Journal of Industry, Competition and Trade (2024) 24:19
https://doi.org/10.1007/s10842-024-00430-9

Generative Artificial Intelligence, Content Creation, and Platforms

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Received: 10 April 2024 / Revised: 9 July 2024 / Accepted: 20 September 2024 /
Published online: 3 October 2024

Abstract
Generative AI (GenAI) is a rapidly growing technology that is expected to transform business and society. An important question is how it will affect platforms and their ecosystems, especially human-generated content upon which many platforms rely. We develop an analytical model to study the economic impact of content platforms that use GenAI, namely GenAI content platforms (GCPs). A GCP connects consumers to content generated by creators or the GenAI and offers APIs and tools to developers who build new applications in a third market. We find that although platforms have incentives to moderate the use of GenAI, this technology increases prices and reduces the quantity and number of content creators. This effect is not homogeneous, as GenAI has less influence on competitive or high entry-cost markets. Consequently, consumer welfare in content markets is reduced, but this decline varies by market. Overall, our analysis contributes to the platform and the AI economics research literature by providing testable hypotheses about the impact of GenAI in platform settings.

Keywords Artificial Intelligence (AI) · Generative Artificial Intelligence (GenAI) · Platforms · Content creators · Competition · Welfare

JEL Classification L11 · L13 · L82

1 Introduction

Generative Artificial Intelligence (GenAI) is a type of Artificial Intelligence (AI) capable of generating text or other media following a user prompt. GenAI relies on neural network models trained using large quantities of data (Cao et al. 2023; OpenAI 2023; Susarla et al. 2023). Large-scale models that generate text and perform other natural language processing tasks are called large language models (LLMs). ChatGPT, introduced by OpenAI in November 2022, is the most well-known example of an LLM application.

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GenAI is advancing rapidly, attracting significant research, general public, and business attention (Brynjolfsson and McAfee 2016; Rahwan et al. 2019; Dwivedi et al. 2021). Some observers expect this technology will alter the creative process and disrupt how we live and work (Duan et al. 2019; Berente et al. 2021; Dwivedi et al. 2023). For instance, GenAI promises the automated creation of high-quality content, and its productivity impact is estimated to be \$2.6 trillion to \$4.4 trillion annually (McKinsey 2023).

However, this opportunity is accompanied by several challenges, ranging from model hallucination (Wired 2023a), biases, and ethical concerns about a jobless future for content creators and other knowledge workers (Ford 2015; Noy and Zhang 2023). The possibility of machines monopolizing creativity and crowding out human creators raises risks for business and society as GenAI changes creators' incentives (De Cremer et al. 2023). Under this disruptive scenario, GenAI could destroy its learning foundations (human-created content), leading to technology and market failure. Representatives of Stack Overflow, Reddit, and Wikimedia have expressed concern that such technology may drive out users and create the need for some form of compensation (Somers 2023).

Despite these concerns, several companies race to build GenAI-powered products such as search (Wired 2023b). Although such tools could dramatically improve information searches, they also threaten content creators who may experience declining website traffic as GenAI-powered search engines summarize and synthesize the content users seek (Somers 2023). This is a delicate situation for search platforms, as they must provide a comprehensive response to users' prompts and, simultaneously, avoid harming the incentive to create new content, as producers without traffic will not create content that feeds the GenAI powered search. This case also raises numerous questions concerning companies and authorities (CMA 2023; Federal Trade Commission 2023). Currently, ChatGPT offers the possibility of using its API to create new services. Microsoft partnered with OpenAI to add GenAI capabilities to its Bing search engine. At the same time, Google is experimenting with summarization by providing a short and complete response to user queries. The two services appear to be on a collision course, where the same platform offers a typical search service, content generated by GenAI, and APIs that let developers innovate. Therefore, it is crucial to understand to what extent GenAI will crowd out content creators and what the impact will be on consumers and society.

This paper studies the economic impact of GenAI in platform settings. It aims to characterize the market consequences of platforms that use GenAI technologies, namely GenAI content platforms (GCP). For clarity and illustrative purposes, we focus on the case of search engines. We develop an analytical model in which a GCP mediates between content producers and consumers, facilitating access to content and providing content summaries. It implies that the platform extracts some of the surplus from content producers by reducing the number of consumers who use the content and increasing interaction with the platform (search engine). This harms content producers but provides the platform with enough data and resources to give developers tools to innovate and create new services on top of the platform.

Our work contributes to the platform economics literature (Evans 2003; Rochet and Tirole 2003; Parker and Van Alstyne 2005; Hagiu 2006; Bakos and Katsamakas 2008) that has recently analyzed creator economy platforms (Bhargava 2022). It offers an analytical model that captures the role of GenAI in platforms.

Second, it contributes to the AI economics literature (Agrawal et al. 2019; Varian 2019) that studies a broad range of topics, including labor replacement or augmentation (Acemoglu and Restrepo 2018, 2022; Lebovitz et al. 2022; Bresnahan 2023), competitive advantage (Krakowski et al. 2023), liability rules (Buiten et al. 2023), and pricing by AI algorithms (Calvano et al. 2020, 2023; Klein 2021; Sanchez-Cartas and Katsamakas 2022, 2024). Our paper contributes to this buoyant literature by proposing a theoretical model to address the impact of GenAI technology on human-produced content, where we pay attention to how this technology can change the incentives to compete and produce content. Our model does not pretend to be exhaustive. Still, it aims to capture the impact of the essential features of this technology (summarization of a large amount of content, reduction of traffic to content producers, or the enablement of third-party developers) on competition and market welfare in a stylized way.

