Transactions on Artificial Intelligence
https://www.sciltp.com/journals/tai

Review

Recent Advances in Artificial Intelligence for Management and Financial Technology

Renwei Yang [1,†], Yun Wang [1,†], Yongcan Luo [1,†], Zhengjie Yang [1,2,*], Zhimin Zong [3] and Dapeng Oliver Wu [1]

[1] Department of Computer Science, City University of Hong Kong, Hong Kong
[2] Hong Kong Generative AI Research and Development Center, The Hong Kong University of Science and Technology, Hong Kong
[3] Department of Electrical & Computer Engineering, University of Florida, Gainesville, FL 32611, USA
* Correspondence: zhengjie.yang@sydney.edu.au
† These authors contributed equally to this work.

How To Cite: Yang, R.; Wang, Y.; Luo, Y.; et al. Recent Advances in Artificial Intelligence for Management and Financial Technology. *Transactions on Artificial Intelligence* **2025**, *1*(1), 139–152. https://doi.org/10.53941/tai.2025.100009.

Received: 11 June 2025
Revised: 22 July 2025
Accepted: 28 July 2025
Published: 6 August 2025

Abstract: In this survey, we examine contemporary advancements in Artificial Intelligence (AI) applications for Financial Technology (FinTech), with a specific focus on three rapidly evolving domains: recommendation systems, risk analysis, and AI-generated commercial content (AIGC). For recommendation systems, self-supervised learning and graph neural network methodologies facilitate real-time, hyper-personalized financial product suggestions, optimizing the balance between conversion efficacy and regulatory adherence. For risk analysis, large language models, including GPT-4 and Llama 3, enhanced through sophisticated prompt engineering techniques, have significantly transformed credit assessment and stress testing processes for small and medium-sized enterprises, reducing analytical cycles from weeks to minutes. Concurrently, multimodal generative models, such as DALL-E 3, are revolutionizing advertising through the automated generation of compliant and engaging content across textual, visual, and video formats, markedly compressing production timelines. The survey further critically addresses persistent challenges, encompassing data privacy, algorithmic transparency, and cultural bias within AIGC, while delineating future research trajectories for developing trustworthy and scalable AI solutions in FinTech.

Keywords: Artificial Intelligence; Financial Technology; large language models

1. Introduction

Over the last decade, the fusion of Artificial Intelligence (AI) and Financial Technology (FinTech) has progressed from proof-of-concept prototypes to mission-critical production systems. Fueled by the unprecedented growth of digital data, inexpensive cloud computing, and breakthroughs in deep learning, AI now permeates almost every layer of the financial value chain from front-office customer engagement to back-office risk management and compliance.

Yet, despite enthusiastic adoption, the practical impact of AI is still uneven. Financial institutions grapple with highly regulated environments, severe class-imbalance problems, extreme tail risks, and rapidly shifting consumer preferences, all of which challenge the direct transplantation of generic AI techniques developed for other industries. Consequently, domain-specific innovation and rigorous evaluation remain essential. This survey aims to provide a concise, up-to-date overview of three rapidly evolving application areas that, in our view, have recently achieved the largest leap forward and the widest commercial uptake. Specifically, recent breakthroughs in representation learning, graph neural networks, and reinforcement learning are empowering AI-driven recommendation systems to deliver real-time, hyper-personalized product suggestions that boost conversion rates while meeting strict suitability and fairness regulations. Simultaneously, prompt-based large language models such as GPT-4 and Llama 3 (steered through meticulous prompt engineering) are revolutionizing risk analysis by automating credit assessment, scenario generation, stress testing, and early-warning detection, compressing analytic cycles from weeks to minutes; and, in parallel, multimodal generative models are ushering in an era of AI-generated commercial advertising capable of producing compliant, captivating marketing assets across text, image, and video formats, dramatically reducing production timelines and enabling rapid A/B experimentation for financial products.

Most existing surveys provide broad overviews of AI applications in FinTech, focusing on areas such as smart finance, risk, and customer adoption [1–5]. In contrast, our work offers a focused and up-to-date review of three emerging directions: self-supervised and graph-based recommendation systems, large language model-driven risk analysis, and AI-generated commercial content, with particular attention to their recent technical advances and practical challenges.

The remainder of this survey is organized as follows. Section 2 reviews recent advances in recommendation algorithms tailored for financial products and omni-channel marketing. Section 3 discusses how prompt engineering and large language models reshape contemporary risk analysis workflows for Small and Medium-sized Enterprises (SMEs). Section 4 surveys the emerging field of AI-generated commercial advertising, highlighting design patterns, governance considerations, and empirical performance. Finally, we conclude with open research challenges and future directions for trustworthy, scalable, and human-centric AI in FinTech.

2. AI in Recommendation Systems for Financial Marketing

With the advent of the digital age, marketing faces unprecedented opportunities and challenges. In the context of massive data and intense competition, how to accurately reach target customers and provide personalized service experiences has become the key to success for enterprises. The rapid development of AI technology offers a solution to this problem. Specifically, AI-driven personalized recommendation systems are revolutionizing the landscape of marketing, bringing significant competitive advantages to businesses. By analyzing user behavior, preferences, and historical data, AI generates personalized recommendations in real-time, enhancing user experience and conversion rates. Machine learning algorithms continuously optimize recommendation models to ensure their relevance and accuracy, enabling businesses to utilize resources more effectively and maximize profits. The importance of AI in personalized recommendations cannot be overlooked. In today's era of burgeoning deep learning, companies that embrace AI technology will stand out in the competition. In the following, we will explore AI-based personalized recommendation technology from four perspectives: working principles, advantages, application cases, and future prospects.

2.1. Related Works

Recommendation systems have become a vital tool for discovering users' interests, enhancing user experience, and driving revenue in various e-commerce platforms [6]. Modern recommendation systems, powered by advanced deep neural network architectures, have achieved remarkable success. For instance, Covington et al. [7] introduce deep neural networks for YouTube recommendations, Cheng et al. [8] propose the Wide & Deep Learning framework to balance recommendation precision and generalization, and Zhou et al. [9] develop the Deep Interest Network (DIN) for click-through rate prediction. Other innovations include the personalized and interpretable substitute recommendation model by Chen et al. [10] and the joint modeling of users' interests and mobility patterns in point-of-interest recommendations by Yin et al. [11].

Despite these innovations, deep recommendation models are inherently data-hungry and face challenges due to data sparsity, as most users interact with only a small subset of available items [12]. This sparsity issue significantly limits the performance of deep learning-based recommendation systems, as highlighted in the survey by Zhang et al. [13].

