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Intellectual Property Policy Dilemmas of Generative AI in Employee Training: Ownership Definition and Legal Adaptability

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Abstract

This study looks at the issues with intellectual property policy that arise when generative AI is used in corporate training settings. When platforms, businesses, and employees work together to create content, ownership complexities are not sufficiently addressed by traditional legal frameworks. The study examines how local businesses deal with ownership uncertainties through contractual innovations and operational practices by comparing current copyright and service invention laws and using empirical case studies from Beijing, Shanghai, and Shenzhen. The analysis highlights basic flaws in the existing legal frameworks, which demand human authorship and are unable to handle the distributed contributions that come with AI-assisted content creation. These flaws result in regulatory gaps that put significant investments at risk of legal repercussions. While updating service invention laws to acknowledge "occupational intellectual outputs" beyond conventional technical accomplishments, the study suggests an integrated framework that makes use of China's Data Twenty Articles to create a three-tier rights architecture that includes data resource holding, processing, and operation rights. Using quantifiable contribution assessments across knowledge density, innovation degree, and application value dimensions, this framework presents a dynamic value distribution model. With the help of blockchain-based attribution systems and specialized dispute resolution procedures, the realistic implementation approach uses phased pilot programs in various industries and geographical areas. When AI increasingly mediates the production of organizational knowledge, the suggested framework provides policy tools for striking a balance between innovation incentives and stakeholder protection, laying the groundwork for more extensive intellectual property reforms.

Keywords: generative artificial intelligence; intellectual property rights; employee training; ownership attribution; legal framework adaptation

1. Introduction

A stark lack of sophistication in IP norms addressing ownership of AI-generated content is revealed by the use of generative AI in corporate training [1]. As companies use BERT-like models to generate training instances in large quantities, attribution of ownership becomes non-trivial when human, algorithmic, and commercial contributions intersect [2]. The shortcomings of the corporate training environment regulations concerning platform services, staff experience, and proprietary knowledge are exacerbated by China's Interim Measures of Generative AI Services [3]. The implications of traditional ideas of authorship and economic rights on AI systems, which integrate general knowledge with organization-specific findings in outputs, are contradicted by this shared data pool [4].

Basic ideas about creativity and authorship are undermined by the philosophical debate surrounding the ownership of AI-generated content; it also calls into question whether AI systems are autonomous creators or merely tools [5]. Current copyright laws in the US and the EU require human authorship as a condition for protection, but this regulatory gap has left billions of dollars spent on AI-generated training materials without any legal protection [6]. There is limited protection for training processes under fair use, which may not deal effectively with issues of downstream ownership when DNNs produce outputs using reverse engineering, such as those in multi-party collaborative applications [7]. The authorship issue is not limited to individual creators but also includes multi-stage value chains involving training data suppliers, model developers, prompt engineers, and content users [8]. The incarnational, collective process of creating AI-generated content, where human creative expression took the form of proximate engineering, curation, and tuning rather than distal authorial expression, is typically not supported by current IP mechanisms [9]. Global players have been finding it difficult to adhere to a variety of regulations worldwide due to the dispersion of regulatory benchmarks [10, 11] As businesses heavily invest in the creation of AI-generated content with little to no clear corporate own interests or protection, this regulatory disjunction highlights the urgent need for such a broad-ranging rubric that considers the unique characteristics of AI-created content while balancing the diverse interests of the stakeholders in an increasingly automated creative world.

Different approaches are demonstrated by international attempts to regulate AI-generated content; the EU is closer to a unified, transparent, and accountable regulatory framework, while the US is more toward market-driven contractual approaches [12]. The tension between promoting innovation by making training data available to everyone and protecting innovators' and creators' economic interests is still at the core of the policy discourses [13]. The proposed exceptions to copyright for AI training seek to reconcile these tensions in the face of high economic interests [14]. Legal doctrines are updated to take into account the advent of new technologies, as is evidenced by attempts to accommodate AI training within the framework of the GDPR, which illustrates the intricate mesh of data protection, intellectual property, and innovation policies [15]. The EU's AI Act enforces copyright without solving basic ownership issues and so privileges means over end [16]. Pioneering writings in this vein urge us to move "beyond copyright," in which discussions of property and authorship have been traditionally formulated, to sui generis forms designed to reward innovation and creativity [17]. Proposals for copyright law reform that specifically address AI-generated content offer a variety of models for allocating ownership, from new collective rights management systems to expanded work-for-hire doctrines, but agreement is still difficult to come by due to the wide range of stakeholder interests [18].

