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THE ECONOMIC IMPORTANCE OF FAIR USE FOR THE DEVELOPMENT OF GENERATIVE ARTIFICIAL INTELLIGENCE

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Executive Summary

Generative AI (GenAI)—artificial intelligence systems that can create new and original content like text, code, images, music, and even novel molecules—represents a pivotal technology for U.S. economic competitiveness and global leadership. Paradigm-shifting innovations like GenAI are rare; only a handful of prior technologies like the steam engine, electricity, and the internet have been termed a "general purpose technology." Given its potential to transform industries ranging from healthcare to national defense, GenAI's development is increasingly critical to maintaining America's technological edge. Industry research estimates that GenAI could add anywhere from $2.6 to 7.9 trillion to the global economy annually through 2040 (see 1.1 GenAI's Economic Value at the Sector Level), with the potential to transform over 80% of existing occupations. Substantial productivity gains from GenAI in several high-profile industries have already been demonstrated—26-39% returns in pharmaceutical R&D, 27-35% improvements in financial services—signaling that whatever nation leads in GenAI development will shape the global economic trajectory for decades to come.

This paper explains how fair use—a cornerstone of U.S. copyright law that permits certain uses of copyrighted works without authorization, especially when they provide broader public benefits—can unlock GenAI's full potential. Because GenAI systems learn to create new content by analyzing billions of existing works, fair use reduces the inefficiencies and burdens of licensing regimes by enabling developers to train these systems without negotiating with millions or billions of copyright holders, avoiding ruinous if not impossible transactional costs and fostering innovation. By providing a flexible framework that balances copyright protections with innovation, fair use has historically fostered transformative technological advances. Its application to GenAI development is critical for sustaining the technology's continued advancement.

Our analysis rests on three key themes, all of which are supported by extensive empirical evidence.

- **The Transformative Economic Impact of GenAI:** Industry-wide data, organizational case studies, and controlled experiments demonstrate significant productivity gains and value creation due to GenAI across the economy, with benefits for both large enterprises and small businesses. In addition to these direct gains, GenAI is already generating measurable scientific and technological spillovers—accelerating discovery, enhancing research efficiency, and catalyzing innovation across domains. These broad-based effects are characteristic of a general-purpose technology and suggest compounding long-term benefits.

- **Fair Use as a Critical Enabler of Innovation and U.S. Technological Leadership:** Investment patterns and startup activity show that fair use jurisdictions, particularly the

United States, have attracted more GenAI-related investment and fostered greater innovation.

- **Economic Inefficiencies of Alternative Approaches to Fair Use:** Comparative analyses of copyright licensing regimes, statutory exemptions, and liability-based approaches—particularly those considered or implemented outside the United States—reveal significant economic barriers that would impede GenAI development and risk U.S. technological leadership.

The evidence supporting these themes is compelling. For example, our analysis shows how fair use jurisdictions attract substantially more GenAI investment: venture capital investment in GenAI firms between 2019 and 2024 flowed overwhelmingly to the U.S., reaching $53.6 billion compared to just $6.8 billion in Europe. Granted, VC funding allocation depends on several factors and legal standards, but the inadequacy of alternative copyright approaches suggests that these legal standards are correlated with thriving investments in AI. This pattern holds true for the most promising AI startups as well - of the top 50 such companies identified by Forbes in 2024, 39 were based in the U.S., accounting for $33 billion of the $34.7 billion total investment in these leading firms.

Our analysis also shows that there would be substantial economic costs associated with alternative policies to fair use. Licensing schemes for millions of works would be prohibitively expensive. Copyright exemption systems that feature prescriptive rules rather than more flexible standards are structurally less amenable to technological change. Expanded liability frameworks could expose developers to potential damages ranging from $750 million to $150 billion per model (see section 3.2.4 — The Economic Risks of Expanded Liability), effectively halting model development in the U.S., particularly by startups and smaller AI firms.

At this critical juncture, policymakers have an opportunity to reinforce this legal framework that has long supported American innovation. The evidence shows that maintaining the flexibility of fair use while fostering practical solutions is crucial to realizing GenAI's transformative potential. This balanced approach will help ensure that the United States can secure its position as a global leader in artificial intelligence while delivering benefits to society for generations to come. Given the global competition to lead AI, delays in upholding fair use principles for GenAI development could cede technological advantages to foreign competitors, as early leaders benefit from cumulative investments and innovations that are incredibly hard to overcome once established.

1. The Transformative Economic Impact of GenAI

Generative AI (GenAI) represents one of the most significant technological advances of the modern era, with early evidence suggesting its potential to drive substantial economic value across sectors and different-sized organizations. While we are still in the early stages of adoption of GenAI, it is already generating meaningful productivity gains, cost reductions, and innovation opportunities. This section examines evidence from economic analyses and industry projections, organizations implementing GenAI solutions, survey research, and academic studies to characterize the technology's economic impact.

1.1 GenAI's Economic Value at the Sector Level

GenAI is already affecting a broad array of economic sectors, including drug-discovery research,[2] finance,[3] fashion,[4] accounting and law,[5] and agriculture,[6] and it holds significant potential to transform economic growth and labor productivity (see Table 1). A study published by McKinsey & Company estimates that 63 specific generative AI use cases across 16 business functions could deliver $2.6 to $4.4 trillion in economic benefits annually when applied across industries. When accounting for broader productivity improvements across knowledge work, beyond these specific use cases, this study estimates that the total economic benefits could range from $6.1 trillion to $7.9 trillion annually. Separately, Goldman Sachs estimates that global GDP growth could increase by $7 trillion (7%) over the next 10 years.[7] GenAI's effects will be pervasive, impacting almost every industry and eventually altering the nature of work in over 80% of occupations.[8]

As shown in Table 1, GenAI's transformative potential is particularly evident in several key sectors. In biotechnology and pharmaceuticals, GenAI is projected to generate $60-110 billion of annual value across the industry value chain, while dramatically improving returns on R&D investment — from 4% for traditional drug development to 26-39% for AI-developed drugs in the preclinical stage. The agricultural sector could see up to $250 billion in value creation across the $4 trillion global food production industry through reduced labor and input costs alongside improved yields. In financial services, front-office investment banking productivity is expected to increase by 27-35% by 2026, potentially generating an additional $3.5 million in revenue per front-office employee. And the retail sector also stands to benefit significantly, with McKinsey projecting that GenAI could add between $150 billion and $275 billion to operating profits in the apparel, fashion, and luxury sectors over the next 3-5 years.

Table 1: GenAI's Contribution to Growth, Productivity, and Sector Transformation

SECTOR	PROJECTIONS	SOURCE
Overall Economy	$2.6-7.9 trillion annual value contribution (2023-2040) (see extended discussion in section 1.1 GenAI's Economic Value at the Sector Level)	McKinsey 2023[9]
Software	$175-200 billion growth in enterprise software spending by 2027	Schneider and Shah (2024)[10]
Biotech & Pharmaceuticals	$60-110 billion annual value across pharmaceutical value chain through efficiency gains in R&D, clinical development, operations, commercialization, and medical affairs	Shah, Bleys, Viswa, Zurkiya, and Leydon (2024)[11]
Biotech & Pharmaceuticals	Drug discovery cost reductions: 15-22% (3-5 years), 22-33% (5-7 years), 44-67% (peak adoption) based on senior R&D executive survey	Carroll and Anderson (2024)[12]
Biotech & Pharmaceuticals	Return on R&D improvements: 6-20% (AI drugs in clinical stage), 26-39% (AI drugs preclinical stage) compared to 4% (traditional drugs)	Winston (2024)[13]
Agriculture	$250 billion value potential in $4 trillion global food production industry through enhanced on-farm economics, reduced labor/input costs, increased yields, and improved sales/productivity/efficiency	Nuscheler et al (2024)[14]
Retail (Fashion)	$150-275 billion addition to operating profits in apparel, fashion, and luxury sectors over 3-5 years	Harreis et al. (2023)[15]
Finance (Investment Banking)	27-35% front-office productivity boost resulting in $3.5 million additional revenue per front-office employee by 2026	Gopalakrishnan et al. (2023)[16]