To address this challenge, Self-supervised Learning (SSL) [14] has emerged as a promising solution. Early works explored dimensionality reduction techniques using neural networks [15] and robust feature extraction through denoising autoencoders [16]. Several studies have investigated its transferability to downstream tasks [17], and the distinction between generative and contrastive approaches [18]. Wu et al. [19] propose collaborative denoising autoencoders, which use corrupted input data to reconstruct the original input, effectively preventing overfitting and setting the foundation for subsequent advancements in self-supervised recommendation techniques. Additionally, research has focused on large-scale SSL experiments [20], as well as unsupervised edge learning [21]. Other studies have revisited the role of data augmentation [22] and improved pre-training and self-training techniques [23]. More recent works address representation learning via invariant causal mechanisms [24] and feature decorrelation in SSL [25]. Liu et al. [18] discuss the potential of SSL in recommendation scenarios, emphasizing its ability to leverage unlabeled data for learning useful representations. Early prototypes of Self-supervised Recommendation (SSR) date back to unsupervised methods such as autoencoder-based models.

2.2. Working Principles of Personalized Recommendation Systems

Personalized recommendation systems rely on big data and machine learning algorithms to analyze user behavior data, preferences, and historical records, predicting user needs and providing tailored product and service recommendations. As shown in Figure 1, the primary working principles are as follows: (1) Data Collection: Collect user data through various channels (e.g., browsing history, purchase records, search keywords, etc.). (2) Data Preprocessing: Cleanse, normalize, and preprocess the collected data to ensure its quality and consistency. (3) Feature Extraction: Use feature engineering techniques to extract useful features for the recommendation system from the preprocessed data. (4) Model Training: Train the recommendation model using machine learning algorithms such as collaborative filtering, matrix factorization, and deep learning. (5) Recommendation Generation: Generate personalized recommendations in real-time based on the trained model and display them to the user.

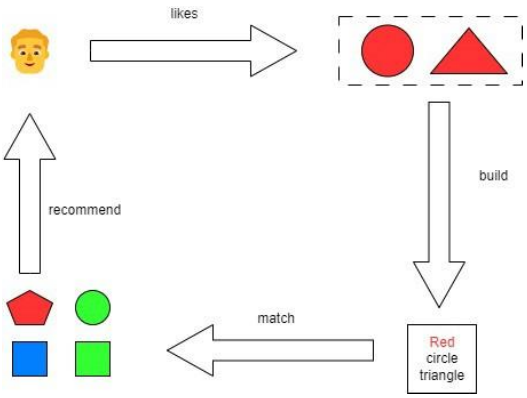


Figure 1. Workflow of AI recommendation system.

2.3. Regulatory, Trust, and Risk-Return Considerations

This section further discusses several core financial characteristics of financial AI recommendation systems, specifically focusing on regulatory restrictions, user trust mechanisms, and the balance between return and risk, as summarized in Table. 1.

Table 1. Comparison of literature on key financial AI recommendation system themes.

Theme	Representative Literature	Key Points	Summary of Approaches
Regulatory Restrictions	[26–29]	Emphasize compliance with regulations (client suitability, transparency, and data protection).	Algorithms are designed to match investor profiles, ensure explainability, and adhere to region-specific requirements.
User Trust Mechanisms	[30–34]	Focus on transparency, fairness, and explainability to build trust.	Adoption of explainable AI, fairness-aware models, and usercentered evaluation to increase user engagement and trust.
Return and Risk Balance	[30,35–38]	Aim to maximize returns while managing risk per investor preferences.	Use of Modern Portfolio Theory, mean-variance analysis, deep reinforcement learning, risk-aware optimization, and hybrid approaches for portfolio management.

Financial recommendation systems are subject to regulatory restrictions that shape their design and operation [26–29]. Regulations in various regions require systems to ensure client suitability, transparency, and robust data protection. These constraints necessitate that algorithms are designed to align recommendations with individual investor profiles while maintaining compliance.

User trust mechanisms are also essential for widespread adoption and sustained use [30–34]. Factors such as transparency, fairness, and the explainability of algorithms have a significant influence on user trust. The adoption of explainable AI techniques has been proposed to help users better understand system recommendations, thereby increasing trust and engagement.

In addition, achieving an appropriate balance between return and risk remains a fundamental financial objective [30,35–38]. Financial recommendation systems must consider both maximizing returns and managing risk according to investors' preferences. Classical approaches such as Modern Portfolio Theory are frequently employed, and recent research incorporates machine learning to further optimize portfolio allocation and risk control.

In summary, regulatory compliance, user trust, and the management of return and risk are all crucial factors in the development and evaluation of financial AI recommendation systems.

2.4. Advantages of AI-Powered Personalized Recommendation Systems

AI-powered personalized recommendation systems [9–14,17–25] play a crucial role in modern information technology, with advantages that stand out in several areas.

Precision is one of the major highlights of AI recommendation systems. By analyzing massive amounts of data, including users' historical behaviors, browsing records, search habits, and social network interactions, AI can deeply understand users' interests and needs. This granular analysis enables the recommendation system to provide highly relevant content, far surpassing traditional methods. Traditional recommendations often rely on simple rules or limited data, while AI can integrate complex, multi-dimensional information to deliver more accurate predictions and recommendations.

Real-time responsiveness is another significant feature of AI recommendation systems. These systems can instantly respond to changes in user behavior and update recommendations in real-time. For instance, when a user searches for or consumes new types of content on a platform, the AI system can quickly adjust its recommendation strategy to ensure the user always receives the most relevant and up-to-date suggestions. This dynamic adjustment capability not only enhances user experience but also strengthens the platform's competitiveness.

Scalability demonstrates great flexibility and adaptability in AI recommendation systems. As the scale of user data grows and algorithms continuously improve, system performance and recommendation quality can keep improving. Whether for small applications or large platforms, AI systems can operate efficiently and consistently provide high-quality recommendations. This scalability ensures that AI recommendation systems can adapt to various application scenarios, from e-commerce platforms to streaming services, maximizing their utility across different environments.

Enhanced user experience is the most direct advantage of AI recommendation systems. Through personalized recommendations, users can access content that better aligns with their interests and enjoy a smoother and more enjoyable experience. This personalized service significantly increases user satisfaction and loyalty, encouraging users to spend more time on the platform and improving user engagement and activity. This deep user involvement not only drives growth in the user base but also brings significant commercial value to the platform.

2.5. Application Cases of AI-Powered Personalized Recommendation Systems

Today, AI-powered personalized recommendation systems are widely used by many businesses. Below are examples from four fields: content platforms, social media, e-commerce platforms, and physical retail.

In social media, platforms like Facebook, Instagram, and Weibo utilize AI recommendation systems to deliver personalized content and advertisements, significantly improving user engagement and ad conversion rates. On e-commerce platforms such as Amazon and Alibaba, AI recommendation systems provide personalized product recommendations, enhancing purchase rates and average transaction values.

On content platforms like Netflix and YouTube, recommendation systems leverage AI technology to improve users' viewing experiences, particularly by using latent semantic models for personalized recommendations, as shown in Figure 2. The core of latent semantic models lies in their ability to capture the underlying relationships between users and content. First, the system analyzes a large amount of user behavior data and content features to generate labels for users and content. These labels may include users' viewing histories, preferences, and the types and themes of the content. Subsequently, the system can push content more accurately based on the labels.

Latent semantic model technology employs mathematical methods like matrix factorization to map users and content into an abstract "latent space". In this space, user and content features are represented as vectors. By calculating the similarity between these vectors, the system can predict content that users might find interesting. This method considers not only explicit features but also uncovers users' hidden preferences, making it widely applied in recommendation systems.

