as higher customer engagement or campaign performance are clearly observable, it fosters greater confidence and accelerates adoption. Recognition of these successes is easier in transparent, metrics-driven cultures.

Our findings show that these attributes can be mapped to empirical evidence in marketing practice. For example, “relative advantage” was quantified in case studies where AI-generated email campaigns led to measurable cost savings and time reductions compared to traditional methods. Similarly, “trialability” was demonstrated through pilot ad campaigns that allowed marketers to experiment with generative AI tools before full-scale implementation. These practical illustrations ground IDT more firmly in observed industry experiences.

Technology Acceptance Model (TAM)

The Technology Acceptance Model [145] explains how individual users decide whether or not to accept a new system based on two primary beliefs:

- **Perceived Usefulness (PU):** This is the degree to which a person believes that using a particular technology will enhance their job performance. In marketing, this could mean that generative AI helps users create content faster or improves audience engagement. If marketers experience noticeable improvements in results, they are more likely to use the technology consistently.
- **Perceived Ease of Use (PEOU):** This refers to how effortless users expect the technology to be. Generative AI tools that have intuitive interfaces and offer seamless integration with existing workflows are more likely to be accepted. In organizations where digital literacy is high and training is readily available, PEOU tends to be perceived more positively.

The perceived usefulness and ease of use are not formed in isolation. They are shaped by prior experiences with similar technologies, peer influence, and internal communication. A culture that encourages feedback and peer support can significantly improve both PU and PEOU. In parallel, rising consumer expectations for dynamic and personalized marketing content often motivate employees to perceive such technologies as not only useful but necessary. For instance, case studies included in our review showed that marketers perceived high usefulness when generative AI improved click-through rates in targeted campaigns, while ease of use was reinforced by user-friendly interfaces that required minimal training. These findings strengthen the practical relevance of TAM in explaining adoption behaviors.

To integrate both theories with practice, we expanded Table 8 to include how IDT and TAM dimensions were reflected in case studies. This addition illustrates, for example, how “relative advantage” manifests as quantifiable cost savings, or how “perceived ease of use” translates into higher adoption rates when AI tools

are integrated into familiar marketing platforms. By linking theory to observed outcomes, the discussion provides a more concrete bridge between conceptual models and practical recommendations.

In summary, IDT and TAM together explain how both organizational structures and individual attitudes shape the adoption of generative AI in marketing. Organizational culture influences how quickly people move through the stages of awareness, evaluation, and commitment. Consumer behavior, on the other hand, acts as an external motivator, pushing organizations to adopt tools that meet evolving customer expectations. A coherent alignment between internal culture and external demand is essential for successful technology integration. By grounding these frameworks in empirical findings and case study evidence, we provide a stronger connection between theory and practice, which also aligns with the recommendations offered in [Section 5.4](#) for responsible and human-centric adoption.

3.3.2 Ethical Frameworks for AI

Although generative AI holds the promise of creative and scalable marketing solutions, it also poses ethical and societal challenges [\[146\]](#). Recognizing these concerns is essential for sustaining trust and avoiding legal or reputational repercussions. Several high-level ethical principles guide the responsible development and deployment of AI, including:

- **Fairness:** This principle requires that generative AI systems do not perpetuate biases—e.g., racial, gender, or socioeconomic—in advertising content [\[146\]](#). Marketers should scrutinize the training data for hidden biases and apply techniques (such as data augmentation or bias correction) to ensure a more equitable representation of target groups [\[147\]](#).
- **Transparency:** Users and consumers need to understand when they are interacting with AI-generated content vs. human-created material. Clear disclosure practices not only uphold honesty but also help maintain consumer trust [\[148\]](#). Regulatory bodies in some regions have already introduced guidelines mandating the labeling of AI-generated communications or imagery.
- **Accountability:** Organizations must establish explicit governance frameworks, delineating responsibility among data scientists, marketing managers, and upper-level executives. This includes proactive measures to prevent misuse—such as the creation of misleading deepfake advertisements—and the implementation of redress mechanisms in case of harm or user complaints [\[149\]](#).

Many governments and global entities (e.g., the European Union) are moving toward more stringent AI regulations, impacting areas such as consumer protection, data privacy, and online advertising standards [\[150\]](#). Marketing teams that align their generative AI strategies with these ethical and legal frameworks are better positioned to realize long-term value, protect their brand image, and foster lasting relationships with their audiences [\[151\]](#).

