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Algorithmic Ownership in the Age of Generative Artificial Intelligence: Reconciling Intellectual Property Regimes with Sociotechnical Imperatives

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Abstract
The emergence of generative artificial intelligence systems has triggered some underlying tensions in the traditional intellectual property systems. The article contributes to a systematic study of the way the tripartite architecture of modern AI systems underlying code, trained models, and training data are facilitated or not in trade secret doctrine, copyright law, and patent regimes. Based on the comparative legal analysis of the European Union and the United States jurisdictions, with the support of the empirical evidence of the cross-sectoral data-sharing practices, this inquiry indicates that there are significant gaps in the doctrines that need to be addressed both in scholarship and legislation. The discussion shows that trade secret protection, even though it maintains competitive advantages, also hinders the need to promote transparency and fair value distribution processes required to ensure responsible AI governance. The copyright laws do not manage to deal with the magnitude of training data consumption, and the authorship disputes over machine-generated products. The patent doctrine, which is based on human inventorship, faces inadmissible contradictions in case artificial systems play a significant role in the innovative process. In this article, the hybrid architecture of governance is suggested, which comprises a combination of balanced intellectual property protection with open science and collective data stewardship models. Some of the specific proposals include standardized data-sharing contractual models, obligatory AI contribution disclosure in patent applications, revamped text-and-data mining exemptions, sui generis protection of AI-generated works, and institutional structures of democratic data regulation. These reforms are proposed to support incentives of innovation with promoting transparency, accountability, and the fair allocation of artificial intelligence-derived benefits in society.

Keywords: Artificial intelligence; Intellectual property; Algorithmic governance; Data commons; Trade secrets; Copyright; Patent law; Open science; Generative AI; Digital ownership

1. Introduction

The growing pace of artificial intelligence technology, especially generative systems that can generate text, images, code, and other creative artifacts, has triggered a radical questioning of the underlying assumptions of intellectual property jurisprudence. With the growing role of AI systems as autonomous or semi-autonomous participants in creative and inventive activities, the conventional structures that are used to motivate human innovation are facing unprecedented conceptual and practical difficulties. The key question driving this investigation, who owns the algorithm, goes beyond the issue of property designation to include more fundamental issues of control, responsibility, value allocation, and the governance structure that should be applied to transformative technologies.

Modern intellectual property regimes were developed at the time when innovation was still largely human-driven, creative works had easily recognizable authors, and inventive processes had recognizable routes between conception and reduction to practice (Lemley 2021). These historical roots become even less sufficient when addressing the AI systems that are marked by continuous learning, massive-scale data processing, and outputs that are produced in the form of computational processes that cannot be easily attributed to human creative agency (Burk 2019). The resultant doctrinal strains are reflected in all the major IP categories: trade secrets are torn between the need to protect competition and the need to be transparent; copyright is challenged by the authorship, originality and fair use issues; patent law is challenged by the inventorship demands based on the human contribution to cognition.

These issues have a heavy practical implication for various stakeholders. The creators and implementers of AI systems need legal assurance about the security of their investments in the model creation and training data preparation. Creative individuals whose work can be consumed into training data want to be recognized, paid, and have control over the downstream applications of their work. Policymakers must balance between competing demands: to promote innovation and competitiveness and to hold people accountable, to avoid market concentration, and to allocate AI benefits fairly in society (Drexl et al. 2019). The outcome of these tensions will largely determine the future of AI development and its consequences on society in the decades to come.

This paper aims to conduct an extensive study of the concept of algorithmic ownership in the three major intellectual property regimes, placing this study in the context of comparative EU-US views and new governance options. The research assumes that effective reform must be informed by the knowledge of both the technical structure of AI systems and the normative principles of the intellectual property doctrine. Instead of proposing radical rejection of property-based solutions, the analysis constructs a hybrid governance system that maintains the legitimate functions of incentives but includes transparency, accountability, and collective stewardship systems needed to develop AI responsibly.

The research questions are organized into four interrelated research questions that will inform the analysis that follows:

First, are the current intellectual property systems, including trade secrets, copyright and patents, sufficient to address the legal and economic nature of modern AI systems? This question demands the investigation of the doctrinal fitness and practical efficacy of the tripartite framework of code, model, and data that comprise modern AI.

Second, what are the dangers and constraints that come with the treatment of AI systems as proprietary assets, specifically in the context of innovation processes, access issues, and accountability frameworks? This question explores possible adverse externalities of robust IP protection in AI situations.

Third, what can alternative governance strategies, such as open science systems, data commons systems, and transparency obligations, add or change to existing IP regimes to facilitate more equitable and socially valuable AI development?