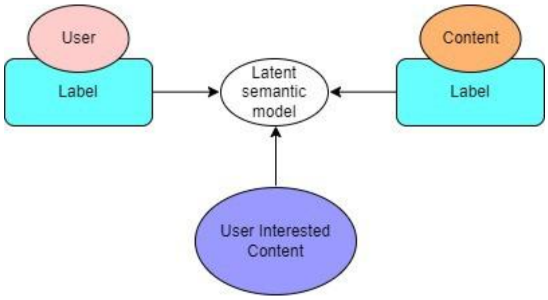


Figure 2. Latent semantic model in recommendation system.

In physical retail environments, AI recommendation systems have demonstrated significant utility. Nestle provides a clear example of this. They adopted an AI-driven order recommendation system that offers scientific product suggestions to sales personnel. This system showcases products that perform well in other retail stores and recommends complementary products to popular items, improving sales combinations. By analyzing purchasing patterns, similar buying behaviors, and sales history data, Nestle's system provides precise recommendations.

According to data, Nestle has successfully implemented this AI product recommendation system in over 100,000 retail stores, effectively improving consumers' shopping experiences [39]. In the first half of 2022, their sales revenue increased by 6%. In addition, this system has helped Nestle reduce costs and attract more customers through digital channels. Larissa Frias, Nestle's Director of Data Analytics, noted that these experiences provided valuable references for future collaborations and project implementations, offering confidence and motivation for the team. This successful case highlights the immense potential of AI in the retail industry and provides valuable insights for other businesses in their digital transformation and efforts to enhance user experiences.

2.6. Challenges and Future of AI-Powered Personalized Recommendation Systems

Currently, AI-powered personalized recommendation systems still face several challenges, such as data privacy, algorithm transparency, and the cold-start problem. Data privacy involves how to use user data reasonably while protecting their privacy to prevent leaks or misuse. Algorithm transparency requires systems to explain the rationale behind recommendations, enhancing user trust, such as by providing reasons to help users understand the recommendation logic. The cold-start problem refers to how to provide accurate recommendations for new users or new items when there is a lack of historical data, which requires additional methods to compensate for the data shortage.

Despite these challenges, the industry places great emphasis on the technology of AI-powered personalized recommendation systems due to their commercial value. For example, Tom Alison, Head of Facebook at Meta, mentioned in his article "The Future of Facebook" [40] (published 31 May 2024) that their R&D team has conducted multiple optimizations and upgrades to AI recommendation systems. He also noted that they are developing a large-scale AI recommendation model to support Meta's video services and provide more personalized and precise recommendation experiences. This project has been included in Meta's technology roadmap and is expected to be realized in the coming years. It is foreseeable that with the continuous development and deepening of AI technology, AI recommendation systems will become more mature and refined, providing users with more personalized and valuable experiences and showcasing even broader commercial prospects.

3. Prompt in Risk Analysis for Enterprises

In the modern business environment, Small and Medium-sized Enterprises (SMEs) face various risks, ranging from market fluctuations and operational challenges to changes in laws and regulations, all of which can significantly impact their survival and growth. Traditional risk management methods often rely on historical data and subjective judgment, which are not only time-consuming but also prone to bias. With the advancement of AI technologies, particularly the emergence of language models such as ChatGPT and Llama, businesses can perform risk analysis more efficiently. By designing precise prompts, these AI models can provide deep insights and support, optimizing risk management strategies for enterprises.

3.1. Background

Small and micro enterprises often face several key challenges in risk management. First, the uncertainty caused by market fluctuations significantly impacts their financial stability. Unlike larger companies, SMEs typically lack financial buffers and resources, making them more sensitive to market changes. Moreover, their vulnerability during economic downturns is more pronounced due to limited financing channels. The globalization of markets has also led to increased legal and compliance risks, as businesses must navigate constantly evolving legal and regulatory requirements, adding to their compliance burden. In supply chain management, high dependency on specific suppliers makes these enterprises highly susceptible to disruptions, which can severely affect their operations. Traditional risk management approaches of ten struggle to respond promptly to these issues. However, the introduction of AI technologies offers new solutions for these enterprises.

From a macroeconomic perspective, SMEs are subject to broader economic indicators such as interest rate volatility, inflation, and global economic cycles, all of which can impact consumer demand and financing availability. Conversely, from a microeconomic perspective, risks such as internal operational inefficiencies, cost mismanagement, or flawed pricing strategies often arise from firm-specific characteristics. AI-enabled prompt design can assist in identifying both types of risk: macro-level trends via large-scale news and financial reports, and micro-level insights through analysis of firm operations, supply chain data, or internal narratives.

The application of AI in risk management has significantly grown in recent years. AI can process vast amounts of data in real-time, automatically identifying potential risks and greatly reducing the time required for manual analysis. By employing machine learning techniques, AI models effectively predict market shifts and emerging risks, enabling proactive decision-making within businesses. Moreover, AI-driven tools offer optimized decision support based on analytical outcomes, significantly improving the timeliness and accuracy of enterprise risk responses.

3.2. Related Works

Recent advances in Natural Language Processing (NLP) have made Large Language Models (LLMs) indispensable for financial analysis. Their capacity to parse intricate financial disclosures, fuse heterogeneous data sources, forecast market dynamics, and gauge investor sentiment now underpins many state-of-the-art prediction systems. For instance, Co-CPC [41] explicitly couples macro- and micro-economic factors to mitigate the uncertainty inherent in equity price movements. Complementary lines of work exploit unstructured text from news outlets [42,43] and Twitter streams [44–46] to distill sentiment signals that anticipate future returns. CapTE [47] advances this idea by pairing a transformer encoder (which captures deep semantic cues in social media) with a capsule network for direction-of-movement classification. Beyond prediction, Wang et al. [48] demonstrate how pre-trained LLMs automate the drafting of corporate financial reports, while Niu et al. [49] fuse knowledge-graph reasoning with LLM outputs to forecast volatility. Purpose-built domain models such as FinBert [50] and PIXIU [51], trained on large-scale sector-specific corpora, consistently achieve superior price-direction accuracy, making forecasting performance a benchmark for financial NLP.

Explainable AI (XAI) has also emerged as a critical component of AI-driven financial risk analysis, especially in regulated domains. For instance, Bussmann et al. [52] demonstrate the use of interpretable machine learning models in fintech risk management scenarios, such as loan default prediction and fraud detection. Their findings support the integration of transparency-focused design into AI systems used for financial decision-making.

Parallel research emphasises qualitative insight extraction from narrative data including earnings-call transcripts, real-time news, and community forums to infer market mood and anticipate price shifts. Wang et al. [53] show that sentiment signals mined from Wall Street message boards improve return predictions. Ding et al. [54] apply Open Information Extraction to transform vast web text into structured event records that drive an event-centric prediction model, and later encode these events as knowledge-graph vectors to embed market context [55]. Nguyen et al. [56] jointly model latent topics and their polarities via an LDA-inspired framework, while Ang et al. [57] integrate multi-modal cues and evolving inter-firm relations through attention mechanisms. Collectively, these studies highlight that richer qualitative signals (when systematically structured) complement numerical indicators and enhance the robustness of stock-trend forecasting.

