MACHINES WILL NOT REPLACE US –

GENERATIVE AI, ARTISTS' LABOUR MARKETS, AND THE NEED FOR CERTIFICATION

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This version: 16 April 2026

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Abstract. Prospective consequences of generative artificial intelligence for artists'/creators' labor markets concern many stakeholders. This paper identifies measures for making the best of this novel technology within that sector by harnessing insights from the specialized economics literature on cultural economics. It covers intrinsic motivation and self-service, matching and personalization, multi-product strategies and evasive action by creators, as well as reputational and positional good attributes – going well beyond the extant literature on artificial intelligence. The potential of generative artificial intelligence is first discussed by comparing data on output costs relative to the costs of creating works in traded, labor-intensive processes as well as current retail prices, including simulated values for coming years. It goes to show that creators have scope for competing with 'machines' on price. Second, we discuss perceptions of quality, and why human creations are held in higher regard, as long as users are aware of modes of production. We then briefly discuss responses by creators to cope with technological change, and compare various policy options within our framework. In conclusion, we call for certification of human creations (or the reverse of labelling output of generative artificial intelligence), as an essential step towards a sustainable situation for all stakeholders.

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Keywords: cultural industries, artificial intelligence, technological change.

1. INTRODUCTION

For all the unmissable hype around artificial intelligence (AI) in general, and generative AI (genAI) in particular, it is early days to assess any impact of the latter on artists'/creators' labor markets. An intuitive way to illustrate that point is to ask yourself two questions. First, what has been the last novel, film or tv series, music recording, or painting that you engaged with? Second, is that cultural expression generated by a human or by genAI? Most people will have two responses. On the one hand, they will recall a human creation. Hence, early days. On the other, if that work has been generated over recent years, many will realize that they cannot be sure, to what extent genAI has been applied in the creation process, even if human creators are attributed. This non-transparency is a key theme in this paper.

As yet there is little empirical evidence on any impact of genAI on artists' labor markets, other than initial explorations of stakeholders' perceptions and attitudes (e.g. Epstein et al. 2023; Kawakami and Venkatagiri 2024; Messer 2024; Lovato et al. 2024).[1] Any apparent limitations of current genAI technology are routinely

[1] A notable exception is a working paper by Makridis (2025), finding evidence for "early task reallocation" but little support for any earnings decline or other "labor market harm" due to genAI among artists residing in the USA.

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dismissed as temporary phenomena, assuming that the technology will continue to become much more powerful and efficient in the near future, also because users will develop more sophisticated applications. In any case, the potential of genAI to replace human creators (Tuncdogan and Acar 2023; AbuMusab 2024) has deeply upset some stakeholders (Goldberg and Lam 2025; Milmo 2026). To be sure, complete replacement is extremely unlikely, as most commentators acknowledge, and, for better or for worse, concern for creators' well-being may not yet trump the quest for developing a promising general-purpose technology such as AI.

Any substantial replacement has the potential to disrupt the CCI, as well as to uproot how social scientists address the cultural and creative industries (CCI). The state-of-the-art analytical definition of CCI consists of three criteria. CCI supply: (1) symbolic goods and service, that is creative/cultural works are signifiers, whose emotional impact and value can far exceed their objective technical specifications; (2) goods generated by human creative labor; and (3) goods that have the potential for intellectual property protection, especially copyright. The latter two of these components could become much less relevant with the diffusion of genAI. The labor-intensity of CCI stands in question, should capital-intensive genAI become a predominant input in the production of novel cultural signifiers. Furthermore, copyright does not apply to genAI output and the use of copyright works for genAI training processes fall under copyright exceptions and limitations in EU legal jargon, or fair use rules in the US and fair dealing rules in the UK, which have roughly equivalent counterparts in many

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countries around the world. That illustrates the potential for more profound change in the CCI due to genAI than we have experienced for a Century.

This paper harnesses insights from the specialized economics literature on cultural and creative industries – the economics of arts and culture aka cultural economics – to identify measures for making the best of genAI within that sector. In this respect it goes well beyond the current literature.

The paper proceeds as follows. Section 2 briefly takes stock of the economics literature on genAI and CCI so far, clarifies terminology, and discusses characteristics of CCI as well as related issues raised by genAI (complemented by an APPENDIX on different types of works and appropriate multi-product strategies in response to genAI). The focus is narrowly on choices between modes of production. Section 3 discusses the costs of genAI output relative to costs of creating works and current retail prices, and uses that data to discuss future developments based on simulations (accompanied by another APPENDIX documenting the processing of data in section 3). Section 4 complements this with a discussion of the nebulous but essential issue of perceived quality of cultural signifiers. The concluding section 5 discusses basic implications for creators' business models in the presence of genAI as well as policy implications. Ultimately, we argue for measures to certify modes of production as the most promising option to safeguard dynamically sustainable further development of creators' labor markets and genAI.

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2. LITERATURE AND FUNDAMENTAL THEORY

2.1 What is genAI and what does it do?

For the purposes of a fundamental economic analysis, we can restrict discussions of the specifics of genAI technology to a minimum. For more comprehensive coverage of historic developments, technical issues and variety, as well as the challenge of developing a universally adequate, analytical definition see, e.g., Anantrasirichai and Bull (2022) or Garcia-Peñalvo & Ingelmo (2023).[2] The following description also serves as an ostensible definition.

GenAI refers to the development and application of stochastic methods by learning algorithms to process data, identify patterns, and produce useful and unique outputs. In the most popular applications of genAI, users can submit specific and relatively concise data referred to as prompts that signal a specific request. The genAI model processes a prompt (and any additional user data) and responds by generating a tailored, novel and potentially valuable output that reassembles aspects of its training data and applies identified patterns within it – often in such a sophisticated manner that the specifics of the assembly process are beyond human comprehension. Over repeated prompting and curation of output, users can improve process results. Today, genAI technology can handle any type of media content as prompt input or as output, from human language

[2] In a systematic literature review of 637 recent articles to do with genAI, Garcia-Peñalvo & Ingelmo (2023) define genAI "[…] as the production of previously unseen synthetic content, in any form and to support any task, through generative modeling", and specify in a footnote that "generative modelling" is: "Understood as modelling the joint distribution of inputs and outputs."

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texts, computer code, sound, to still and moving images, including *digital representations* of performances and physical objects.[3]

GenAI models take shape by processing vast amounts of training data. Sophisticated genAI models require specialized hardware, which is quite costly, and considerable amounts of energy. With these inputs, learning algorithms process data and automatically alter their own code, without specific human intervention. That makes genAI capital-intensive, despite three caveats: (1) so far, some specialized human labor is required to initiate and sustain any innovative – novel and useful – genAI service; (2) as a rule, much of the input data has been created in labor-intensive processes; and (3) so-called 'supervised learning' is common, where human agents 'show' the AI how to classify and process, or what types of outputs are desirable or not.[4]

GenAI applications entail two essential value propositions in the context of CCI. First, genAI **reduces the costs of generating signifiers** by replacing some of the relatively costly input of human labor.[5] Users can employ comparatively short prompts to make genAI provide more complex signifiers in a speedier and

[3] Specific genAIs models are often (still) specialized on some types of media content. However, various genAIs with their own special application strength may be accessible through the same user interface, and there is a trend towards convergence into multi-input and -output models.

[4] In essence, the latter means that human agents generate tailored input data to complement bulk processing of data from other sources. Finally, the data generated by users can also be used for updating and improving the service.

[5] Prompting and curation replace much of the specific creation effort, say the skills and time required for creators to formulate literary texts, compose and play instruments, arrange musical works, use paint and brush, shoot audiovisual still and moving images, or code for video games.

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cheaper manner than would be feasible in traditional, labor-intensive processes of creation. Second, genAI allows for **personalization of signifiers** and perhaps even for users to employ self-service. The costs of producing signifiers with genAI – the time and skills required for prompting and curation – may (have) become so low that genAI can be effectively used not only by skilled and specialized creators, who seek to generate value for others, but also by common end-users, who are in it for their own, consumptive purposes only. Key to both these value propositions is that the genAI service keeps the required effort for users low, as it 'fills in the gaps' in what has not been explicitly requested by the user. In other words, genAI matches prompts with patterns in relevant aspects of its training data.

This raises the question to what extent these new services will come to replace deliberate, value-generating actions (work) by human creators. This is a question of relative costs as well as the perceived quality of genAI output compared to cultural works. We separately discuss these two aspects in later parts of the paper. However, genAI requires suitable training data, including data produced by human creators (Shumailov et al. 2024; Dhar 2024), so that heedless applications of this technology to replace labor could become self-defeating.

In this context, it is a problem that some necessary conditions for efficient market co-ordination are not met, as the mutable and complex operations of genAI are associated with non-transparency and high transaction costs. On the one hand, it is very costly to document to a human, on what basis any specific

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genAI output has been generated.[6] This includes any input data – for general training or for any specific genAI application, say the generation of a text or image in response to a prompt that eventually draws relatively heavily on a specific subset of data. Furthermore, across vast amounts of data, establishing licenses, relative contributions, and conducting corresponding payments entails high transaction costs, which may often exceed the value of potential royalty fees. Furthermore, suppliers of genAI services have little individual incentives to invest in resolving such issues. As things are, they get to use lots of copyrighted works for free, protected by non-transparency, copyright exceptions (Handke et al. 2022), and terms of services of online platforms permitting subsequent use of uploaded works for genAI training. In turn, there are suboptimal incentives for rational creators to invest in creating works that are suitable for genAI. Due to the large range of extant works that are available as input data, this may not have become a major issue yet. However, in the long run, that may come to pass.