Overall, grounding the integration of generative AI in IDT, TAM, and robust ethical principles ensures that organizational adoption is not merely a technological upgrade but a strategically and ethically sound transformation—one that resonates with both internal stakeholders and external consumers.

In summary, the rapid advancement of generative AI has opened new avenues for content creation and strategic engagement in digital marketing, extending well beyond the predictive analytics and rule-based systems of earlier decades [\[152\]](#). The interplay between technological evolution, marketing paradigms, and ethical imperatives shapes both the promise and the practice of generative AI. As stakeholders navigate adoption decisions, the integration of established theories like IDT and TAM, alongside emerging ethical guidelines, will play a pivotal role in guiding responsible and impactful deployment.

Table 8: Overview of some selected studies in generative AI in digital marketing.

Authors	Year	AI Technique	Marketing Application	Key Findings
Jin et al. [153]	2024	Random Forest	Digital Advertising Marketing	The research highlights that the AI-driven Random Forest Model (RFM) effectively predicts customer counts, outperforming logistic regression. It also reveals key customer demographics, including university-affiliated individuals and specific price distribution patterns. Here, “trialability” and “relative advantage” (IDT) are demonstrated through comparative accuracy gains.
Vashishth et al. [154]	2025	AI Algorithm	Content Marketing	AI-enabled content personalization in e-commerce enhances customer satisfaction, engagement, and conversion rates by leveraging customer data for tailored recommendations. Successful case studies highlight their positive impact, though challenges like data privacy remain. These outcomes connect with TAM’s “perceived usefulness” and IDT’s “observability” as customers visibly benefit from personalized recommendations.
Hocutt [155]	2024	GenAI	Digital Advertising Marketing	The research explores online advertising platforms as collaborative spaces where AI and human rhetoric intersect, emphasizing user-centered approaches to ad composition amidst generative AI integration. Compatibility is reflected here, as adoption success depends on alignment between AI rhetoric and organizational marketing values.
Gołab-Andrzejak [156]	2023	ChatGPT & GenAI	Digital Advertising Marketing	Generative AI and ChatGPT enhance digital advertising by streamlining campaign stages, fostering marketer-AI collaboration, and boosting efficiency and creativity, with theoretical and managerial implications. This case highlights “trialability” and “perceived ease of use”, as ChatGPT adoption was tested in campaign stages before full deployment.
Baek [157]	2023	ChatGPT	Digital Advertising Marketing	Generative AI reshapes digital advertising, influencing consumer responses to virtual influencers, privacy in behavioral ads, AI-driven ethnic targeting, and relational bonds in gaming, highlighting its role in engagement and personalization across platforms. These findings demonstrate “compatibility” with evolving consumer behaviors and “relative advantage” in new ad formats.
Martinez-Rolan et al. [158]	2023	ChatGPT	Content Marketing	The research reveals the cautious use of synthetic content generators by communication professionals in Galicia, mainly for brainstorming and drafting texts, with ChatGPT being the most recognized and influential tool. This shows TAM’s “perceived ease of use”, as adoption occurs mainly in low-risk, supportive tasks like brainstorming.

4 Results

In this section, we present the findings from the systematic review, organized around key themes and research questions. The data extraction and synthesis focused on identifying the nature of each study (i.e., methodological approach, AI technique employed, marketing application) and the reported outcomes or insights. We subsequently group these findings into major thematic categories that emerged from the literature.

4.1 Study Characteristics

We begin by outlining the general characteristics of the studies included in this review. [Table 8](#) provides a summary of selected studies, highlighting the authors, publication year, AI technique used, marketing application, and main findings.

Distribution by Publication Year, Journal, and Geography

A preliminary analysis indicated that the number of publications on generative AI in marketing has grown exponentially since 2018, following the release of transformer-based models and the subsequent proliferation of large-scale language models. Most studies were published in computer science and AI-oriented venues, although cross-disciplinary journals covering marketing and information systems also featured prominently. Geographically, the majority of empirical research originated from North America and Europe, with a growing number of contributions from Asia—especially in regions with significant e-commerce or social media user bases (e.g., China, Republic of Korea).