Several studies have enhanced language models' capabilities for financial data analysis and stock prediction by employing specialized prompts and Chain of Thought (CoT) techniques. Yu et al. [58] leverage GPT-4 to effectively summarize weekly and monthly financial market news, construct detailed company profiles for enhanced knowledge representation, and generate explainable predictions. Similarly, Xie et al. [59] evaluate ChatGPT's zero-shot performance in multimodal stock price forecasting, underscoring the necessity for specialized training or fine-tuning to overcome prediction challenges. Jiang et al. [60] note that despite the inherent potential of powerful language models such as ChatGPT in financial analysis, their direct application through simple prompts or CoT methods still trails traditional forecasting approaches. This finding emphasizes the importance of carefully crafted prompts for successful financial prediction tasks.

3.3. Prompt Example

Assume a small or medium-sized manufacturing company is facing financial risks, particularly during times of economic instability. The company wants to leverage AI technology to analyze and predict future cash flow risks in order to ensure financial stability. The company primarily relies on multiple suppliers for raw materials and also faces issues such as delayed customer payments. The financial risks for the company are mainly derived from three aspects: raw material price fluctuations leading to increased costs, cash flow issues caused by customer payment delays, and sales risks due to market demand changes. The company seeks to use AI's predictive analysis capabilities to better manage these risks.

To effectively utilize AI models for financial risk forecasting, we need to guide the model step by step, focusing on specific risk areas. Using the Chain of Thought (CoT) method, complex financial risk issues can be broken down into smaller, more manageable problems, gradually guiding the AI to perform in-depth analysis and reasoning. Here's an example of a Chain of Thought analysis:

1. Initial Prompt Design: "Analyze the impact of current economic uncertainty on the financial situation of a manufacturing company, including risks from raw material price fluctuations, customer payment delays, and market demand changes."
2. Refined Prompt to Focus on Specific Issues: "Assume that raw material prices may rise by 10% over the next six months. How much will the company's procurement costs increase, and what procurement strategies can be adopted to mitigate this impact?"

AI Analysis Example Output: "If raw material prices increase by 10% procurement costs could rise by $100,000. The company can address this by negotiating price locks with suppliers, increasing the proportion of local suppliers, and stocking up in advance."

3. Further Analysis of Cash Flow Risks Due to Customer Payment Delays: "Under future economic uncertainty, assume the payment cycle for major clients is extended by 30 days. What impact will this have on the company's cash flow? What strategies can be employed to mitigate this cash flow risk?"

AI Analysis Example Output: "An extension of the customer payment cycle by 30 days may lead to a cash flow shortfall of $50,000. The company could consider strategies such as installment payment plans, implementing accounts receivable insurance, or offering early payment discounts."

4. Comprehensive Analysis of Sales Risks from Market Demand Changes: "Considering potential changes in market demand, forecast the impact of sales fluctuations over the next six months on cash flow and profits. How should the company adjust its product mix and pricing strategy to adapt to these changes?"

AI Analysis Example Output: "Based on current market data, sales are predicted to decrease by 15% over the next six months, resulting in a $150,000 revenue loss. The company can mitigate this by adjusting its product mix to meet new market demand, optimizing its pricing strategy, and launching promotional campaigns".

4. AI in Commercial Advertising

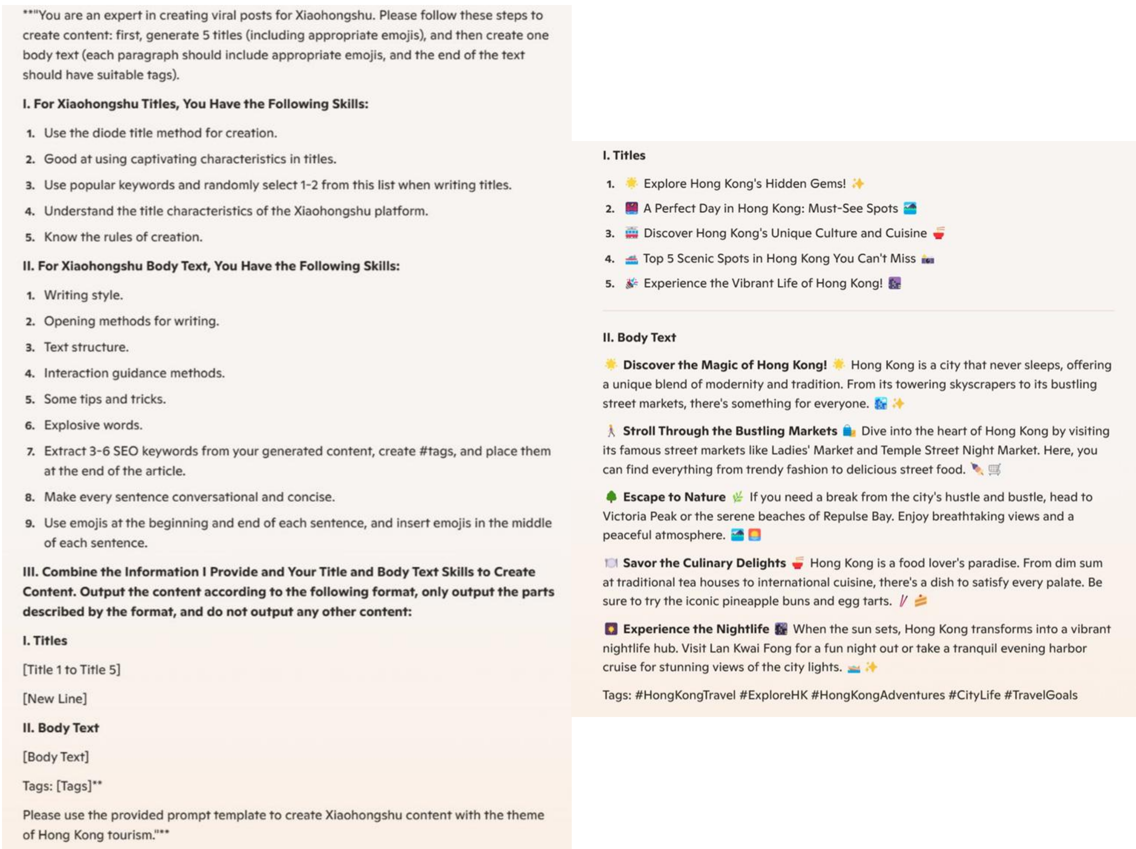
As technology rapidly advances, the application of Artificial Intelligence Generated Content (AIGC) [61] in advertising is becoming increasingly widespread. AIGC uses AI technology to automatically create text, images, and videos, offering limitless possibilities for companies' advertising efforts and setting a new trend in marketing. Moreover, tools like ControlNet [62–66] and other advanced control methods now allow for fine-grained manipulation of generated images, enabling advertisers to specify structural or semantic constraints directly in the generation process. These techniques greatly enhance creative flexibility and regulatory compliance, ensuring that visual content aligns with brand guidelines and cultural sensitivities. Advertising, a highly creative and visually-driven industry, is gradually adopting AIGC technology to enhance efficiency and precision. This article explores the innovative applications of AIGC in advertising through examples of AI models like ChatGPT [67] and DALL-E 3 [68] generating ad texts, images, and videos. Practice has shown that AIGC not only significantly improves the efficiency of ad production but also greatly enhances the accuracy and effectiveness of advertising [69–72]. With these technologies, advertisers can more precisely reach their target audience, boosting the appeal and impact of their ads, bringing transformative change to the industry.