Besides this initial account, a thorough review of the economics literature on genAI is beyond the scope of this paper. It is already bursting at the seams with arguably more original content. Early literature reviews include Lu and Zhou (2021) as well as Hang and Chen (2022). Advanced formal (macro-)economic models are presented, for instance, in Acemoglu and Restrepo (2018) as well as Acemoglu (2025). A key theme in the literature is indeed that AI is a special case of automation, displacing traded labor applications (Acemoglu and Restrepo

[6] In a sense, this also documents how genAI may indeed fulfill tasks that would have been too costly to conduct in labor-intensive processes.

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2018; Colombo et al. 2019; Zarifhonarvar 2024). For empirical work, with very limited coverage of CCI, see for instance, Lane and Saint-Martin (2021), Acemoglu et al. (2022), Duch-Brown et al. (2022), Acemoglu and Johnson (2024), Hampole et al. (2025), or Gosh et al. (2025). Results vary widely and require frequent updates, as technology advances. Regarding issues to do with copyright in particular, see Gans (2026). Instead let's turn to some unfamiliar issues in the literature, drawing on cultural economics.

2.2 Characteristics of CCI and further issues raised by genAI

A brief clarification of terminology is required. Both human creators and genAI can produce signifiers – symbolic expressions that trigger desirable associations among users that go vastly beyond the immediate physical attributes of the product.[7] We refer to signifiers produced by human creators as 'works' (according to legal jargon in copyright law), and to signifiers produced with limited input from human agents (prompts) by genAI as 'output'. Where neither of the two modes of production predominates or hybrid modes are in focus, we refer to 'products'. All these terms are defined as sub-sets of 'signifiers'. The paper is consistently focused on signifiers and the prospective effects of genAI on creators – or "creative inputs", rather than on "humdrum inputs", in the CCI according to the terminology of Caves (2000).

[7] We do not include computer code in our discussion.

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Creators operate in peculiar markets (cf. Caves 2000; Towse 2001; Alper and Wassall 2006; Menger 2006; Towse 2006; Handke & Dalla Chiesa 2022). According to the specialized literature of cultural economics, the CCI are characterized by a unique combination of traits. There is almost certainly a complex web of causal associations between them, which have not been fully disentangled. For this article, this is not necessary, however.

The following also features some formal modelling. The purpose is not to specify any equilibrium but to illustrate essential meanings of alleged economic characteristics of human creators and the CCI, in as far as they bear on the effects of genAI on artists labor markets. In contrast to, for instance, Acemoglu (2025) our modelling does not assume competitive markets but monopolistically competitive markets, explores several other stylized facts regarding the CCI, and focuses on artists/creators. For a micro-economic model dealing with welfare economic issues of genAI and copyright, see Gans (2026). The latter consistently separates copyright authors and suppliers of genAI services, some of whose outputs are substitutes for works (and the others are unrelated). By contrast, our model addresses any economic agents, who seek to generate signifiers in the most cost-efficient manner feasible, including end-users. Suppliers of genAI services are not treated as direct competitors of creators, but as suppliers of a service that allows other parties to generate related goods to human-created works, which are mostly substitutes due to income and time constraints of end-users.

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2.3 The baseline model

An economic agent seeks to produce cultural signifiers of a given value y with two types of available inputs, labor, l, and capital, k, at an exogenously given state of technology, θ (cf. Foster and Rosenzweig, 2010). The corresponding production function can be initially specified as

$$y = g_\theta(l,k)$$

The agent seeks to maximize profits according to the function:

$$\pi_\theta(C_l,C_k) = \max_{l,k} g_\theta(l,k) - C_l - C_k$$

In our parsimonious model, this entails minimization of the agent's costs. As a rule, any production of signifiers requires both labor and capital. Let l represent traded, labor-intensive modes of production to some, exogenously given and constant degree, and k represent modes of producing equivalent output with genAI as a capital input, which requires less creative human labor, also to a constant degree.

For simplicity, let y also represent any stages of production that can be disentangled over a range of tasks, whose contribution to the value of final goods is strictly additive, and over which l and k are perfect substitutes. Then for each task, the agent faces a binary choice between two production modes, one of which involves genAI and less labor inputs. After expanding the cost functions, we get a choice set of

$$y = \begin{cases} f_l + q_y c_l \\ f_k + q_y c_k \end{cases}$$

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We are strictly interested in choices regarding modes of production. For simplicity, let's assume that y is fixed and equivalent to utility u. This corresponds to a situation where all prices are profit-maximizing with perfect excludability, perfect appropriability for the producer, and non-rivalry in consumption, so that price equals marginal utility per undifferentiated user. This modeling choice also approximately corresponds to a situation where the share of value that accrues to suppliers is constant. Then total value (or utility, U) for end-user(s) of y and the associated suppliers' revenues can be specified as

$$U = qp = R$$

with q denominating the quantity of units of that signifier sold – copies in the case of reproducible signifiers –, p denominating price, and R denominating the supplier's revenues without transaction costs.[8]

2.4 Cost structures

Like any information good (or service), CCI exhibit cost structures with high – upfront and partially sunk – fixed costs. Where multiple users are served with non-exclusive access to an extant work (a ready-made), there are relatively low and often non-increasing marginal costs for serving additional users (Landes and Posner 1989; Caves 2000; Towse 2019; cf. Shapiro & Varian 1999).

[8] Our model can of course be extended to cover sets of differentiated agents according to their quality-adjusted costs, a mass of differentiated users according to their willingness to pay for specific signifiers, and some convex function for marginal value of signifiers (diminishing marginal utility).

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For specific genAI models, the setup and fixed costs tend to be much higher than for traded, labor-intensive creative projects. That is, for in-house production, as a rule $f_l < f_k$, but marginal costs per novel signifier may be much lower. In practice, producers of signifiers within the CCI buy genAI services from large specialized suppliers. Therefore, prices for genAI services constitute the relevant costs for the economic agents we take into focus. From this perspective, we discuss the available evidence regarding relative cost advantages of genAI and human creativity in section 3 as well as APPENDIX 1.

2.5 Intrinsic motivation to create and self-service

The seminal Caves (2000) emphasizes so-called intrinsic motivation to create as characteristic for creative industries. Empirical work consistently documents that creators' (risk-adjusted) financial rewards are on average relatively modest compared to other professions (Throsby 1994; 2001; Towse 1997; Caves 2000; Frey 2000). Many creators seem willing to invest time and money – and to generate value for others – without a competitive pecuniary return. The standard economic explanation is compensating differentials: creative work may be less unpleasant and/or entail relatively great, non-pecuniary benefits, such as self-expression and/or accumulation of social capital, compared to other work.[9] Let's assume that genAI applications are a case in point of 'other work'.

[9] Alternative explanations of creators' below average earnings are risk-seeking (Rosen 1981; Benhamou 2003) or systematically biased, optimistic expectations (Towse 2001).

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In essence, the effective costs for intrinsically motivated creators are reduced by some $m \geq 0$, so that

$$y_l = f_l + qc_l - m$$

If m only applies to creative work or is greater there than for genAI, in reasonably efficient markets this limits the adoption of genAI to displace creative labor or otherwise reduces welfare increases from displacement.

For the probable consequences, the exact source of intrinsic motivation matters. With pleasant work – intrinsically motivated in a narrow sense – some differentiation seems likely. Across multiple tasks within the production of a final creative work, some tasks may be more pleasant than others. In such constellations, genAI may allow human creators to disentangle and delegate less pleasant tasks to genAI and focus on pleasant tasks and thus become more productive (increasing m). On the other hand, intrinsic motivation can be sensitive to perceptions of opportunistic behavior by other parties (crowding out), for instance when less intrinsically motivated agents apply genAI to supply substitutes, perhaps even with the substituted works being used as genAI training data. This could reduce m or even change its sign.[10]

Where the accumulation of social capital and thus the benefits of goodwill by other parties is the source of so-called intrinsic motivation (here "intrinsic" can be misleading and we better speak of non-pecuniary extrinsic benefits), effective

[10] Here, crowding theory (Frey and Jegen 2001; DiGaetano and Mazza 2017) as a staple of cultural economics is useful.

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attribution of creators is central. GenAI does not reliably attribute creators of training data, which will undermine the accumulation of social capital, reducing m .

A related issue is self-service. Agents may not just be in it for the benefits of making works available to other parties (monetary revenues in the case of sales). Agents may also experience use value from the signifier in question in a process of self-service. With self-service, total revenues $R < U$. (Where signifiers are non-rival in consumption, self-service does not conflict with making signifiers available to further parties.) In our parsimonious model, this reduces revenues by one unit, see below.

$$R = \begin{cases} qp \ \ if\ the\ producer\ is\ only\ in\ it\ for\ the\ money \\ (q-1)p \ \ if\ the\ the\ producer\ is\ a\ user\ herself\ (self-service) \end{cases}$$

In practice, agents may of course appreciate the signifiers they helped bring about more than representative other users, for instance due to excellent matching for specific preferences (see section 2.6). In the context of genAI, self-service may play a central role, as it allows agents – including end-users – to bring about signifiers without incurring the fixed costs of acquiring creative skills, say play a musical instrument.

2.6 Differentiated works, matching and personalization

Cultural works are differentiated. Effective copyright protection is a means to ensure this. As a rule, creators are in monopolistic competition based not only on price but also product attributes. Users exhibit differentiated preferences (Caves

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2000) and taste for variety, either because they seek novel experiences (Bianchi 2002) or because of taste formation (cf.: Blaug 2001; Seaman 2006).