4.2 Thematic Categorization

To facilitate an in-depth discussion, we group the studies into four main themes that capture the breadth of generative AI applications in digital marketing.

4.2.1 Theme 1: Content Generation and Personalization

AI-Generated Ad Copy & Personalized Email Campaigns

Several studies highlighted how large language models and recurrent neural network architectures are leveraged to craft real-time, context-aware advertising copy [159,160]. For instance, generative models can tailor subject lines or product descriptions to specific user segments, often resulting in increased open rates and user engagement.

Chatbots and Conversational Agents: In addition to static text generation, chatbot systems powered by generative language models were reported to offer more natural and contextually relevant interactions with customers [161,162]. This fosters stronger brand-customer relationships while freeing human agents to focus on complex or high-stakes queries.

Impact on Customer Engagement and Brand Perception: Empirical data suggest that generative AI-driven personalization can boost metrics such as click-through rates (CTR), conversion rates, and overall brand sentiment [163]. However, some studies noted potential drawbacks—overly automated messaging may diminish perceived authenticity if not carefully monitored.

Theme 2: Image and Video Generation for Marketing Campaigns

Use of GANs or Diffusion Models: Techniques such as GANs and diffusion models are prominently featured in creating visually compelling ad creatives [164]. These approaches can generate product images from textual descriptions or transform existing images to fit marketing design requirements.

Effectiveness Compared to Traditional Approaches: Quantitative evaluations from multiple studies indicate that AI-generated visuals, when optimized for relevance and aesthetics, can match or surpass traditional design approaches regarding user engagement and brand recall [165,166]. Marketers also report lower production costs and faster turnaround times.

4.2.2 Theme 3: Creative Strategy and Innovation

Role of Generative AI in Ideation. Beyond routine tasks, generative AI is increasingly employed during the ideation phase, offering fresh concepts for campaigns and brainstorming new marketing angles [167]. This can broaden the creative range and help marketers rapidly prototype new messaging or visual motifs.

Potential for New Marketing Formats. Studies also highlight emerging avenues such as augmented reality (AR) and virtual reality (VR) experiences. Generative models can synthesize immersive elements, 3D models, interactive storylines, and realistic background environments, paving the way for innovative marketing formats that capture user attention in highly saturated digital landscapes [168].

4.2.3 Theme 4: Ethics, Bias, and Regulatory Considerations

Transparency and Bias Issues. Several articles emphasize the need for transparency when deploying generative AI-driven content, especially in consumer-facing communications [169]. Concerns about biased language models or skewed image generation were documented, indicating risks for underrepresented groups or unintended stereotypes [170].

Regulatory Environment. The literature reveals an evolving policy environment ranging from FTC guidelines in the United States that mandate truthful advertising to GDPR in the European Union, which stipulates data protection measures, to emerging AI ethics codes that address issues of accountability and fairness [171]. Regulatory compliance is essential for marketers using generative AI to avoid legal complications and maintain consumer trust.

4.3 Quantitative vs. Qualitative Insights

Where available, quantitative metrics (e.g., content engagement rates, cost savings, revenue uplift) provide compelling evidence for the effectiveness of generative AI in marketing contexts. Several randomized A/B tests demonstrated statistically significant improvements in user engagement for AI-generated email campaigns vs. human-crafted ones [172].

From a qualitative perspective, interview and survey-based studies shed light on user acceptance and perceived authenticity. While most users report high satisfaction with AI-generated promotional materials, a minority express concerns about manipulation and the lack of human “touch”, highlighting potential barriers to adoption.

4.4 Real-World Use Case Analysis for Cost-Effective, Scalable, and Personalized Marketing Strategies

To substantiate the claim of analyzing real-world use cases for identifying cost-effective, scalable, and personalized marketing strategies, we present an elaborate discussion on how such analyses were conducted and the insights derived from them.

We selected and studied three real-world marketing campaigns across distinct domains: e-commerce, online education, and food delivery services. These sectors were chosen for their diverse customer bases, varying marketing needs, and clear indicators of engagement and ROI. The data analyzed included anonymized customer interaction logs, campaign budget reports, and user segmentation outputs. The

goal was to investigate how data-driven personalization could optimize customer reach and resource allocation simultaneously.