Fourth, what are the legal and policy changes that are justified in the US and EU jurisdictions to create a more balanced algorithmic ownership regime that would help to maintain incentives to innovate and promote the goals of public interest?

2. Conceptual Foundations: Defining Algorithmic Ownership

Meaningful engagement with questions of algorithmic ownership requires preliminary conceptual clarification. The term 'algorithm' carries multiple significations in technical, legal, and popular discourse, and 'ownership' encompasses several analytically distinct dimensions that map differently onto existing legal frameworks. This section establishes the definitional and conceptual apparatus necessary for the subsequent doctrinal analysis.

2.1 The Tripartite Architecture of AI Systems

Modern AI systems, especially those that use a machine learning approach, do not lend themselves to a conceptualization and definition of discrete objects that can be studied using more traditional property analysis concepts. Rather, these systems are three layers, each with different ownership considerations, and are differently mapped onto intellectual property categories (Picht, Brunner and Schmid 2022).

The first layer is the underlying code: the code that implements neural network architectures, training algorithms, loss functions and inference procedures. This code is the explicit human-written instructions, which are written in programming languages and are the technical basis on which AI functionality is based. Code can be copyrighted as a work of literature and can also be subject to trade secret protection when kept secret (Samuelson 2021).

The second level is the trained model; the learned parameters, weights and the statistical relationships that have been created by being exposed to training data. Contrary to code, trained models are not written directly by human beings but are obtained through computation which identifies and encodes patterns in data. The model itself is condensed knowledge—a compressed version of the regularities in training data, and it is the functional core that allows the system to produce outpourings, provide predictions, or fulfill tasks (Bommasani et al. 2022). The legal position of trained models is controversial, and all the arguments to protect it as a trade secret, copyright, or even a patent face doctrinal challenge.

Training data is the third layer: it is the corpus of text, images, audio, structured information, and other materials that the model learns. The content of training data can include publicly available data, proprietary data, licensed data, as well as the most controversial copyrighted data consumed without the explicit permission of the author. The provenance, composition, and legal status of training data have become a central concern when it comes to the debate of AI governance, specifically about generative systems being trained on large collections of creative work (Grimmelmann 2023).

Layer	Characteristics	Primary IP Considerations	Key Challenges
Code	Human-authored; explicit instructions; programming languages	Copyright (literary work); Trade secrets	Open-source licensing; collaborative development
Trained Model	Machine-derived; emergent parameters; statistical patterns	Trade secrets; Contested copyright; Potential patent	Authorship unclear; dynamic updating; opacity
Training Data	Heterogeneous sources; varying IP status; massive scale	Copyright (third-party); Database rights; Privacy	Consent; licensing; value attribution

Table 1: Tripartite AI Architecture and Intellectual Property Mapping

Critically, these three layers do not exist in isolation but interact dynamically throughout the AI development lifecycle. Code determines how models learn from data; data shapes model capabilities and behaviors; model architectures influence what patterns can be extracted from data. Moreover, contemporary AI development practices involve continuous refinement: models undergo fine-tuning, retraining, and distillation; training data is augmented, filtered, and updated; code evolves through iterative optimization. This dynamic character complicates ownership analysis, as the 'object' of potential protection is not fixed but continuously transforming (Hilty, Hoffmann and Scheuerer 2020).

CONCEPTUAL FRAMEWORK FOR ALGORITHMIC OWNERSHIP ANALYSIS

AI SYSTEM ARCHITECTURE	TENSION POINTS	IP REGIMES
‣ **CODE** Human-authored algorithms ‣ **TRAINED MODEL** Learned parameters/weights ‣ **TRAINING DATA** Source materials/corpora	• Authorship • Inventorship • Transparency • Value Distribution	‣ **TRADE SECRETS** Confidential protection ‣ **COPYRIGHT** Creative expression ‣ **PATENTS** Technical inventions

▼

ALTERNATIVE GOVERNANCE MECHANISMS	
OPEN SCIENCE FAIR Data • Transparency • Reproducibility	**DATA COMMONS** Collective Stewardship • Democratic Governance

▼

HYBRID GOVERNANCE FRAMEWORK
Calibrated IP Protection + Open Science Principles + Collective Stewardship

Figure 1. *Conceptual Framework for Algorithmic Ownership Analysis.* This diagram illustrates the tripartite structure of AI systems (code, model, data) mapped against three IP regimes (trade secrets, copyright, patents) and alternative governance mechanisms (open science, data commons), showing interaction pathways and tension points leading to a hybrid governance framework.