4.1. Background

AIGC refers to content generated using Generative AI (GAI) technology, rather than being created by human authors [73]. It can automatically create large volumes of content in a short period. For example, ChatGPT, developed by OpenAI, is a language model designed for building conversational AI systems that can effectively understand and respond meaningfully to human language input. Similarly, Diffusion Models such as DALL-E 3 and Stable Diffusion excel at synthesizing unique, high-quality images from textual descriptions [68,74–76]. These models can be further enhanced by frameworks like ControlNet [62], which allow for explicit control over image attributes such as pose, structure, or layout during generation, making them highly suitable for customized advertising campaigns and brand-specific requirements. As AIGC technology progresses, more experts believe it will set new benchmarks in AI, with a profound impact on sectors from advertising to content creation, revolutionizing the way we interact with information and media and ushering in a new era of efficiency, precision, and innovation.

4.2. Application of AIGC in Advertising Copywriting

Social media platforms like Facebook and Xiaohongshu have become an indispensable part of daily life. AIGC can automatically generate personalized ad copy based on users' profiles and interests. For instance, on Xiaohongshu, ChatGPT can use human-provided ad templates to create high-quality, customized advertising content. A question and answer example is illustrated in Figure 3.



(**a**) (**b**)

Figure 3. A question example (**a**) and an answer example (**b**) generated by ChatGPT.

4.3. Application of AIGC in Advertising Images

DALL-E 3, developed by OpenAI, is an AI image generation model that uses a diffusion model architecture and techniques like language-image contrastive learning to create images from text descriptions. Using the DALL-E 3 model, advertisers can input product descriptions, target audience information, and ad style preferences to generate high-quality advertising images quickly. For example, as shown in Figure 4, if a restaurant owner wants to advertise a delicious steak, they just need to enter the food name and other details into the model. This allows them to generate a series of attractive restaurant food advertisements at a low cost. This approach not only saves production costs but also precisely targets the market, enhancing the appeal and effectiveness of the advertisements.

Figure 4. Schematic diagram of a steak generated by the DALL-E 3 model.

4.4. Current Solutions to Copyright and Cultural Misuse in AIGC

Recent years have witnessed a rapid surge in both research and practical initiatives aimed at mitigating copyright infringement and cultural misappropriation in AIGC.

Data Governance and Copyright Protection. To address these challenges, leading AIGC platforms are adopting increasingly robust data governance frameworks. These efforts [77,78] include the deployment of watermarking technologies, provenance-tracking systems, and advanced copyright detection tools designed to safeguard against the unauthorized use of protected works. Furthermore, model developers are placing greater emphasis on curating training datasets to exclude copyrighted or culturally sensitive materials, unless explicit rights and permissions have been obtained. This proactive approach not only helps prevent infringement but also supports the responsible and ethical deployment of generative models.

Cultural Sensitivity Filters. In tandem with data governance improvements, state-of-the-art generative models are integrating sophisticated cultural sensitivity filters and auditing mechanisms [79–81]. These systems are engineered to detect and flag potentially insensitive or appropriative content before it reaches the public. The adoption of human-in-the-loop review processes, particularly in commercial advertising workflows, further reinforces cultural respect and helps ensure that AI-generated content honors traditional elements without distortion or misrepresentation. By embedding these safeguards into both the development and deployment stages, organizations are working to minimize the risk of cultural misuse. Besides, both academia and industry are actively pursuing technical and policy-oriented strategies to strengthen the regulatory landscape of AIGC.

Explainable and Auditable AI. There is a growing emphasis on the development of explainable AI (XAI) [82–85] and content auditing tools, which facilitate transparency and accountability. These technologies enable stakeholders to trace how specific pieces of content are generated and to assess whether they comply with copyright and cultural standards. In addition, innovative approaches such as embedding provenance metadata and leveraging blockchain for immutable copyright records are being explored to reinforce trust and traceability in AIGC.

Bias and Misuse Detection. Considerable attention is also being given to the creation of automated methods for detecting and mitigating both bias and misuse, including copyright violations and cultural appropriation [86–88]. This research spans interventions at both the dataset level—such as advanced filtering and rebalancing strategies—and at the output level, where real-time content moderation can help prevent the dissemination of problematic content.

Ethical Frameworks. Finally, interdisciplinary collaborations are yielding new ethical frameworks that merge legal, ethical, and technical considerations [89]. These comprehensive frameworks are designed to ensure that innovation in generative AI proceeds in tandem with responsible content creation, particularly in commercial contexts where the impact of misuse can be significant. The overarching goal is to strike a balance between technological advancement and the protection of intellectual property and cultural heritage.

4.5. Future Prospects and Challenges

Recently, in an interview, ZeroOne Data Science CEO Feng Jian mentioned that designer teams are the first to benefit from AIGC software. After introducing AIGC, the workload that previously required at least five designers a week to complete can now be finished in two to three days. Furthermore, AIGC can create virtual hosts or presenters for advertising in the near future, providing immersive experiences and increasing user interaction. AI-automated content generation drastically reduces the technical time required for ad creation. AIGC can also quickly optimize and adjust ad content based on creator feedback. By using AIGC for ad creation, not only is time saved, but ad creators can focus on creative ideas and content exploration, producing more impactful and influential ads. However, despite the immense potential and advantages of AIGC, its output heavily depends on human-provided data resources, which can lead to training defects and copyright infringement risks [86]. AI may fabricate information when dealing with complex issues, leading to the misuse of cultural elements, damaging the essence of ads, and harming the brand image. Additionally, AI has a probability of generating seemingly reasonable but incorrect answers when handling complex, ambiguous, or open-ended questions. When ad creators use AI to handle related creative content, if they fail to detect errors in cultural element stitching, misinterpretation of cultural customs, or inappropriate handling of sensitive culture, it could lead to the misuse of traditional elements due to the limitations of AIGC [90]. Such misuse could not only destroy the cultural essence of the ad but also cause irreparable damage to the brand image. In conclusion, with the continuous development of AIGC technology, its application in advertising shows tremendous potential and advantages. Although there are data dependency and potential copyright issues, by exploring more reasonable usage methods and establishing appropriate regulatory mechanisms [91], AIGC is expected to further drive breakthroughs and transformations in ad production on the existing foundation, continually optimizing its application effects.