1.2 GenAI's Economic Value for Individual Organizations

GenAI is already driving measurable economic value at the organizational level, as documented by numerous reports of significant productivity and efficiency gains (see Table 2). For example, in healthcare, Northwestern Medicine's implementation of GenAI-powered clinical documentation technology has allowed physicians to see 11.3 additional patients monthly while reducing note-taking time by 24%. In financial services, companies are seeing dramatic improvements in both efficiency and security: JPMorgan's AI-powered cash flow management software has reduced manual work by up to 90% for corporate clients, while Mastercard's predictive AI technology has both doubled its detection rates for compromised cards and achieved up to 200% fewer false positives in fraud detection. Professional services firms are also experiencing substantial gains. Accounting and consulting firm PwC reports that employees regularly using AI

tools see 20-40% productivity improvements, allowing them to focus on higher-value strategic work. A McKinsey & Co. study projects that GenAI could add between $150 billion and $275 billion to operating profits in the apparel, fashion, and luxury sectors over the next 3-5 years.

These early implementations demonstrate that GenAI's economic impact spans both customer-facing innovations and internal operational efficiencies, creating measurable value across organizations.

Table 2: Economic Value Created by GenAI Technologies at Specific Organizations

INDUSTRY	COMPANY	GENAI BENEFITS/OUTCOMES	SOURCE
Accounting	PwC	PwC found that employees who regularly use AI tools see 20-40% productivity gains. With time saved, they're able to focus on more strategic work and bring more value to clients.	PwC (2024)[17]
Healthcare	Northwestern Medicine	Northwestern Medicine physicians piloted a GenAI-based technology called Dragon Ambient eXperience, or DAX Copilot. Physicians who used it during at least 50% of appointments saw an additional 11.3 patients per month, experienced a 24% drop in note-taking time, and a 17% decrease in after-hours work.	Bruce (2024)[18]
Pharmaceuticals & Biotechnology	Bayer	Bayer's GenAI model, called E.L.Y. (Expert Learning for You), upskills agronomists and other farmer-facing employees, enabling them to quickly and accurately address questions related to agronomy, farm management, and Bayer agricultural products. E.L.Y. is already enhancing productivity for over 1,500 frontline employees in the United States.	Bayer (2024)[19]
Retail	Amazon	Amazon Q, Amazon's GenAI assistant for software development, has reduced the company's software upgrading process from 50 developer-days to just a few hours (this is 4,500 developer-years of work for over a thousand developers compared to manual upgrades) and performance improvements estimated at $260 million in annual cost savings.	Cholkar (2024)[20]
Financial Services	Mastercard	Mastercard leverages GenAI to enhance cardholder protection and ecosystem security. Its predictive AI technology doubles the detection rate of compromised cards, reduces false positives in fraud detection by up to 200%, and accelerates the identification of at-risk or compromised merchants by 300%.	Mastercard (2024)[21]
	Morgan Stanley	98% of wealth management team advisors now rely on AI tools, such as the AI @ Morgan Stanley Assistant, an internal chatbot designed to answer financial advisors' questions. Document accessibility has surged from 20% to 80%, significantly reducing search times and boosting retrieval efficiency.	OpenAI case study on Morgan Stanley[22]

1.3 Academic Research on GenAI's Economic Value

While industry case studies provide valuable real-world evidence of GenAI's economic impact, academic research offers a more rigorous measurement of the technology's specific effects on productivity and performance (see Table 3). Across multiple sectors and job functions, academic studies consistently demonstrate that GenAI tools drive substantial improvements in efficiency, workplace productivity, and output quality. These studies range from survey-based work to randomized trials involving thousands of workers in specific professional contexts.

The research described in Table 3 reveals particularly strong productivity gains in task completion speed and quality. Studies of professional services show that workers using GenAI completed 12% more tasks 25% faster while achieving 40% higher quality ratings. Similar patterns emerge in software development, where developers using GenAI-powered coding assistants demonstrated 56% faster task completion rates while maintaining code quality. Notably, these benefits often prove most significant for novice and lower-skilled workers. In customer-support settings, for instance, GenAI tools drove a 34% productivity improvement for less experienced staff. These research findings complement the organizational case studies by providing robust evidence of GenAI's economic value across diverse workplace contexts.

Table 3: Academic Research Demonstrating GenAI's Economic Value

SECTOR	RESEARCH DESIGN	GENAI-RELATED OUTCOME	SOURCE
U.S. Small Businesses	Survey of U.S. small and medium-sized business owners and senior decision-makers	64% are already using such tools or planning to do so within the next two years, and 83% already use AI for digital advertising. Report using to save time and money, boost efficiency, help their business grow, drive sales, improve customer service, and more.	Connected Commerce Council (2024)[23]
Customer Support	Experiment using 5,179 customer support agents; GenAI assists in resolving customer issues	14% increase in issues resolved per hour; 34% improvement for novice and low-skilled workers	Brynjolfsson, Li and Raymon (2025)[24]
Professional Services	Experiment using a sample of 758 consults completing tasks with differing levels of access to GPT-4	Completed 12% more tasks at a 25% faster rate and with 40% higher quality than a control group. The performance of lower-skilled workers increased 43% relative to their non-GenAI-enabled performance.	Dell'Acqua et al. (2023)[25]
Professional Services	Experiment using a sample of 444 professionals with work-related writing tasks with ChatGPT	37% improvement in time to completion; Average quality evaluation increased by 0.45 standard deviations	Noy and Zhang (2023)[26]
Software	Examine 218,345 professional software developers and 880 million code changes from 2022-2024	GenAI increased developer productivity measured as billable coding effort per day by 4%, while maintaining code quality	BlueOptima (2024)[27]
Software	Controlled experiment using GitHub Copilot for programming tasks	Users of GenAI completed tasks 56% faster than a control group	Peng et al. (2023)[28]
Retail / E-commerce	Survey of 52 global Fortune 500 retail executives.	GenAI-enabled chatbot reduced time to complete orders by 50-70%	Sukarevsky et al. (2024)[29]
Retail / E-commerce	A survey of 213 executives	31% have active GenAI use cases; 69% see improved efficiency and 48% cost reductions	Harvard Business Review Analytic Services (2024)[30]

1.4 Spillover Effects, Complementary Technologies, and Social Welfare Benefits

The innovation described above creates positive "spillover effects" across the technology supply chain. The development and deployment of GenAI systems drive demand for advanced semiconductors, specialized AI hardware, high-performance computing infrastructure, and energy-efficient data centers. In the first eight months of 2024 alone, Microsoft, Meta, Google, and Amazon invested approximately $125 billion in AI infrastructure, with total industry-wide spending expected to exceed $300 billion in 2025.[31] GenAI systems could also enhance the value of complementary technologies like sensors and robotic systems, leading to increased demand for these tools. Not surprisingly, optimism among business leaders runs high, with a 2023 survey showing that 93% expect GenAI to bring value to their business, 84% anticipate a positive impact on their workforce, and more than half forecast it leading to expanded headcount.[32]

Beyond these quantifiable productivity gains, GenAI promises benefits extending beyond what is captured by traditional economic measures, improving societal well-being and the quality of life across society.[33] From democratizing education[34] to upskilling workers[35] and improving health outcomes,[36] GenAI has the potential to benefit society at large. The window for securing these benefits, however, is limited.