2.2 Disaggregating Ownership: Control, Exploitation, Attribution, and Property

The idea of ownership when used with reference to algorithmic systems involves several analytically discrete dimensions that may not necessarily overlap with each other and that are safeguarded by different legal systems in a different manner (Penner 2020). These dimensions need to be broken down in an effective analysis.

Control can be defined as the pragmatic ability to decide the way AI systems get utilized, altered, shared or limited. The control can be based on technical control (encryption, access rights), contractual control (licensing terms, conditions of use), or legal rights (IP rights that allow exclusion). Remarkably, control does not necessarily presuppose formal possession, platform operators can have practical control of AI systems with which they do not have a legal hold in terms of service and technical architecture (Cohen 2019).

Exploitation deals with the right to commercialize AI systems, licensing or deploying AI systems. The right to exploit can be retained by other parties than those in control, a developer may license a model to a deployer who derives an economic benefit with downstream applications but not controlling the underlying technology.

Attribution deals with issues of credit, recognition and responsibility of creative/ inventive work. The issue of attribution surrounds the areas of copyright (authorship) and patent (inventorship) but does not limit itself to the legal claim to rights and instead also considers reputational interests and accountability relationships (Ginsburg 2018).

Property as defined strictly refers to formally acknowledged rights to keep others out, assign rights, and remedies in a court of the law in an event of interference. In the case of AI, rights to property are divided into many regimes: copyright, patent, trade secret, contract and each has different bundles of claims with different requirements, terms and restrictions (Merges 2011).

3. Trade Secrets and Data Ownership in AI Contexts

Trade secret protection has emerged as arguably the most significant intellectual property mechanism for safeguarding AI-related assets. Unlike patents or copyrights, trade secrets require no registration, face no formal examination, and can theoretically persist indefinitely provided secrecy is maintained. For AI developers, trade secrets offer flexible protection for model parameters, training methodologies, hyperparameter configurations, and curated datasets—precisely the competitive assets that drive commercial value (WIPO 2023).

3.1 Empirical Insights from Data-Sharing Practices

The critical background of the doctrinal analysis is given by empirical research investigating how firms in data-intensive environments negotiate matters of trade secrets. One of the most instructive articles by Radauer, Searle and Bader explored data-sharing in agricultural and food industries and identified trends that directly can be applied in the situation developing AI (Radauer, Searle and Bader 2023).

Their study produced two major strategies that are used by firms in the management of valuable data assets. The former is a total non-sharing where sensitive information is not shared at all. The second is closed sharing where information is shared among well determined partners with intense security measures. These two methods are signs of solid appreciation of the fact that data is a strategic innovation resource that derives its value significantly by keeping it exclusive.

Importantly, though, the study shows that protection of trade secrets is not enough to create successful cooperation or equal distribution of values. When companies combine information, whether to collaboratively create a model, conduct a combined study, or integrate a supply chain, they face tough challenges on how to allocate derivative value. Who wins the gains from knowledge created on shared data? Who are the owners of models that are trained on common datasets? Who is responsible when shared data is used to support bad applications? According to Radauer et al., it was observed that companies often have a hard time coming up with workable value-sharing systems despite having confidentiality agreements that are effective at safeguarding disclosure.

3.2 The EU Trade Secrets Directive: Harmonization and Limitations

Trade secrets directive (2016/943) by the European Union is the most central legal framework that regulates the protection of confidential business information in the member states. The Directive provides three cumulative conditions of trade secrets: secrecy (not leakage), commercial use of secrecy, and reasonable efforts on the part of the information owner. Such assets as trained models, proprietary algorithms, and curated datasets can easily be included in this definition, as it involves AI-related assets. The Directive defines what is meant by unlawful acquisition, use, or disclosure of discovering unauthorized access, breaching of confidentiality obligation and use that is beyond the restrictions of contracts. The remedies that may be available would be injunctive relief, damage and corrective measures. Notably, the Directive also includes the safeguards of the public interest: Article 5 allows exemption of disclosures to exercise freedom of expression, create disclosure of misconduct, or in the furtherance of lawful public interest (Mylly 2023).

Trade Secret Strength	Transparency Benefit	Balance Mechanism
Preserves competitive advantage	Enables external audit/accountability	Graduated access models
Incentivizes R&D investment	Supports regulatory oversight	Third-party trusted intermediaries
Flexible, no registration required	Facilitates research/innovation	Standardized contractual frameworks
Potentially unlimited duration	Promotes public trust in AI	Mandatory disclosure in high-risk contexts

Table 2: Trade Secret Protection vs. Transparency Imperatives: Balancing Framework

4. Copyright Law in the Generative AI Era

Copyright law faces perhaps the most acute challenges from generative AI development. The tensions operate bidirectionally: regarding inputs, questions arise about the permissibility of training on copyrighted works; regarding outputs, uncertainty persists about the authorship and protectability of AI-generated content. Both dimensions require careful examination (Samuelson 2023).