Our article provides testable hypotheses about the impact of GenAI technologies on platforms and theoretical foundations to recent empirical evidence (Burtch et al. 2023; Huang et al. 2023; Xue et al. 2023; Wang and Zheng 2024; Zhao et al. 2024). We find that GenAI technologies may reduce the number of content creators and the level of content in the market. Moreover, if GenAI companies can choose how much they can extract from content creators, it is never optimal for them to cut them out completely. Thus, implementing GenAI technologies may lead to a concentration in content markets but will not put all creators out of work. In addition, we find that increases in entry costs or competition in the content market may reduce the pernicious effect of GenAI. In other words, concentrated markets will be the most affected by GenAI technologies. However, these effects are not robust to small changes in the model. In this regard, we establish conditions under which these effects can go opposite directions, as recent evidence suggests (Peukert et al. 2024). From a social point of view, our results show that GenAI increases prices and reduces the number of content creators, which unequivocally leads to a reduction in consumer welfare. This result provides a basis for recent claims that GenAI technologies harm content creators, such as the New York Times' recent lawsuit against OpenAI over the AI use of its content (New York Times 2023). However, this reduction may be (partially) offset by creating a new market for third-party developers and other services (Bloomberg Intelligence 2023).

The rest of the paper is organized as follows. Section 2 presents the model, and Section 3 presents the model analysis and results. Section 5 analyzes a model extension. Section 5 is the welfare analysis, and Section 6 is the conclusion.

2 Model

The model considers a platform that enables the interaction of three types of agents: a representative consumer, a representative developer, and a large number of content producers. In other words, our model considers a three-sided market. Figure 1 shows the relationship among all the types of agents.

2.1 Consumers

We model the consumer side assuming a representative consumer. The consumer interacts with content and the numeraire, representing any other product. Formally, the representative consumer's preferences are described by the following Cobb–Douglas function:

$$U = q_0^{1-\gamma}\overline{q}^{\gamma}, \text{with } 0 < \gamma < 1 \tag{1}$$

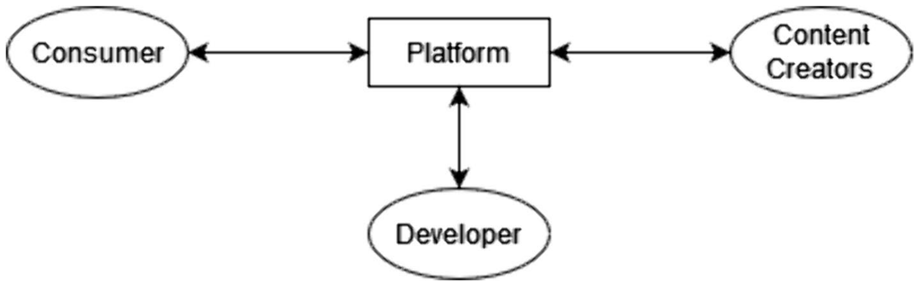

Fig. 1 Agents and their relationships

where q_0 is the numeraire and $\overline{q}$ is an index that aggregates all the different varieties of content. We assume this index is defined by a CES function, $\overline{q} = \left(\sum_{\forall i} q_i^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$ where q_i is the quantity consumed of variety i. In other words, users do not consume a single variety of content. Commonly, people consume different types of content, such as news, music, or movies. We assume that the consumption of different varieties of content can be represented by this CES function, where $\sigma > 1$ is the elasticity of substitution between any two varieties and represents how easy it is for the consumer to substitute a content variety.

Moreover, the consumer decides on the purchase of content considering the "effective" (or hedonic) price, p_i, charged by the content creator. The concept of hedonic price has been used in platform literature when referring to the cost paid by users, either in monetary terms or in inconvenience (Rochet and Tirole 2008; Weyl 2010). Following this literature, we define it as the value of attention or the consumer's willingness to pay not to be bothered by an advertisement. At the same time, this hedonic price could represent the value of such attention for an advertiser (i.e., her willingness to pay to display such an ad). Furthermore, the consumer tolerates the annoyance of advertisements to a certain extent. We model this feature as a budget constraint, $q_0 + \overline{pq} \leq y$, where y denotes the annoyance tolerance threshold or attention (which can also be defined as the monetary value of consumer's attention), $\overline{p}$ the hedonic price index of $\overline{q}$, where $\overline{pq}$ represents annoyance cost for the consumer when she spends time interacting with content.

2.2 Developers

Developers are an essential part of the GenAI ecosystems. OpenAI and other LLM providers offer APIs that allow developers to build on the LLM. In the context of search engines, Bing Search gives developers the possibility of "surfacing relevant information from billions of web documents" that could be used to create apps, experiences, or other analyses.[1]

The developer side is modeled using a representative developer. We assume that the developer produces new applications or services following a Cobb–Douglas production function in which content variety (or number of content creators, n) is the input, $z = k(n)^{\alpha}$, where k represents actual output per unit input, and α represents diminishing returns technology. The more content variety, the greater the production of applications by the developer. Note that the developer is subject to indirect network effects, as her output depends

[1] https://www.microsoft.com/en-us/bing/apis

on the number of content creators on the other side. However, we assume this relationship is not linear, as commonly assumed in the platform literature, but we explicitly model output creation. This way, we can attend to other commonly omitted effects, such as technology or developer productivity. We further assume that the developer has a uniform value v for each unit of output created. A similar assumption can be found in the analysis of cumulative innovation (Chang 1995), and platform openness (Parker and Van Alstyne 2018). Therefore, the developer's surplus is given by $v \times k(n)^{\alpha}$. Note that we assume that the developer's output depends only on the number of content creators. We relax this assumption in the model extension (Sect. 5).

2.3 Content Creators

Suppose there are many symmetric content creators, each producing a different variety of content in a market without barriers to entry (free entry). Each creator is small with respect to the market, in the sense that there is no strategic interdependence among them. They interact indirectly through aggregate demand effects, but each creator faces a downward-sloping demand curve and, therefore, enjoys market power (Anderson et al. 1992). We denote the profits of content creator i as $\pi_i = p_i q_i (1 - \delta) - c q_i - e$, where q_i is the quantity demanded of variety i, c is the marginal cost, e represents the entry costs, and p_i is the effective (or hedonic) price of that variety, which captures the monetary value of consumer's attention. As commonly assumed in the platform literature, consumer demand negatively depends on this price, which represents the idea that attention's value (and annoyance) is related to how exclusive content is. For instance, viewing an advertisement in a newspaper is less annoying and profitable than an ad in a research journal, which is also considered highly controversial (Fugh-Berman et al. 2006). The parameter δ represents the effect of the platform on creators' revenues, and its precise interpretation will be clear in the following sections. Lastly, we assume content creators decide to be active in the market if they expect non-negative profits and set quantities that maximize their profits. In this sense, the entry costs play an essential role in representing the opportunity costs of the external option (i.e., what content creators would obtain if they chose not to participate in this market). For example, some creators have already considered provisions to prevent web scraping or AI summarizing their content. These entry costs, therefore, represent the profits of opting out of this market.

