Risk Analysis of AIGC in Market Regulation

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Abstract: The rapid rise of AIGC technology has greatly promoted the development of the digital economy, but also brought a series of potential risks. AIGC technology has made great progress in the generation of text, pictures, audio, and video. And its products have been applied in various scenarios in the consumer market, demonstrating its ability to significantly improve production efficiency and reduce service costs. In the meantime, the potential risks and violation it brings should alert regulatory authorities. The data, resources and capital monopoly of the big tech companies may affect the innovation of AIGC technology and market. The AIGC technology has improve the efficiency and quality of generative content and data analysis, which provides convenience for merchants to implement anti-competitive behaviors such as false advertisements and price discrimination. It may also interfere with the regulatory authorities by generating false leads or producing content to affect public opinion. This article is intended to provide policymakers, antitrust enforcers, market participants, and the public with a comprehensive understanding of the risks regarding market regulation relevant to AIGC.

Keywords: AIGC, market regulation, unfair competition, monopoly, risk analysis.

1 Introduction

In recent years, Artificial Intelligence Generated Content (AIGC) technology has been the headlines due to its astonishing performance and efficiency[1]. The text generation model represented by ChatGPT [2-3] and the image generation model represented by DALL-E 2 [4] have aroused discussions as soon as they were released. Combined with domain data, AIGC technology enters the vertical domain at an astonishing speed. At present, products derived from general models such as ChatGPT have been applied to all aspects of the consumer market to help merchants provide high-quality services at low cost.

While embracing new technology, it is also important to notice the market risks brought about by AIGC, including capital monopolies in the AIGC market and the synthetic information generated by AIGC misleading consumers and regulatory authorities. Stakeholders should strengthen their awareness of the risks of AIGC technology, and enhance risk prevention awareness and supervision, to achieve technological innovation and harmonious social development.

The structure of this article is as follows: firstly, an introduction to the development of AIGC technology in four aspects: natural language generation, image generation, video generation, and audio generation. Secondly, an overview of the current applications of AIGC technology in

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consumer markets. Lastly, a discussion on the risks posed by AIGC technology in the field of market regulation.

2 The development of AIGC technology

AIGC, through learning and analyzing massive amounts of data, enables computers to simulate human creativity and judgment, automatically generating content that meets human needs. The development of AIGC technology can be traced back to the 1950s when computer scientists began attempting to use computers to generate language models. With the continuous development of machine learning and deep learning technologies, AIGC technology has made rapid progress. The following sections will discuss the development of AIGC technology in four aspects: natural language generation, image generation, video generation, and audio generation.

2.1. Natural language generation

Natural Language Generation (NLG) is one specific application of AIGC, focusing on generating natural language texts that align with specific communication objectives. Popular research directions in NLG include text summarization, text expansion, text rewriting, question answering, and dialogue systems. Text summarization involves compressing long texts into shorter ones, typically including tasks such as text summarization [5], question generation [6], and distractor generation [7]. Text extension tasks are to generate complete sentences or texts through meaningful words, such as short text expansion [8] and topic writing [9]. Text rewriting aims to rewrite texts into a different style [10]. Question answering focuses on generating accurate, clear, and relevant answers to satisfy users' information retrieval and question-answering needs [11]. Dialogue system aims to generate natural, fluent, and meaningful responses in conversations to facilitate communication and interaction between humans and machines. [12].

There are several common models for NLG tasks. Recurrent Neural Network (RNN) [13] is a classic sequence model that generates output sequences by using the hidden state of the previous time step as the input to the current time step. Transformer [14] is an attention-mechanism-based model composed of stacked self-attention layers and feed forward neural network layers. It can process input sequences in parallel, enabling the model to understand long-distance dependencies and capture contextual information effectively. Copy and Pointing Mechanisms [15] aim to address the issue of inaccurate reproduction of factual details. They use a combination of a generator and a pointing mechanism to handle out-of-vocabulary words and vocabulary repetitions, and are widely applied in abstract summarization tasks. Generative Adversarial Network [16] is a framework based on adversarial training. The generator is responsible for generating fake samples that approximate the real data distribution, while the discriminator distinguishes between generated samples and real samples. This adversarial training improves the generation capability of the generator, resulting in more realistic samples. Graph Neural Network (GNN) [17] is used to process NLG tasks based on graph structure. Through message passing, it captures dependency information between nodes and enables independent propagation on each node, ignoring the input order of nodes and achieving higher computational efficiency.