The shortcoming of the available legal tools is particularly significant in the space of corporate training, given the fuzzy boundaries of authorship, employment, and technological tools; as a result, existing copyright exceptions fail to offer a clear indication for businesses operating at the crossroads of AI-assisted content creation [19]. International, EU, and UK copyright regimes reveal considerable differences in addressing AI-generated outputs, thus posing compliance difficulties for (MNEs) which intend to roll out AI-driven training systems across jurisdictions with competing legislatively-driven obligations [20]. Despite extensive scholarly attention to AI and intellectual property issues, existing research has largely overlooked the specific challenges arising in employee training contexts where organizational knowledge, individual expertise, and AI capabilities intersect to create hybrid forms of intellectual property that defy conventional categorization. This study addresses this critical gap by proposing an integrated framework that leverages China's Data Twenty Articles and Service Invention Regulations to establish clear ownership structures for AI-generated training content, providing both theoretical innovation through the conceptualization of "occupational intellectual outputs" and practical guidance through locally implementable policy tools that balance innovation incentives with stakeholder rights protection in the rapidly evolving landscape of AI-enhanced corporate education.

2. Legal Dilemmas in AI-Generated Training Content: Current Framework Analysis

2.1 The Complexity of Ownership in Corporate Training Scenarios

Generative AI platforms generate more complex puzzles of ownership outside of current IP frameworks, as training content generation also implicates relationships between the platform’s programming and the knowledge and expertise of an employer’s workforce. However, the range within this content spectrum, from generic skill-building to very specific technical training materials, creates a complexity in determining the distribution of rights amongst the stakeholders. General skill training often may utilize a high degree of the platform’s offerings of standard content for the masses that get hardly customized at the enterprise level, whereas subject matter technical content includes a large amount of proprietary knowledge and assumed subject matter expert knowledge and so it's a spectrum of user inputs and not a black and white concept of owning content. That's because compliance training is often situated at a unique confluence of laws and corporate practices: it references material that becomes public domain law but does so in the context of a company's particular interpretation and application of those same standards. The development of enterprise culture materials in the scenario of AI-assisted training is the most personalized and creative, as they need to be particularized (e.g., culture, daily routines, strategic visions) to work well and can efficiently utilize the AI power for generating a scalable amount of materials based on your custom need.

Existing legal norms regarding the source and reuse of educational work cannot easily resolve the complex claims of ownership that arise from the multi-step process of AI-amplified educational training development, which reveals mixed contributions from various actors at each stage. HR departments attempt to "integrate" organizational priorities and pedagogical strategies into the basic collection of training materials by establishing training architectures and training goals during the task analysis process. These goals guide the subsequent AI-based content generation. Complex stakeholder contributions are made to AI-generated training materials through the stages of instructor customization, SME review, and prompt engineering. This results in overlapping ownership claims that call for methodical attribution frameworks. To systematically analyze these overlapping contributions and their implications for ownership determination, a comprehensive stakeholder contribution matrix has been developed, as shown in Table 1.

Table 1: Stakeholder Contribution Matrix in AI-Generated Training Content Development

Training Content Type	Platform Provider	Enterprise	Employees (Domain Experts)	Employees (Training Facilitators)	Total
Generic Skill Training	70%	15%	10%	5%	100%
	- Standard templates	- Learning objectives	- Minor customization	- Delivery adaptation	
	- Base algorithms	- Platform selection	- Quality review	- Pedagogical adjustments	
	- Content libraries	- Budget allocation	- Error correction	- Audience targeting	
Specialized Technical Training	25%	35%	30%	10%	100%
	- AI	- Proprietary	- Technical	- Context	

	processing power	methods	expertise	adaptation	
	- Generation framework - Model capabilities	- Strategic direction - Resource provision	- Content validation - Knowledge injection	- Learning facilitation - Feedback integration	
Compliance Training	35%	35%	20%	10%	100%
	- Regulatory databases - Update mechanisms - Template structures	- Policy interpretation - Implementation strategy - Organizational context	- Risk assessment - Compliance verification - Legal accuracy check	- Scenario development - Case customization - Training deployment	
Enterprise Culture Training	20%	45%	25%	10%	100%
	- Generation tools - Creative algorithms - Format templates	- Values definition - Vision communication - Brand guidelines	- Culture articulation - Best practice curation - Employee insights	- Story integration - Interactive design - Engagement strategies	

***Note**: Percentages indicate relative contribution weight in the total content creation process for each training type. Contributions are measured across four dimensions: content origination, knowledge input, creative direction, and implementation refinement.*

Table 1 illustrates the varying levels of contribution from different stakeholders across four distinct training content types, revealing that platform providers dominate generic skill training with 70% contribution through standard templates and content libraries, while enterprise culture training shows enterprise-led development with companies contributing 45% through values definition and vision communication, domain experts adding 25% through culture articulation and practical insights, and platforms providing only 20% in basic generation tools, demonstrating that ownership allocation in AI-assisted training development cannot follow traditional single-author models but must accommodate multiple legitimate claims based on differentiated contribution intensities that shift dramatically across varying training contexts.