2.4 Platform Using Generative Artificial Intelligence

We assume the platform maximizes its profit by partially capturing content creators' revenue and extracting the developer's surplus. Formally, the platform profits are $\Pi = n \times pq \times \delta + vk(n)^{\alpha} - fn$, where $n \times pq$ are the revenues of n creators in the content market and δ is the *content generation quality* responding to the needs of users, which we assume is normalized between 0 and 1. If $\delta = 0$, the platform does not generate any content. If $\delta = 1$, the platform generates content so well that the consumer will always prefer the platform AI-content. The higher the δ, the more revenue is extracted from creators. An example of this content is AI-generated summaries on search engines, such as Bing, Google and new GenAI search services like Perplexity. Intuitively, summaries prevent the consumer from accessing web pages. That way, the platform retains the consumer and can monetize her attention. Implicitly, content can be provided by creators or as a summarized version by the platform, but the consumer does not care about who provides it. We will

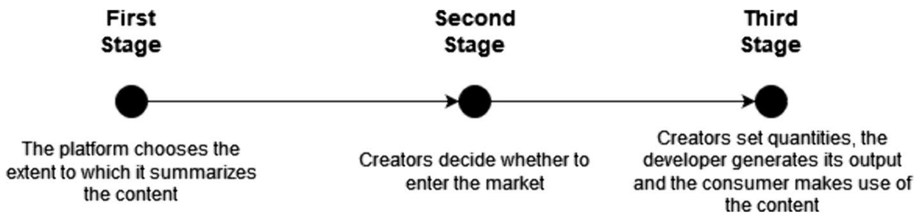

Fig. 2 Timing

stick to this example throughout the article, although many of our results can be applied to other GenAI platforms that automatically generate content. In this sense, we will refer to δ as the *summarization quality*.

The second term in the profit function is the surplus extracted from the representative developer. Since the platform knows the reservation value of the representative developer, it will extract the whole surplus. Although this assumption seems strong, it does not affect our insights about the content market. What may affect our results is our assumption about what data the developer has access to. As discussed previously, we assume the developers access data about all content creators in this case, but Sect. 5 relaxes this assumption. Finally, it is costly to maintain the platform, fn, where f is the marginal cost of keeping an additional content creator. We implicitly assume that investing in summarization (or content generation) quality is costly because it requires more creators (i.e., a larger training dataset). This is a departure from traditional quality investment assumptions, where the level of quality is directly related to cost. Here, the link is indirect via the size of the training dataset. This parameter accepts an alternative interpretation, as it may represent the copyright enforcement cost per content creator. Given recent compensation requests (and closed deals with websites that host creators, such as Reddit),[2] this parameter helps us understand the effect of a tighter copyright framework on the GCP.

The platform maximizes profits by choosing the level of summarization. It faces a trade-off between summarizing content, which reduces the incentive to provide content (and the number of creators), and having enough creators to incentivize developer and consumer participation. In other words, GenAI creates a new dilemma as its monetization by the platform hurts creators, who, in turn, are less incentivized to provide content that GenAI depends on, creating a negative feedback loop.

Our work is closely related to Bhargava (2022), which studies the content creator economy, but a key difference is the role of the platform. In Bhargava (2022), the platform chooses the price and level of advertising. In contrast, in our work, the price is determined by a market clearing price. It depends on the content creators' decisions, which is more akin to the web search engine market in which platforms do not set the advertising of independent web pages or content platforms where creators choose their sponsors.

2.5 Timing

The game has three stages (Fig. 2). In the first stage, the GenAI platform chooses the level of summarization quality (δ). In the second stage, content creators observe δ and decide

[2] https://techcrunch.com/2024/05/16/openai-inks-deal-to-train-ai-on-reddit-data/

whether to enter the market. In the third one, content creators set quantities, the developer uses the data provided by the platform to generate output, and the consumer uses the content.

Other works that address the content creator economy consider that the creators' decision precedes the platform revenue policy (Bhargava 2022). This timing seems reasonable to address the current content market, but it fails to capture the nascent nature of GenAI, where platforms make decisions based on content already created. On the other hand, it can be argued that this timing limits the strategic behavior of content creators. However, it does not preclude the possibility that creators' decisions influence the summarization decision, as shown in the following section.

3 Analysis and Results

3.1 Benchmark Model: Platform Without GenAI

Suppose that GenAI technology is not available or the use of GenAI is not feasible, either because collecting and processing data is prohibitively expensive or because its use is banned. This case will serve as a benchmark to compare the impact of GenAI on search or other content platforms.