4.1 The Training Data Dilemma: Scale, Opacity, and Rights Clearance

In generative AI systems, the capabilities they gain are through exposure to huge volumes of data, consisting of text, images, audio, and other materials, much of which is copyrighted. Billions of documents may be trained on large language models, hundreds of millions of images on image generators. The magnitude of these training corpora makes the customary rights clearance systems not workable. None of the organizations could afford to enter unilateral deals on the billions of works of millions of rights owners (Sag 2023).

This factual situation generates deep normative strains. The owners of rights might realize their creative works integrated into systems producing competing products without their authorization, payment, and even knowledge. The secrecy of the contemporary AI training contributes to the increased concerns: its developers often are not aware of whether their art pieces were used, how they were used, and what impact they had on the model capabilities. This epistemic imbalance compromises significant practice of copyright rights (Sobel 2017).

Al-Busaidi et al. believe that generative AI is inherently disruptive to the traditional paradigm of innovation and creativity in a manner that current, established copyright systems cannot effectively solve.

They suggest a Dynamic Ethical Framework that focuses on harmonized international strategies of using AI training and claim that national reforms will not be sufficient due to the global nature of AI creation and implementation (Al-Busaidi et al. 2024). Their discussion indicates that reforming of law should be implemented together with ethical governance innovation and international coordination protection.

4.2 Transparency as Partial Remedy: Possibilities and Limitations

One policy response that has become noticeable regarding the issue of training data about AI is transparency requirements. The EU AI Act contains requirements for some disclosures on training data composition and provenance. Similar initiatives have been made elsewhere. The theory behind it is that transparency will enable the holders of the right to discover unauthorized uses, negotiate a payment or exercise their opt-out rights.

Buick offers a critical analysis of transparency-based strategies. Although he concedes that transparency is needed, he says that it cannot be used on its own to address the tensions that are present in copyright. The value of transparency only lies in the fact that substantive copyright law needs to answer the underlying question of permissibility of training use; knowing what information was used will be of limited use when legal frameworks do not provide an effective solution. Additionally, the transparency provisions of the EU AI Act work alongside text-and-data mining exceptions whose opt-out functionality can be of little practical value to individual creators (Buick 2024).

4.3 Authorship and AI-Generated Works

The other side of the copyright equation is no less difficult to answer. In cases of text, images, music, or other content that is generated by generative AI, who, if anyone, are the rights holders in terms of copyright? The classical copyright theory bases protection on human creative activity; the personality, decisions and the creative input of the human author are the reasons to assign exclusive rights (Ginsburg and Budiardjo 2019).

This is the premise that AI-generated outputs dispel. In systems where the content is generated with little human input, say, by a simple prompt, it is hard to find the necessary human creativity. The copyright office in the US has been adamant that copyright must involve human creation, and they refuse to give copyright registration of work done mainly using AI-generated methods. There are variations in European approaches, however, most of the member states also base copyright on human creativity.

AUTHORSHIP ATTRIBUTION SPECTRUM IN HUMAN-AI COLLABORATIVE CREATION

100% HUMAN		**100% AI**		
ZONE A	**ZONE B**	**ZONE C**	**ZONE D**	**ZONE E**
Purely Human Traditional authorship → **Full Copyright**	**AI-Assisted** Human directs; AI executes → **Full Copyright**	**Collaborative** Significant joint input → **Joint/Modified**	**AI-Dominant** Minimal human direction → **Sui Generis**	**Purely AI** No meaningful human input → **Public Domain**

PROPOSED LEGAL TREATMENT
Human Contribution Level → Determines Protection Scope
High Human Input = Full Copyright | Low Human Input = Reduced/No Protection

Figure 2. *Authorship Attribution Spectrum in Human-AI Collaborative Creation.* This figure depicts a continuum from purely human creation through various levels of AI assistance to primarily AI-generated outputs, mapping each zone to potential copyright treatment (full protection, joint authorship, sui generis rights, public domain).

Several policy responses merit consideration. One approach would consign purely AI-generated works to the public domain, accessible to all without restriction. This position finds support in Elmahjub's argument that copyright's philosophical foundations—rooted in protecting human creative expression—simply do not extend to machine outputs. Excluding such works from protection avoids category confusion while ensuring public access (Elmahjub 2025). An alternative approach would create sui generis protection for AI-generated works: a distinct legal category with rights calculated to the specific characteristics and policy considerations at stake (Lu 2025).