2.2 Inadequacy of Existing Legal Frameworks

The application of copyright law to AI-generated training content encounters fundamental obstacles in determining whether such outputs meet the originality threshold required for protection, as the creative height of machine-generated content remains contested in legal scholarship and judicial interpretation [21]. The ambiguity surrounding what constitutes a "creative act" in human-AI collaboration becomes particularly pronounced when employees use AI tools to generate training materials, as the distinction between mechanical assistance and creative contribution resists clear delineation. The requirement for human authorship in copyright law creates an insurmountable barrier for protecting AI-generated content as traditional works of authorship, even when substantial human creativity guides the generation process through sophisticated prompt engineering and iterative refinement. The paradox identified in the DABUS judgment extends beyond patent law to encompass all forms of intellectual property, where courts struggle to reconcile the economic reality of AI-generated value with legal frameworks premised on human creativity [22].

Corporate works and work-for-hire doctrines offer limited solutions to the ownership challenge, as these frameworks assume human employees as the original creators whose rights transfer to employers through employment relationships or contractual arrangements. The impossibility of designating AI systems as employees or contractors leaves a conceptual gap in applying work-for-hire principles to AI-generated training content, forcing enterprises to rely on uncertain theories of derivative rights or tool ownership that lack clear legal foundation. The fair use doctrine, while potentially protecting the training of AI models on copyrighted materials, does not resolve downstream ownership questions when those models generate new training content that may inadvertently reproduce protected elements from their training data [23]. The risk of infringement liability cascades through the value chain, as training materials generated by AI systems may contain unidentified reproductions of copyrighted works, exposing enterprises to legal challenges from original content creators whose works contributed to model training. These multifaceted legal challenges create a complex landscape of uncertainty that can be visualized through a comprehensive framework analysis, as presented in Figure 1.

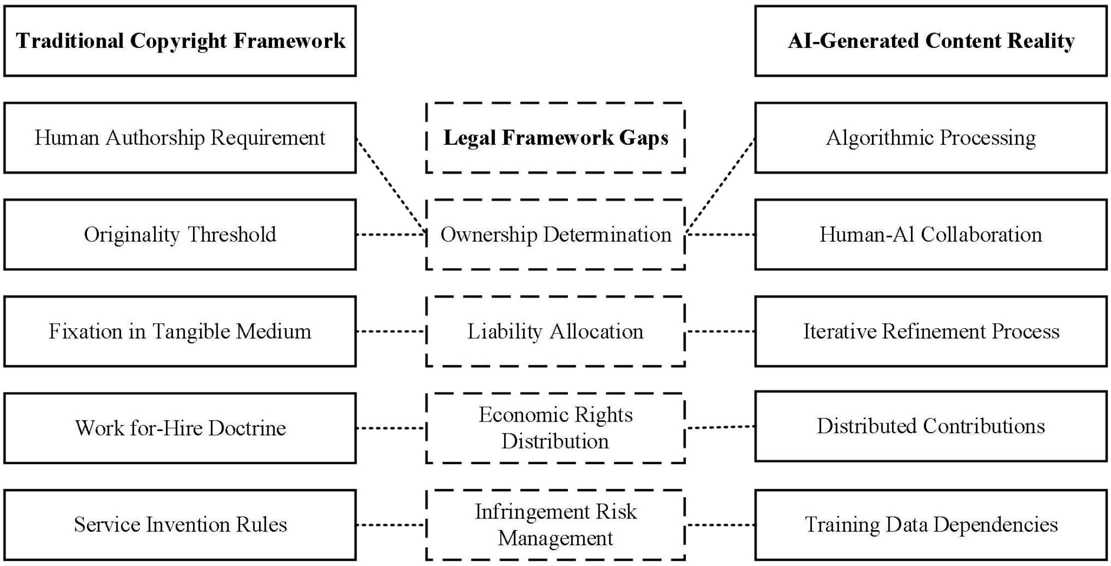

Figure 1: Legal Framework Gaps in AI-Generated Content Protection

Figure 1 demonstrates the conceptual disconnects between traditional copyright frameworks and the realities of AI-generated content, with the left side showing established legal doctrines requiring human authorship, originality, and fixation, while the right side illustrates the characteristics of AI-generated training content that involve algorithmic processing, iterative refinement, and distributed contributions, revealing critical gaps where legal doctrine provides no adequate guidance for ownership determination, liability allocation, or economic rights distribution in the context of corporate training materials.