In economic treatments of product differentiation and differentiated preferences, matching problems are central. Let's treat this in terms of a spatial competition model, in which the effective value of y is a portion of a theoretically perfect match value y_j^* by some mismatch b, so that for a single user j we get

$$y_j = y_j^* - b$$

Mismatch may be mitigated by some costly personalization technology by a factor $h \in (0,1]$, which shifts the product closer to the user preference, so that without fixed costs for personalization

$$y_j^h = y_j^* - bh - c_h$$

Personalization will be used where $y_j^h > C + bh + c_h$ and $bh > c_h$. For the full set of users with equivalent valuations as well as costs and including fixed costs of the personalization technology, we get

$$Y^h = qp - qbh - f_h - qc_h$$

One potential benefit of genAI is that it allows for cheaper personalization of signifiers, which could reduce matching problems compared to situation with a more definite supply of ready-made works. Note that f_h may be low, where genAI users apply services produced by another party.

There are several options:

1. GenAI is applied to generate signifiers ad hoc based on a user's prompt.

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2. Users feed extant signifiers into a genAI model and ask for alterations. This increases the number of input tokens compared to shorter prompts in human language, reduces the prompting costs (labor), and decreases the number of output tokens, since many aspects of the output are simply copied.
3. GenAI is used for customization, where the same genAI output is made available as a ready-made to several users, which are expected to have similar preferences.

However, matching will not be costless nor perfect with genAI. After all, genAI users must invest time in prompting and output curation (labor) and pay genAI suppliers. With ad hoc personalization, genAI output will usually be much more specific and detailed than any (number of) prompts, which entails some degree of mismatch. This holds in particular for complex signifiers, such as films. Furthermore, personalization will have limited benefits, where product space is already crowded and well matched. In many CCI, hundreds of thousands of extant product variants are available.

2.7 Multi-product strategies

Creators tend to supply multiple product variants within the same product category (e.g.: novels, songs, and paintings), and/or participate in teams to jointly produce more complex works (e.g.: larger stage performances, technically sophisticated video games, or films) in a relative quick succession. Creators are

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also regularly (participating in) supplying distinct types of works. For instance, musicians usually supply compositions and sound recordings, as well as stage performances, or stage actors also contribute to film productions.

One rationale for multi-product strategies is spreading fixed costs over various goods and services. Another is reducing entrepreneurial risk. Like any suppliers of novel, innovative goods and services, suppliers of signifiers face demand uncertainty (e.g.: Baumol 1986; Caves 2000; Kretschmer et al. 1999). Risk mitigation through diversification of output is well familiar.[11] Multi-product strategies are constrained by the costs of production and diminishing marginal utility, as well as by any demand substitution between product variants, as consumption of cultural signifiers takes time.

Regarding the latter point, different works supplied by the same supplier may also be complements over longer periods of time, however, as users with incomplete quality information and taste for variety move from one product variant to another. For potential users, signifiers have pronounced experience good attributes (Nelson 1970; Towse 1997; Ginsburgh and Throsby 2006). On the level of specific works, demand takes shape over a complex process of experimental usage, taste formation, and limited products searches where users

[11] For instance, let's discuss expected demand q^* as $q^* = q + \varepsilon$, with ε some random element normally distributed around a mean of 0 and a variance of σ^2. Then across a set of n uncorrelated products total demand Q is $Q = \sum_{i=1}^{n} q_i + \varepsilon = nq + \sum_{i=1}^{n} \varepsilon$ and relative demand uncertainty is $\frac{1}{\sqrt{n}}$, strictly decreasing in n.

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seek out and process pre-purchase information (cf. Bikhchandani et al. 1992; Cameron 1995; Blaug 2001; Throsby 2003; Potts et al. 2008).

In this context, another important motivation for multi-product strategies is the apparent need for creators to develop a reputation and exploit complementarities between various goods they are recognizably associated with. To capture the essential, let the aggregate value of a set of complementary signifiers Y_s supplied by the same creator s, and which are published in chronological order, be

$$Y_s = (n-1)\alpha + \sum_{i=1}^{n} (y_i + ... + y_n)$$

with $\alpha \geq 0$ and assumed independent of n for simplicity.

Complementarity may come about in various ways, which are hard to disentangle. For instance, users may have decreasing search costs for works from creators they are already aware of. Users may also exhibit greater expected, risk-adjusted utility among users for additional works from creators they have already had good experiences with. They may accumulate creator-specific consumption capital. Thus, reasonably high-quality creators can establish a brand.[12]

However, for human creators, in this context it is problematic that genAI regularly does not attribute works and creators. As long as they are not visibly acknowledged, creators gain no reputational benefits when 'their' works are used as genAI training data.

[12] Some specific genAI models may also develop this kind of cumulative benefits.

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APPENDIX 1 contains a taxonomy of different types of works and genAI output, with differentiated potential for substitution. In essence, this implies that creators can take evasive actions to the diffusion of genAI by focusing on supplying works for which genAI output constitutes (as yet) weaker substitutes. APPENDIX 1 also contains a more detailed discussion of the cost structures for human creativity and genAI applications regarding different types of signifiers.

2.8 Public good attributes

Finally, cultural signifiers tend to have pronounced public good attributes (Landes and Posner 1989; Towse 1997; Ginsburgh and Throsby 2006). Important aspects of creative works tend to be non-excludable and non-rival in consumption. They can thus give rise to positive externalities. This may apply to works and output alike.

However, creators may enjoy indirect appropriability (Liebowitz 1989). With effective attribution, demand for other, complementary services, which creators supply, will increase due to unauthorized copying or spillovers. The underlying mechanism corresponds rather well to our formal discussion of multi-product strategies. Partial, indirect appropriation for creators entails additional rewards for adequate multi-product strategies. Positive externalities may be associated with goodwill and greater willingness to be generous and donate among some agents, or with public funding and support (Seaman 1985; 2006; Frey 1997). Without effective attribution of input works used as training data for genAI

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services, indirect appropriability is undermined. Public good attributes are associated with insufficient private investments in supplying new creative works, including works suitable to train genAI models.

3. COST EMPIRICS AND SIMULATIONS

This section discusses the costs – and only the costs for now – of genAI applications to produce signifiers relative to costs associated with supplying traded, labor-intensive works. We focus on the market for (copies of) signifiers made available online. For works, we cover literary texts representing relatively simple signifiers and audiovisual entertainment such as films, representing complex signifiers. For genAI, we cover ad hoc generation, where the full personalization benefits of the technology transpire.

To illuminate the scope for suppliers of works to compete with genAI on price, we compare the costs of ad hoc production of genAI output of equivalent technical specifications to:

1. The costs of creating new works
2. The costs of making available an extant work online
3. Current retail prices of works

To be sure, the following discusses estimated costs based on the *best available* empirical cues. That is a substantial qualifier (cf. Acemoglu 2026). As a rule, no

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generalizable direct information on production costs is publicly available. What is clear, however, is that the quality-adjusted marginal costs of genAI services have been decreasing at a very high rate over recent years. We thus adopt relatively optimistic assumptions regarding current genAI costs and regarding prospective changes in relative genAI costs. The idea is to avoid underestimating the potential of genAI and to generate qualitative results that hold for some years to come. Given non-transparency and the vast uncertainty associated with a disruptive, multi-purpose technology in its early stages, such as genAI, we mostly report the scale of comparisons in orders of magnitude. This already yields some reasonably consistent, fundamental results.

3.1 Costs of creation

One of the peculiar features of CCI is that it is next to impossible to pin down how much it costs to create a work of competitive quality. Firms operate under incomplete information or even uncertainty, and compete on partially untested product attributes as well as on costs.[13] Furthermore, traded cultural industries – as well as genAI – exhibit substantial and partially sunk costs combined with non-increasing marginal costs. Marginal cost pricing is not sustainable.

[13] For any cultural signifier, there is no reliable and reasonably narrow corridor regarding optimal aggregate investments *ex ante*. The question 'how much does it cost to create a new novel, a song, or a film' of cost-adjusted competitive quality has no straightforward answer. For genAI, the situation is similar for now, due to a quick procession of process and product innovations.

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In any case, on average artists and creators generally earn significantly less from their creative work than national average incomes when controlling for education, and sometimes even below national minimum wages for employees, which is feasible because creators are often self-employed (see e.g.: Abbing 2008; Mangset et al. 2018; Ehlinger et al. 2024; EENCA 2020**;** National Endowment for the Arts 2025). What is more, creators' income tends to be volatile and highly skewed in favor of a tiny minority of superstars, who managed to accumulate a strong reputation (Rosen 1981; Adler 1985). Some very low estimates of the costs of creation simply come about because creators work unpaid, consistent with intrinsic motivation or with long-term, multi-product strategies.

In the following, we simply assume financial costs of creation – in the traded I-mode of production – of $20,000 for novels and $1 million for a feature film. Costs will vary by 2 orders of magnitude in both directions, probably with a skewed distribution towards the lower end. As we shall see, this is 'precise' enough to support the type of qualitative results we are after.

3.2 Costs of making available extant works online

The cloud service provider Amazon Web Services (AWS) charges around $.1 per gigabyte (GB) for outbound traffic, and, with extra costs for gateways, etc., about $.2 per GB. Google Cloud charges $.12 per GB for outbound traffic (Sankar 2024). Underlying (marginal) costs for Internet service providers themselves are estimated to be much lower, e.g.: <$.01. However, fixed costs are high and in

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these relatively mature markets with scale economies, suppliers can be expected to charge substantial mark-ups. In any case, even private households usually pay much less than $0.3 per GB for transferring data via the Internet, but fees are usually charged as fixed fees for connection, covering many GBs of data transfer without extra charge. Let's assume that specialized distributors of cultural works online also incur variable costs, and generously work with an estimated upper bound for aggregate marginal cost incurred by sender and recipients of $0.50 for 1GB of data (representing works) made available online. We exclude transaction costs throughout.