The analysis of the game starts by considering the final stage. The representative consumer maximizes her utility subject to her attention constraint: $q_0 + \overline{pq} \leq y$. Solving for the optimal quantity of $\overline{q}$ (content) consumed yields: $\overline{pq} = y\gamma$. In other words, the consumer spends a constant share of her attention on content hosted by the platform. Using this result, we can obtain the demand for each variety of content (q_i). Formally, the consumer wants to maximize the quantities consumed of each variety subject to her attention constraint, which is equivalent to maximizing the CES function $\overline{q}$ subject to $\sum_{\forall i} q_i p_i \leq \gamma y$. After a bit of tedious algebra, we can denote the quantity of content demanded of each variety as

$$q_i = \left(\overline{p}^{\sigma-1}\gamma y\right)p_i^{-\sigma} \tag{2}$$

As expected, the demand for a particular variety decreases in its own hedonic price but depends positively on the price of all other varieties. Intuitively, the higher the cost imposed on users when consuming content, the less demand for it. This is in line with the fact that platform consumption decreases in the number of ads (Shon et al. 2021). Note that the relationship between the representative consumer and the content creators is just a stylized version of the S-D-S model of monopolistic competition (Spence 1976; Dixit and Stiglitz 1977). To properly characterize demand levels, it is convenient to determine the hedonic price index, $\overline{p}$. We can do that by introducing Eq. 2 in the CES function, using the fact that $\overline{pq} = y\gamma$. Then, we have

$$\overline{p} = \left(\sum_i p_i^{-(\sigma-1)}\right)^{\frac{-1}{\sigma-1}} \tag{3}$$

By imposing the symmetric assumption, $\overline{p} = pn^{\frac{-1}{\sigma-1}}$, where n is the number of content creators. Note that the hedonic price of content (price index) is decreasing in the number of creators (or varieties) since the elasticity of substitution is higher than one. Intuitively, the greater the competition in the content market, the lower the prices (or the hassle of ads).

Moving on to content creators, we can determine the quantities and the hedonic price, assuming the platform does not summarize content (δ = 0). Content creators choose quantities, and the market clearing prices are set according to the inverse elasticity rule; it is straightforward that

$$\frac{p_i - c}{p_i} = \frac{1}{\sigma} \leftrightarrow p_i = \frac{\sigma}{(\sigma - 1)}c \tag{4a}$$

$$q_i = \left(\overline{p}^{\sigma-1}\gamma y\right)p_i^{-\sigma} = \frac{\gamma y(\sigma - 1)}{nc\sigma} \tag{5a}$$

Note that, without GenAI, the content market is described by the simplified version of the S-D-S model. In this case, content creators make $\pi_i = \frac{\gamma y}{n\sigma} - e$ and, imposing the free entry condition, $\pi = 0 \leftrightarrow n = \frac{\gamma y}{e\sigma}$.

In this case, the platform does not use GenAI but still offers services to developers ($vk(n)^\alpha$).In other words, this benchmark represents the situation before the launch of ChatGPT, when platforms offered APIs to developers (such as the search API) using only platform data. Although the recent debate has revolved around the extent to which to allow scraping data from the Internet, for simplicity, we focus on the extreme cases of not using GenAI or allowing no scraping (benchmark), or no friction in data collection and processing (platform with GenAI).

3.2 Platform with GenAI

The final stage of the model is common to both approaches; thus, we can move to the content creators' stage and determine the quantities and the hedonic price when the platform summarizes content (δ ≠ 0). Assuming that content creators choose quantities and the market clearing prices are set according to the inverse elasticity rule, it is straightforward that

$$\frac{p_i(1-\delta) - c}{p_i} = \frac{1-\delta}{\sigma} \leftrightarrow p_i = \frac{\sigma}{(\sigma - 1)(1-\delta)}c \tag{4b}$$

An immediate consequence of the presence of the platform using GenAI technologies that summarize content is that hedonic prices rise compared to the benchmark. If the GenAI platform captures a significant portion of content creators' revenues (δ), they will be less incentivized to produce content.

$$q_i = \left(\overline{p}^{\sigma-1}\gamma y\right)p_i^{-\sigma} = \frac{\gamma y(\sigma - 1)(1-\delta)}{nc\sigma} \tag{5b}$$

Therefore, it is straightforward to observe that profits monotonically decrease in δ compared to the benchmark. Note that profits are given by $\pi_i = \frac{\gamma y(1-\delta)}{n\sigma} - e$, if we impose the free-entry condition, $\pi = 0 \leftrightarrow n = \frac{\gamma y(1-\delta)}{e\sigma}$, we observe that the summarization effect of the GenAI platform (δ) also influences the number of active content creators in the market.

Lemma 1 *The summarization quality of the GenAI platform* (δ) *increases prices and reduces the level of content and its variety* (*number of active content creators*).

The recent drop in web traffic in Stack Overflow after the launch of ChatGPT[3] *or the decline in organic search traffic for publishers in the US last year after the launch of Google's AI-powered search*[4] *could be explained by this Lemma. These drops have raised concerns among content creators, especially among journalists who consider that these tools "have the potential to destroy journalism and media brands as we know them," as Mathias Döpfner, chairman and CEO of Axel Springer stated.*[5] *This result also provides a testable hypothesis for the future, highlighting that the amount or variety of content will decrease due to GenAI technologies. We already observe a decline in the quality of search results on platforms that rely on GenAI, as stated by Google itself.*[6] *As our results point out, the decline in traffic may create a disincentive to produce content that will reinforce this loop by decreasing the variety of content. Recent evidence suggests that this may also be the case of Stack Overflow or Stack Exchange (Burtch et al. 2023; Xue et al. 2023; Wang and Zheng 2024).*

Let us now move on to the first stage. The platform chooses its summarization quality (δ). The optimal level of quality is given by,

$$\delta^* = 1 - \left(\frac{f - e\sigma}{v\alpha K}\right)^{\frac{1}{\alpha-1}} \frac{\sigma e}{\gamma y} = 1 - \left(\frac{f - e\sigma}{v\alpha K}\right)^{\frac{1}{\alpha-1}} * \frac{1}{\widehat{n}} \tag{6}$$

where $\widehat{n} = n(\delta = 0) = \frac{\gamma y}{e\sigma}$. Note that $\delta^* \neq 0$, highlighting the platforms' incentive to summarize and profit from content creators. To understand its effect on content creators, we can substitute δ^* in the expression for the equilibrium number of content creators. Substituting δ^* into n, we have:

$$n^* = \left(\frac{f - e\sigma}{v\alpha K}\right)^{\frac{1}{\alpha-1}} \tag{7}$$

Proposition 1 *An independent GCP operating in a content market is incentivized to summarize it, which will lead to a reduction in human-produced content.*