The substantial economic value that GenAI creates—from driving productivity gains to enabling new market opportunities—depends on these systems' ability to learn from diverse training data. Without access to a broad range of high-quality training materials spanning different domains, industries, and forms of human knowledge, GenAI systems would be severely constrained, possibly proving inadequate for the complex real-world applications that drive their economic impact. As global competitors rapidly develop their own GenAI capabilities, the legal framework governing access to training data becomes increasingly critical to maintaining U.S. technological leadership.

The aforementioned evidence demonstrates that GenAI's economic potential is substantial. However, realizing these benefits depends critically on the legal framework governing how GenAI systems learn and develop. This raises urgent questions about how copyright law should govern the use of copyrighted materials in training GenAI models. Part 2 of this paper argues that the U.S. doctrine of fair use provides the most appropriate framework for realizing GenAI's economic potential while appropriately balancing the interests of rights-holders and innovators—a balance that becomes especially crucial as we examine how copyright law shapes both GenAI's development and America's competitive position in the global AI race.

2. Fair Use as a Critical Enabler of Innovation and U.S. Technological Leadership

> *"The founders of Google have said they could never have started their company in Britain. The service they provide depends on taking a snapshot of all the content on the internet at any one time and they feel our copyright system is not as friendly to this sort of innovation as it is in the United States. Over there, they have what are called "fair use" provisions, which some people believe gives companies more breathing space to create new products and services."*
>
> – Former UK Prime Minister, David Cameron

2.1 Understanding Fair Use's Economic Impact on GenAI Development

As the global race for AI leadership intensifies, the U.S. copyright doctrine of "fair use" plays an increasingly vital role in enabling innovation while protecting creative rights. This role becomes particularly crucial as international competitors adopt more permissive copyright frameworks—including broader research exemptions or relaxed fair use standards—that could provide their AI developers with competitive advantages in accessing comprehensive training datasets. Fair use allows GenAI developers to train their systems on diverse data while protecting rights holders' interests—a balanced approach that has proven essential for rapid technological advancement. (For further information about fair use, please see our Technical Appendix.)

The fair use framework provides significant economic advantages over alternative approaches to managing copyrighted content in GenAI training. While many other countries rely on complex licensing schemes or narrow exemptions, fair use in the U.S. enables efficient GenAI development by reducing transaction costs and minimizing market inefficiencies. In contrast, alternatives to fair use that are characterized by lengthy negotiations, high compliance costs, and rigid restrictions can create substantial barriers to innovation that are particularly burdensome for startups and smaller companies. In contrast, fair use's flexible framework has consistently enabled technological breakthroughs while maintaining appropriate protections for creators.

Table 4: Summary of Statutory Fair Use Factors in the Context of GenAI Training*

FACTOR	DESCRIPTION
Purpose and Character of the Use	Evaluates whether the use is commercial or nonprofit educational and if it is "transformative"—serving a different purpose than the original. Commercial uses are less likely to be fair, while transformative uses have stronger fair use protections–although transformativeness is a matter of degree and must be balanced with other considerations, including commerciality. GenAI training is best characterized as transformative and not directly commercial because the purpose of GenAI is new work creation rather than profit from direct copying.
Nature of the Copyrighted Work	Assesses the protected versus unprotected elements within the work. This is relevant when copying serves to extract unprotected elements rather than exploit the work directly. GenAI training is likened to software reverse engineering, where copying occurs to understand unprotected elements (general styles) and not to distribute copied works. Thus, it supports fair use by focusing on creating new works rather than profiting directly from the original.
Amount and Substantiality of the Portion Used	Considers the quantity and quality of copied material. Courts have approved complete copying when necessary for transformative purposes. GenAI training often requires entire works, but this aligns with approved fair uses if done to achieve a transformative purpose without substituting for the original work, as seen in cases like Google's book search tool.
Effect on the Potential Market or Value	Examines if the use competes with or substitutes the original, affecting its market value. Any market impact must be meaningful and not hypothetical. For transformative uses, market harm is less certain. GenAI training raises new questions, as it enables new work creation that may broadly compete but does not directly substitute specific original works. Occasional similar outputs to training data do not necessarily imply market harm.

* 17 U.S. Code § 107

Fair use enables efficient development of GenAI technology by reducing transaction costs and mitigating market failures while protecting copyright holders' legitimate interests. This protection stems from fair use's built-in safeguards that examine the market impact and require transformative use, ensuring that new technologies complement rather than substitute for original works. This flexible doctrine has historically enabled transformative technologies to flourish, as exemplified by its role in protecting time-shifting recordings via VCRs and the indexing of web content by search engines, ultimately creating substantial economic value through new markets and industries.

Understanding how fair use applies to GenAI reveals three critical economic mechanisms through which this framework enables the benefits documented in Part 1. By examining these mechanisms—innovation incentives, creation cost reduction, and market expansion—we can better understand why fair use provides an optimal foundation for GenAI development.

2.2 How Fair Use Enables Innovations That Benefit Consumers and Producers

The U.S. fair use doctrine's flexible approach delivers significant economic advantages over more restrictive frameworks by reducing transaction costs and addressing market failures—situations where excessive transaction costs or coordination problems would otherwise prevent socially beneficial uses of copyrighted works.[37] This doctrine has historically supported the growth of numerous consumer-beneficial technologies, including search technologies, digital libraries, and educational platforms/course management systems, by appropriately balancing broader societal benefits with individual copyright holders' interests—precisely the situation we face with GenAI development.[38]

Applying fair use to GenAI training creates three key economic benefits: (1) driving innovation and investment; (2) increasing information flows and reducing creation costs; and (3) creating new market opportunities. Below, we examine the empirical evidence for each of these effects.[39]

2.2.1 Driving Innovation and Investment

Fair use incentivizes investment in industries such as software development, internet search, and web services.[40] In combination with several key court rulings, fair use has given the U.S. a comparative advantage in attracting such investment.[41] Take cloud storage, for example. After an appellate court decision that narrowed potential liability for cloud storage in 2008, venture capital financing increased for U.S. cloud storage companies by around $1 billion in the following two-and half-years.[42] By the same token, less favorable rulings around the same time in France and Germany led to a significant reduction in venture capital for cloud storage firms in both countries. Even outside the U.S., fair use correlates with stronger investment in the tech sector. Recent research shows a 6% higher level of R&D spending by technology and hardware firms in non-U.S. countries that adopted fair use-like provisions (such as Israel's and Singapore's flexible copyright exceptions — see also Table 5) compared to those that did not.[43] Similarly, high-tech hardware firms in Singapore grew faster after the introduction of fair use-like provisions in 2006.[44]

GenAI investment and startup activity are heavily concentrated in the United States. Venture capital investment in GenAI firms between 2019 and May 2024 totaled $53.6 billion in the U.S., as compared to only $6.8B in Europe, $4.7B in Asia, and $1.4B in the rest of the world.[45] The broader statistics on AI startups in the 2013-2022 period suggest a correlation between fair use and VC-backed AI innovation picture, with the U.S. dominating European countries, and other fair use countries performing well for their size (see Table 5), and the U.S. has close to 80% of the most promising AI companies as selected by Forbes in partnership with Sequoia and Meritech Capital.[46] (See Table 6.)