Regarding books containing literary texts, a sizable novel contains around 100,000 words. George Orwell's 1984 has ca. 80,000 words, Harry Potter books range between ca. 77,000 and 260,000 words, and the original Lord of the Rings trilogy has around 500,000 words in total.[14] As a rule of thumb, one word accounts for 16 bits of digital code, so that a 100,000-word novel accounts for 1.6 million bits. (Throughout, we exclude any cover imagery and illustrations.) One GB is 8 billion bits. Then the marginal costs for a one-off transfer of 10,000 novels via the Internet would be around one $ – one hundredth of a cent per novel.

Streaming audiovisual content transfers about 1 GB of data per hour for standard definition (SD; 480p) and about twice as much for a range of resolutions referred to as high definition (HD; e.g.: 1080p). For top-end resolution, data transfer

[14] All of these wordcounts refer to original versions in English.

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reaches 7 GB or more for 4K Ultra HD quality, and 15 GB for 8K. However, these extremely high resolutions have little marginal benefit where audiovisual content is displayed on common hardware devices, such as smartphones, tablets or PC screens, or all but the most advanced tv screens. The exact amounts are subject also to compression algorithms used by platforms (Anonymous 2025). That implies marginal costs of $0.75 for a 90-minute film in SD and $1.50 for HD.

3.3 The costs of genAI output

The costs of generating ad hoc genAI output are much higher than copying costs. To be sure, the only reliable information available to the public is prices charged, which may reflect oligopolistic pricing strategies by genAI suppliers rather than technical issues. To get an overview of genAI prices, we use the price aggregator pricetoken.ai (last visited on 16 March 2026). For large language models (LLMs) as well as image and video genAI models, it covers multiple models for each of the 8 to 10 leading suppliers.[15]

See APPENDIX 2, where we develop a range of estimated costs for literary works and audiovisual entertainment, subject to genAI models of varying capacities and prices used. For genAI output of the same number of meaningfully arranged

[15] The site also provides timeseries, indicating that prices charged for any specific models have regularly been constant in nominal terms. We checked data on other sources, such as (Kavusturucu 2026). Note that some legacy models are available free of charge, such as GPT-5.2 or Gemini 3.1 Pro and Gemini 3.1 Flash at present (March 2026), albeit with tight usage restrictions inhibiting ambitious/professional use.

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words as a novel, 'initial genAI costs' for a single prompt range from $.05 (with GPT-5 Nano) to $24 (with GPT-5.4 Pro). For audiovisual entertainment of the same duration as a feature film (90 minutes) and of an image resolution sufficient for casual home use, initial genAI costs range between $81 (with MiniMax Hailuo 02 512p) to $3,780 (with Sora 2 Pro 1080p).

3.4 Main results regarding cost and price proportions

The most basic results from our comparisons are the following:

1. Considering sheer technical metrics only, genAI already has the potential to vastly reduce the costs of producing signifiers by partially replacing labour.
2. The costs of ad hoc genAI output far exceed the marginal costs of copying and making available of extant works.
3. The proportion between the costs of ad hoc genAI output and current retail prices of works varies between simpler and complex signifiers.

TABLE 1 provides an overview using simulated values for the larger, more valuable variants covered in APPENDIX 2 (TABLES A2.1 and A2.2) – novels for literary texts and feature films for audiovisual entertainment. In the simulations we use the lowest and highest 'initial costs' for ad hoc genAI output, subject to

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the genAI model used, multiplied by ten.[16] We emphasize reporting of proportions, as a rule rounded down to the nearest order of magnitude for lower bounds and rounded up for upper bounds, to signal considerable uncertainty.

TABLE 1: Current proportions between the costs of ad hoc genAI output and costs as well as retail prices for works of equivalent technical specifications

	Literature (1) (simple signifiers)	**Audiovisual entertainment** (2) (complex signifiers)	
	Gen AI is …		**Caveats and likely trends**
Costs of generating a signifier of equivalent technical specification	1 to 5 orders of magnitude **cheaper**	1 to 5 orders of magnitude **cheaper**	Unclear as yet whether technical cost advantages compensate for any perceived quality disadvantages (see section 4).
Marginal costs of supplying users	1 to 5 orders of magnitude **more costly**	2 to 4 orders of magnitude **more costly**	May decrease if costs of genAI continue to fall more rapidly than costs of copying; but copying will remain much cheaper than selective recombination and the rate of

[16] For very short texts, which are not featured in TABLE 1, this factor may seem high. Note however that here, the opportunity cost of time for prompting will be relatively high, i.e. will far exceed the operating costs of the genAI model.

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			productivity increases will converge over time.
Current retail prices	1 order of magnitude **cheaper** to 1 order of magnitude **more costly**	'Not much more costly' to 3 orders of magnitude **more costly**	Suppliers of works may reduce effective prices, lowering them or adopting subscriptions and bundling strategies.

NOTES:

(1) For a novel, we assume (opportunity) costs of creation of $20,000. Dividing this 'central tendency'-estimate for the costs of creation by the extreme estimates for genAI costs (ca. $Cents 5.3 and $24 times ten) suggests that genAI output is between 83 times and 40,000 times cheaper than creating a new work (displayed above as 1 to 5 orders of magnitude after rounding). The copying costs of making an extant novel available are ca. $Cent .01 (excluding transaction costs), which is between ca. 53 and 24,000 times cheaper than genAI costs (also 1 to 5 orders of magnitude). Regarding retail prices, the most adequate comparison are novels in the format of ebooks, as they are unaffected by manufacturing costs of paper books, and which are usually sold at prices ranging between $2 and $15. For lack of better information, we use $5, which implies that such common retail prices are between roundabout 10 times higher and roundabout 5 times lower than genAI costs. Here, we round up both proportions to 'one order of magnitude'.

(2) For a feature film, we assume costs of creation of $1 million. Relating this to the extreme estimates for genAI costs ($81 to $3,780 times ten), ad hoc genAI costs are between ca. 26 times and 1,200 times cheaper (1 to 5 orders of magnitude after rounding). With copying costs of $.75, genAI output is between 108 and 5,040 times more costly (2 to 4 orders of magnitude). Retail prices for streams, cinematic performances, and copies of feature films vary widely. Permanent copies of feature films for home use (and delivered via the Internet)

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most closely correspond to the user experience that genAI could provide. Here prices also vary between $2 for older titles in low-demand and SD formats and $30 or above for few novel hits (or higher in excellent technical quality, such as 4k resolution). We work with an estimated typical retail value of $10, which implies that genAI output of similar technical specification is between ca. 8 and 380 times more costly ('not much more costly' to 3 orders of magnitude more costly).

The rough-and-ready proportions reported in TABLE 1 entail some useful insights:

1. With publicly available and verifiable information, great uncertainty remains as to the present and near-term potential of genAI to displace creators. Stakeholders ought to think in contingencies.
2. The costs of generating ad hoc genAI output are already considerably lower than the costs of creating works, despite particularly wide intervals between reasonable estimates. Section 4 turns to the essential additional discussion of perceived value rather than merely technical specifications.
3. At the same time, the marginal costs of supplying users with copies of extant works are a small fraction of the costs of ad hoc genAI output. This has the following implications:
    a. Suppliers of works have scope to compete with genAI on price. They can lower effective retail prices, and still charge above marginal costs. However, for suppliers of new works, it will become harder to recoup the costs of creation in the presence of genAI substitutes.

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Suppliers of extant works – of which there are very large stocks – can compete with genAI on price.

b. Self-service of end-users applying genAI will remain restricted to a small minority of users with exceptionally high willingness to pay for personalization services in the presence of extant works.

c. However, there may be great potential to develop restricted personalization options of specific components of works, where differentiation of user preferences is particularly strong, or for customization of high-value signifiers to distinct user groups. For those purposes, the most promising proportion of labour and capital inputs remains unclear. Key questions are whether works will remain overrepresented among the most popular signifiers, justifying additional partial matching investments; and to what extent end-users prefer limited, curated adaptation options within ready-made templates over greater flexibility and choice, coupled with greater uncertainty.

4. In principle, any pressure on current retail prices of works is more pronounced for simple creative works for now. However, in the specific case of literary works, genAI output may be a weaker substitute for printed books, which still the most popular format for many literary works.
5. Some of the cost proportions are consistent and large enough to have some confidence in these insights.

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3.5 Caveats and longer-term simulations

There are two main caveats. First, genAI prices may include markups if suppliers enjoy market power. Eventually, with non-increasing marginal costs this must come about for suppliers to recoup setup and fixed costs. Then there would be scope for decreasing prices – and thus users' costs – of applying genAI. However, the reverse is at least as probable: at this early stage in the diffusion of the technology, suppliers likely compete *for* the market, using penetration pricing well below average costs to maximize market shares and secure long-term profit prospects similar to platforms in two-sided markets (e.g.: Geroski, P. A. 2003; Liu and Chintagunta 2009; Fainmesser and Galeotti 2016; Yoon 2026). An exception may be some of the most powerful genAI models supplied by the market leader OpenAI, which enjoys a large market share and strong brand. Yet here the margins are very wide – at least three orders of magnitude and more probably four – so that some confidence in the qualitative results is justified.