The intersection of labor law and intellectual property rights in AI-assisted content creation reveals additional complexities that existing service invention regulations cannot adequately address. Current service invention frameworks focus primarily on technical innovations and patentable inventions, lacking provisions for knowledge products and creative works that constitute the majority of training content. The narrow definition of "technical achievements" in service invention regulations excludes most forms of training materials, even when such content embodies substantial organizational knowledge and employee expertise that provides competitive advantage. The absence of clear reward mechanisms for AI-assisted creation demotivates employee participation in training content development, as contributors lack assurance of recognition or compensation for their intellectual contributions to AI-generated outputs. The treatment of training content in employee separation scenarios remains particularly problematic, as neither intellectual property law nor labor law provides clear guidance on whether AI-generated materials created during employment remain accessible to departing employees who contributed expertise to their development.

2.3 Local Implementation Challenges and Case Studies

The different stances taken by Chinese firms in Beijing, Shanghai, and Shenzhen highlight the practical difficulties of policing AI-created training content ownership and regional responses to manage those risks, in which contractual innovation and creative operating practices are used to fill regulatory gaps. The tech industry in Beijing has led the way in developing three-party contracts between platforms, companies, and workers that establish revenue-sharing agreements for technical training content generated by AI. However, the enforcement of these contracts proves problematic when there is disagreement over the extent of the relative contribution of the parties. [24]. In contrast to standard litigation processes, which frequently take 18 months to resolve, the Zhongguancun Science Park's intellectual property protection center offers expedited procedures for AI ownership disputes, resolving cases in 30 days.

An alternative strategy is being pursued by Shanghai's financial industry, which is concentrating on layered authorization models that differentiate between core proprietary content and auxiliary training materials. Different rights would be granted according to content sensitivity and strategic value. Major financial services institutions have introduced pay-for-performance models in which AI ML-based compliance training materials prompt micropayments to contributing staff according to metrics that reflect operational performances. This creates economic incentives for the dissemination of information resources but aligns with an enterprise-wide policy in which the enterprise maintains control over content dispersion. Pudong New Area’s pilot program has kicked off innovation in how to treat AI-generated training content as tradable data assets, although valuation methods and transaction mechanics are still nascent and controversial in the market. In order to provide an overview of the differences and similarities of the sub-national implementation models, a comparison has been made among China’s major economic regions, which are presented in Table 2.

Table 2: Comparative Analysis of Local Implementation Models

City/Region	Primary Industry	Ownership Model	Compensation Mechanism	Dispute Resolution	Innovation Features
Beijing (Zhongguancun)	Technology	Trilateral Agreements (Platform-Enterprise-Employee)	Revenue Sharing Model (Proportional to contribution)	Fast-track IP Center (Target: 30 days vs. Traditional: 18+ months)	Platform-Enterprise-Employee contracts; Contribution-based allocation; Voluntary negotiation framework
Shanghai (Pudong)	Financial Services	Layered Authorization (Hierarchical rights structure)	Usage-based System (Micropayments per deployment)	Industry Mediation (Banking association-led)	Core vs. Peripheral content distinction; Data trading pilot program; Automated payment triggers
Shenzhen (Qianhai)	Manufacturing	Core-Periphery Model (Proprietary core + Open periphery)	Hybrid Approach (Core: Enterprise retained; Periphery: Open access)	Regulatory Sandbox (Experimental framework)	Blockchain attribution system; Open-source generic content; Collective ownership experiments

Table 2 systematically compares this situational set, highlighting how Beijing's tech firms are accenting cooperative trilateral pacts featuring revenue sharing in proportional form and accelerated dispute resolution in a target to complete dispute resolution in 30 days via the Zhongguancun IP Protection Center. Meanwhile, Shanghai's finance houses are preferring hierarchical layered approval processes involving usage-based micropayment systems and industry association-led arbitration. Shenzhen's factories prefer pragmatic core-periphery distinctions with blockchain-based attribution tracking and experimental collective ownership configurations in the Qianhai regulatory sandbox. This is according to local industrial structure/regulatory environment/innovation ecosystem set-and scheme-level cohorts notwithstanding, which all are operating in the same national legal regime for AI-generated training content ownership [25].