As Table 5 shows, Israel and Singapore—both countries with flexible copyright frameworks similar to U.S. fair use—achieve the highest AI investment rates relative to GDP at 2.2% and 1.1% respectively, significantly exceeding larger economies like China (0.5%) and major European countries (0.1-0.2%). This pattern suggests a correlation between flexible copyright frameworks and robust AI investment, and suggests that legal certainty around data use may be a factor in attracting venture capital and fostering AI innovation ecosystems. Granted, U.S. leadership in AI investment and innovation cannot be attributed to fair use alone—factors like robust capital markets, strong technical talent pools, and established technology ecosystems also play crucial roles—but the legal certainty provided by fair use creates an important enabling environment for AI development that complements these other advantages.

Table 5: AI Startup Companies and Funding by Country (2013-2022)[47]

COUNTRY	NUMBER OF STARTUPS	PRIVATE INVESTMENT	INVESTMENT AS % OF NOMINAL GDP
Israel*	401	$11,000,000,000	2.2
Singapore*	165	$5,000,000,000	1.1
United States*	4,643	$249,000,000,000	0.9
China	1,337	$95,000,000,000	0.5
United Kingdom	630	$18,000,000,000	0.5
Canada	341	$9,000,000,000	0.4
France	338	$7,000,000,000	0.2
India	296	$8,000,000,000	0.2
Germany	245	$7,000,000,000	0.1
Japan	294	$4,000,000,000	0.1

An * indicates the country has fair use-like provisions

Table 6: AI Startup Companies on the Forbes 50 List (April 2024)[48]

COUNTRY	NUMBER OF STARTUPS	VENTURE CAPITAL FUNDING
United States*	39	$33,010,000,000
France	2	$592,000,000
Canada	2	$529,000,000
United Kingdom	2	$258,000,000
Netherlands	2	$101,000,000
Germany	1	$100,000,000
Sweden	1	$82,000,000
Australia	1	$31,000,000

An * indicates the country has fair use-like provisions

2.2.2 Reducing Creation Costs

By allowing the use of copyrighted materials for purposes like research, science, education, and technological innovation, fair use promotes the dissemination of information which in turn enhances human capital and enriches society in a multitude of ways.[49] Fair use also incentivizes investment in value-enhancing derivative goods and follow-on innovations by increasing access to inputs and reducing development costs.[50]

Digital technologies have already lowered production and distribution costs for creators (especially for smaller or less prominent creators) across a range of content, including books, music, and movies.[51] Building on this trend, GenAI represents significant expansion in this reduction of barriers to creation. Digital services have already demonstrated how technological progress can benefit both established and emerging creators through reduced production costs, expanded distribution channels, and enhanced discovery mechanisms[52] – benefits that extend to consumers through greater choice and access.[53]

Like the digital technologies that preceded it, GenAI tools will facilitate creation by increasing creator productivity and lowering production costs.[54] The impact can already be seen across a range of copyright-related industries. Consulting firm McKinsey & Company estimates that GenAI can improve software developer productivity by 35-45%, and significantly speed up other development tasks such as documentation and code improvement by 30-50%.[55] Video game developers use GenAI tools to reduce the time and cost of a variety of essential production features, like building backgrounds and smoothing out gameplay.[56] Similarly, movie studios use GenAI tools to speed up time-consuming tasks like video editing and rotoscoping.[57] Surveys of book authors report that they are using GenAI to assist with a variety of tasks, from grammar checks to language translation.[58] Thus, GenAI is poised to reduce the cost of creation, enabling a greater volume of creative work to come to market.[59]

2.2.3 Creating New Market Opportunities For Copyright Owners

Historical evidence demonstrates that technologies supported by fair use often create new markets and revenue streams for copyright owners, despite early concerns about potential harm.[60] The 1984 Supreme Court case Sony Corp. v. Universal City Studios provides a compelling example: while movie studios initially opposed video recording technology, the Supreme Court's ruling that recording television shows for later viewing (time-shifting) was fair use enabled VCR adoption to reach 90% of U.S. households by the mid-2000s.[61] While this development likely altered moviegoing habits, it created a lucrative new revenue stream from home video sales and rentals that significantly expanded the overall market for filmed entertainment, and demonstrates how new technologies can create value even as they reshape existing business models.[62]

Fair use has also enabled market expansion in the digital era. The Google Books project, which digitized approximately 25 million books under fair use, increased physical book sales by 4.8% on average and raised the likelihood of a sale by 7.7 percentage points—with stronger effects for less popular titles.[63]

Table 7: Historical Examples of Fair Use Technologies Creating Market Growth

EXAMPLE	MEDIUM	TECHNOLOGY/ INITIATIVE	ECONOMIC GROWTH IMPACT	SOURCES
VCR Adoption	Film	VCRs	The home viewing market doubled box office revenue, with 90% U.S. household penetration by the mid-2000s	Lee (2010), Vogel (2007), von Lohmann (2008)[64]
Google Books	Publishing	Digitization of 25 million books	Increased physical book sales by 4.8%; 7.7% higher likelihood of sales, especially for less popular titles	Nagaraj and Reimers (2023)[65]

GenAI appears poised to continue this trend of creating new opportunities for copyright owners. Early evidence suggests GenAI is enhancing web search accuracy and efficiency,[66] potentially improving product discovery and consumer matching. GenAI could thus further enhance the AI-powered recommendation systems that have shown significant potential to increase consumer engagement with content.[67] New markets are also emerging in education,[68] where Morgan Stanley projects GenAI could generate $16 billion in additional education-related content needs over the next several years.[69]

2.3 The Economic Importance of Clear Liability Frameworks for GenAI Outputs

Clarifying liability frameworks for GenAI outputs is critical to realizing the technology's transformative economic potential. Direct liability frameworks—which narrowly limit legal responsibility primarily to bad actors who intentionally cause harm (i.e., direct liability) rather than extending it broadly to technology developers—reduce uncertainty, minimize litigation risks, and encourage innovation and investment, particularly given the potentially detrimental combination of unclear legal standards and untraceable ownership for many works in training datasets. Direct liability refers to legal responsibility for the harm caused by one's own actions, such as users who actively prompt systems to produce infringing outputs. Overly broad secondary or even tertiary liability frameworks, with contributory or vicarious liability for user-generated content on a service, in contrast, create significant economic costs, stifling the development and deployment of generative AI technologies.

Direct liability for GenAI outputs should remain limited to users who intentionally prompt systems to produce outputs that infringe copyright. Shifting liability to developers would impose substantial economic costs, possibly chilling innovation and discouraging investment in AI technologies. Secondary liability frameworks play a key role in balancing creators' rights with technological progress by targeting intentional or active facilitation of infringement. Secondary liability refers to the legal responsibility that arises from the original or primary liability. For GenAI tools, these latter frameworks are more appropriate, as they minimize litigation risks and allow developers to focus on innovation rather than costly defensive measures.

A narrow approach to liability for GenAI outputs ensures that uncertainty or excessive litigation risks do not undermine the economic potential of generative AI. The current U.S. framework—combining fair use doctrine with established secondary liability standards from cases like Sony v. Universal and MGM v. Grokster—strikes the right balance by focusing liability on users who engage in direct infringement and limiting secondary liability to cases of clear facilitation or financial benefit. This approach allows developers to continue innovating while protecting creators' rights and driving economic growth, thus maintaining U.S. leadership in AI technology.

While fair use clearly benefits innovation and enhances economic growth, alternative frameworks for governing GenAI development have been proposed. At this pivotal moment in GenAI's evolution, understanding why these alternatives fall short becomes critical—not just for maintaining fair use but also for preserving America's technological leadership. As other nations race to establish competing frameworks, assessing the strengths and weaknesses of each approach takes on new urgency for U.S. policymakers and innovators alike.