Second, the costs of suppliers of genAI prices may continue to fall at a rapid rate. An exact trend is hard to specify. Performance-adjusted marginal costs per 'inference' have fallen very rapidly, decreasing by factors between 9x and 900x annually – subject to the specific performance benchmark – according to Cottier et al. (2025). On the other hand, setup and training costs have increased over the last years, by factors greater than 2 per year (Ismail 2025). OpenAI's GPT-4, released to market in March 2023, is reported to have cost around $100 million to

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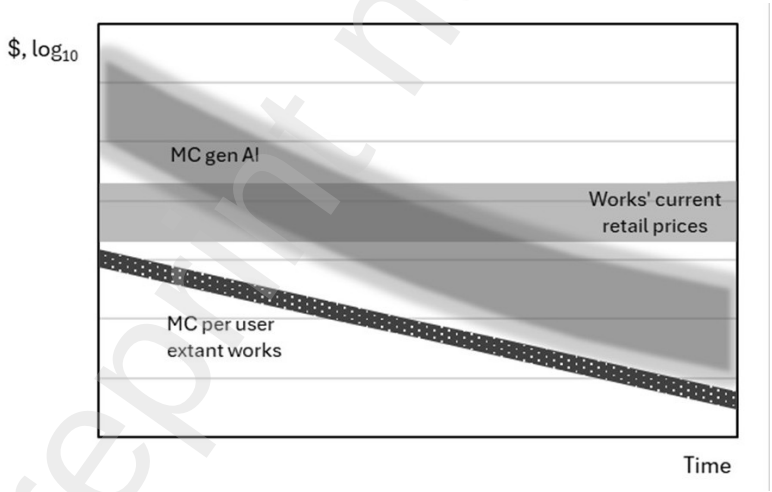
set up, with later base models, such as Google's Gemini Ultra (released in February 2024) having been considerably more expensive (Agbai 2026). Quality adjusted prices have also fallen, by over 90% between March 2023 and January 2025 (22 months) for text-to-text applications and text-to-image applications, but at a decreasing rate according to André et al. (2025; see also André et al. 2025b). Decreasing rates of performance increases are typical for maturing new technologies. Furthermore, the costs of data transfer (copying costs) for extant works also decrease over time, and traded, labour-intensive creativity may also exhibit productivity gains, if at a relatively slow rate. Nonetheless, any discussion of current genAI costs and prices risks becoming swiftly obsolete.

FIGURE 1: Simulated values regarding relevant marginal costs and prices concerning works and genAI output for feature films from the present and over the next seven years



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To steel our insights against the latter caveat, FIGURE 1 depicts simulated data based on cost- and retail price-ranges estimated for feature films. The starting point of the simulation corresponds to the current situation, as discussed above, and the simulation covers eight years. The costs of work creation are not included. With large enough intrinsic motivation and/or in cases of newcomers seeking to establish a reputation, as well as productions involving established superstars, costs of creation scatter across the upper third of the Figure and above. The edges of the plot for genAI costs are deliberately fuzzy to signal pronounced uncertainty. We assume that the marginal costs of ad hoc genAI output of the same technical specifications will continue to quickly decrease, but at a decreasing rate. In the simulation depicted in FIGURE 1, costs initially fall by 80% each year but that gradually decreases to approximately 50% over six years and remain constant thereafter. For copying costs of extant work, we assume a constant rate of performance increases by 50% throughout. This implies that marginal genAI costs converge on copying costs, but will remain substantially higher. For retail prices, we include a constant range of prices ($2 to $10) for comparison.

At the outset, the lower bound for the marginal costs of ad hoc genAI is one to four orders of magnitude higher than the upper bound for retail prices. (For literary texts, the lower bound of genAI costs is already well below the full range of retail prices, consistent with a move to the right in FIGURE 1.) Under our reasonably optimistic assumptions regarding genAI, this will change: the full range of the probable marginal costs of ad hoc genAI output (MC genAI) falls

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below works' current retail prices in the left quarter of FIGURE 1. However, copying will remain much cheaper than selective recombination. Thus, suppliers of works will permanently be able to charge prices above marginal costs (MC per user for extant works), while retaining a price advantage relative to genAI. Suppliers of works can lower retail prices (not depicted). In a sense, measures with similar effects are already underway, with bundling and subscription services for reproducible works such as music and audiovisual entertainment.

Overall, based on the current information, our qualitative results as listed at the end of section 3.4 are likely to hold for a while. This begets the question of relative and perceived value of works and genAI output.

4. RELATIVE PERCEIVED VALUE: SAME SAME, BUT DIFFERENT

Initially, we have argued that the two essential relative benefits of genAI applications are (1) cheaper personalization to improve matching, and (2) lower quality-adjusted costs than labor-intensive creativity. So far, we have shirked a notoriously nebulous issue: what are cultural signifiers good for? This section zooms in on this challenging but inevitable concern in as far as it relates to the relative value of works and genAI output.

4.1 Gimmicks?

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Some genAI artworks have sold for high prices or received awards (Tatler T-Labs Team 2025).[17] However, it is important to distinguish cases where a product is appreciated for being an early and prominent application of a novel technology, from that technology providing a superior substitute to older technologies.[18] In some cases, early genAI output pushing the boundaries of what seemed possible, may have been gimmicks.

The boom and bust in the market for arts-related NFTs is consistent with some temporary appreciation of goods associated with new technologies that then collapsed (Fridgen et al. 2024; Gherghelas 2025). Similar effects might have boosted the market value and attention that some early genAI output has received. By now, there is much concern with 'slop', perceived as of low value or even a nuisance, also because it may make it harder to find 'authentic', human-generated works on some CCI-related platforms (e.g.: Madsen and Puyt 2025). It is too early to be sure.

4.2 Personalization benefits?

Users of works appreciate (AI-based) personalization of recommendations, which are a feature of all major services making works available online. GenAI personalization by users employing self-service does not concern better

[17] Examples are Obvious' "Portrait of Edmond Bellamy" (2018), Mario Klingmann's "Memories of a Passersby I" (2018), and Ai-Da Robot's "$1m+" (2024); see (Tatler T-Labs Team 2025).

[18] The somewhat imprecise term in economics is 'scarcity value'. After all, all goods and services are scarce to varying degrees.

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matching at lower search costs for extant works, however, but the possibility to adapt extant works (personalization) or even to generate novel signifiers based on prompts (ad hoc output provision and self-service).

Regarding the latter option, this requires users to know what they want in a signifier, or to learn it over an iterative process of output curation and prompt refinement (Openlaender et al. 2023). This drives up the costs of self-service applications of genAI. Skilled creators may find new job opportunities to train users or to act as intermediaries between end-users and genAI.

The former personalization option of adapting extant works requires that the genAI user operates under a copyright license to be lawful. To the best of our knowledge, there is little evidence that such options are much appreciated. Suppliers' experiments with such personalization services are very limited. In a choice experiment conducted before the diffusion of genAI of a representative sample of the Dutch population including modification rights – a precondition for lawful personalization of copyright works – Handke et al. (2016) find no significant effect on willingness to pay for such rights across a range of works.

Combined with our documentation that self-service and personalization with genAI is costly compared to experimental use of extent works to identify good matches, it seems that net benefits are very modest and/or restricted to a minority of applications and users, in the presence of vast and diverse repertoires of extant works. Further research is required whether users gradually develop stronger preferences for personalization, as they become used to genAI. That is

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another open question, leaving us to ponder the perceived quality of genAI output.

4.3 Disclosure effects

A thriving empirical literature addresses the perceived value of signifiers subject to users' awareness whether the product has been created by humans or produced by genAI. By and large, users appreciate the same signifier less if they are informed that it is genAI output (e.g.: Shank et al. 2023; Malecki et al. 2025; Ansani et al. 2025). These are specific instances of so-called 'algorithm aversion', 'disclosure effect' (Sikhondze et al. 2025) or 'Lovelace effect' (Malecki et al., 2025).[19] Apparently, perceived value is not only about the intrinsic features of signifiers but heavily influenced by perceptions regarding the production process. This raises several questions:

One is whether genAI output that users prompted for themselves is also perceived to be of low value. The empirical literature has mostly studied creators rather than self-servicing end-users. It suggests that limited genAI contribution is by and large perceived to make creators operate more efficiently (Guo et al. 2025). However, genAI use seems to homogenize the resulting signifiers (Dosi and Hauser (2024); Zhou and Lee 2024). To the best if our knowledge, there are no studies covering end-users without specialized skills.

[19] For a limited exception, see Croby and McKenzie (2025).

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Another related question is whether greater appreciation of works relative to genAI output is a temporary phenomenon, as users have not acquired the consumption capital/skills and trust to appreciate what genAI does. Arguably, there are good reasons that some disclosure effect will be *permanent*. We discuss three of these in the following.

4.4 Scarcity

First, according to the economic-marginalist theory, the (market) value of any good (or service) depends on the perceived value in use as well as scarcity. In as far as genAI output is cheaper to produce than works, output is less scarce and bound to be perceived as less valuable.

4.5 Relational goods

Many goods (or services) are appreciated not only for the utility an individual experiences when making use of the work by herself, but for the positive consequences that engagement with the good has for relationships with others (e.g.: Uhlaner 1989; Bruni and Stanca 2008).[20]

[20] For formal economic modelling, see Capecchi et al. (2018) and Becchetti et al. (2011). Klamer (2002) also refers to this as 'shared goods'. However, that expressions is more commonly used to refer to excludable and rival goods, which tend to be underutilized, for instance cars or tools in most private households. If transaction costs can be reduced enough, there is thus scope for sharing them with others. However, cultural signifiers have pronounced public good attributes.