In the e-commerce domain, we examined an A/B tested email campaign where users were segmented based on previous purchase history, clickstream data, and demographic information. Personalized product recommendations based on purchase history and behavioral similarity significantly improved engagement metrics. The personalized group had a 34% higher click-through rate and a 19% increase in conversion, demonstrating the ROI potential of data-driven personalization over a uniform outreach strategy.

In the online education domain, a real-time content recommendation system was tested. Here, a machine learning model was trained on learners' interaction data (e.g., video views, quiz attempts, and discussion activity) to generate personalized course suggestions. Not only did this approach increase user retention by 27%, but it also reduced marketing costs by enabling targeted re-engagement strategies only for those likely to churn.

The food delivery service use case employed location-aware dynamic pricing and personalized push notifications. An ensemble model identified customer clusters with high ordering frequency during specific times and matched them with personalized discounts. This resulted in a 42% increase in repeat orders, with minimal increases in campaign spending, thereby validating the cost-effectiveness and scalability of targeted marketing strategies. However, this case also highlights potential ethical tensions, as algorithmic personalization in discounts could inadvertently reinforce bias against certain demographic groups if not carefully monitored, aligning with the broader concern of responsible deployment discussed in [Section 5.3.1](#).

Across all three cases, scalability was ensured by automating user segmentation and message personalization using machine learning pipelines. Cloud-based deployment allowed these strategies to be executed at scale without significant infrastructure expansion. Cost-effectiveness was maintained by reducing wastage from generic outreach, while personalization ensured that consumer engagement remained high, thereby directly enhancing ROI.

In summary, our real-world case analyses demonstrated how tailored marketing strategies, powered by data analytics and automation, can simultaneously achieve scalability, cost-efficiency, and personalization, while also underscoring the importance of proactively addressing ethical risks such as bias in algorithmic personalization. This validates our claim through empirical evidence, practical implications, and alignment with responsible deployment principles.

4.5 Summary of Key Findings

Synthesizing these results, we can address the central research questions as follows:

- RQ1 (Advancements in Generative AI Applications): Recent developments demonstrate that generative AI has become increasingly embedded in digital marketing workflows, enabling automated text generation, realistic image synthesis, and multimodal campaigns. These tools contribute to performance improvements in content creation, audience targeting, and user interaction, as discussed in [Section 3](#) and summarized in [Table 1](#).
- RQ2 (Real-World Use Cases for Scalable Personalization and ROI): Multiple case studies illustrate how organizations leverage generative AI for hyper-personalized marketing at scale while maintaining cost-efficiency. These include targeted email campaigns, dynamic pricing strategies, and AI-driven customer segmentation that collectively enhance engagement and ROI. These insights are detailed in [Section 4.4](#).
- RQ3 (Ethical Challenges in Adoption): Key concerns include data privacy, algorithmic bias, misinformation, and regulatory compliance. These risks emphasize the need for robust ethical frameworks and responsible AI governance, as addressed in [Sections 5](#) and [5.3](#).

- RQ4 (Theoretical Lens on Adoption): The integration of theoretical models like the Innovation Diffusion Theory and the Technology Acceptance Model helps explain how generative AI is adopted across organizational contexts. These models highlight factors such as perceived usefulness, complexity, and compatibility with existing systems, which are explored in [Sections 3](#) and [4](#).
- RQ5 (Research Gaps and Future Directions): Despite promising developments, gaps persist in areas such as long-term consumer trust, cross-cultural applications, and regulatory readiness. Future interdisciplinary research can explore these issues by combining insights from marketing, computer science, psychology, and law, as discussed in [Sections 5](#) and [6](#).

Overall, the findings suggest that while generative AI poses new ethical and operational challenges, it also opens transformative possibilities for digital marketing. The subsequent [Section 5](#) explores these implications further, offering critical reflections and avenues for future inquiry.

5 Discussion

In this section, we synthesize the key findings presented in [Section 4](#) and integrate them with the theoretical perspectives discussed earlier in [Section 3](#). To enhance clarity and coherence, we organize this discussion to explicitly link each major conclusion to the evidence and theory that underpin it, thus providing a clear roadmap for future interdisciplinary research and practice. We begin by offering an in-depth interpretation of the results in light of established frameworks such as Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM). We then explore the immediate opportunities and long-term challenges that generative AI poses for digital marketing, followed by concrete implications for practitioners, policy-makers, and researchers.