3. Economic Inefficiencies of Alternative Approaches to Fair Use

3.1 The Economic Case for Fair Use

3.1.1 Minimizing Legal and Economic Uncertainty Through Fair Use

Fair use reduces the inefficiencies and burdens of licensing regimes by enabling developers to train GenAI systems without prohibitive negotiations with copyright holders—from millions of identifiable registered entities to billions of unregistered creators whose works receive automatic copyright protection — assuming such negotiations are even possible, as there is often no way to know who these creators are or how to find them.

Beyond the significant administrative hurdles and amplified liability risks for developers unable to navigate fragmented compliance systems, licensing regimes would be prohibitively costly, making it impossible for new startups to enter the market. Fair use provides a clear and legally recognized framework, minimizing these risks and permitting the flourishing of the AI developer market. By defining boundaries for transformative uses, fair use limits potential liability from inadvertent infringement claims or secondary liability concerns. Under 17 U.S.C. § 107[70], "the fair use of a copyrighted work [. . .] is not an infringement of copyright."

Moreover, fair use avoids the inefficiencies of alternatives such as licensing markets, which suffer from prohibitive transaction costs and valuation challenges. Compulsory licensing schemes, though structured, would impose similar burdens and risks driving GenAI development overseas to jurisdictions with more flexible laws. In contrast, fair use offers a manageable approach that reduces uncertainty, litigation risks, and compliance costs—particularly for smaller companies and startups. Without this protection, the economic burden of navigating restrictive frameworks would deter investment in GenAI innovation and harm productivity growth across sectors.

3.1.2 Dispelling Myths About GenAI Training and Outputs

Critics sometimes argue that GenAI models merely copy or memorize training data, leading to calls for more restrictive frameworks. However, the economic evidence provided in Section 1 shows that GenAI creates substantial new value rather than substituting for existing works. This ability to create new economic value while preserving existing markets is crucial. Thus, it is essential to understand that GenAI models do not merely replicate their training data but instead create new and original output based on predictions by statistical models which have learnt patterns from training data—a process that creates novel content. (For more information about how such transformation works, please see our Technical Appendix.[71] A related analysis of training data myths has also been conducted by the Disruptive Competition Project).[72]

Mischaracterizing GenAI's relationship with training data introduces unnecessary restrictions that would stifle innovation, undermine AI use, prevent AI-based advances in science and technology and reduce material economic benefits. Such restrictions would be particularly damaging to U.S. competitiveness, as countries with more flexible frameworks would naturally gain significant advantages in AI development and deployment enabling them to become more productive than U.S. firms and create value in ways that U.S. firms cannot. The U.S. may risk losing the projected gains in labor productivity and potential economic value created across different sectors of the economy (see Table 1) if it stifles GenAI development.

3.1.3 Protecting Rights Holders Without Stifling Innovation

Practical solutions, such as partnerships like those pursued by Reddit[73] demonstrate how rights holders' concerns can be addressed without undermining fair use principles. These targeted agreements show that collaboration between innovators and rights holders is both feasible and effective when limited to a well defined subset of material that has accurately identified rightholders and raises no unresolvable ownership questions. Indeed, GenAI-related content licensing agreements account for about 10% of Reddit's total revenue - roughly $171 million in 2024.[74]

Broad licensing mandates, often proposed as safeguards for rights holders, may instead impose unnecessary burdens on developers and rights-holders alike, particularly when targeted solutions could readily address rights holders' concerns. Licensing mandates can impose inhibitive transaction costs and administrative burdens that may undermine innovation. Beyond direct costs, transaction costs also encompass opportunity costs associated with delays and administrative burdens. Extended negotiations or complex licensing mandates can slow down product launches or limit strategic flexibility, leading to substantial economic losses in the face of the unprecedented pace of GenAI progress and innovation. In the past, similar transaction frictions impeded the launch of many entertainment streaming services, causing some to be delayed for years and others to be canceled.[75] In contrast, fair use provides a flexible baseline that balances the interests of rights holders with those of innovators. By avoiding the inefficiencies of broad licensing mandates, targeted solutions allow resources to be directed toward creating value rather than compliance. This balanced approach ensures that innovation flourishes while creator rights are respected.

3.2 Economic Analysis of Fair Use Alternatives for GenAI Training

In this section, we examine three major alternatives to fair use and explain why each could be less effective than the current U.S. fair use framework. The alternatives are: (1) voluntary licensing markets, (2) compulsory licensing schemes similar to those used for music, and (3) specific

copyright exemptions like those adopted in other countries. Table 8 describes these alternatives and summarizes their key limitations, which we analyze in more detail below.

Table 8. Summary of Major Alternative Approaches to Fair Use in GenAI Training

APPROACH	KEY LIMITATIONS
Licensing Markets: A system where copyright holders must individually grant permission for their works to be used in GenAI training, with license fees negotiated through market mechanisms. Companies developing GenAI would need to obtain and pay for licenses from each rights holder whose work they want to include in their training data.	This approach features very high transaction costs due to the large sizes of training data sets and the complexity of assessing the impact of specific works on AI models. Opportunistic behavior by copyright holders (e.g., withholding for potential litigation, bringing inferior inputs to market because of information asymmetry) could lead to market failure and harm to consumers and innovation. Pricing is difficult, as the contribution of any single work may be either negligible or impossible to ascertain. It could also induce less diversity in market outcomes if a wide range of works are excluded due to licensing conflicts.
Compulsory Licensing: A statutory system where the government sets mandatory licensing terms and rates for GenAI training, removing copyright holders' ability to refuse licensing or negotiate individual terms. Similar to mechanical licensing for musical compositions, this would establish fixed compensation rates that GenAI developers must pay, but rights holders must accept.	This method is also characterized by high transaction costs and could lead to GenAI firms relocating outside the U.S. to jurisdictions with more favorable laws. The complexity of licensing large data sets would hinder GenAI development, and without the connection to direct usage (as seen in musical compositions), compensation distribution becomes more challenging.
Copyright Exemptions: These are observed in jurisdictions like Japan, Singapore, the UK, and the EU, where specific exemptions for text and data mining (TDM) allow some forms of GenAI training.	These exemptions vary widely: Japan and Singapore offer broader exemptions, while the U.K. limits exemptions to noncommercial TDM, and the EU's DSM Directive allows for academic TDM and also TDM for other purposes, with the possibility for copyright holders to opt out in the latter category. Despite their value, these exemptions are seen as a second-best option to the broader flexibility provided by U.S. fair use which is a more inclusive, adaptable framework applicable to diverse uses of copyrighted works.

We note that there are also two ways in which the current fair use framework could be modified: limiting the scope of fair use and expanding liability under the fair use doctrine. These could involve, for example, narrowing fair use through judicial interpretation or legislative action (such as excluding commercial AI uses) or broadening developers' liability exposure through stricter secondary liability standards. However, these modifications would undermine the very flexibility and balance that make fair use effective in the first place.