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Creative works seem to be a case in point. Consider the following examples: A performance where a visitor enjoys the presence and perceivable emotional responses of other visitors. The additional pleasure of playing a piece of music with others or for others rather than alone. The pleasure derived from conversations about specific creative works – say a book or a film – with others, who have also engaged with the same work or type of works (Adler 1985). And, the pleasure of feeling that with a specific creator, another capable and reputable human being has been concerned with a similar issue that intrigues the user.

In terms of more conventional microeconomics and digital ICT, a closely related concept is that of network effects. Relational good attributes are a specific reason, why network effects on the level of specific creators and/or works may come about.[21]

Where this holds for works, genAI applications to generate personalized output are imperfect substitutes for human-generated works. On the one hand, personalized ad hoc genAI output does not to the same extent entail shared experiences (a) with technically identical signifiers between various users, nor (b) between users and specific creators. On the other, where genAI output is disseminated as a ready-made, user-user shared experiences are more easily

[21] The relational benefits of creative works may be appreciated as an end in itself or as a means to other ends, say social cohesion, effective communication, and trust. They may also give rise to positive externalities and/or foster the market value of creative works. For our purposes, it is not necessary to try and disentangle these issues. Here, it suffices to establish that creative works are often appreciated for the apparent relational benefits they bring about.

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enabled. However, any greater abundance of product variants makes it less probable that different users will 'synchronize', i.e. engage with the same product variant(s). Holding other things equal, the more effective genAI is in lowering the quality-adjusted costs of creation, the less likely it is that synchronization benefits will transpire. Furthermore, users still have no specific human creator as a relationship counterpart.

Overall, there is a permanent qualitative difference between human-generated works and genAI output regarding their 'relational good'-attributes. It remains to be seen *to what extent* this affects relative value and substitution effects.

4.6 Positional goods

Positional goods are appreciated for their effect on the relative position of agents in society. Closely related concepts are prestige value (Keasbey 1903) and conspicuous consumption (Veblen 1899). As ranks are inevitably scarce, that easily results in zero-sum games, where any costs incurred in jostling for position can constitute a net loss for society, as one woman's gain is another's loss, whereas for relational goods, social interaction yields aggregate benefits for all participants (Schneider 2007; Carlsson et al. 2007).

The concept of positional goods has mostly been applied to address processes of social stratification and the categorical concept of social class as emergent phenomena from humans' desire to distinguish themselves relative to others.

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Engagement with expensive and/or prestigious cultural works is a case in point (Bourdieu 1968).

For works, prestige value may come about in various manners: demonstrating exceptional knowledge about some cultural artefacts and genres; possession of famous and scarce works; personal association with producers; ostensible support of the arts; or even the skills to generate valuable works oneself (cf. Bourdieu and Wacquant 2013). Regarding cultural signifiers, the adverse welfare implications of positional good attributes are less pronounced. The production of signifiers tends to require fewer natural resources than large houses or car. Signifiers tend to have public good attributes, so that investments by agents striving for prestige may generate positive externalities to others. In any case, positional good attributes may stabilize the demand for costly works despite genAI, as long as works can be easily distinguished by users and by the people they seek to impress.

5. DISCUSSION AND CONCLUSIONS

5.1 Responses by creators

The diffusion of increasingly powerful genAI as a means to generate signifiers with much less specialized human inputs will require many creators to adapt their business models. Considering the discussion so far, there are various options.

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First, creators can adopt genAI themselves to complement their labor and increase productivity. This may paradoxically stabilize the labor market of creators, if quality of supply and aggregate demand can be fostered, and humans remain more productive regarding some 'hard tasks' (Acemoglu 2025). Second, people with creative expertise can offer intermediation and training services, supporting others to effectively use genAI.

Third, creators can signal 'authenticity'. There are two main options. On the one hand, regarding the level of specific works, creators can document the production process, for instance by making version history information available. However, where the documentation relies on digital data, this may be forged by genAI. Furthermore, users need to be able to easily process that information, which may require standards set by central agents. Thus, we also discuss that option below regarding policy. On the other hand, creators may cultivate multi-product strategies that deliberately signal that a range of complementary goods and services are created by humans. For that to function, signals must be costly to forge. TABLE 2 provides a rough overview of how distinguishable different types of creative works are from genAI at this stage of technology. See APPENDIX 1 for a more detailed discussion. Creators can – and often already do – complement the supply of reproducible cultural works with live performances and the supply of unique cultural works. Advances in integrating 3D-printing and robotics with genAI may come to challenge this option. However, for now genAI does not play concerts.

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TABLE 2: Recognizable distinction between human-generated works and genAI output

		(A) Human creators		
		(a) Reproducible works	**(b) Unique works** (Physical)	**(c) Performances**
(B) genAI	**(d) Personalized output**	Low	Very high	High
	(e) Ready-mades (Digital)	Low	Very high	Very high
	(f) Ready-mades (Physical [iii])	Low	High	High

NOTES:

See APPENDIX 1 for a detailed discussion of this taxonomy of signifiers.

Fourth, creators can also abandon reproducible works and rather focus on performances and unique works. However, this would likely sever ties with large parts of the potential audience, who tend to conduct product searches online.

5.2 Policy implications

There is a wide and increasingly urgent debate on public policy initiatives that may be required in response to current or prospective impacts of genAI on

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creators and CCI. Our analysis helps identify a couple of strengths and weakness of widely discussed policy options.

As things are, we have identified several challenges. GenAI can reduce the costs of producing signifiers and entail matching benefits through cheaper customization and personalization. There are also spill-overs, as genAI services trained on works have other applications than generating cultural signifiers. This comes at considerable costs, as it undermines the position of creators. At the current state with non-transparency and limited financial compensation of rightsholders, main concerns are:

1. GenAI may reduce intrinsic motivation of creators.
2. Without effective attribution of input works, genAI compromises creators' ability to benefit from reputation aggregation and indirect appropriability.[22]
3. There may also be asymmetrical information problems, where users cannot distinguish between genAI output and works, so that all signifiers suffer from disclosure effects.
4. Extending on the latter point, in the long run, all stakeholders may suffer when the flow of new works is adversely affected. This includes genAI suppliers, who thrive on suitable training data. Markets may hardly fix the problem, as each genAI supplier can hope for competitive advantages if they free-ride on other parties' investments in creativity.

[22] GenAI models that report some sources have started to mitigate that problem, but are relatively costly, non-transparent, and selective in what sources they acknowledge.

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In light of the concepts and main insights provided in this paper, let's briefly assess main policy options to mitigate such issues.

Copyright licenses

One type of suggested fixes is that genAI suppliers should operate under specific copyright licenses, be liable to document intensity of use and financially compensate rightsholders, like many other professional users of works. This would change the current situation, in which genAI suppliers either benefit from non-transparency or claim that their activities fall under copyright exceptions and limitations or so-called save harbor provisions. To reduce average transaction costs (including monitoring and enforcement costs) in the market for such licenses and royalties, collective management is an option (Besen 2023; Handke and Watt 2025).

In our framework, the advantages of such a system would be better incentive alignment between creators and genAI suppliers and genAI users. Nonetheless, the costs for genAI suppliers for documenting use could be very high – over and beyond the payments to rightsholders. Furthermore, genAI suppliers could try and circumvent such measures, for instance by relocating to territories with more lenient rules, or simply lose out to competition from abroad. Given fierce competition for technological leadership in genAI not only on the level of firms but also states, this option may not be politically feasible for now.

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Harm-based compensation

Based on a meticulous formal analysis, Gans (2026) thus argues against new legal obligations and corresponding costly enforcement measures aimed at genAI suppliers. Instead, he favors harm-based compensation of rightsholders. However, this may be largely ineffective, as rightsholders will find it very hard to document specific harm, that is reduced sales or other benefits for specific works against some counterfactual without genAI. After all, demand for works is notoriously hard to predict.

Technical means to obstruct use of works as genAI training data

Another option is for creators and rightsholders to use technical measures that make it harder to use works as training data (Shan et al. 2024). Such options may strengthen the negotiation position of rightsholders, but continuous reliance on costly measures to inhibit transformative use is hardly a satisfying option. For instance, it will indiscriminately also affect legitimate uses.

Certification of works or labelling of genAI output

Finally, let's consider certification of works as human-generated, or, alternatively, the reverse measure of labelling of genAI output. Certification could help to fix asymmetrical information problems due to the disclosure effect. The basic principle is similar to certified organic food or garments, denominations of origin that exist for products such as wine or fashion, fair trade certificates, or

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certificates for artisanal products (Livat et al. 2019).) The challenge is to make certification cheap and effective.

Certification of works requires creators to employ costly measures, such as documenting versions (Aburass and Rumman 2024; Barros 2025). Individual creators may find it hard to employ them.

Labelling of genAI output is feasible to some extent by watermarking and cryptographic signatures. However, genAI suppliers and users have little incentives to employ effective labelling, as this likely reduces the value of outputs.

It may thus require implementation of AI detection tools and metadata inspection by other parties to identify genAI output and distinguish it from works. To be sure, no certification will work perfectly, and it will be hard to deal with hybrid cases, which we expect to become very common. To rise to that challenge may require collective action by collecting societies or public authorities. A reasonable compromise may be achieved by two measures. First, to allow for gradations in certificates. Second, to limit punitive measures and simply develop a certification agency that can withdraw the right to use certification of authentic human-generated works if suppliers fail to register sufficient information or signifiers are flagged by AI detection measures.

6. CONCLUDING REMARKS

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This paper has introduced several specific characteristics of CCI and artists'/creators' labor markets to debates on the implications of genAI. It has also provided some indication of the likely speed of core developments – while acknowledging the limits of such exercises in the context of swift and radical technological change –, and discussed likely responses by creators as well as some policy options.