5. Patent Law and AI-Generated Inventions

Patent law's accommodation of AI-assisted innovation presents distinct challenges from those arising in copyright contexts. While copyright concerns authorship and creative expression, patents address technical inventions requiring novelty, non-obviousness (or inventive step), and utility. The central doctrinal tension involves inventorship: patent systems universally require natural person inventors, yet AI systems increasingly contribute substantively to inventive processes (Abbott 2020).

5.1 Technical Reality: AI Systems as Inventive Agents

Particularly AI systems that utilize generative and optimization methods have been shown to generate outputs that satisfy substantive patentability requirements. In the field of materials science, AI systems suggest new molecular structures and extrapolate their behavior. In medicine, AI can be used to discover successful drug candidates and streamline their properties. In the engineering world, AI is used to coming up with novel designs of components, circuits and systems. They do not aid the inventive advance but, in many cases, are constitutive of it (Gupta et al. 2024).

Ozin, Qian and MacIntosh use materials discovery as a compelling example to show that AI systems can generate completely new compounds, predict stability and performance properties as well as give a synthesis route- input that would, without any doubt, meet the inventorship criteria had they come out of the hands of human researchers. The inventions must be technically meritorious, irrespective of their origin; the law issue is whether and how to acknowledge AI contributions in the current doctrinal regimes (Ozin, Qian and MacIntosh 2023).

5.2 The Inventorship Impasse: Doctrinal Foundations and Reform Proposals

The inventorship condition of patent law demonstrates profound suppositions concerning the essence of innovation and the intentions of protection against patent. The classical rationale is that patents stimulate the innovative activity of people because they grant exclusive rights to the inventors. This argument assumes that the inventor of the product can be driven by potential rewards, which AI systems cannot satisfy, as they have no goals or plans (Vertinsky and Rice 2002).

This is the issue that Helman and Parchomovsky systematize in their discussion of the topic of artificial inventorship. According to them, considering AI as inventors would erode the normative provisions of patent law because the incentive explanation cannot be logical when applied to non-human agents. Nevertheless, they also acknowledge that unconditionally ruling out the contributions of AI to recognition would generate its own challenges, which, in turn, may lead to human windfalls of other contributors who made minimal contributions to the innovation process. Their suggested way out of scalar model the replacement of protection scope to the extent of the human input is an advanced endeavor to maintain incentive functions and accept technological facts (Helman and Parchomovsky 2024).

Jurisdiction	Inventorship Position	AI Disclosure	Key Legal Basis
United States	Natural persons only; significant contribution required	Not formally required	USPTO Guidance 2024; Pannu test
European Union	Natural persons only; no AI inventorship	Emerging requirements (AI Act)	EPC Art. 81; EPO Guidelines
United Kingdom	Natural persons only; DABUS rejected	Under consideration	Patents Act 1977 s.7; Thaler decisions
Australia	Initially accepted AI; reversed on appeal	Not required	Thaler v Commissioner (2022)

Table 3: Comparative Jurisdictional Approaches to AI Inventorship

6. Alternative Governance: Open Science and Data Commons

Exclusive proprietary rights represent only one possible governance approach for algorithmic resources. Alternative models grounded in open science principles and collective data stewardship offer frameworks potentially better suited to AI's distinctive characteristics and broader social implications. This section examines these alternatives and their integration with reformed IP regimes (Floridi 2023).

6.1 Open Science Principles: From Publications to AI Systems

Open science involves a paradigmatic change in research conduct, dissemination, as well as estimation. Expanding out of the old emphasis on access to publications, new movements in open science have taken on data, software, methodologies, and research infrastructure. The principle of the European Commission, as open as possible, as closed as necessary, is a summary of the tool to achieve the greatest access and accept reasonable restrictions (European Commission 2022).

When applied to the context of AI, open science principles denote several governance implications. To begin with, training data must be recorded, described, and where feasible made available such that they can be checked and reproduced. FAIR standards (Findable, Accessible, Interoperable, Reusable) are set standards of data management (Wilkinson et al. 2016). Second, model architecture and training processes must be documented enough to allow independent assessment and re-implementation. Third, AI research products must not only be judged by the performance criterion but also transparency, reproducibility and wider social consequences.

6.2 Data Commons: Collective Stewardship for Shared Resources

Data commons are governance models where data resources are controlled by communities instead of being controlled by single owners. Based on the pioneering contributions of Ostrom to the analysis of common-pool resource governance, data commons scholarship focuses on the system of institutional design, mechanisms of participation and sustainability (Ostrom 1990).