GenAI reduces the number of content creators operating in the market and the variety of content, leading to higher prices. As expected, an increase in GenAI costs (or copyright enforcement costs), f, mitigates this effect $\left(\frac{\partial\delta^*}{\partial f} < 0\right)$. Interestingly, increasing the elasticity of substitution, σ, has a similar effect $\left(\frac{\partial\delta^*}{\partial\sigma} < 0\right)$. These results show that increased down-

[3] https://venturebeat.com/ai/is-chatgpt-domination-hitting-stack-overflow/

[4] https://web.swipeinsight.app/posts/google-s-ai-overviews-cause-publisher-traffic-decline-estimated-2b-ad-revenue-loss-5991

[5] https://www.wsj.com/tech/ai/news-publishers-see-googles-ai-search-tool-as-a-traffic-destroying-nightmare-52154074

[6] https://blog.google/products/search/ai-overviews-update-may-2024/

stream competition or strengthening copyright protection limits the impact of GenAI technologies. GenAI platforms can profit from markets where content creators enjoy significant market power or content has limited cross-substitution.

Corollary 1 *Competitive content markets and markets with well-defined copyrights will be less affected by GenAI content platforms.*

Corollary 1 also provides an interesting hypothesis to test in the future as GenAI technologies take off. Therefore, the promotion of competition by public authorities may mitigate the effects of GenAI.

However, it is also expected that markets with higher barriers to entry (high entry costs) may be less affected. Note that the effect of entry costs in the summarization parameter is negative.

$$\frac{\partial \delta^*}{\partial e} = -\frac{\sigma(\alpha\sigma e - \alpha f + f)\left(\frac{f-e\sigma}{v\alpha K}\right)^{\frac{1}{\alpha-1}}}{(1-\alpha)\gamma y(f-e\sigma)} < 0$$

Another interpretation of this result is that of considering entry costs as the opportunity costs for content creators. In this sense, the better the external options for content creators, the lower the summarization. Intuitively, opportunity costs work as an increase in competition from the platform's point of view. In other words, an increase in the elasticity of substitution (σ) has a similar effect to an increase in the entry costs ($\text{sign}\left\{\frac{\partial \delta^*}{\partial e}\right\} = \text{sign}\left\{\frac{\partial \delta^*}{\partial \sigma}\right\} < 0$). This provides an exception to the previous insight as it could be possible to find markets where players enjoy significant market power but that are less affected than other competitive ones. Under this model lens, this case is possible if the market exhibits significant barriers to entry either in the content market (downstream) or the GenAI technology market (upstream).

On the other hand, other factors intensify the effect of GenAI technologies. The higher the attention share that the representative consumer allocates to content hosted by the platform (γy), the greater the effect of these technologies. Considering that Americans spend more time on Google than on YouTube and Facebook combined, the impact of search engines powered by GenAI is expected to be of utmost relevance.[7]

Furthermore, the better GenAI technologies (K) or the more valuable third-party developer's outputs (v), the stronger the effect of GenAI-powered search on the downstream market. These results also suggest that close monitoring of GenAI results on the developer market is advisable. In fact, GenAI technologies are under scrutiny, as many generate outputs in a legal grey zone, such as deep fakes, identity fraud, plagiarism, or unqualified practice (Federal Trade Commission 2023). Improper regulation of GenAI technologies in these areas may create an incentive to intensify data collection, which will damage content markets.

Finally, this model also provides some guidelines for empirical work. It is unlikely that the quality of summarization will be known in the future as it may be a well-kept secret of

[7] https://www.pcmag.com/news/americans-spend-nearly-60-billion-hours-a-year-on-google

companies. However, we can rewrite Eq. 6 to express it as a relationship between before GenAI ($\widehat{n}$) and after GenAI (n^*) content levels,

$$\delta^* = 1 - \frac{n^*}{\widehat{n}} \tag{8}$$

Note that $\delta^* \in [0,1]$. The proof is as follows. Since $\widehat{n} \geq n^*$, δ is bounded from above, and its maximum can only be reached if $n^* = \widehat{n}$, which only happens if $\delta^* = 0$. This expression offers empirical guidance, as it suggests that the summarization degree is a function of before and after content levels on the platform. On the other hand, if $n = \frac{\gamma y(1-\delta)}{e\sigma}$, it is straightforward that $n^* \to 0 \quad if \quad \delta \to 1$. Equation 8 also helps answer another question: Do GenAI platforms have incentives to limit their own use of GenAI? Given the dependency on training data, they will moderate themselves, as too much summarization may collapse the market. Note that the larger the pre-GenAI level of content creators ($\widehat{n}$), the lower the summarization quality.

4 Extension: GenAI Summarization and Developer Data

Previously, we assumed that the summarization quality does not affect the data that developers use, $z = k(n)^{\alpha}$; intuitively, the developers have access to all the content data available to the platform. In this extension, developers have access to data that is affected by the summarization quality of the platform. Therefore, $z = k(\delta n)^{\alpha}$. Intuitively, the production function of the developers is affected by the quality of output from the platform's GenAI technology. Alternatively, this may represent the case that developers only have access to the data of creators who agreed to the platform training their GenAI on their content.

Then, the platform profit function becomes: $\Pi = n \times pq \times \delta + vk(\delta n)^{\alpha} - f\delta n$. Note that the main findings concerning stages 2 and 3 remain constant, as this alternative specification only modifies the initial stage.

To simplify the model and ensure tractability, we assume $\alpha = 1$; the role of α is apparent in the previous model. In this alternative case, the optimal level of summarization is now given by

$$\widetilde{\delta} = \frac{1}{2} + \frac{e\sigma}{vK - f}\frac{1}{2} \tag{9}$$

This condition holds as long as $vK\text{-}f > 0$ (see Appendix). Comparing Eqs. (6) and (9), there are two crucial differences in how market parameters affect the optimal summarization quality. First, the signs are inverted. This is a consequence of the curvature induced by α. In fact, if we consider $\alpha = 1$ in Eq. (6), the effect of $e\sigma$ is the same in both models. This result highlights that it is crucial to determine whether training data present diminishing or constant returns, as it determines the sign of the effect. Interestingly, depending on the technology employed by the third-party developer, more competition or better external options for content creators can increase the summarization quality for some platforms and decrease it for others. In other words, the effect of GenAI-powered search on content creators may vary depending on how third-party developers operate on the other side of the market. This effect does not depend on the platform decisions and highlights that authorities should pay careful attention to the technologies employed by third-party developers.