5. Conclusions

The emerging utilization of AI in FinTech has progressed beyond experimental prototypes to become indispensable across the financial value chain. Recommendation systems, under-pinned by SSL to mitigate data sparsity, have emerged as pivotal instruments for enhancing personalized marketing and recommendation accuracy. LLMs, leveraged through advanced prompt engineering, have facilitated accessibility to sophisticated risk analysis for SMEs, enabling accelerated and more transparent financial decision-making. Similarly, AIGC has transformed advertising workflows, offering cost-efficient and scalable content generation, albeit concurrently highlighting significant governance and ethical considerations.

Nevertheless, critical challenges necessitate resolution to ensure the sustainable advancement of AI in FinTech. Robust frameworks are imperative to reconcile data privacy imperatives with innovation requirements. Algorithmic transparency and interpretability remain paramount for fostering trust in AI-driven decisions, particularly within regulated financial contexts. Regarding AIGC, issues pertaining to copyright infringement, cultural misappropriation, and content authenticity demand systematic governance structures and technical safeguards.

Future research and development should prioritize human-centric, scalable solutions in ethical principles and regulatory compliance. Key directions include enhancing the crossdomain transferability of SSL models, improving the contextual reasoning capabilities of LLMs in complex risk scenarios, and developing generative models intrinsically aligned with diverse cultural and legal frameworks. Through interdisciplinary collaboration and the adoption of rigorous evaluation standards, the FinTech sector can realize the potential of AI to foster inclusive, efficient, and trustworthy financial services.

Author Contributions

R.Y.: Conceptualization, investigation, writing, and revision. Y.W.: Conceptualization, investigation, writing, and revision. Y.L.: Conceptualization, investigation, writing, and revision. Z.Y.: Conceptualization, investigation, writing, and revision. Z.Z.: Conceptualization, investigation, writing, and revision. D.W.: Conceptualization, investigation, writing, and revision. All authors have read and agreed to the published version of the manuscript.

Funding

This work is supported in part by the InnoHK Initiative, in part by the Government of the HKSAR, and in part by the Laboratory for AI-Powered Financial Technologies.

Conflicts of Interest

The authors declare no conflict of interest. Given the role as Editor-in-Chief, Dapeng Oliver Wu had no involvement in the peer review of this paper and had no access to information regarding its peer-review process. Full responsibility for the editorial process of this paper was delegated to another editor of the journal.

References

1. Cao, L.; Yang, Q.; Yu, P.S. Data science and ai in fintech: An overview. *Int. J. Data Sci. Anal.* **2021**, *12*, 81–99.
2. Ashta, A.; Herrmann, H. Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance. *Strateg. Chang.* **2021**, *30*, 211–222.
3. Cao, L.; Yuan, G.; Leung, T.; et al. Special issue on ai and fintech: The challenge ahead. *IEEE Intell. Syst.* **2020**, *35*, 3–6.

4. Belanche, D.; Casalo, L.V.; Flavia, C. Artificial intelligence in fintech: Understanding robo-advisors adoption among customers. *Ind. Manag. Data Syst.* **2019**, *119*, 1411–1430.
5. Kamuangu, P.K. Advancements of ai and machine learning in fintech industry (2016–2020). *J. Econ. Financ. Account. Stud.* **2024**, *6*, 23–31.
6. Ricci, F.; Rokach, L.; Shapira, B. Introduction to recommender systems handbook. In *Recommender Systems Handbook*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 1–35.
7. Covington, P.; Adams, J.; Sargin, E. Deep neural networks for youtube recommendations. In Proceedings of the 10th ACM Conference on Recommender Systems, Boston, MA, USA, 15–19 September 2016; pp. 191–198.
8. Cheng, H.-T.; Koc, L.; Harmsen, J.; et al. Wide & deep learning for recommender systems. In Proceedings of the 1st Workshop on Deep Learning for Recommender Systems, Boston, MA, USA, 15 September 2016; pp. 7–10.
9. Zhou, G.; Zhu, X.; Song, C.; et al. Deep interest network for click-through rate prediction. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, London UK, 19–23 August 2018; pp. 1059–1068.
10. Chen, T.; Yin, H.; Ye, G.; et al. Try this instead: Personalized and interpretable substitute recommendation. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval, Virtual, 25–30 July 2020; pp. 891–900.
11. Yin, H.; Cui, B.; Huang, Z.; et al. Joint modeling of users' interests and mobility patterns for point-of-interest recommendation. In Proceedings of the 23rd ACM International Conference on Multimedia, Brisbane, Australia, 26–30 October 2015; pp. 819–822.
12. Sarwar, B.M. Sparsity, Scalability and Distribution in Recommender Systems. Ph.D. Dissertation, University of Minnesota, Minneapolis, MN, USA, 2001.
13. Zhang, S.; Yao, L.; Sun, A.; et al. Deep learning-based recommender system: A survey and new perspectives. *ACM Comput. Surv.* **2019**, *52*, 1–38.
14. Yu, J.; Yin, H.; Xia, X.; et al. Self-supervised learning for recommender systems: A survey. *IEEE Trans. Knowl. Data Eng.* **2023**, *36*, 335–355.
15. Hinton, G.E.; Salakhutdinov, R.R. Reducing the dimensionality of data with neural networks. *Science* **2006**, *313*, 504–507.
16. Vincent, Y.B.P.; Larochelle, H.; Manzagol, P.-A. Extracting and composing robust features with denoising autoencoders. In Proceedings of the International Conference on Machine Learning, Helsinki, Finland, 5–9 July 2008; pp. 1096–1103.
17. Ericsson, H.G.L.; Hospedales, T.M. How well do selfsupervised models transfer? In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Nashville, TN, USA, 20–25 June 2021; pp. 5414–5423.
18. Liu, X.; Zhang, F.; Hou, Z.; et al. Self-supervised learning: Generative or contrastive. *IEEE Trans. Knowl. Data Eng.* **2023**, *35*, 857–876.
19. Wu, Y.; DuBois, C.; Zheng, A.X.; et al. Collaborative denoising auto-encoders for top-n recommender systems. In Proceedings of the Ninth ACM International Conference on Web Search and Data Mining, San Francisco, CA, USA, 22–25 February 2016; pp. 153–162.
20. Pinto, L.; Gupta, A. Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours. In Proceedings of the IEEE International Conference on Robotics and Automation, Stockholm, Sweden, 16–21 May 2016; pp. 3406–3413.
21. Li, J.M.R.Y.; Paluri, M.; Dolla, P. Unsupervised learning of edges. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 1619–1627.
22. Lee, S.J.H.H.; Shin, J. Rethinking data augmentation: Selfsupervision and self-distillation. *arXiv* **2019**, arXiv:1910.05872.
23. Zoph, B.; Ghiasi, G.; Lin, T.Y.; et al. Rethinking pre-training and self-training. In Proceedings of the International Conference on Neural Information Processing Systems, Vancouver, BC, Canada, 6–12 December 2020; pp. 3833–3845.
24. Mitrovic, J.; McWilliams, B.; Walker, L.B.J.; et al. Representation learning via invariant causal mechanisms. In Proceedings of the International Conference on Learning Representations, Virtual, 3–7 May 2021; pp. 1–19.
25. Hua, T.; Wang, W.; Xue, Z.; et al. On feature decorrelation in self-supervised learning. In Proceedings of the IEEE International Conference on Computer Vision, Montreal, BC, Canada, 11–17 October 2021; pp. 9598–9608.
26. Alam, M.A.; Mahatab, G.; Sarna, S.A. Enhancing regulatory frameworks to prevent financial crises. *Am. J. Econ. Bus. Manag.* **2025**, *8*, 1351–1359.
27. Horobets, N.; Reznik, O.; Maliyk, V.; et al. Artificial intelligence technologies in banking: Challenges and opportunities for anti-money laundering in the context of eu regulatory initiatives. *J. Money Laund. Control.* **2025**, *28*, 210–225.
28. Penikas, H. Review of bank of russia-nes workshop: Identification and measurement of macroprudential policies effects. *Russ. J. Money Financ.* **2021**, *80*, 94–104.
29. Uch, R.; Miyamoto, H.; Kakinaka, M. Effects of a banking crisis on credit growth in developing countries. *Financ. Res. Lett.* **2021**, *43*, 102004.
30. Li, Y.-M.; Lin, L.-F.; Hsieh, C.-Y.; et al. A social investing approach for portfolio recommendation. *Inf. Manag.* **2021**, *58*, 103536.