3.2.1 Why Licensing Markets Could Fail

A licensing market for GenAI training data faces several fundamental challenges that could lead to market failure. First, the costs to search for IP owners and contract with them will be prohibitively high because assembling a training dataset requires negotiating with millions of copyright holders, many of whom may be unknown, deceased, or involved in unresolved ownership disputes, competing claims from multiple parties, or complex rights transfers—creating administrative costs that would likely exceed any individual work's contribution to the model. Second, valuing individual inputs to generative AI models is daunting, as there is currently no practical method for determining how much any particular work contributes to the model's learned parameters or affects the value of its outputs.[76] Third, opportunistic behavior by copyright holders (for example, withholding licenses for potential litigation or offering works with anti-AI "poison"[77]) could exacerbate market inefficiencies, leading to market failure and harm to users. These factors could result in an underprovision of the GenAI tools, low-quality tools, or higher prices for users. We discuss each of these issues in greater depth below.[78]

Search and Contracting Costs

Firms can incur significant costs related to the licensing of copyright, including the time, effort and legal fees necessary to identify the copyright owners, collect information on pricing and terms, and negotiate contracts.[79] To provide some perspective, it might take 18 months or more for a music streaming service to secure copyright licenses from just 15 major labels and licensing collectives in order to launch a service.[80] The high number of owners led to video streaming services like BBC's iPlayer taking more than five years to acquire the copyright licenses necessary to launch successfully.[81] Because transaction costs tend to increase substantially as the number of copyright owners who must be contracted with grows, products and services that rely on contracting with a large number of copyright owners can be difficult to bring to market.[82]

In the case of GenAI, the search and bargaining costs will likely be prohibitive because of the extremely large number of copyright owners from whom licenses would be necessary to build a sufficiently sized training dataset.[83] Under a licensing regime, building a market-leading LLM on copyrighted data would likely require identifying and negotiating with millions of copyright holders, creating administrative costs per copyright holder that may often exceed their work's contribution to the model.[84] To appreciate the magnitude of this cost constraint, consider that the cost of using outside counsel to draft and negotiate a basic licensing agreement typically ranges from $450 to $1,500 per hour.[85] Clearly, negotiating with each copyright holder individually and drafting a customized licensing agreement would add millions of dollars in legal fees to the development process. Even if the GenAI developer relied on a standard contract instead, the execution of millions of contracts may still be costly, and would not address the issue of valuation.[86]

Empirical evidence shows that search and contracting issues can be significant even in settings where the number of potential contracting parties is smaller than what would be associated with GenAI. For instance, the substantial burden of identifying and negotiating licenses is evident from the dearth of academic research that uses text and data mining (TDM) techniques in countries that lack fair use or TDM exceptions.[87] While comprehensive empirical data comparing TDM research output across different copyright regimes remains limited, the available evidence is suggestive. For instance, the United States accounts for approximately 47% of academic publications involving TDM techniques. Granted, this disparity could reflect multiple factors beyond copyright frameworks, including research infrastructure, funding levels, and institutional focus on computational methods, but the relative scarcity of systematic comparative studies on this topic itself illustrates the challenge: researchers in more restrictive copyright jurisdictions may be deterred from pursuing research that could face legal uncertainty, creating a feedback loop where the absence of such research makes it difficult to document the full extent of the problem.

Bargaining Costs and Valuation

Determining prices in IP markets is notoriously challenging.[88] We anticipate that the difficulty in establishing market value in the market for training data could exceed that of other IP markets, such as those for patents. Several factors complicate price determination. First, estimating the economic value of any particular work used in training will be exceedingly difficult. GenAI systems are trained on millions of works containing trillions of tokens, making it likely impossible to determine any single work's contribution to model performance.[89] This valuation challenge is further complicated by the interdependence of works within training datasets, with some works being substitutes that decrease the value of other works and others being complements that enhance the value of other works.[90] Therefore, using common approaches to patent valuation, such as the incremental earnings method that requires estimating the marginal contribution of the patent to the product's value, will likely be unfeasible. Even if technically feasible, the cost of isolating a work's impact will likely exceed its value to the model.[91]

Second, other common IP valuation approaches appear unsuitable in the training data context. The cost-plus method uses reproduction costs or replacement costs to estimate a baseline value to IP, then applies a margin. While understanding creation costs could be useful for a patent given that it is theoretically unique, the same uniqueness may not extend to training inputs that may be easily substitutable. Income-based methods often use potential lost profits from licensing to derive a fair price. Such an approach would place copyright holders with the impossible task of estimating how GenAI might affect future demand for their work—something even leading GenAI developers cannot reliably predict. Using market comparisons could also be problematic, as it requires identifying transactions with similar inputs and having knowledge of the price and terms of the agreements. Absent intermediaries that make the price and terms of a large quantity of transactions public, it will likely be difficult for copyright owners and GenAI developers to reliably use market pricing.

Opportunistic Behavior

Strategic behavior by copyright owners could increase the potential for market failure in many ways. First, copyright owners may have the incentive to hold out until the GenAI developer has already incurred a sunk cost into the project (such as licensing with other copyright owners or purchasing computing assets), as doing so could enhance their bargaining power and potential to raise input prices. This behavior is an example of the classic holdup problem[92], where a company makes irreversible investments that give a supplier power, like utilities relying on coal mines or natural gas on pipelines.[93] Second, a way to reduce contracting and valuation problems is to offer a standard contract with a pre-specified offer (likely a price per token); however, doing so may incentivize copyright owners to offer only their lower-value works, which could impact model performance. Third, GenAI trained on licensed input could still produce output that potentially infringes on non-licensed copyrighted work, which could encourage copyright owners to withhold their work while anticipating a potentially lucrative lawsuit down the road. Without protection from secondary liability, GenAI developers could be overwhelmed by litigious copyright owners using such a submarine strategy.[94,95]

3.2.2 Compulsory Licensing: An Impractical Model

Compulsory licensing also falls short as an alternative to fair use for GenAI training. While U.S. copyright law enables compulsory licensing for musical compositions—where fees are clearly tied to measurable usage through copies distributed or streams performed—this model cannot easily translate to GenAI training. With music, a more valuable song will be played more than a less valuable song, and thus, in principle, usage can be measured and compensation distributed fairly. GenAI's complex use of training data makes determining the training value of any particular copyrighted work almost impossible, which restricts the ability to tie price to value. While attribution-based models may be technologically feasible in the future, their accuracy currently remains unproven.

Moreover, such a scheme would still face significant transaction costs related to the identification of and payments to copyright owners, which combined with the licensing fees, could make GenAI models very costly to bring to market. In addition, the cost to transact with small copyright owners will likely exceed the payment to them, creating deadweight loss. Consider for example what it would cost to license tokens for a current state of the art model like OpenAI's GPT-4, which was supposedly trained on approximately 13 trillion tokens. A typical book has about 100,000 tokens, so even a modest licensing fee of $1 per 100,000 tokens would yield $130 million in licensing fees, an extremely high cost to add to the already hefty cost of training. Besides, the costs do not end there: the developer must still identify the copyright owners and make payments to them. In the case of a large copyright owner, the cost to identify and complete payments may not be too significant, but for smaller owners, those costs could exceed the total payments to them. These barriers would likely drive GenAI development to other jurisdictions with more favorable laws, undermining U.S. technological leadership.

3.2.3 Copyright Exemptions: A Less Flexible Approach

Several countries have adopted specific copyright exemptions for AI training, but in our view, these are less effective than the U.S. fair use doctrine. Japan offers the broadest approach, covering essentially all "nonexpressive" uses that embrace GenAI training. Singapore follows a similar model but adds an important limitation: training must use only lawfully accessed works, prohibiting the circumvention of technological protection measures. The U.K.'s approach is significantly narrower, limited to noncommercial text and data mining, effectively excluding most commercial GenAI development.

The EU's approach, codified in the Directive on Copyright and Related Rights in the Digital Single Market (DSM Directive),[96] creates two distinct regimes: Article 3 provides exemptions for academic research, while Article 4 allows limited rights for commercial purposes. Crucially, the Article 4 exception allows copyright holders to opt out and restrict their works from being used in AI training—a limitation that is likely to significantly restrict available training data.