Proposition 2 *The presence of diminishing or constant returns on the developer side may alter the effect that barriers to entry, costs, and elasticity of substitution can have on the optimal level of GenAI summarization.*

Interestingly, if the summarization activity is prohibited ($n \times pq \times \delta = 0$), then $\widetilde{\delta} = 1/2$. Although GenAI platforms would be unable to capture revenues from content creators directly, they will continue to collect data as long as the developer is a source of revenue. This case implies that prohibitions or negative court rules for GenAI platforms accused[8] of scraping copyrighted content without credit or compensation will not hinder the development of such platforms. Platforms will continue to benefit from offering services to developers even if content creators opt out or GenAI summarization engines are banned. In this case, the platforms will operate as usual, collecting and processing data (without summarizing it) that other developers use for other applications. Since the second term in Eq. 9 is positive, it is straightforward that δ is higher when summarization is possible. Therefore, the previous effect on prices, demands, profits, and the number of content creators is robust to this specification.

If we compare the no-summarization case ($\widetilde{\delta} = 1/2$) to the previous model (Eq. 6), it is direct that δ^* is always above $\widetilde{\delta} = 1/2$ if $\alpha = 1$. The effect of GenAI on the market is greater if summarization quality does not influence the quality of data that the developer has access to, $z = k(n)^\alpha$. However, there are exceptions. If $\alpha \neq 1$, the previous insight only holds as long as demand in the content market without GenAI technologies is significantly larger than when GenAI is present, $n(\delta^*) \leq \frac{n(\delta=0)}{2}$. Therefore, the presence of diminishing returns in the developer production function may lead to a situation in which the summarization may be lower when it does not influence the data that the developer has access to ($z = k(n)^\alpha$) than when summarization limits it ($z = k(\delta n)^\alpha$).

If we consider the number of content creators in this alternative scenario, we have

$$n = \left(\frac{1}{e\sigma} - \frac{1}{vk - f}\right)\frac{\gamma y}{2} \tag{10}$$

As before, it is straightforward to show that the number of content creators in this scenario is lower than in the case without GenAI technology ($\delta^* = 0$). This result reinforces that of Proposition 1, which also holds in this case. Additionally, note that Eq. 8 is still valid in this case, and the role of the elasticity of substitution and costs is still the same, reducing the number of content creators in the market. This further emphasizes the model's usefulness for empirical testing, as the relationship between the optimal summarization quality and the number of content creators is robust to different model specifications.

However, it is interesting to note the contrasts between the two cases. The attention share that the representative consumer allocates to content (γy) played no role in determining the number of content creators in the first model, but it plays a positive role here. In the first model, the optimal summarization quality depends negatively

[8] https://www.newsmediaalliance.org/wp-content/uploads/2023/10/AI-White-Paper-with-Technical-Analysis.pdf

on the consumer's budget allocation, leading to lower summarization. This occurs because increasing the proportion of attention allocated to content implies an increase in demand, which in turn increases the costs of the GenAI technology. However, the GenAI technology affects the number of content creators proportionally, which offsets the effect in equilibrium. In the second model, consumer allocation does not affect the optimal summarization quality. That implies that consumer budget allocation affects the number of content creators in equilibrium.

Corollary 2 *The attention share that the representative consumer allocates to content* (γy) *leads to increases in the number of content creators if developer's production function depends on the GenAI summarization, namely* $k(\delta n)^{\alpha}$, *and presents no diminishing returns.*

5 GenAI Welfare Impact

We analyze how the market outcome presented earlier compares to social planner benchmarks. Suppose the existence of a GenAI platform is given, and that a social planner can set the variety of content (number of content creators) in the market. In other words, the social planner takes the platform's presence as given and only cares about the consumer, developer, and content producers (Belleflamme and Peitz 2015). Since prices and content creators' total gross profits do not depend on the number of content creators, the socially optimal number of content creators is given by

$$\max_{n} \quad U(n) + v \times k(n)^{\alpha}$$

In this case, this social planner will always prefer to have more variety than what the market provides. This holds regardless of the summarization level and whether we assume that the consumer subsidizes the opportunity costs of content creators. Even in such a case, the market provides too little variety. Therefore, we can summarize the impact of GenAI technologies on consumers in the following proposition.

Proposition 3 *GenAI technologies reduce consumer welfare in the content market* (*Proof. see appendix*).

This result highlights that GenAI technologies can harm consumers, developers, and content creators. This conclusion supports recent claims by some content creators, such as The New York Times, that this technology hurts their business (New York Times 2023). However, caution should be exercised with this conclusion as it considers the platform as an exogenous entity. The social planner could instead set the summarization quality to maximize the utilities of all players. The comparison between both approaches could be seen as the possibility of intervening in the downstream (content provision) or upstream market (GenAI technology).

Assuming that the social planner chooses the summarization quality that maximizes the platform profits, consumer surplus, and content providers' profits, we can identify the tensions between the different market participants.

We can see this formally by assuming that the social planner maximizes $W = n \times pq \times \delta + U + vk(n)^{\alpha} + n\pi - ne - fn$, the first-order condition highlights this tension, as it can be written as $\frac{\partial W}{\partial \delta} = \frac{\partial \Pi}{\partial \delta} + \frac{\partial U}{\partial \delta}$, note that $\frac{\partial U}{\partial \delta} < 0$, which implies that the incentive to provide summarization is reduced compared to the market solution. The platform provides too much summarization from a social point of view.

Comparing the social interests of consumers and the platform shows that they have competing interests, indicating a social trade-off. Furthermore, depending on whether the social objectives favor the consumer or developer side, the social optimum may imply some summarization. Although this may lead to less human-produced content and higher prices, it allows for creating other markets.