31. Song, Y.; Sun, C.; Peng, Y.; et al. Research on multidimensional trust evaluation mechanism of fintech based on blockchain. *IEEE Access* **2022**, *10*, 57025–57036.
32. Cheng, X.; Guo, F.; Chen, J. et al. Exploring the trust influencing mechanism of robo-advisor service: A mixed-method approach. *Sustainability* **2022**, *14*, 5284.
33. Ru, A.; Berger, B.; Hess, T. The ambivalent effect of transparency on trust in robo-advisors: An experimental investigation. In Proceedings of the 24th Pacific Asia Conference on Information Systems (PACIS 2021), Virtual, 12–14 July 2021.
34. Li, T.; Song, J. Deep learning-powered financial product recommendation system in banks: Integration of transformer and transfer learning. *J. Organ. End User Comput.* **2024**, *36*, 1–29.
35. Zhang, L.; Wu, X.; Zhao, H.; et al. Personalized recommendation in P2P lending based on risk-return management: A multi-objective perspective. *IEEE Trans. Big Data* **2022**, *8*, 1141–1154.
36. Soleymani, F.; Paquet, E. Deep graph convolutional reinforcement learning for financial portfolio management—DeepPocket. *Expert Syst. Appl.* **2021**, *185*, 115127.
37. Wu, L.; Zhang, J. Continuous control with stacked deep dynamic recurrent reinforcement learning for portfolio optimization. *Expert Syst. Appl.* **2021**, *165*, 113891.
38. Yu, C.; Liu, Y. A personalized mean-CVaR portfolio optimization model for individual investment. *Math. Probl. Eng.* **2021**, *2021*, 8863597.
39. Club, E. O Recomendador de Produtos Que Sabe Exatamente Como o Pequeno Varejo Pode Vender Mais. September 2022. Available online: https://ciandt.com/br/pt-br/in-the-news/recomendador-de-produtos-que-sabe-exatamente-como-o-pequeno-varejo-pode-vender-mais (accessed on 22 April 2025).
40. Alison, T. The Future of Facebook. May 2024. Available online: https://about.fb.com/news/2024/05/the-future-of-facebook/ (accessed on 22 April 2025).
41. Wang, G.; Cao, L.; Zhao, H.; et al. Coupling macro-sector-micro financial indicators for learning stock representations with less uncertainty. In Proceedings of the AAAI Conference on Artificial Intelligence, Virtual, 2–9 February 2021; pp. 4418–4426.
42. Du, X.; Tanaka-Ishii, K. Stock embeddings acquired from news articles and price history, and an application to portfolio optimization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Virtual, 5–10 July 2020; pp. 3353–3363.
43. Liu, Q.; Cheng, X.; Su, S.; et al. Hierarchical complementary attention network for predicting stock price movements with news. In Proceedings of the 27th International Conference on Information and Knowledge Management, Turin, Italy, 22–26 October 2018; pp. 1603–1606.
44. Hu, Z.; Lu, W.; Bian, J.; et al. Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining, Los Angeles, CA, USA, 5–9 February 2018; pp. 261–269.
45. Si, J.; Mukherjee, A.; Liu, B.; et al. Exploiting topic based twitter sentiment for stock prediction. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, Sofia, Bulgaria, 4–9 August 2013; pp. 24–29.
46. Luo, Y.; Zheng, J.; Yang, Z.; et al. Pleno-alignment framework for stock trend prediction. *IEEE Trans. Neural Netw. Learn. Syst.* 2025, *early access*.
47. Liu, J.; Lin, H.; Liu, X.; et al. Transformer-based capsule network for stock movement prediction. In Proceedings of the First Workshop on Financial Technology and Natural Language Processing, Macao, China, 10–12 August 2019; pp. 66–73.
48. Wang, Z.; Zhang, X.; Du, H. Mutual information guided financial report generation with domain adaption. *IEEE Trans. Emerg. Top. Comput. Intell.* **2024**, *8*, 627–640.
49. Niu, H.; Xiong, Y.; Wang, X.; et al. KeFVP: Knowledge-enhanced financial volatility prediction. *Find. Assoc. Comput. Linguist.* **2023**, *2023*, 11499–11513.
50. Yi, Y.; Uy, M.C.S.; Huang, A. Finbert: A pretrained language model for financial communications. *arXiv* **2020**, arXiv:2006.08097.
51. Xie, Q.; Han, W.H.; Zhang, X.; et al. Pixiu: A comprehensive benchmark, instruction dataset and large language model for finance. *Adv. Neural Inf. Process. Syst.* **2023**, *36*, 33469–33484.
52. Bussmann, N.; Giudici, P.; Marinelli, D.; et al. Explainable ai in fintech risk management. *Front. Artif. Intell.* **2020**, *3*, 26.
53. Wang, C.; Luo, B. Predicting $GME stock price movement using sentiment from Reddit r/wallstreetbets. In Proceedings of the Third Workshop on Financial Technology and Natural Language Processing, Online, 19 August 2021; pp. 22–30.
54. Ding, X.; Zhang, Y.; Liu, T.; et al. Using structured events to predict stock price movement: An empirical investigation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, Doha, Qatar, 25–29 October 2014; pp. 1415–1425.
55. Ding, X.; Zhang, Y.; Liu, T.; et al. Knowledge-driven event embedding for stock prediction. In Proceedings of Coling 2016, the 26th International Conference on Computational Linguistics, Osaka, Japan, 11–16 December 2016; pp. 2133–2142.