In particular, with the rapid advancement of deep learning technology, Transformer-based pre-trained language models, such as BERT [18], BART [19], GPT-2 [20] and GPT-3 [21], trained on large-scale corpora, have demonstrated powerful language understanding and generation capabilities, significantly improving the performance of NLG tasks.

2.2. Image generation

Image generation models can be divided into generative adversarial network (GAN) models [16, 22-25], variational autoencoder (VAE) models, flow-based models, and diffusion models [26], which constitute the cornerstone of the image generation field. Image generation tasks include unconditional generation and conditional generation. The former directly generates images from the latent space, and the latter generates images based on input prompts, with specific tasks such as image editing, style transfer, and text generation images.

Text-to-image (T2I) is a popular task in current research and application, and it was first implemented by conditional generative adversarial network(cGAN) [23]. Subsequent research focuses on progressive generation [24-25], which aims to produce high-quality images, and text-image alignment [22, 27], which aims to discover complex relationships between text and images. Mapping text and image feature to the same feature space has become the leading way to improve text and image alignment performance. CLIP [28] encodes text-image pairs through Transformer to generate tokens pairs, and uses dot product operations to measure similarity. DALL-E [29] employs vector quantised variational autoencoder(VQ-VAE) and Transformer to encode text feature and image feature in the same feature space, transforming T2I generation into sequence-to-sequence translation problems. Diffusion model is the mainstream model of new generation image generation, which has the advantages of high image quality, stable convergence compared with GAN model, and simple objective function. Diffusion models can be easily embedded in downstream tasks and have been successfully applied to T2I task. GLIDE [30] trains a T2I and an up-sampled diffusion model for cascade generation. By combining CLIP and diffusion model, DALL-E 2 has significantly improved the quality of the generated image compared with DALL-E. VQ-diffusion [31] and Stable Diffusion [32] perform T2I generation in latent space rather than pixel space to improve efficiency.

At present, the T2I task has achieved remarkable results, and has been used in open source models such as Stable Diffusion.

2.3. Video generation

Despite significant advancements in image generation, progress in video generation has been relatively slower, due to the scarcity of large-scale high-quality video datasets and the complexity of modeling high-dimensional video data. Early research focused on simple video generation, such as moving digits or specific human actions [33]. Following the success of image generation tasks, Sync-DRAW [34] is the first method to utilize VAE with recurrent attention for text-to-video(T2V) generation. Following research extended GAN from image generation to T2V generation [35]. To generate more realistic scenarios, some studies are beginning to introduce more complex models and techniques. GODIVA [36] employs 2D VQVAE and sparse attention to support more realistic scene generation. NUWA [37] extends GODIVA and proposes a multi-task learning framework for a unified representation of various generative tasks. CogVideo [38] and Video Diffusion Models (VDM) [39] introduce additional timing attention modules in the model to further improve the performance of video generation. In addition, some researchers are beginning to consider the use of image priors to simplify the learning process. MoCoGAN-HD [40] views the video generation task as a task to find trajectories in the potential space of a pre-trained fixed image generation model.

These approaches employ different model structures and training strategies to address the challenges of video generation, aiming to enhance the quality and diversity of generated videos. By leveraging prior knowledge, multi-task learning, and specific model design, these methods have made progress in overcoming the challenges of data deficiencies and modeling high-dimensional video data.

2.4. Audio generation

In audio representation learning, self-supervised learning (SSL) [41] can effectively reduce the sampling space of the generated algorithm. Also inspired by vector spaces, SoundStream [42] proposes a hierarchical architecture for carrying high-dimensional representations of semantic information. In addition, spectrogram autoencoders, such as Auto-MAE [43], are used to learn audio representations from audio spectrograms through mask-based self-supervised learning based on a mask autoencoder (MAE) [44]. MSPM [45] utilizes audio spectrogram transformation and joint discriminatory, generative mask spectrogram modeling. This reconstruction-based self-supervised learning approach demonstrates the effectiveness of heterogeneous image-to-audio conversion. Currently, there are active researches in text-to-audio generation. DiffSound [46] is the first research to explore text-to-audio generation, it obtains audio coding from VO-VAE for discrete diffusion process, using CLIP representation for mask text generation. AudioLM [47] introduces discrete activation of a mask language model pre-trained on audio and produces grammatically appropriate speech or music. AudioGen [48] proposes a method to generate audio samples autoregressively from text input.