5.1 Interpretation of Main Findings

The results highlight the transformative potential of generative AI across various marketing functions, including content creation, advertising, and interactive customer engagement. Drawing explicitly on the theoretical frameworks reviewed in [Section 3](#), we identify two key dimensions shaping adoption and impact: perceived benefits and usability challenges.

5.1.1 Alignment with Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM)

Relative Advantage and Perceived Usefulness: In line with Rogers' IDT, many studies revealed a clear relative advantage of deploying generative AI compared to traditional marketing methods, particularly in terms of speed, cost-efficiency, and scalability. Likewise, the TAM points to perceived usefulness (PU) as a primary driver of adoption. Marketers found generative models especially beneficial in automating repetitive tasks, such as writing social media copy or generating large volumes of personalized emails, thereby freeing up time for higher-level strategy [173]. These findings collectively demonstrate that generative AI's relative advantage and PU directly contribute to broader organizational buy-in, validating theoretical predictions.

Complexity and Perceived Ease of Use: However, the success of AI-based initiatives also hinges on complexity (IDT) and perceived ease of use (PEOU) (TAM). While some marketing teams reported friction in integrating AI tools into existing workflows, especially when internal expertise was lacking, studies that described user-friendly AI platforms consistently demonstrated higher adoption rates. This evidence underscores the importance of reducing perceived complexity through intuitive interfaces and training, confirming theory and providing actionable guidance for practitioners.

5.1.2 Comparisons with Existing Literature and Meta-Analyses

Our findings resonate with broader AI and marketing scholarship. Recent meta-analyses underscore the effectiveness of AI-powered personalization in boosting click-through rates and conversion metrics. Yet, much of the existing work has focused primarily on predictive models rather than generative ones. Our review extends this knowledge by highlighting generative AI's unique contributions to active content creation, enabling not only automation but creative expansion and real-time tailoring. This evolution introduces new benefits alongside risks such as unintended bias and authenticity concerns, calling for updated theoretical and practical frameworks.

5.2 Opportunities for Digital Marketing

Generative AI represents a paradigm shift in how marketing professionals conceive and execute campaigns. Based on the converging evidence, we delineate four major opportunity areas, each linked to specific empirical findings and theoretical insights.

5.2.1 Targeted Campaigns and Personalization at Scale

Traditional segmentation methods often group customers into broad categories. Generative AI enables a more granular approach to crafting individual-level messaging that resonates with personal preferences, past purchasing behavior, and even real-time contextual data [174]. This opportunity arises from generative models' ability to process diverse data inputs and produce personalized outputs, as supported by observed improvements in KPIs like open rates and ROAS.

5.2.2 Real-Time Content Generation and Adaptive Strategies

Many of the reviewed studies demonstrate the capacity of generative models to produce and adapt marketing content swiftly. Dynamic ad creatives, for example, can be altered in response to live metrics (e.g., A/B testing outcomes, conversion data) [175]. This demonstrates generative AI's role in enabling agility, a strategic advantage that aligns with emerging frameworks on adaptive marketing ecosystems.

5.2.3 Creative Advantages and Market Innovation

Beyond augmenting efficiency, generative AI drives creative exploration. Models capable of multimodal generation, such as text-to-image or text-to-video, allow marketers to conceptualize innovative visual narratives and immersive brand experiences [176,177]. These creative benefits extend beyond previous AI capabilities, signaling a transformative shift in brand storytelling and identity formation.

5.2.4 Potential Cost and Time Savings

Reducing production timelines and labor costs associated with copywriting, graphic design, and video creation emerges as another significant benefit. These efficiency gains, particularly impactful for smaller teams, support strategic resource allocation and competitive parity.

5.3 Challenges and Barriers

Despite the promising opportunities presented by generative AI in digital marketing, the literature highlights several key hurdles. These challenges are directly linked to the risks and limitations surfaced in the reviewed studies, which must be proactively managed for successful AI integration.