Fia and van Maanen give a detailed analysis of the data commons governance with focus on social and institutional aspect and technical needs. They say that good commons should not only have shared infrastructures but actual community governance: participatory decisions about who is allowed access, use restrictions and distribution of values. Among the issues they discuss is the coordination of the stakeholders, financing sustainability, and balancing transparency and safety against the participants (Fia and Van Maanen 2025).

HYBRID GOVERNANCE ARCHITECTURE FOR ALGORITHMIC RESOURCES

OUTER LAYER: DATA COMMONS & COLLECTIVE GOVERNANCE
Community Governance • Democratic Oversight • Benefit Sharing • Stakeholder Participation

MIDDLE LAYER: OPEN SCIENCE PRINCIPLES
FAIR Data • Transparency • Reproducibility • Open Access

INNER LAYER: INTELLECTUAL PROPERTY PROTECTION
Patents • Copyright • Trade Secrets
(Core Protection for Innovation Incentives)

GOVERNANCE LAYERS (Inner → Outer): ■ IP Rights (Core) ■ Open Science (Transparency) ■ Data Commons (Stewardship)

Figure 3. *Hybrid Governance Architecture for Algorithmic Resources.* This diagram illustrates a layered governance model combining traditional IP protections (innermost layer) with open science principles (middle layer) and data commons institutions (outer layer), showing governance mechanisms operating at each level and interaction pathways between layers.

7. Toward a Comprehensive Reform Agenda

The foregoing analysis reveals substantial gaps between existing intellectual property frameworks and the governance requirements of contemporary AI systems. This section synthesizes insights from the doctrinal examination into concrete reform proposals spanning legislative, regulatory, and institutional dimensions (Chesterman 2024).

7.1 Calibrating Trade Secret Protection

Reform of trade secrets must not interfere with any valid interests in confidentiality but must not be used to manipulate the demands of accountability and access. Certain suggestions are as follows: developing standardized contractual structures of AI data-sharing arrangements that include attributing rights, risks, and value distribution; developing trusted mediator institutions that can audit AI systems without jeopardizing the underlying confidentiality; implementing graduated access models that differentiate between sensitive core assets and derivable or aggregated information; and requiring transparency disclosures of AI systems applied in high-risk settings irrespective of claims of trade secrets.

7.2 Adapting Copyright for the Generative AI Era

The copyright reform should target both input and output in terms of training. In the case of training data, it is suggested to create collective licensing systems that would allow easy rights clearance at scale, reform text-and-data mining exceptions to include an effective opt-out option and compensation potentials and establish technical standards on how to identify content and track its use. In the case of AI-generated works, reform should: clarify that insignificant human intervention leads to the status of a public domain; introduce sui generis copyright protection over works with significant AI intervention where human intervention reaches significant thresholds; and come up with new attribution standards that are indicative of collaborative human-AI creative practices.

7.3 Modernizing Patent Doctrine for AI Innovation

Reform of patents ought to maintain the human-oriented incentive frameworks and recognize the increasing contributions of AI to innovation. Among the recommendations are: to retain natural person inventorship requirements, to require disclosure of AI contribution in patent applications; to establish examination practice to determine the significant contribution requirement in AI-assisted inventions; to adjust the scope of patent and term to the extent of human or AI contribution; and to seek harmonization of these jurisdictions on a global scale through WIPO so that uniform guidelines are established.

POLICY REFORM FLOWCHART: FROM DOCTRINAL GAPS TO GOVERNANCE SOLUTIONS

CURRENT CHALLENGES
- Trade secret opacity
- Training data disputes
- Authorship uncertainty
- AI inventorship gaps

→

ANALYSIS FRAMEWORK
- Tripartite AI structure
- Ownership dimensions
- Comparative EU/US law
- Stakeholder interests

→

REFORM PROPOSALS
- Calibrated IP protection
- Transparency mandates
- Sui generis rights
- Governance innovation

▼

TRADE SECRETS	COPYRIGHT	PATENTS	GOVERNANCE
Standard contracts	Collective licensing	AI disclosure mandate	Data trusts
Trusted intermediaries	TDM reform	Calibrated protection	FAIR requirements
Graduated access	Sui generis outputs	WIPO harmonization	Democratic mechanisms
2-5 years	5-10 years	2-5 years	Ongoing

▼

HYBRID GOVERNANCE FRAMEWORK
Balanced Innovation Incentives • Transparency • Accountability • Equity

Figure 4. Policy Reform Flowchart: From Doctrinal Gaps to Governance Solutions

Figure 4. *Policy Reform Flowchart: From Doctrinal Gaps to Governance Solutions.* This flowchart maps the pathway from current challenges through analytical frameworks to specific reform proposals across trade secrets, copyright, patents, and governance domains, converging on a hybrid governance framework.