Research in audio generation is advancing toward higher quality, greater diversity, and more semantic. Self-supervised learning methods, conditional generation techniques, and semantic modeling are key areas of current research, providing new insights and technical means for audio generation. With the continuous advancement of technology, audio generation will play an increasingly important role in domains such as music synthesis and speech recognition.

3 The application status of AIGC in the consumer market

AIGC technology has made great progress in natural language generation, image generation, video generation and audio generation. Combined with large-scale domain data, it can create scenario-based and customized models and tools, bringing infinite possibilities to various fields. In recent years, a large number of AIGC tools have been applied to the consumer market, significantly improving production efficiency in related fields and reducing the cost of various services. The following chapters will explain the application status of AIGC technology in four aspects: business analysis, brand promotion, customer service robot and word-of-mouth communication.

3.1. Business analysis

Business analysis expects enterprises to use quantitative statistical methods and technologies to analyze the historical data they have, and use it to guide strategic decisions and business development. In this process, enterprises use data processing tools to process and analyze business, operation, and industry information. AIGC products, especially large language models such as ChatGPT, have strong semantic understanding and analysis capabilities, which can efficiently and conveniently extract key information from unstructured financial reports, industry reports and other data to analyze consumer preference, study competitors and predict market trends. Its ability of sentiment analysis can also mine positive, neutral, or negative stances implicit in Q&A and comments, which can be used to assess the attitudes of the market and competitors.

Shulex VOC, a Chrome extension integrated ChatGPT/GPT4, can provide high-quality consumer demand analysis, insights of preference and product trend analysis based on orders, reviews and other information. The results can be used to guide product development, merchant selections, sales strategies, and customer service strategies. Additionally, Shulex VOC can optimize product names and key feature descriptions, improving product visibility and ranking on search engines. Hekka, an e-commerce platform owned by Asia Innovations Group, exploits ChatGPT to analyze keywords and marketing conversion rates, locate user needs, and track market trends. After integrating AIGC technology, Hekka's search engine optimization (SEO) comprehensive operational efficiency increased by 69% , and the comprehensive traffic conversion efficiency increased by 43% [49].

3.2. Brand promotion

Brand promotion include in-store promotion, channel promotion, consumer interaction promotion, media promotion, etc. This process involves the production of product brochures, exhibition boards, promotional posters, advertising design, copywriting, etc., which consumes a lot of manpower and material resources. AIGC has a strong ability to generate text, images and videos, and can assist merchants in copywriting, beautification of product images, advertising design, and publicity plan design based on the provided keywords. It greatly improves the production efficiency of publicity materials, reduces labor costs and accelerates the production cycle.

The e-commerce platform Hekka uses Stable Diffusion to generate AI models to intuitively display fitting effects and outfit ideas. For a long time, taking and beautifying product photographs for e-commerce platforms has consumed a lot of manpower and financial resources, but Hekka, using AIGC technology, breaks this dilemma. According to reports, the production cost of Hekka's product images has dropped by 95%, and the production cycle of model pictures has dropped to 200 pictures per day[49]. Based on keywords and product data, individual merchants can use image generation tools such as Midjourney and Flair to edit and beautify product photographs, and text generation tools such as Jasper and SmartPush to automatically generate product introductions, marketing emails and marketing copywriting.

3.3. Customer service robot

Customer service robot is a scenario where AIGC can be directly utilized. It can provide customers with 24-hour high-quality service and reduce the pressure on customer service agents.

Technological breakthroughs in large language models such as ChatGPT have improved the intelligence level of customer service robots. ChatGPT can automatically generate frequently asked questions (FQA) based on the provided documents and manuals, which is more efficient than building a knowledge base manually. ChatGPT's powerful complex language understanding ability and context understanding ability enable the customer service robot can not only fully understand customer problems, but also maintain the coherence and consistency of multiple rounds of dialogue. In addition, customer service robots using AIGC technology can also provide multilingual services, intelligent form filling services, etc.

Powered by ChatGPT, Chatalog allows users to create their own exclusive customer service robots by uploading websites and documents. The customer service robot can respond to user questions in real time and provide accurate answers based on the uploaded information. Chatalog customer service robot can also reply to messages on WhatsApp, Instargam, Facebook and other platforms, instantly reply to Instargam live messages, and send product links in private messages.