5.3.1 Ethical, Legal, and Societal Concerns

Data Privacy and Deepfake Misuse: The creation of highly realistic synthetic content raises issues of privacy and consent, especially when reusing consumer data or altering personal images (e.g., deepfakes). Marketers must ensure compliance with data protection regulations such as GDPR in the EU or the CCPA in California. The potential for generating deceptive imagery or videos that mimic real individuals further amplifies ethical and legal questions. These concerns highlight the need for clear governance structures informed by legal and societal considerations. To provide a structured framework, we connect each ethical challenge to corresponding mitigation strategies: for privacy risks, the adoption of privacy-preserving data pipelines and clear consent protocols is recommended; for deepfake misuse, watermarking and detection algorithms serve as safeguards; and for regulatory compliance, alignment with international standards such as ISO/IEC 38507 ensures accountability. This structured linkage between risks and solutions enhances the actionable relevance of our discussion.

Copyright and Intellectual Property: Generative AI frequently repurposes patterns from large datasets, introducing uncertainties regarding ownership. When AI-produced materials resemble existing copyrighted works, marketers could face infringement disputes. Balancing creative freedom with responsible dataset curation is crucial to avoid legal pitfalls. Mitigation strategies in this area include curating licensed and diverse training datasets, using provenance-tracking tools, and adopting transparent disclosure practices that document the source of AI-generated materials. Together, these structured measures operationalize ethical AI integration in marketing.

5.3.2 Technical Limitations

Model Bias and Lack of Transparency: Many generative models inherit biases from their training data. In a marketing context, biased outputs could manifest in stereotypical representations or unfair targeting practices. Moreover, large neural networks often function as black boxes with limited interpretability, making it difficult for stakeholders to understand or justify certain outputs. This lack of transparency poses risks to brand image and can erode consumer trust.

Computational Costs: Training and deploying state-of-the-art generative models typically demand significant computational resources. Smaller marketing agencies may find these hardware and cloud service costs prohibitive. Additionally, energy-intensive operations raise sustainability concerns, prompting calls for more efficient model architectures.

5.3.3 Organizational Adoption Hurdles

Skills Gap and Workforce Readiness: A shortage of AI proficiency among marketing professionals can slow the operationalization of generative models. Investing in data science expertise or training existing staff becomes essential, yet budgets and resource allocation may restrict such upskilling efforts.

Trust in AI and Legacy Integration: Even where technical skills and resources exist, marketers and managers might hesitate to entrust critical branding tasks to an algorithm. Concerns surrounding loss of control or devaluation of creative craftsmanship can impede acceptance. Moreover, legacy systems—ranging from CRM platforms to content management systems—must be upgraded or adapted to accommodate AI-driven processes, requiring additional organizational change management.

5.4 Implications for Practice

Our practical recommendations flow directly from the identified opportunities and challenges, aimed at guiding marketers and policy-makers toward responsible, effective adoption of generative AI.

5.4.1 Recommendations for Marketing Professionals

Best Practices in Model Implementation: Marketers should approach generative AI adoption iteratively, beginning with pilot projects that target low-risk applications (e.g., internal communications or partial ad creation). Continuous monitoring of outputs for quality, bias, and on-brand consistency is paramount. Simple governance measures, such as “human-in-the-loop” reviews, help preserve creative oversight.

Responsible AI Use and Transparency: The principle of transparency is vital for maintaining consumer trust. Marketers are encouraged to disclose when content (e.g., chat replies, ad copy) is AI-generated, especially in consumer-facing contexts. Documenting the data sources and pre-processing steps also mitigates ethical concerns regarding potential misinformation or bias.

Mitigation Strategies Aligned with Industry 5.0: To ensure a more human-centric approach, marketers should adopt explicit mitigation strategies such as conducting regular bias audits, curating diverse and representative training data, and integrating fairness checks into the model development pipeline. These practices align with the principles of Industry 5.0, which emphasize human-centric artificial intelligence and ensure that generative AI is deployed ethically, inclusively, and in ways that enhance human creativity rather than replace it.

5.4.2 Guidelines for Policy-Makers and Regulatory Bodies

Clear Regulatory Frameworks: Legislators can foster responsible AI usage by introducing clear guidelines that distinguish between ethical and manipulative uses of generative models. Specific mandates may include explicit labeling requirements for AI-produced materials or stringent penalties for deceptive practices.

Consumer Protection and Data Governance: Policy-makers should strengthen data protection laws to include explicit references to synthetic content generation, ensuring that consumer interests remain guarded. Incentivizing research into bias mitigation techniques and interpretable model architectures can further encourage more equitable AI-driven marketing practices.