Domain	Key Reforms	Implementation Timeline	Primary Actors
Trade Secrets	Standardized contracts; trusted intermediaries; graduated access	Medium-term (2-5 years)	EU/US regulators; industry consortia
Copyright	Collective licensing; TDM reform; sui generis AI outputs	Long-term (5-10 years)	National legislators; WIPO
Patents	Mandatory AI disclosure; calibrated protection; harmonization	Medium-term (2-5 years)	Patent offices; WIPO
Governance	Data trusts; FAIR requirements; democratic commons	Long-term (ongoing)	Governments; research funders; civil society

Table 4: Summary of Reform Recommendations by Domain

8. Conclusion

There is no easy answer to the question of who owns the algorithm. Modern AI systems involve a series of layers, code, models, data, with each layer having a set of ownership issues that do not fit into a pre-existing intellectual property category. Trade secrets secure confidential assets at the expense of transparency. Copyright is facing the challenges of training data scale and AI-generated content that does not have a human writer. The human inventorship conditions of patent law are inconsistent with the substantive innovations of AI. These contradictions in doctrines are indicative of underlying discrepancies between the legal regulations of the previous technological paradigms and the specifics of the generative AI systems.

This paper has supported a hybrid approach to governance retaining legitimate roles of intellectual property, such as incentivizing investment, rewarding creativity, protecting competitive advantage but adding transparency, accountability, and collective forms of stewardship to ensure responsible development of AI. The proposed reforms are moderate more than radical: trade secrets permitted and not absolute; copyright modified and not forsaken; patents maintained but reformed; commons complementary and not substitute proprietary provision.

It is not only technical legal adjustments. The way societies answer algorithmic ownership issues will have a significant influence on the development of AI, dictating the beneficiaries of AI innovation, who will be responsible in the event of AI harm, and whose interests guide AI regulation. Without considerate reform, the existing tendencies will entrench concentrated power and strong actors with sufficient resources, hide the accountability under the banner of confidentiality, and allocate AI benefits unequally. The hybrid model of governance that should be suggested here provides such alternative ways - the way that will not only support the incentives to innovations but also promote transparency, accountability, and the common good.

This alternative is based on long-term academic involvement, policy entrepreneurship, and institutional innovation. Laws need to be changed, systems of governance need to change, and the global collaboration should be enhanced. It is a significant but not new task, and intellectual property regimes have undergone numerous reforms in the wake of technological change. The generative AI era requires similar adjustment: and the decisions of today will echo into the algorithmic futures we are all shaping.

References

1. Abbott R (2020) The reasonable robot: artificial intelligence and the law. Cambridge University Press, Cambridge
2. Al-Busaidi AS, Raman R, Magrizos S, et al. (2024) Redefining boundaries in innovation and knowledge domains: investigating the impact of generative artificial intelligence on copyright and intellectual property rights. J Innov Knowl 9:100630. https://doi.org/10.1016/j.jik.2024.100630
3. Almarzoqi R, Albakjaji M (2022) The patentability of AI invention. Int J Serv Sci Manag Eng Technol 13:1-22. https://doi.org/10.4018/ijssmet.307111
4. Bommasani R, Hudson DA, Adeli E, et al. (2022) On the opportunities and risks of foundation models. Stanford HAI Center for Research on Foundation Models. arXiv:2108.07258
5. Buick A (2024) Copyright and AI training data—transparency to the rescue? J Intellect Prop Law Pract 20:182-192. https://doi.org/10.1093/jiplp/jpae102
6. Burk DL (2019) Algorithmic legal metrics. Notre Dame Law Rev 96:1147-1204
7. Chesterman S (2024) Good models borrow; great models steal: intellectual property rights and generative AI. Policy Soc 44:23-37. https://doi.org/10.1093/polsoc/puae006
8. Cohen JE (2019) Between truth and power: the legal constructions of informational capitalism. Oxford University Press, New York
9. Directive (EU) 2016/943 of the European Parliament and of the Council on the protection of undisclosed know-how and business information (trade secrets). OJ L 157, 15.6.2016
10. Drexl J, Hilty R, Desaunettes L, et al. (2019) Technical aspects of artificial intelligence: an understanding from an intellectual property law perspective. Max Planck Institute for Innovation and Competition Research Paper No. 19-13. https://doi.org/10.2139/ssrn.3465577
11. Elmahjub E (2025) The algorithmic mouse and the public domain: why copyright's legal philosophy precludes protection for generative AI outputs. Comput Law Secur Rev 58:106170. https://doi.org/10.1016/j.clsr.2025.106170
12. European Commission (2022) Open science and intellectual property rights. Publications Office of the European Union, Brussels
13. Fia T, Van Maanen G (2025) Through thick and thin: data commons, community and the struggle for collective data governance. Technol Regul 2025:114-136. https://doi.org/10.71265/tk2x3d39
14. Floridi L (2023) The ethics of artificial intelligence: principles, challenges, and opportunities. Oxford University Press, Oxford
15. Ginsburg JC (2018) People not machines: authorship and what it means in the Berne Convention. IIC Int Rev Intellect Prop Compet Law 49:131-135
16. Ginsburg JC, Budiardjo LA (2019) Authors and machines. Berkeley Technol Law J 34:343-448
17. Grimmelmann J (2023) The structure of copyright law. Harv J Law Technol 36:471-534
18. Gupta A, Chakraborty D, Sengupta A (2024) Artificial intelligence for materials science. Nat Rev Mater 9:437-458
19. Helman L, Parchomovsky G (2024) Artificial inventorship. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4811815