3.4. Word-of-mouth communication

Word-of-mouth can significantly influence consumer attitudes and behaviors. Consumers sharing product experience on social media is an important way of word-of-mouth communication. Merchants also promote their products by posting product information on social media and hiring online celebrities to post product reviews and evaluation videos. AIGC technology can assist in generating illustrated evaluation content, short video script production, scene storyboard production, and special effects processing, lowering the threshold for making evaluation videos. AIGC technology has also spawned social media virtual human bloggers, also known as metaHumans, who have realistic characters, post life photos and short videos on social media, and have language expressions and behavior habits that are no different from real people. Figure 1 shows two famous virtual human bloggers: Lil Miquela from Instagram on the top and imma from Little Red Book on the bottom. These virtual human bloggers are often affiliated with a commercial organization for product promotion.

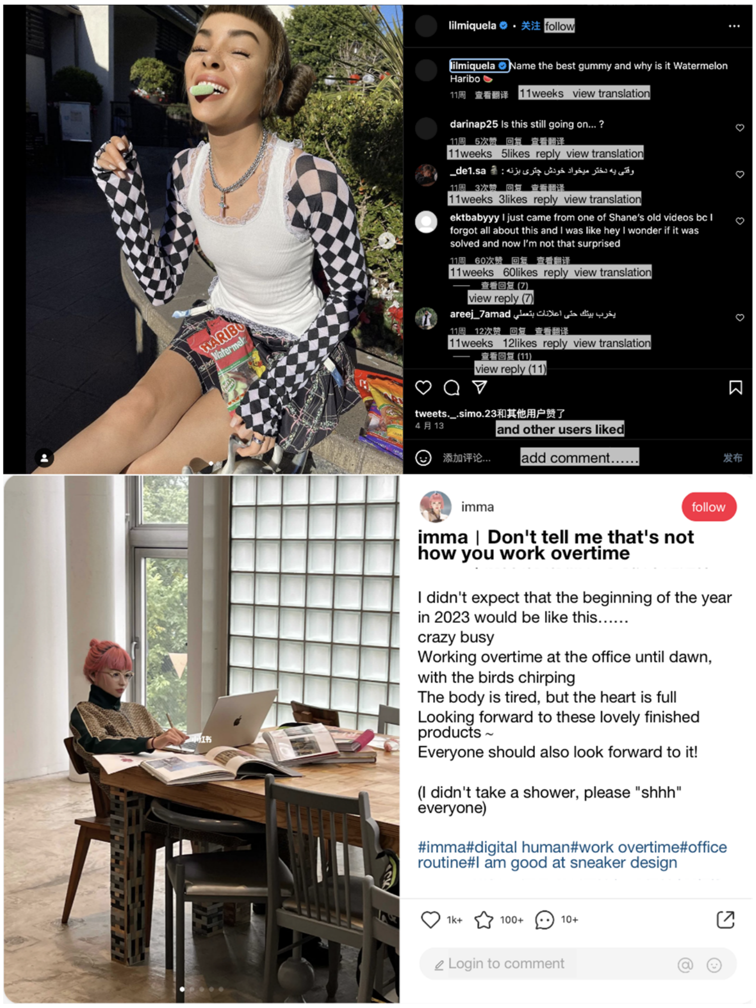

Figure 1: Virtual human bloggers on social media.

The famous virtual blogger Lil Miquela was once believed by fans to be a real person. She releases her singles, shares her lifestyles, and interacts with other online celebrities on social media platforms. It wasn't until hackers breached her account that she was identified as a virtual human made by 3D computer animation company Modelingcafe. Lil Miquela has business collaboration with Chanel, Supreme, Fendi, Prada and other brands, and "wears" the latest couture of the season to promote the brand. Along with Trump and Rihanna, she was once included in Time's annual list of "Most Influential People on the Internet".

4 Risks in market regulation

4.1. For the AIGC market

The rapid development of AIGC technology has spawned a series of software and products used in various industries, rapidly building an upstream and downstream industrial chain from hardware to software to services, and forming a market for AIGC products. However, as an emerging market, the AIGC market has many companies that already have market dominance in the Internet field, which raises some concerns about potential monopoly risks.