For society at large, genAI entails considerable promises. There is little point in allocating scarce public resources to hinder genAI application and development for the sole purpose of protecting established business models in the traded CCI. The point is rather to support transitions so as to adapt the 'division of labor' between creators and genAI users and usage in a dynamically sustainable manner.

However, for all its apparent benefits, the diffusion of genAI is currently very likely to undermine intrinsic motivation of creators, and has certainly already undermined creators' ability to appropriate some of the value they generate through reputation aggregation and indirect appropriation. What is more, asymmetric information problems arise, where customers cannot distinguish works from genAI output, adversely affecting all stakeholders.

In our perspective, it is improbable that genAI suppliers and users will spontaneously become more transparent or that governments will enforce transparency and financial compensation of rightsholders. The opportunity costs are probably too high. Instead, we argue for certification to distinguish works

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from genAI output, so that users can tell the two apart. Creators are thus protected from the 'disclosure effects', users enjoy relational benefits, and users' willingness to pay for works based on prestige value can be sustained. If that succeeds, creators may even enjoy net benefits from productivity increases throughout society due to AI. After all, creators are subject to Baumol' s cost disease (Baumol and Bowen 1965),[23] but technological change tends to increase incomes and spare time. Thus, demand for normal goods and luxury goods, such as works, may increase, and intrinsic motivation to create may become more influential (cf.: Cowen 1996).

Last but not least, there are other reasons to develop certification of genAI output beyond the CCI, such as avoiding identity theft and fake news. Combined with such concerns, it seems that certification of genAI output will come about – sooner rather than later.

[23] Baumol's cost disease implies that with technological change, capital-intensive industries become productive more rapidly than labor-intensive industries and artisanal modes of production. Thus, relative costs of labor-intensive products rise over time. With higher opportunity costs, the arts experience an inevitable decline unless subsidies prop them up.

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APPENDIX 1: Gradated genAI effects across different aspects of the CCI and evasive actions

In practice, creators regularly supply a range complementary goods and services, for which genAI applications can provide substitutes to various degrees. TABLE A1.1 presents stylized facts regarding the production function for signifiers with human creators or with genAI, distinguishing types of applications and the corresponding formats of signifiers.

[INSERT TABLE A.1.1 HERE]

A.1.1 Human creators

For human creators, we distinguish three applications and corresponding product formats. First, ***reproducible works*** are disseminated as digital code via ICT infrastructure. This includes human language text, sound recordings, or audiovisual media content made available online. We do not include the special case of physical media carriers, which still plays a substantial role for fiction literature and books. Second, for ***unique works*** such as physical paintings or sculptures, there are either no identical copies available (which requires excludability), or some original version is more appreciated than any copies (which requires effective documentation of uniqueness and authenticity). In that case aggregate demand is fixed to 1, and prices tend to be much higher than for

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reproductions. In practice, there are hybrid cases, where more or less faithful reproductions of works are supplied, but suppliers can still develop credible signals of exclusivity and authenticity, say by a signature and in the case of limited editions. For simplicity, we focus on extreme cases. Third, ***live performances*** are time- and space-specific services, such as theatrical and musical performances, events, and exhibitions. Here, shadow prices, including travel expenses, often exceed prices for admission. Venues tend to have limited capacity, and congestion may entail disutility and indivisibility in the production function.[24]

Regarding setup and fixed costs, human creators regularly incur costs of education and training to acquire durable skills, enhancing their productivity up to a reasonably competitive level. These costs are akin to setup costs – the one-time expenses initially incurred to prepare a production project – for capital assets, and they tend to result in quite durable human capital. The corresponding benefits regularly accrue on an individual level; in other words, they are general training costs. The full economic (opportunity) costs rarely exceed a few hundred thousand $ and may be much lower. Greater investments are rarely justified, as individual humans have limited capacity, no matter how skilled they become. Further training will tend to occur 'on the job' of creating potentially valuable goods and services.

[24] Note that unique works can be used as an input for exhibitions, but that the economic characteristics of unique works and exhibitions as final goods differ.

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On the other hand, there are the costs of creation required for humans to generate any specific work. As discussed by Caves (2000; 2003), creative human labor is regularly organized in small and/or temporary teams. Many human creators generate simple creative works, such as literary works, by themselves. For more complex creative works, several human creators make substantial contributions in joint or sequential production processes. Teams of creators tend to be relatively small and/or operate temporarily for the completion of specific project. This suggests that the minimum efficient scale in human creativity is modest, probably because human creators have capacity constraints, that is, the quality of their contribution suffers if they engage with many creative projects over short periods of time.

Within the ordinal scale developed in this section, the costs of creation per work are 'very high' for all types of works when measured in the opportunity cost of time. However, intrinsically motivated creators may experience creative labor as generating value for them, which results in reduced costs, or in the extreme, even a benefit, in contrast to standard assumptions of labor.

The marginal costs of providing an additional user with access to an extant work are minuscule for reproducible works, and low but subject to capacity constraints and high shadow prices (e.g. traveling costs) for performances and exhibitions

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(Throsby 1994; Towse …). For pure cases of unique works, marginal costs play virtually no role.[25]

A.1.2 GenAI

For genAI, we distinguish applications and output formats according to a combination of two binary categories. First, whether output is generated ad hoc for each user based on prompts, or whether genAI output is subsequently made available to further users as a 'ready-made', that is as virtually identical copies.[26] Second, whether the final product is strictly in a digital format, or whether it has a three-dimensional and physical component that requires corresponding capital goods or manufacturing stages beyond the capacities of genAI.

Applications of genAI to produce specific signifiers are more capital-intensive than human production. For genAI, the rough equivalent to human training costs are the development costs of a new AI model. GenAI development costs are less divisible, much higher, and primarily generate capital assets with few capacity constraints due to low and non-increasing marginal costs of generating additional signifiers after setup is complete. GenAI apparently requires high setup costs – for access to suitable IT hardware, data collection, programming of

[25] There may be transaction costs, however, or transportation costs associated with trading of physical objects.

[26] In particular, we mean no further personalization of the core signifier applying genAI. Of course, users may only access excerpts, or ready-mades may be disseminated in conjunction with personalized recommender systems or reviews and commentary.

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learning algorithms, data analysis, and often human-supervised training. There tend to be dozens or hundreds of highly trained experts involved. The total costs to develop large language models (LLMs), for instance, range between a couple of millions to several hundred million $ (see section 3.5).[27] GenAI also entails fixed costs to sustain the infrastructure and update the service, which requires energy and access to state-of-the art computing capacity.

Once a genAI model is operational, applying it to generate a specific, novel signifier of the same technical specifications – e.g.: in terms of resolution and runtime – as a work are much lower and regularly non-increasing. There are vast economies of scale and scope. This is consistent with a relatively low number of genAI services being supplied.

Where genAI is applied to produce personalized digital output, the costs of creation are incurred for every instance of use. We thus classify average costs as 'intermediate', i.e. the same category as reproducible works. The potential for average cost advantages of genAI per signifier supplied to a user only fully transpires if genAI output is also supplied as ready-mades. Then, minute differences in perceived value play a central role.

By definition, genAI produces signifiers in the underlying format of digital code. To produce physical objects, it must be combined with manufacturing processes.

[27] We exclude local, small-scale generative AI models, which may be accomplished for a couple of thousand $, which generally are not capable to generate signifiers that would match human works, even just regarding technical specifications. As a rule, buying access to larger, general purpose LLMs is much cheaper and provides higher quality output for a greater variety of purposes.

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With personalization, logical complements are robotics and additive manufacturing with 3D-printers. Where genAI output is used to produce physical ready-mades, more traditional serial production may be feasible. In either case, the unit costs are much higher than for digital output.

A.1.3 Evasive action

GenAI output has very similar formats, as well as dissemination and usage processes, as reproducible cultural works, and thus certainly constitutes a closer substitute than for performances and unique works. For all we know, reproducible cultural works are also strongly represented in genAI training data (rather than representations of other works purposely digitized for the purpose of 'feeding' AI). Furthermore, genAI does by definition only produce digital output. Substitution for unique physical objects or performances will be much weaker due to much higher costs.[28] Thus, holding other things equal, creators will explore evasive action, by putting greater emphasis on generating revenues with non-reproducible and format-distinct works.

Similar developments are observable in some CCI in the context of recent technological change. For instance, in the music industry, revenues from marketing reproducible works have decreased with online piracy and the rise of

[28] GenAI may of course become an input into production processes for any of these types of signifiers, with ambiguous effects as productivity and demand increases, but some labor may be displaced (Acemoglu 2025).

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online platforms, whereas revenues from live concerts, licenses for professional use, and merchandise have become much more important.

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APPENDIX 2 - Estimated genAI costs for literary works and audiovisual entertainment

[INSERT TABLE A2.1 HERE]

TABLE A.2.1 reports genAI prices for various large language models (LLMs). For the three cheapest LLMs supplied by different firms and the four most expensive models per output token.

$$C_{lit} = (l_{pro} + t_{in}p_{in} + t_{out}p_{out} + l_{cur})n_{pro}$$

Total costs for producing output akin to literary works with genAI (C_{lit}) are composed of the labour costs associated with writing prompts (l_{pro}; assumed constant for simplicity), the number of input tokens used (t_{in}) times the price per input token (p_{in}), the number of output tokens used (t_{out}) times the price per output token (p_{out}), plus any labour costs associated with curating in the sense of ensuring quality of output (l_{cur}; also assumed constant), all of which multiplied by the number of prompts used (n_{pro}) before quality seems sufficient, with $n_{pro} \in \mathbb{N}_1$ and $l_{pro}, t_{in}, p_{in}, t_{iut}, p_{out}, l_{cur} \geq 0$.