While Japan's broader exemption[97] provides a more flexible approach than that of the EU, it still lacks the adaptability of U.S. fair use. Purpose-specific exemptions create rigid boundaries, making them less suited to address the evolving challenges of GenAI development. In contrast, the U.S. fair use doctrine avoids these limitations by providing courts with a flexible standard that can balance innovation and copyright protections without requiring constant legislative updates.

3.2.4 The Economic Risks of Expanded Liability

Holding GenAI developers liable for copyright infringement would likely have a chilling effect on the growth and economic benefits of GenAI. Under current law, statutory damages per infringed work typically range between $750 and $30,000 but can rise to $150,000 per work if an infringement is deliberate.[98] Considering an LLM trained on a dataset containing one million copyrighted works, the potential liability could be staggering, ranging from $750 million ($750 x 1M) to $150 billion ($150,000 x 1M).[99]

Prior research shows that increasing either liabilities or the uncertainty associated with potential liability can slow or even halt economic activity. In a 2008 copyright case in France, a consortium of copyright holders sued Wizzgo, alleging its DVR technology which allowed for the private recording of TV shows, violated their rights. The French high court made five summary judgments against Wizzgo, which immediately halted the development of DVR technology in France, a decision that may have led to a negative spillover effect on venture capital investment in cloud computing and storage services.[100] Similarly, in the 2011 district court opinion in the Cariou v. Prince copyright case,[101] the lower court's decision to extend infringement liability to market intermediaries had an immediate effect on the appropriation art value chain. The ruling abruptly

decreased art auctions, significantly reduced sales, and shifted transactions to foreign auction houses, resulting in an estimated $300 million in forgone value.[102] Broadly, empirical evidence suggests that increasing liability, litigation costs, or uncertainty regarding such factors tend to have a negative effect on economic activity.[103]

These liability concerns have significant and immediate implications for U.S. competitiveness and innovation. While the U.S. currently leads in GenAI development and adoption, the AI market remains at an early stage, and this leadership position is far from secure. As a general-purpose technology, realizing GenAI's full potential requires significant investment in complementary technologies[104] and experimentation. Restricting fair use or expanding liability would have immediate and far-reaching consequences: developers and researchers would face higher compliance costs, reduced access to comprehensive training datasets, and increased legal uncertainty. These factors would make GenAI development prohibitively expensive, particularly for small and medium-sized enterprises that lack the resources to navigate a restricted framework.

Introducing new liability associated with training at this critical juncture in GenAI's development could allow companies in other countries to establish technological leads that would be hard to overcome once established. The technological advantages gained through cumulative investments could create lasting disparities in both cost and capability. The window for establishing lasting competitive advantages in GenAI development may not be very wide, and increased exposure to lawsuits and liability claims would discourage investment in GenAI technologies and force developers to limit their innovation to avoid legal entanglements. This would disproportionately affect early-stage and small-scale innovators, reducing competition and slowing progress in the AI sector. The consequences extend beyond economic concerns—if progress is slowed in the U.S. but continues elsewhere, U.S. companies could fall behind, with implications for national security, technological sovereignty, and America's global leadership position.

These analyses of alternative approaches reveal a crucial insight: attempts to replace or restrict fair use would likely undermine the very innovation and economic growth that GenAI promises. The transaction costs, market inefficiencies, and expanded liabilities created by these alternatives would especially harm smaller innovators and startups—the very entities that often drive technological breakthroughs.

3.3 Why Fair Use Remains Optimal

The limitations of alternative approaches—from licensing schemes to specific exemptions and liability expansions—underscore why the U.S. fair use doctrine provides an appropriate framework for GenAI development.[105] Beyond avoiding the practical and economic barriers that limit other approaches, fair use actively enables innovation and creates substantial economic

value. Maintaining and reinforcing this framework will be critical to sustaining U.S. leadership in an increasingly competitive global AI landscape.

Conclusions

The economic evidence for the importance of fair use is compelling: by enabling broad access to training data, it has helped create GenAI systems that are driving substantial productivity gains in professional services, reducing drug discovery costs, and creating billions in value across sectors from healthcare to agriculture. The concentration of AI investment in fair use jurisdictions—with the U.S. attracting $53.6 billion in GenAI venture funding compared to just $6.8 billion in Europe—suggests that fair use may play an important role in fostering innovation.

Alternative approaches like licensing regimes or rigid copyright exemptions would create significant barriers to innovation through prohibitive transaction costs and excessive liability risks. Historical evidence shows how fair use enables market growth: from doubling film industry revenue through home video rentals to increasing book sales through digital access. This flexible framework continues to drive economic value by reducing uncertainty and supporting investment, particularly benefiting smaller firms and startups—benefits that are expected to expand dramatically as AI transforms the economy.

The window for securing U.S. leadership in GenAI development may soon close as other nations rapidly advance their capabilities. Any delay in reinforcing fair use principles risks surrendering permanent technological advantages that will be difficult to reclaim in the future. As countries compete to attract AI investment and development, restrictive policies risk driving innovation overseas, threatening not just U.S. technological leadership but also economic competitiveness, national security, and America's broader position as a global innovation hub. U.S. firms currently lead in scientific advances, product development, and adoption of these transformative technologies. At this critical juncture, policymakers have an opportunity to reinforce the legal framework that has long supported American innovation. By maintaining the flexibility of fair use while fostering practical solutions like targeted agreements, the United States can secure its position as a global leader in artificial intelligence, delivering transformative benefits to society for generations to come.

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46. Note the Forbes list may be U.S. centric. However, the average funding level for U.S. firms on the list ($846 Million) far surpasses that of the typical funding levels for non-U.S. firms.

47. An * indicates the country has fair use provisions (Band and Gerafi, 2018; The Fair Use/Fair Dealing Handbook). Data Source for the Table: EdgeDelta: The Future is Now: AI Startup Statistics in 2024 (May 23, 2024) and authors' calculations. Dollar numbers rounded.

48. An * indicates the country has fair use provisions (Band and Gerafi, 2018; The Fair Use/Fair Dealing Handbook). Data Source for the Table: Forbes.com https://www.forbes.com/lists/ai50/ Dollar numbers rounded.

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50. Excessive IP rights tend to reduce follow-on innovation. For instance, research finds that patents reduce follow-on innovation by 20% to 40% (Murray and Stern, 2007; Williams, 2013). Patent citations increase 50% when rights are invalidated (Galasso and Schankerman, 2015). Murray, F., & Stern, S. (2007).“Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. Journal of Economic Behavior and Organization, 63(4): 648–87. Williams, H.L. (2013). Intellectual property rights and innovation: Evidence from the human genome. Journal of Political Economy, 121(1): 1-219. Galasso, A., & Schankerman, M. (2015). Patents and cumulative innovation: Causal evidence from the courts. The Quarterly Journal of Economics, 130(1): 317-369.

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71. The U.S. Copyright Office has also examined these technical questions in detail, discussing how GenAI systems transform training data into statistical patterns rather than storing or reproducing specific works. See: Lutes, Brent A. ed., Identifying the Economic Implications of Artificial Intelligence for Copyright Policy: Context and Direction for Economic Research, U.S. Copyright Office, 2025. https://www.copyright.gov/economic-research/economic-implications-of-ai/

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75. Hargrave, I. (2011) and DiCola and Tourve (2014).