4.1.1. Data monopoly and computing resources

AIGC is a technology that relies on massive training data sets, algorithms, and high-performance computing resources. We should be wary of the monopoly of resources to form the Matthew effect that the strong get stronger and raise the market entry threshold.

Most Internet companies gather and generate a large amount of data during their development process. At the same time, they have a large number of scientific and technological talents to develop algorithms and process data with high-performance computing power. Therefore, technology giants with a dominant position in the market often have a dominant position in the data, algorithms, and computing power they possess in the industry.

AIGC technology, compared with the previous computer algorithm and artificial intelligence technology, is much more dependent on data volume and data diversity. Taking ChatGPT as an example, it is supported by the GPT-3.5 model and has undergone GPT-1, GPT-2, and GPT-3 three iterations. The number of model parameters increased from 117 million to 175 billion, and the amount of pre-training data increased from 5GB to 45TB.

According to OpenAI, the developer of ChatGPT, since 2012, the computing power required for global head AI model training has doubled in about 3-4 months, and it has increased by as much as 10 times each year. In May 2020, Microsoft invested US$1 billion to build a supercomputer with more than 285,000 processor cores and 10,000 GPUs for OpenAI, hosted on its cloud platform Azure. According to Bloomberg, it took 1.287 gigawatt hours to train ChatGPT-3.

Compared with computing power resources, data resources have caused many controversies because of their copyright, privacy, originality and other issues. Many countries have successively legislated to protect data rights. However, while discussing how to protect data rights, we should also pay attention to the possible data monopoly and technology monopoly risks caused by the protection of data rights.

In October 2022, Getty Image, the well-known stock image company announced a strategic partnership agreement with BRIA, an Israeli developer of proprietary AI visual content tools, providing licenses of its images and metadata. In February 2023, Getty Image filed a lawsuit in court, accusing Stability AI, the company that owns the deep learning text-to-image model Stable Diffusion, of using more than 12 million pictures for training without authorization, which constitutes infringement. The world’s leading software development platform GitHub and the OpenAI team jointly developed a paid code generation tool CoPilot based on code from GitHub, which include more than 28 million public repositories. In addition, OpenAI s with the stock image giant Shutterstock in 2021 to obtain its pictures and data authorization for model training.

More and more data are pouring into a smaller and smaller circle. The size of data is the most important entry barrier for AIGC market. One thing about big data is that the value of data increases exponentially with the increase of data volume. The value of 10,000 pieces of data is far greater than 100 times that of 100 pieces of data. Therefore, the owner of massive amount of data occupies an absolutely strong position in the research of AIGC technology. Unreasonable restrictions on the authorization, circulation and use of data will create higher industry barriers, and the data monopoly will lead to a technology monopoly, which will inevitably limit the development of AIGC technology.

Western countries have relatively clear regulations on the copyright protection of data and databases. In the United States, databases with creative or original arrangement and selection can be protected by copyright law; in Europe, the Database Directives clearly regulate what kind of data and databases are protected by intellectual property rights. In recent years, China has gradually carried out the protection of intellectual property rights of data. Since 2022, China National Intellectual Property Administration has carried out data intellectual property protection pilots in places including Beijing and Shanghai. Regulation of data intellectual property has been enacted and data intellectual property registration has begun. Including data in the protection of intellectual property rights not only protect the interests of relevant parties, but could also cause abuses of intellectual property rights, such as refusing data authorization, charging high authorization fees, attaching unreasonable terms, which would limit the circulation of data and monopolizing AIGC technology in leading platform companies.

Therefore, in order to keep the vitality of the AIGC market in China, while protecting data intellectual property rights, it is also necessary to ensure that data owners with market dominance exercise their intellectual property rights correctly. Acts of abusing market dominance such as fees, refusal of licenses, tying sales, or adding unreasonable terms that violate the "Provisions on Prohibiting the Abuse of Intellectual Property Rights to Exclude and Restrict Competition” should be avoided.

4.1.2. Monopoly capital

Today, the alliance between technology giants has gradually become a trend. Getty Image, the stock image platform mentioned earlier, participated in a new round of financing for BRIA as an investor in April 2023, months after the announcement of a strategic partnership agreement between the two companies. GitHub and OpenAI, the development team of the paid code generation tool CoPilot, are both closely related to Microsoft. As a major investor in OpenAI, Microsoft is also the parent organization of GitHub since 2018.