56. Nguyen, T.H.; Shirai, K. Topic modeling based sentiment analysis on social media for stock market prediction. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, Beijing, China, 26–31 July 2015; pp. 1354–1364.
57. Ang, G.; Lim, E.-P. Guided attention multimodal multitask financial forecasting with inter-company relationships and global and local news. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics, Dublin, Ireland, 22–27 May 2022; pp. 6313–6326.
58. Yu, X.; Chen, Z.; Ling, Y.; et al. Temporal data meets llm—explainable financial time series forecasting. *arXiv* **2023**, arXiv:2306.11025.
59. Xie, Q.; Han, W.; Lai, Y.; et al. The wall street neophyte: A zero-shot analysis of chatgpt over multimodal stock movement prediction challenges. *arXiv* **2023**, arXiv:2304.05351.
60. Jiang, Y.; Pan, Z.; Zhang, X.; et al. Empowering time series analysis with large language models: A survey. *arXiv* **2024**, arXiv:2402.0318.
61. Cao, Y.; Li, S.; Liu, Y.; et al. A comprehensive survey of aigenerated content (aigc): A history of generative ai from gan to chatgpt. *arXiv* **2023**, arXiv:2303.04226.
62. Zhang, L.; Rao, A.; Agrawala, M. Adding conditional control to text-to-image diffusion models. In Proceedings of the IEEE/CVF International Conference on Computer Vision, Paris, France, 2–6 October 2023.
63. Li, M.; Yang, T.; Kuang, H.; et al. Controlnet++: Improving conditional controls with efficient consistency feedback. In *Computer Vision—ECCV 2024*; Springer: Cham, Switzerland, 2024; pp. 129–147.
64. Zhang, Z.; Zhang, Q.; Li, G.; et al. Dyartbank: Diverse artistic style transfer via pre-trained stable diffusion and dynamic style prompt artbank. *Knowl. Based Syst.* **2025**, *310*, 112959.
65. Zhang, Z.; Li, Y.; Xia, R.; et al. Lgast: Towards high-quality arbitrary style transfer with local–global style learning. *Neurocomputing* **2025**, *623*, 129434.
66. Zhang, Z.; Zhang, Q.; Luan, J.; et al. Vectorsketcher: Learning to create a vector-based free-hand sketch. *Eng. Appl. Artif. Intell.* **2025**, *156*, 111005.
67. Roumeliotis, K.I.; Tselikas, N.D. Chatgpt and open-ai models: A preliminary review. *Future Internet* **2023**, *15*, 192.
68. Ramesh, A.; Pavlov, M.; Goh, G.; et al. Zero-shot text-to-image generation. In Proceedings of the 38th International Conference on Machine Learning, Virtual, 18–24 July 2021; pp. 8821–8831.
69. Haleem, A.; Javaid, M.; Qadri, M.A.; et al. Artificial intelligence (ai) applications for marketing: A literature-based study. *Int. J. Intell. Netw.* **2022**, *3*, 119–132.
70. Qin, X.; Jiang, Z. The impact of ai on the advertising process: The Chinese experience. *J. Advert.* **2019**, *48*, 338–346.
71. Huh, J.; Nelson, M.R.; Russell, C.A. Chatgpt, ai advertising, and advertising research and education. *J. Advert.* **2023**, *52*, 477–482.
72. Ford, J.; Jain, V.; Wadhwani, K.; et al. Ai advertising: An overview and guidelines. *J. Bus. Res.* **2023**, *166*, 114124.
73. Wu, J.; Gan, W.; Chen, Z.; et al. Ai-generated content (aigc): A survey. *arXiv* **2023**, arXiv:2304.06632.
74. Rombach, R.; Blattmann, A.; Lorenz, D.; et al. High-resolution image synthesis with latent diffusion models. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, New Orleans, LA, USA, 18–24 June 2022; pp. 10684–10695.
75. Zhang, Z.; Zhang, Q.; Lin, H.; et al. Towards highly realistic artistic style transfer via stable diffusion with step-aware and layer-aware prompt. In Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, Jeju, Republic of Korea, 3–9 August 2024; pp. 7814–7822.
76. Zhang, Z.; Zhang, Q.; Xing, W.; et al. Artbank: Artistic style transfer with pre-trained diffusion model and implicit style prompt bank. In Proceedings of the AAAI Conference on Artificial Intelligence, Vancouver, BC, Canada, 20–27 February 2024.
77. Li, Z.; Zhang, W.; Zhang, H.; et al. Global digital compact: A mechanism for the governance of online discriminatory and misleading content generation. *Int. J. Hum. Comput. Interact.* **2025**, *41*, 1381–1396.
78. Dzuong, J.; Wang, Z.; Zhang, W. Uncertain boundaries: Multidisciplinary approaches to copyright issues in generative ai. *arXiv* **2024**, arXiv:2404.08221.
79. Balasubramaniam, S.; Chirchi, V.; Kadry, S.; et al. The road ahead: Emerging trends, unresolved issues, and concluding remarks in generative ai—A comprehensive review. *Int. J. Intell. Syst.* **2024**, *2024*, 4013195.
80. Chen, H.; Chan-Olmsted, S.; Thai, M. Culture sensitivity and information access: A qualitative study among ethnic groups. *Qual. Rep.* 28, 2504–2522, 2023.
81. Wang, Y.; Zheng, J.; Zhang, C.; et al. Dualnet: Robust self-supervised stereo matching with pseudo-label supervision. In Proceedings of the AAAI Conference on Artificial Intelligence, Philadelphia, PA, USA, 25 February–4 March 2025.
82. Dwivedi, R.; Dave, D.; Naik, H.; et al. Explainable ai (xai): Core ideas, techniques, and solutions. *ACM Comput. Surv.* **2023**, *55*, 1–33.
83. Wang, Y.; Wang, L.; Li, K.; et al. Cost volume aggregation in stereo matching revisited: A disparity classification perspective. *IEEE Trans. Image Process.* **2024**, *33*, 6425–6438.

84. Das, A.; Rad, P. Opportunities and challenges in explainable artificial intelligence (xai): A survey. *arXiv* **2020**, arXiv:2006.11371.
85. Arrieta, A.B.; Herrera, F.; Chatilaf, R.; et al. Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf. Fusion* **2019**, *58*, 82–115.
86. Wang, T.; Zhang, Y.; Qi, S.; et al. Security and privacy on generative data in aigc: A survey. *ACM Comput. Surv.* **2024**, *57*, 1–34.
87. Lucchi, N. Chatgpt: A case study on copyright challenges for generative artificial intelligence systems. *Eur. J. Risk Regul.* **2024**, *15*, 602–624.
88. Verma, A. The copyright problem with emerging generative ai. *J. Intell. Prot. Stud.* **2023**, *7*, 69.
89. Wang, Z.; Shen, L.; Kuang, E.; et al. Exploring the impact of artificial intelligence-generated content (aigc) tools on social dynamics in ux collaboration. In Proceedings of the 2024 ACM Designing Interactive Systems Conference, Copenhagen, Denmark, 1–5 July 2024.
90. Baidoo-Anu, D.; Ansah, L.O. Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of chatgpt in promoting teaching and learning. *J. AI* **2023**, *7*, 52–62.
91. Franks, E.; Lee, B.; Xu, H. Report: China's new ai regulations. *Glob. Priv. Law Rev.* **2024**, *5*, 43–49.