Corollary 3 *The social optimum regulation of GenAI technologies faces a trade-off between the interests of consumers and developers.*

6 Conclusions

This article analyzes the economic effect of GenAI when used by content platforms. A GenAI content platform (GCP) trains a GenAI model using the content generated by third-party creators, responds to consumer queries, and offers an API for developers to build new applications by accessing the GenAI model.

Our work provides testable hypotheses about the economic impact of GenAI technologies. We find that GenAI technologies reduce the quantity of content and the number of content creators and increase prices, hurting consumers. These results provide theoretical foundations for recent empirical evidence that finds lower quality and quantity of questions and answers on Q&A platforms like Stack Overflow and Stack Exchange after the disruption of LLMs (Burtch et al. 2023; Xue et al. 2023; Wang and Zheng 2024). Similarly, the introduction of GenAI affects the incentives of content creators. Our results highlight that variety (understood as the number of content creators) will decrease with the introduction of GenAI. Recent evidence highlights that this may be true for some types of content creators, but not all (Peukert et al. 2024). Therefore, our work provides a theoretical foundation for these empirical results and highlights other aspects that may influence these effects, such as the impact of returns to scale on developer production, the alternative options of content creators, the strengthening of copyrights, or the consumers' share of attention. Moreover, these effects are not homogeneous, as competitive markets seem less influenced by this technology. Similarly, we find that GenAI may lead to welfare losses if we look only at the content market, but this technology may enable the creation of new markets. Nonetheless, whether the surplus created in these new markets offsets the losses in the content market is a question for future research.

GenAI technology can be a useful tool for content creators: it can be used to automate trivial tasks, assist in the creation process, and democratize access to content creation. However, when platforms use GenAI as an additional layer between users and content creators and as a tool to extract more value from creators, then it can have negative unintended consequences. Therefore, platforms and policymakers must pay particular attention to how exactly GenAI is used.

Despite the findings, the model is highly stylized and leaves out many interesting details for simplicity. For example, recent evidence suggests that quality has degraded due to the implementation of GenAI (Burtch et al. 2023; Wang and Zheng 2024). After significant media coverage, Google has even been forced to explain it.[9] Moreover, not all search

[9] https://blog.google/products/search/ai-overviews-update-may-2024/

queries are equal; recent empirical results highlight that GenAI may lead to a substitution of trivial questions for more complex ones (Quinn and Gutt 2023; Sanatizadeh et al. 2023). This implies that the summarization effects may be limited to some content, limiting the scope of its impact and the number of content providers affected. Similarly, recent evidence highlights different responses from content creators to the introduction of GenAI (Peukert et al. 2024), and future work needs to consider heterogeneity on this market side. Moreover, we assume the developer has no bargaining power for simplicity and tractability, but that limits the scope of the derived insights. Although the model captures core mechanisms relevant to content platforms using generative AI (summarization of content, reduction of traffic to content producers, interest of third-party developers), substantial future research is needed to capture and analyze the complexities that are not in the model, including novel business models and competition.

Appendix

Proof of Lemma 1

The representative consumer's utility is given by $U = q_0^{1-\gamma}\overline{q}^{\gamma}$, $0 < \gamma < 1$, where q_0 is the numeraire, $\overline{q} = \left(\sum_{\forall i} q_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$ is the quantity of a composite differentiated good defined by an index of the CES type, q_i is the quantity consumed of variety "i" and $\sigma > 1$ is the elasticity of substitution. Following the S-D-S model (Spence 1976; Dixit and Stiglitz 1977), the representative consumer maximizes its utility subject to a budget constraint: $q_0 + \overline{pq} \leq y$, where $\overline{p}$ is the price index of the differentiated good and "y" is the income. Formally:

$$\max_{\overline{q}} U = \left(y - \overline{pq}\right)^{1-\gamma}\overline{q}^{\gamma}$$

The first-order condition (FOC) yields: $\overline{pq} = y\gamma$ (Consumer spends a constant share of budget). Now, by maximizing the CES function subject to $\sum_{\forall i} q_i p_i \leq \gamma y$:

$$\begin{array}{c}\max \overline{q} \\ s.t. \sum_{\forall i} q_i p_i \leq \gamma y\end{array} \rightarrow \mathcal{L} = \overline{q} + \lambda(\gamma y - \sum_{\forall i} q_i p_i)$$

Combining the FOC and solving for q, we have the quantity consumed of each variety: $q_i = \left(\overline{p}^{\sigma-1}\gamma y\right)p_i^{-\sigma}$. We extract the price index $\overline{p}$ by introducing q_i in the CES function using the fact that $\overline{pq} = y\gamma$.

Then, we have: $\overline{p} = \left(\sum_i p_i^{-(\sigma-1)}\right)^{\frac{-1}{\sigma-1}}$, and by symmetry, $\overline{p} = pn^{\frac{-1}{\sigma-1}}$, where "n" is the number of firms and σ is the elasticity of CES demand.

Assume content creators have the following profit function: $\pi_i = p_i q_i(1-\delta) - cq_i - e$, where q_i is the demand previously defined, and "e" is the entry cost. By backward induction and supposing that content creators choose quantities, we can characterize the market clearing price according to the inverse-elasticity rule:

$$\frac{p_i(1-\delta) - c}{p_i} = \frac{1-\delta}{\sigma} \leftrightarrow p_i = \frac{\sigma c}{(\sigma-1)(1-\delta)}$$

Substituting into the demand and functions,
$q_i = \left(\overline{p}^{\sigma-1}\gamma y\right)p_i^{-\sigma} = \frac{\gamma y(\sigma-1)(1-\delta)}{nc\sigma}$ and $\pi_i = \frac{\gamma y(1-\delta)}{n\sigma} - e$

By imposing the free-entry condition, we can determine the number of content creators in the market, which proves Lemma 1.

$$\pi = 0 \leftrightarrow n = \frac{\gamma y(1-\delta)}{e\sigma}$$

Proof of Proposition 1

Suppose there is a platform whose profits are given by: $\Pi = n \times pq \times \delta + vk(n)^{\alpha} - fn$, where $n \times pq$ are the profits of n content creators and "f" is the marginal cost of capturing information from an additional firm.