Technology start-ups, especially AIGC related start-ups, not only face strong industry barriers in data, algorithms, and computing power, but also face killing acquisitions from technology giant companies using their capital advantages. Killing acquisitions refer to when incumbent firms acquire innovative targets solely to discontinue the target’s innovation projects and preempt future competition [50]. For example, Meta acquired Within, the VR developer behind fitness app Supernatural; Amazon acquired Quidsi, an e-commerce company of maternal and child products.

Killing acquisitions will not only have the effect of eliminating competition in the market, but also hold back the innovation of the field. Killing mergers and acquisitions originated in the US pharmaceutical industry. About 6% of mergers and acquisitions in this industry are killing acquisitions [50]. The acquirer will stop the research and development of related competing products after the transaction, and the target company has less incentive to innovate because there is no competition. On the other hand, the breakup of AT&T in 1980s allowed other company to enter the industry and let to innovation like the answering machine and modem.

Since the targets of killer acquisitions are mainly start-ups, most of their turnover and market share do not meet the government standard for report during mergers and acquisitions, which increases the difficulty for regulator to spot killer acquisitions beforehand. In order to maintain the innovation vitality of the AIGC market, it is important that regulators pay close attention to the mergers and acquisitions of start-ups by big technology companies, to avoid the technological monopoly caused by monopoly capital, and limit the innovation of AIGC technology.

4.2. For consumers

Fake bloggers, virtual ambassadors, AIGC technology makes seeing no longer believing. In the meantime, consumers profiling system based on AIGC technology even knows consumers better than themselves. While AIGC products bring convenience to merchants, they also bring potential risks to consumers.

4.2.1. Misleading consumers

At present, the text generated by AIGC is already difficult to identify its authenticity, the addition of pictures increases its credibility. The social media robots created by AIGC are no different from ordinary internet celebrities.

Article 6 of the “Anti Unfair Competition Law" stipulates that operators are not allowed to use the same or similar marks as the name, packaging, decoration, etc. of products that have a certain influence on others, so as to mislead people into thinking that they are products of others or that they have a specific connection with others. In February 2023, the stock image platform Getty Image filed a lawsuit in court, alleging that the pictures generated by the deep learning text-to-image generator Stable Diffusion contained blurred Getty Image watermark, which infringed its trademark rights (shown in Figure 2). In March 2023, a number of pictures, generated by AIGC products Midjourney, of the former US President Donald Trump being gang-tackled by New York City police officers went viral on social media (shown in Figure 3). AIGC products can generate trademarks and packaging similar to well-known brands using image generation technology based on the image library; at the same time, it can also generate realistic images of any character with any behavior upon requests. Merchants can use AIGC to generate images similar to celebrities and experts for product promotion, which would mislead consumers.

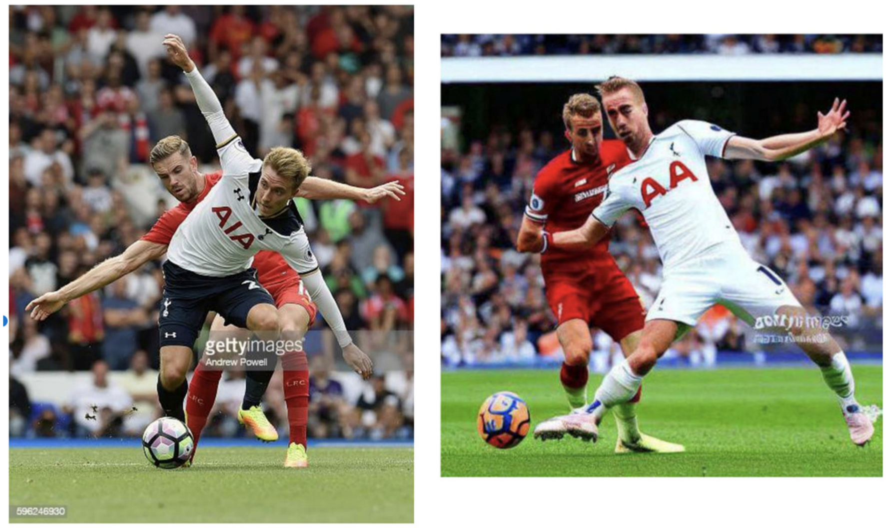

Figure 2: Illustrations from Getty Image's lawsuit. Left: Original photo. Right: Image generated by Stable Diffusion.