To avoid excessive speculation, the 'initial cost' estimates reported in TABLE … only features the segment $t_{out}p_{out}$ of the equation, on which at least the cost for users (but not for the genAI suppliers) is available. For realistic results, the initial costs reported in the three right columns must in all probability be multiplied by a

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factor much greater than 10, especially for the less capable LLMs and for more sizable output.[29]

Accordingly, it is orders of magnitude more costly to supply genAI output of the same technical specification (the number of words, but excluding issues of quality) than to provide users with access to extant works. Only considering the 'initial costs' of a *single* prompt, for the cheapest LLMs the costs of genAI output is already over 5 times greater, and for the costliest LLMs, the factor is 2,400. On the other hand, compared to the (opportunity) costs of the labour required to create literary works without genAI, which is reliably in the tens of thousands of $ in case of a novel, some LLM applications almost certainly already provide a cost advantage or will come to do so as the productivity of genAI increases more rapidly than the productivity of labour. Furthermore, comparison to retail values (say $1 to $20 for a fiction ebook) it is unclear whether and to what extent genAI already undercuts works.

[INSERT TABLE A.2.2 HERE]

For video genAI, costs per minute are reported on tokenprice.ai.[30] Thus, the cost function of producing this type of signifier is simpler than for (literary) texts, See

[29] See an interesting guide on how to co-author with an LLM, see June (2026).

[30] An alternative approach is to specify the number of bits/bytes that need to be meaningfully arranged by genAI for any type of output, which is the case of video is a function of video duration

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EQUATION ⋯ for the total costs for producing video with genAI (C_{vid}), where d denominates the duration of video output in minutes and p is the price charged per minute, and all other elements as specified in equation … .

$$C_{vid} = (l_{pro} + dp + l_{cur})n_{pro}$$

All of the video models can generate standard definition (SD) resolutions of 480p or higher, which are sufficient for casual home use, including modestly sized tv sets. However, audiovisual entertainment is a more complex format that combines scripts (akin to literary text) and sound with video. Thus, total costs for a final good of this type (C_{film})

$$C_{film} = C_{script} + C_{vid} + C_{sound}$$

The curation element (l_{cur}) for this complex type of signifier also entails any measures required to ensure consistency between the numerous clips generated (or the costs of arranging a special deal with suppliers of video genAI to release usage and capacity constraints), as well as script and sound. All tasks could be conducted with genAI and human labor to various degrees. In any case, the full costs of generating audiovisual entertainment output of more than a couple of seconds is probably orders of magnitude greater than the 'initial costs' reported in TABLE A2.2.

Just compared to a fraction of the ad hoc genAI output costs that can be specified with relative precision, streaming costs of extant audiovisual

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and resolution (the number of pixels). However, task-specific models tend to be much cheaper within their realm of application than general-purpose generative systems.

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entertainment are already between 108 and more than 5,000 times less costly, subject to the genAI models used. The real factor will be orders of magnitude greater. On the other hand, producing video clips, tv series, or feature films in traditional, labor-intensive processes is extremely costly. Production budgets for feature films may start as low as $10,000 for some amateur productions, but usually exceed $100,000 and can reach several $100 million for a minority of blockbuster creations. On a project-level, adequate and clever application of genAI may thus already increase productivity and replace labor to some extent, for instance if it can replace expensive props and visual effects or support repetitive tasks in post-production. However, it remains unclear whether genAI can reduce the costs of low-budget audiovisual entertainment.

There are some early indications. OpenAI has announced that an animated feature film, where the video is predominantly produced with genAI called Critterz will premier at the Cannes Film Festival in May 2026. The film has a prospective total production budget of $30 million, much lower than contemporary major animated film projects such as Toy Story 4 or Elio (both by Disney's subsidiary Pixar) of ca. $200 million (Toonkei 2025; Barmack 2025). However, it remains to be seen how Critterz is received by audiences. Besides, live action films may be much harder to generate.

Furthermore, genAI output costs far exceed current (quasi-)retail values of audiovisual entertainment, which range between the value of users' attention to advertising for short online clips on online platforms and up to about $20 for

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cinematic performances of feature films or copies for home use (outside of streaming subscriptions, which cannot be covered here).

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TABLE A1.1: Stylized facts regarding the production function of human-generated works and genAI output

	(1) Applied for:	(2) Format	(3) Setup and fixed costs (largely sunk)	(4) Costs of creation per work/output [i]	(5) Marginal costs per user	(6) Average costs per customer served [ii]
(A) Human creators	**(a) Reproducible works**	Ready-mades disseminated as virtually identical copies; usually digital (e.g.: sound recordings, films, literary texts)	– Intermediate – May be mitigated by high intrinsic motivation – Small minimum efficient scales for creative teams [iii]	Very high and largely sunk	Very low	Intermediate
	(b) Unique works	A singular signifier, usually physical (e.g.: paintings, sculptures, NFTs)	=	=	Not applicable	Very high
	(c) Performances and exhibitions	Time- and space-specific services	=	=	Low but subject to limited capacity and high shadow prices	High
(B) genAI	**(d) Personalized digital output**	Expressed in binary code; generated on-demand	– High – Large minimum efficient scales	Intermediate and variable	Same as costs of creation	Intermediate

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	(e) Digital output disseminated as ready-mades	Expressed in binary code; disseminated to multiple users as virtually identical copies	=	=	Very low	Low
	(f) Personalized physical output	Physical; generated on-demand [iv]	=	High and largely sunk	High	High
	(g) Physical output disseminated as ready-mades	Physical; disseminated to multiple users as virtually identical copies (e.g.: serial production) [iv]	=	High and largely sunk	High	High

NOTES:

[i] There is great variance between simple creative works (e.g.: a literary text) or complex creative works (e.g.: blockbuster movies or technically sophisticated video games). The high/low categorization concerns relative costs compared between human creativity and genAI.

[ii] Based on columns 4 and 5 only, excluding largely sunk costs.

[iii] But considerable scale economies for intermediary (financial risk management, distribution, marketing, and retailing) services.

[iv] Requires applications of additional technologies, such as 3D-printers, where physical output akin to paintings or sculptures are generated. This table does not cover interactive projections and events powered by genAI, which are more akin to performances as long as the projection technology is not yet widely available in private households.

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TABLE A2.1: Costs for a single instance of using various LLM models to produce output corresponding to the number of words for typical literary formats

	Rank from lowest to highest output price [2]	Supplier	LLM	Input price in $ per million tokens	Output price in $ per million tokens	Context window in k	Launched	**Initial costs in $**; only considering output tokens and assuming .75 words per token		
								200 words (poem)	8000 words (essay)	100,000 words (sizable novel)
Lowest prices for output by different suppliers	1	OpenAI	GPT-5 Nano	0.05	0.4	400	Aug/25	0.00011	0.00427	0.05333
	2	Google	Gemini 2.5 Flash-Lite	0.1	0.4	1049	Jul/25	0.00011	0.00427	0.05333
	4	xai	Grok 4.1 Fast	0.2	0.5	2000	Mar/26	0.00013	0.00533	0.06667
	...									
Highest prices for output by	24	Google	Gemini 3.1 Pro Preview	2	12	1049	Feb/26	0.0032	0.128	1.6
	30	xai	Grok 4	3	15	256	Jul/25	0.004	0.16	2

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different suppliers [1]	35	anthropic	Claude Opus 4.6	5	25	1000	Feb/26	0.00667	0.26667	3.33333
	37	OpenAI	GPT-5.4 Pro	30	180	1050	Mar/26	0.048	1.92	24

SOURCES: Own presentation based on selected data from pricetoken.ai (columns 3 to 8), last accessed on 16 March 2026.

NOTES:

[1] Six of the seven most pricey models for input as well as output tokens are supplied by OpenAI.

[2] Out of 37 LLMs; output prices are featured in column D.

TABLE A.2.2: Costs for producing video output using various genAI models (TTV or ITV) to produce video output of typical audiovisual entertainment formats.

Rank from lowest to highest price per minute of output [3]	**Supplier**	**Model** [4]	**Cost per minute**	**Output Resolution**	**Max output duration in seconds**	**Launched**	**Initial costs in $ for video only** [5]	
							30 minutes (tv episode)	90 minutes (short feature film)

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Lowest prices by different suppliers [1]	1	minimax	MiniMax Hailuo 02 512p	0.9	512p	10	Jun/25	27	81
	3	fal	FAL Cosmos 2.5 720p	2.07	720p	6	Jan/26	62.1	186.3
	5	ltx	LTX 2.3 Fast 1080p	2.4	1080p	120	Mar/26	72	216
		...							
Highest prices by different suppliers [2]	42	runway	Runway Gen-4.5 720p	15	720p	10	Dec/25	450	1,350
	48	fal	FAL Sora 2 Pro 1080p	30	1080p	25	Sept/25	900	2,700
	49	veo	Veo 3.1 Standard 4K Preview	36	4k	8	Dec/25	1080	3,240
	50	sora	Sora 2 Pro 1080p	42	1080p	20	Feb/26	1260	3,780

NOTES:

[1] The two cheapest models reported on are from minimax; ranks 3 and 4 are occupied by fal.

[2] Three of the eight most expensive models are supplied by fal, and two each are supplied by sora and veo.

[3] Out of 50 video genAI; (column D; from lowest to highest)

[4] All models featured in this table allow for text and images as input.

[5] Excludes sound, script production, as well as any measures to ensure consistency between the numerous clips generated.

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