Substituting (n, p, q) in Π and maximizing with respect to δ, the first-order condition (FOC) is:

$$\frac{\partial \Pi}{\partial \delta} = \gamma y + vK\alpha \left(\frac{\gamma y(1-\delta)}{e\sigma} \right)^{\alpha-1} \left(-\frac{\gamma y}{e\sigma} \right) + \frac{\gamma y}{e\sigma} f = 0$$

The second-order condition (SOC) guarantees that the equilibrium condition determined by the first-order condition is the unique and global equilibrium:

$$\frac{\partial^2 \Pi}{\partial \delta^2} = vK\alpha(\alpha-1) \left(\frac{\gamma y(1-\delta)}{e\sigma} \right)^{\alpha-2} \left(-\frac{\gamma y}{e\sigma} \right) \left(-\frac{\gamma y}{e\sigma} \right) < 0$$

If we solve the FOC, we have $\delta^* = 1 + \left(\frac{f-e\sigma}{v\alpha K} \right)^{\frac{1}{\alpha-1}} \frac{\sigma e}{\gamma y}$, and by substituting into n, we have: $n^* = \left(\frac{f-e\sigma}{v\alpha K} \right)^{\frac{1}{\alpha-1}}$, which proves Proposition 1.

Proof of Proposition 2

Suppose that $z = k(\delta n)^{\alpha}$ and therefore, the platform maximizes $\Pi = n \times pq \times \delta + vk(\delta n)^{\alpha} - f\delta n$. Assume that $\alpha = 1$, if we maximize profits with respect to δ as previously:

$$\frac{\partial \Pi}{\partial \delta} = \gamma y + vK \frac{\gamma y}{e\sigma}(1-2\delta) - f \frac{\gamma y}{e\sigma}(1-2\delta) = 0$$

$$\delta = \frac{1}{2} + \frac{e\sigma}{vKf} \frac{1}{2}$$

Which is the global and unique equilibrium since the second-order condition verifies $\frac{\partial^2 \Pi}{\partial \delta^2} < 0$ if $vK > f$. If we substitute this δ in $n = \frac{\gamma y(1-\delta)}{e\sigma}$, it is straightforward that $n = \left(\frac{1}{e\sigma} - \frac{1}{vk-f} \right) \frac{\gamma y}{2}$, and the proof of Proposition 2 is straightforward.

Proof of Proposition 3

Suppose the social planner regulates entry only. We consider two potential cases: one in which the planner finances the fixed costs of content creators by a lump-sum transfer on the consumer's income (thus, the disposable income is $y - ne$), and another case where that is not possible. In both cases, the platform is active and sets a non-negative summarization level (δ ≠ 0). Since consumer income is understood as an annoyance tolerance threshold or attention budget, we can assume that *ne* is the monetary value of the attention lost by imposing some annoyance on consumers. For example, an entry cost for content producers is the management of cookies and personal data; a way to reduce this cost is to ask users to opt out if they want, which imposes a cost of attention on them.

Following this case, we know that the consumer allocates a share γ of its attention to content, $\overline{pq} = \gamma(y - ne)$. Because of our assumptions, we know that prices and quantities of content producers are given by $p_i = \frac{\sigma}{(\sigma-1)(1-\delta)}c$, $\overline{p} = pn^{\frac{-1}{\sigma-1}}$, and $\overline{q} = n^{\frac{\sigma}{\sigma-1}}q$. Using the fact that $q_0 = (y - ne) - \overline{pq}$, we can rewrite the utility function as

$$U = K(y - ne)n^{\frac{\gamma}{\sigma-1}}$$

where $K = (1-\gamma)^{1-\gamma}\left[\frac{\gamma(1-\delta)(\sigma-1)}{c\sigma}\right]^{\gamma}$. Because content creators' profits do not depend on the number of content creators and the fixed costs are financed by the representative consumer, the optimal number of content creators is given by maximizing the utility function with respect to *n*.

$$\frac{\partial U}{\partial n} = K\left[\frac{\gamma}{\sigma-1}(y-ne)n^{\frac{\gamma}{\sigma-1}-1} - en^{\frac{\gamma}{\sigma-1}}\right] = 0 \iff n^* = \frac{\gamma y}{e[\gamma+\sigma-1]}$$

Note that a) the optimal number of content creators is independent of the summarization level, b) we do not take into account the developer yet (whose surplus is extracted by the platform completely), if we define the welfare function as $W = U + v * k(n)^{\alpha}$, the first order condition is $\frac{\partial W}{\partial n} = \frac{\partial U}{\partial n} + v\alpha k n^{\alpha-1} = 0$, which highlights that social planner interest in increasing the number of content creators may be even larger. However, this expression also highlights that the social planner's interest in the consumer decreases in δ, which shows the tension between the interests of consumers and developers.

Proof of Corollary 3

Suppose the social planner objective function is given by $W = n \times pq \times \delta + U + vk(n)^{\alpha} + n\pi - ne - fn$. The first order condition is

$$\frac{\partial W}{\partial \delta} = \underbrace{\gamma y + vK\alpha\left(\frac{\gamma y(1-\delta)}{e\sigma}\right)^{\alpha-1}\left(-\frac{\gamma y}{e\sigma}\right) + \frac{\gamma y}{e\sigma}f + U'(\delta) = 0}_{\frac{\partial \Pi}{\partial \delta}}$$

Since $U'(\delta) < 0$, the platform summarizes too much from the social planner's points of view.

Acknowledgements We thank the anonymous reviewers for their careful reading of our manuscript and their many insightful comments and suggestions.

Author Contribution All authors contributed to the study conception, design, analysis and draft preparation equally.

Funding The authors did not receive support from any organization for the submitted work. No funding was received to assist with the preparation of this manuscript.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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