Figure 3: Images of Trump being arrested generated by Eliot Higgins using Midjourney.

Article 8 of the “Anti Unfair Competition Law" stipulates: Merchants shall not make false or misleading commercial advertisements about the performance, function, quality, sales status, user evaluation, and honors of their products to deceive or mislead consumers. In recent days, social media is one of the most important channels for consumers to obtain product information.

Information such as product reviews, user experience, and influencers recommendations will be used as important references when purchasing. Social Media marketing is also the top priority for merchants. Merchants use social media platforms to release new products, invite influencers for try-out, and publish positive reviews to improve product image and achieve publicity purposes. With the development of AIGC for social media platforms, bloggers who share lifestyles on Instagram may be just a well-trained social robot. At the same time, a review post full of details pointing out product defects may be a smear campaign created by merchant to attack its competitor. In this era, it is all about marketing. With AIGC technology, the difficulty for consumers to obtain accurate and true information has greatly increased.

4.2.2. Price discrimination

The machine's ability to read and write has reached an unprecedented level with AIGC technology. Using AIGC, merchants can conduct more accurate consumer analysis, construct consumer profile based on different kind of data, and provide consumers personalized and refined services. At the same time, merchants are well aware of consumers' consumption habits: they know their preferences for products, their expense limit, their spending habits. These accurate and detailed descriptions have become labels for consumers. Those labels, while facilitating merchants to push customized information for consumers, also provide more convenient and more refined guidance for merchants to implement differential treatment such as price discrimination for consumers. Since the consumer analysis is so detailed and tailored, it is very hard for consumers to realize that they have been discriminated.

4.3. For regulators

On May 22, 2023, a picture of an explosion near the Pentagon (shown in Figure 4) went viral on social media and was later confirmed to be false news. Although the picture has obvious AI-generated features, it was still broadly spread, causing a significant drop in the US stock market. The authenticity of false information and the easiness with which it can be generated have brought many potential risks to regulators.

Figure 4: AI-generated image of an explosion near the Pentagon.

4.3.1. False leads

Since the text generated by AIGC is much more human-like than it was before, coupled with the aid of pictures, it becomes more difficult to identify anti-competitive conducts and collect evidence such as misleading information and price discrimination. In addition, merchants can use AIGC to generate a large amount of complaints towards competitors to report to the regulatory authorities. Complaints and reports system is one of the most important channels for regulatory authorities to obtain leads. AIGC technology makes it more difficult to distinguish the true information from complaints, which hinders the investigations.

4.3.2. Public opinion guidance

The text generated by AIGC can also be used to influence public opinion and form online ghostwriters. Public opinion is another important channel for regulatory authorities to obtain leads, and its authenticity and accuracy are of paramount importance. AIGC products are extremely efficient in generating text, so when a company has negative public opinion, the company can use AIGC to quickly generate a large amount of positive press releases. When the negative opinion is overshadowed by massive amount of positive reviews, it won't trigger the public opinion monitoring system and the regulators would easily miss the lead. At the same time, companies can also use AIGC to generate negative articles about rival companies, misleading regulatory authorities with false clues.

5 Conclusion and future work

AIGC technology has made great progress in natural language generation, image generation, video generation, audio generation, etc., and has been widely used especially in consumer field, reducing production costs and improving service efficiency. But AIGC technology is also a double-edged sword. While boosting the digital economy and market, it brings a series of risks to market, consumers and regulators including the monopoly of resource and capital, misleading consumers, price discrimination and interfering with regulation.

This paper would like to draw attentions to the following three aspects regarding regulation of AIGC technology and its applications, ,and suggest the regulatory authorities to act accordingly in the future. First, establish a fair competition mechanism and transparent environment to prevent monopolistic behavior and unfair competition. Ensure the fairness and sustainability of the AIGC market. Second, improve and update corresponding regulatory policies and regulations to prevent abuse and violation. Third, establish an effective complaint and report system and monitoring mechanism to protect consumers' right. Therefore, regulatory authorities should consider actively promoting the implementation of supporting policies, protecting the innovation vitality of the AIGC technology market, achieving a balance between market development and supervision, and ensuring the sustainable development of the digital economy and the stability of the market.

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