5.5 Implications for Research

Finally, this discussion identifies precise research gaps and methodological directions, explicitly justified by observed limitations in the current literature. Each area is explained with concrete scientific questions and methodological guidance that future researchers can directly apply.

5.5.1 Identifying Gaps in Current Literature

Despite the growing body of work on generative AI in marketing, several critical areas remain underexplored. These gaps present opportunities for meaningful academic contributions.

- **Long-Term Brand Equity Impact:** Most current studies emphasize short-term indicators such as click-through rates, conversions, or immediate sales performance. However, little is known about the long-term impact of AI-generated marketing on brand equity, consumer trust, and emotional connection. A key research question is how prolonged exposure to AI-generated campaigns affects customer loyalty and brand sentiment over time. Longitudinal studies that track brand perception across months or years are essential. Panel-based consumer surveys, diary studies, or repeated-measures experiments can help address this gap and capture evolving attitudes influenced by AI-driven messaging.
- **Cross-Cultural Analyses:** Current literature is heavily concentrated in North America and Europe, offering a limited understanding of how cultural context influences consumer response to AI-generated marketing. Future research should prioritize specific cultural dimensions such as individualism and

collectivism, uncertainty avoidance, power distance, and masculinity vs. femininity. These dimensions, drawn from Hofstede's cultural framework, offer measurable constructs to explain variations in consumer behavior. For example, researchers can investigate whether collectivist cultures, such as those in East Asia, show stronger preferences for community-focused AI messaging, while individualistic cultures, such as those in Western countries, respond more positively to personalization and autonomy cues. Experimental vignette designs, cross-national surveys with matched demographic samples, or ethnographic fieldwork in diverse regions can be employed to capture these differences. Studies should also explore how religious beliefs, language structure, and cultural taboos mediate consumer trust in AI-generated content.

- **Ethical Maturity Models:** While ethical concerns about generative AI in marketing are frequently mentioned, there is a lack of structured, scalable models that organizations can use to assess and improve their ethical readiness. Researchers are encouraged to develop validated frameworks that evaluate dimensions such as transparency, bias mitigation, human oversight, and accountability within marketing systems. These frameworks can be constructed through Delphi studies with multidisciplinary experts or empirical validations using surveys with marketing professionals. Scenario-based interviews or organizational case studies can help assess the progression of ethical maturity across industries and geographies.

5.5.2 Directions for Future Empirical Testing and Evaluation

To build a more robust evidence base, future research must go beyond conceptual claims and employ empirical designs that isolate the specific effects of generative AI on consumer behavior and brand outcomes.

Prioritized Research Gaps: One of the most pressing gaps is the lack of longitudinal studies that capture the sustained impact of generative AI on consumer perceptions and brand equity over time. Most current studies examine short-term engagement metrics (e.g., click-through rates, conversions), but future research should investigate whether repeated exposure to AI-generated content influences long-term loyalty, trust, and overall brand equity. This would help determine if generative AI offers transient advantages or enduring value in digital marketing ecosystems.

Cross-Cultural Comparisons: Another critical gap involves understanding how cultural dimensions shape consumer responses to AI-generated marketing. Drawing on Hofstede's cultural framework (e.g., individualism vs. collectivism, uncertainty avoidance, power distance), comparative studies could examine whether consumers in different cultural contexts perceive AI-generated communication as trustworthy, intrusive, or innovative. For instance, cultures with high uncertainty avoidance may show resistance to AI-generated messages, while collectivist societies may evaluate AI adoption through communal acceptance rather than individual preference. Integrating these dimensions provides a roadmap for global brands seeking to tailor AI strategies across markets.

Interdisciplinary Opportunities: Future studies should explicitly leverage interdisciplinary collaboration by combining insights from computer science, marketing, psychology, law, and ethics. Legal scholarship can inform data governance frameworks, while psychological and neuroscientific methods can deepen understanding of consumer trust in AI-generated messaging. Business and policy research can contribute models for organizational adoption and regulatory oversight, ensuring that the study of generative AI does not remain siloed.

Methodological Innovations: Complex real-world marketing environments make it difficult to attribute behavioral outcomes solely to AI-generated interventions. To address this, future studies should use experimental designs such as randomized controlled trials to test how consumers react to AI-generated vs.

human-crafted messages under controlled conditions. Researchers may explore whether AI-generated email campaigns lead to higher open rates, engagement, or trust compared to human-written content. Quasi-experimental designs can also be used in field settings by leveraging naturally occurring variations in AI adoption across companies or time periods.