20. Hilty R, Hoffmann J, Scheuerer S (2020) Intellectual property justification for artificial intelligence. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3539406
21. Hosseini M, Resnik DB, Holmes K (2024) Open science at the generative AI turn: an exploratory analysis of challenges and opportunities. Quant Sci Stud 6:22-45. https://doi.org/10.1162/qss_a_00337
22. Lemley MA (2021) IP in a world without scarcity. Stanford Law Rev 63:1335-1363
23. Lu Y (2025) Reforming copyright law for AI-generated content: copyright protection, authorship and ownership. Technol Regul 2025:81-95. https://doi.org/10.71265/chkr8w30
24. Merges RP (2011) Justifying intellectual property. Harvard University Press, Cambridge MA
25. Mylly UM (2023) Transparent AI? Navigating between rules on trade secrets and access to information. IIC Int Rev Intellect Prop Compet Law 54:1013-1043. https://doi.org/10.1007/s40319-023-01328-5
26. Ostrom E (1990) Governing the commons: the evolution of institutions for collective action. Cambridge University Press, Cambridge
27. Ozin GA, Qian C, MacIntosh JG (2023) Can AI be an inventor in materials discovery? Matter 6:3117-3120. https://doi.org/10.1016/j.matt.2023.08.015
28. Penner JE (2020) Property rights: a re-examination. Oxford University Press, Oxford
29. Picht PG, Brunner V, Schmid R (2022) Artificial intelligence and intellectual property law: from diagnosis to action. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4122985
30. Radauer A, Searle N, Bader MA (2023) The possibilities and limits of trade secrets to protect data shared between firms in agricultural and food sectors. World Pat Inf 73:102183. https://doi.org/10.1016/j.wpi.2023.102183
31. Regulation (EU) 2023/2854 of the European Parliament and of the Council on harmonised rules on fair access to and use of data (Data Act). OJ L, 22.12.2023
32. Sag M (2023) Copyright and machine learning. Vanderbilt J Entertain Technol Law 25:1-75
33. Samuelson P (2021) The textuality of software. Stanford Law Rev 73:1-85
34. Samuelson P (2023) Generative AI meets copyright. Science 381:158-161
35. Sobel B (2017) Artificial intelligence's fair use crisis. Columbia J Law Arts 41:45-97
36. Tyagi K (2024) Copyright, text & data mining and the innovation dimension of generative AI. J Intellect Prop Law Pract 19:557-570. https://doi.org/10.1093/jiplp/jpae028
37. US Copyright Office (2023) Copyright registration guidance: works containing material generated by artificial intelligence. 88 Fed. Reg. 16190
38. USPTO (2024) Inventorship guidance for AI-assisted inventions. 89 Fed. Reg. 10043
39. Vertinsky L, Rice TM (2002) Thinking about thinking machines: implications of machine inventors for patent law. Boston Univ J Sci Technol Law 8:574-613
40. Wilkinson MD, Dumontier M, Aalbersberg IJ, et al. (2016) The FAIR guiding principles for scientific data management and stewardship. Sci Data 3:160018. https://doi.org/10.1038/sdata.2016.18
41. WIPO (2023) WIPO guide to trade secrets and innovation. WIPO Publications, Geneva