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78. Copyright owners themselves may not rectify the underprovision of GenAI that emerges from market failure in the training data market because they have neither the data nor the capability to train GenAI. systems. Even large copyright owners (for example, firms that own multiple newspaper and magazine titles) lack sufficient data to train a cutting-edge LLM. Copyright owners are also likely to use off the shelf GenAI tools or custom tools provided by technology partners rather than to act as developers themselves. See also: Leffer, L. (2024) Artists Are Slipping Anti-AI 'Poison' into Their Art. Here's How It Works. Scientific American March 1, 2024. https://www.scientificamerican.com/article/art-anti-ai-poison-heres-how-it-works/

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80. DiCola and Touve (2014) survey executives of and attorneys representing interactive music services and find significant costs as indicated by the time to acquire licenses needed to launch a competitive service. They find an 18-month median time to acquire rights from just the 10 to 15 major labels and rights collectives, though in some cases negotiations stretched on for several years and when the compulsory scheme was not part of the licensing pathway, negotiations could stretch beyond five years. Dicola, P.C., & Touve, D. (2014). Licensing in the shadow of copyright. Stanford Technology Law Review 17, 397.

81. Hargreaves, I. (2011). Digital Opportunity A Review of Intellectual Property and Growth An Independent Report by Professor Ian Hargreaves. https://assets.publishing.service.gov.uk/media/5a796832ed915d07d35b53cd/ipreview-finalreport.pdf.

82. A number of would-be music or video streaming services failed to launch because of the complexities related to acquiring information and negotiating with copyright owners (Haregrave, 2011).

83. Even if a developer can secure sufficient copyright for training, liability issues may remain unresolved. This is because GenAI models transform inputs in unpredictable ways, outputs might still infringe on non-licensed works, creating liability risks that depend on how courts eventually view secondary liability.

84. Using copyright collectives, like the Copyright Clearance Center, could reduce search and bargaining costs, but would require copyright owners placing works into the center. However, collectives and IP pools can gain market power which raises antitrust concerns.

85. Intellectual property license agreement cost (2025). Contracts Council. https://www.contractscounsel.com/b/intellectual-property-license-agreement-cost#:~:text=agreement%20matters%204.96.-,How%20Much%20Does%20a%20Licensing%20Agreement%20Cost%3F,on%20a%20flat%20fee%20basis (Accessed: 12 February 2025).

86. If the developer must seek out copyright owners, then it would have to skew its licensing efforts towards a much smaller set of large copyright owners in order to keep search and contracting costs manageable. However, foregoing small owners could potentially reduce the quality of the model or give the large owners undue bargaining power.

87. Filippov, S. (2014). Mapping text and data mining in academic and research communities in Europe. Brussels: Lisbon Council. Online: https://lisboncouncil.net/publication/publication/109-mapping-text-and-data-mining-in-academic-and-research-communities-in-europe.html

88. IP markets tend to lack transparency and liquidity. See: Gans, J., & Stern, S. (2010). *Is there a market for ideas?* Industrial and Corporate Change, 19(3):805–837. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1617052

89. Martens, B. (2024). Economic arguments in favor of reducing copyright protection for Generative AI inputs and outputs. Working Paper 09/2024, Bruegel. https://www.bruegel.org/system/files/2024-04/WP%2009%20040424%20Copyright%20final_0.pdf

90. Complementarity can also decrease the provision of GenAI through the tragedy of the anti-commons. When independent owners make separate pricing decisions regarding complementary content, the total price can be excessive, even exceeding the price set by a monopolist. See: Depoorter, B., & Parisi, F. (2002). Fair use and copyright protection: A price theory explanation. International Review of Law and Economics, 21(4): 453–473

91. Even if the marginal contribution could be estimated, deciding on a fair fee structure can be complex. For instance, license fees are often structured as a percentage of final sales, where the percentage should reflect the marginal contribution of licensed IP to the product's end value. However, GenAI models can form the foundation of many other products, which calls into question at what point in the value chain should the revenues be calculated (i.e., as a percentage of the GenAI developer's revenues or from revenues from other firms deploying the model further down the value chain). See Martens (2024) for a full discussion.

92. Williamson, O.E. (1979). "Transaction-Cost Economics: The Governance of Contractual Relations." Journal of Law and Economics, 22(2), 233–261. https://www.journals.uchicago.edu/doi/10.1086/466942

93. Masten, S.E., & Croker, K.J. (1985). Efficient adaptation in long-term contracts: Take-or-pay provisions for natural gas. The American Economic Review, 75(5): 1083–1093; Joskow, P. (1985), Vertical integration and long-term contracts: The case of coal-burning electric generating plants, Journal of Law, Economics, and Organization 1, 33–80.

94. Please refer to Part 2 titled, The Economic Importance of Clear Liability Frameworks for GenAI Outputs and to the section below titled The Economic Risks of Expanded Liability for a deeper discussion of direct and secondary liability.

95. A submarine strategy describes a situation in which a party intentionally hides its IP, waits for another party to make investments in technology that potentially infringe on the IP, then surfaces with an IP claim and often a lawsuit. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019L0790

96. European Parliament, & Council of the European Union. (2019). Directive (EU) 2019/790 of 17 April 2019 on copyright and related rights in the Digital Single Market and amending Directives 96/9/EC and 2001/29/EC. Official Journal of the European Union, L 130, 92–125. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019L0790.

97. Copyright Research and Information Center (CRIC). (n.d.). Copyright Law of Japan. Retrieved from https://www.cric.or.jp/english/clj/cl2.html

98. Thomson Reuters. (2022, December 16). Copyright litigation 101. Thomson Reuters Legal Blog. https://legal.thomsonreuters.com/blog/copyright-litigation-101/.

99. Following the simple procedure laid out in the copyright alliance site. (https://copyrightalliance.org/education/copyright-law-explained/copyright-infringement/copyright-statutory-damages/)

100. Lerner, J., & Rafert, G. (2015). Lost in the clouds: The impact of changing property rights on investment in cloud computing ventures. Harvard Business School, Working Paper 15-082.

101. Cariou v. Prince, 784 F.Supp. 2d 337 (SDNY 2011).

102. Cuntz, A., & Shali, M. (2024). Intermediary liability and trade in follow-on innovation. Journal of Cultural Economics, 48:1 - 42. https://doi.org/10.1007/s10824-023-09470-1.

103. Prior research shows a strong association between increased litigation risk and adverse economic outcomes. Lerner (1995) finds that as IP litigation costs increase, new biotechnology firms avoid patenting in areas with a greater potential for litigation. Cohen, Gurun, and Kominers (2019) find that IP litigation reduces innovation by target firms. Agarwal, Ganco and Ziedonis (2009) find that firms that have a reputation for litigiousness deter human capital movements between firms which suppresses knowledge flows and adversely impacts new startups. Ganco, Miller and Toh (2020) find that an unexpected drop in a firm's litigation ability significantly reduces its ability to create value by innovating in new areas. Similar evidence can be found in the context of product liability. Examining states that adopted product line exemptions (a legal rule extending product liability from the original manufacture to an acquirer that produces the same product line), Balasubramanian, Sivadasan, and Xu (2024) find that the rules resulted in a 10% decline in the probability of manufacturers in the state being acquired and 6.4% increase in the likelihood that they would close, relative to the mean rates of acquisition and closures. Notably, the authors find the product line exemptions depressed new entry into manufacturing in these states, suggesting that the increase in liability may have harmed regional economic growth and employment.

104. Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-Curve: How intangibles complement General Purpose Technologies. American Economic Journal: Macroeconomics, 13: 333–372. https://www.aeaweb.org/articles?id=10.1257/mac.20180386

105. Gans (2024) examines GenAI and copyright policy with analytical models and finds that fair use can lead to higher expected social welfare than alternative copyright regimes. See: Gans, J.S. (2024). Copyright policy options for generative artificial intelligence. http://dx.doi.org/10.2139/ssrn.4707911

Technical Appendix

For additional details about Fair Use Doctrine and How GenAI Works, please refer to the accompanying Technical Appendix.