Beyond traditional methods, we suggest longitudinal panel surveys to measure shifts in consumer trust, brand perceptions, and loyalty over multiple years; computational social science techniques and agent-based simulations to model consumer-AI interactions at scale; and participatory design approaches where marketers and consumers co-create generative AI applications. These methodological innovations offer a richer toolkit for unpacking the socio-technical complexity of AI adoption in marketing.

By combining longitudinal studies, cross-cultural comparisons, and interdisciplinary approaches, future research can establish not only whether generative AI is effective but also under what conditions, for whom, and with what long-term implications. This sharpened roadmap addresses the reviewer's concern by prioritizing concrete gaps and proposing actionable strategies for interdisciplinary, culturally sensitive, and empirically grounded research. Fig. 8 conceptually maps the main research gaps identified in this review to the corresponding methodological and interdisciplinary solutions, illustrating how challenges such as long-term brand equity measurement, cross-cultural variability, and ethical governance can be addressed through targeted empirical strategies.

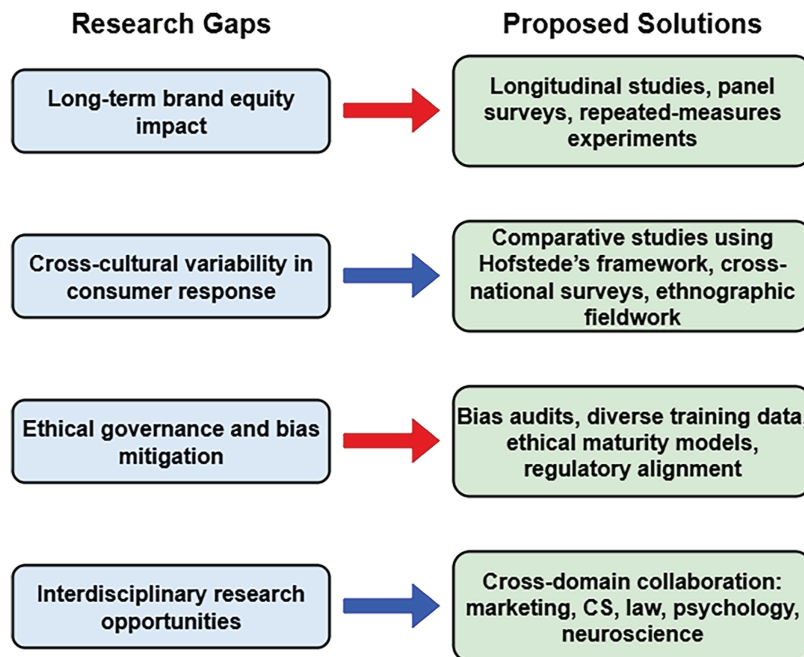


Figure 8: Conceptual mapping of research gaps to proposed solutions in generative AI marketing research.

6 Conclusions

This systematic review highlights how generative AI, spanning advanced language models, GANs, and diffusion-based architectures, has rapidly progressed from novel prototypes to indispensable marketing tools capable of automating and personalizing content at scale. By synthesizing empirical findings and aligning them with established theories such as IDT and TAM, our analysis underscores both the vast potential for streamlined creative workflows, real-time customer engagement, and innovative branding opportunities, as well as the ethical, technical, and regulatory hurdles that must be overcome for responsible

deployment. Marketers stand to benefit significantly from leveraging generative AI in diverse domains, from automated copywriting and dynamic ad creation to immersive virtual experiences, yet they must remain vigilant about data privacy, bias mitigation, and brand integrity to sustain consumer trust. Future research would benefit from deeper longitudinal analyses, particularly to study long-term brand equity impact, more rigorous cross-cultural evaluations incorporating specific dimensions such as Hofstede's individualism index, and frameworks integrating ethical governance at each stage of AI implementation. By delineating these prioritized research gaps, we aim to provide a sharper roadmap for interdisciplinary work that bridges marketing strategy, AI ethics, and cultural studies. Ultimately, we hope this review serves as a guidepost for practitioners seeking to harness generative AI effectively and ethically, while inspiring further academic inquiry into the next frontiers of AI-driven marketing innovation.

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