Tactical products for rights allocation have been developed by Shenzhen's manufacturing sector, focusing on efficiency of operation over extensive rights sharing. They decide to create an open-source model of learning materials for common technology while retaining the essential firm-specific training content (core training content is maintained in an enterprise learning mode). Based on the enterprise's business objectives, such as protecting its competitive edge and taking advantage of the content development ecosystem, the core-peripheral distinction is pragmatic rather than legal. On the one hand, the Qianhai Free Trade Zone's regulatory sandbox permits some experimental ownership schemes that deviate from conventional notions of intellectual property, such as collective ownership of an AI model and a blockchain-based attribution system that tracks the contributions made within intricate content creation workflows.

Although the impact of implementing market-based solutions that lack official legalization and enforcement should be evaluated, these local experiments highlight both the shortcomings of the current legal infrastructure and the capacity of market participants to create their own remedies under regulatory ambiguity. Businesses that operate in multiple jurisdictions face compliance challenges due to local differences. In the absence of standardized national-level regimes, businesses must navigate territorial differences, where acceptable ownership structures in one location may conflict with market norms or regulatory expectations in another.

3. Reconstructing IP Framework: Integrating Data Twenty Articles and Service Invention Principles

3.1 Data Rights Framework Innovation Under the Data Twenty Articles

According to the three-level hierarchy, Data Twenty China Articles permits the model of multiple layers, which includes mining rights, use rights, and product running rights: resource rights, use/processing rights, and product running rights. This model tackles several ownership issues among platforms, businesses, and employees, such as taking into account varying contribution values ranging from algorithmic knowledge to proprietary and domain knowledge. The processing and usage rights layer also makes operations more flexible by allowing users to modify and customize harvested data assets for specific training tasks without requiring a complete ownership transfer. This fosters a collaborative environment where value can be obtained from authorized data transformation while maintaining underlying property rights.

When comparing copyright exceptions for educational content to be used for the training of generative AI across jurisdictions, a common thread is that mechanisms for compensation need to move beyond historical licensing models to accommodate the resource-intensive, iterative, and collaborative efforts of creating AI-assisted content [26]. This also implies that how value is distributed should be better aligned with actual contribution rather than previously negotiated structures of ownership. Expanding this reasoning to data product operation rights in AI-generated training content, monetization opportunities for all involved parties via the flexibly scaled revenue sharing depending on the amount of investment, credibility, and creativity could be created. This multi-faceted rights framework is implemented in corporate practical environments through the creation of a model configuration, containing assignments for a set of rights that refer to a specific category of training content, as schemed in Table 3.

Table 3: Three-Tier Rights Configuration Framework for AI-Generated Training Content

Training Content Type	Rights Layer	Platform Provider	Enterprise	Employees	Total
Generic Skill Training	Data Resource Holding Rights	60%	25%	15%	100%
	Data Processing & Usage Rights	45%	35%	20%	100%
	Data Product Operation Rights	40%	45%	15%	100%
Specialized Technical Training	Data Resource Holding Rights	30%	40%	30%	100%
	Data Processing & Usage Rights	25%	45%	30%	100%
	Data Product Operation Rights	20%	50%	30%	100%
Compliance Training	Data Resource Holding Rights	35%	45%	20%	100%
	Data Processing & Usage Rights	30%	50%	20%	100%

	Data Product Operation Rights	25%	55%	20%	100%
Enterprise Culture Training	Data Resource Holding Rights	20%	50%	30%	100%
	Data Processing & Usage Rights	15%	55%	30%	100%
	Data Product Operation Rights	15%	55%	30%	100%

As shown in Table 3, how the rights are assigned differs significantly by the type of training content, with generic skills training being dominated by the platform for data resource holding rights at 60%, reflecting the standard content and algorithmic capabilities offered by platforms; and enterprise culture training being led by the enterprise for data product operation rights at 55%, given the strategic importance of corporate values and proprietary knowledge. This suggests that the allocation of rights should be differentiated based on the specific nature and strategic importance of different types of training content, enabling platforms to have more rights to standard content while enterprises have greater rights to customized and strategically sensitive content, thus formulating a flexible structure that can be adapted to varying corporate training needs and ensure appropriate recognition of stakeholder interests in all three layers of the rights architecture.

This rights framework incorporates value distribution mechanisms that assess stakeholder contributions across the content production chain. Three phases make up this dynamic distribution model: the value-added distribution based on quality improvement and creation contributions, the first-applied distribution based on investment ratio, and the long-tail distribution based on training effectiveness statistics and use tendency. This distribution mechanism's mathematical specification, shown in Figure 2, outlines transparent and auditable splitting logic that can be implemented via automated payment systems or smart contracts.

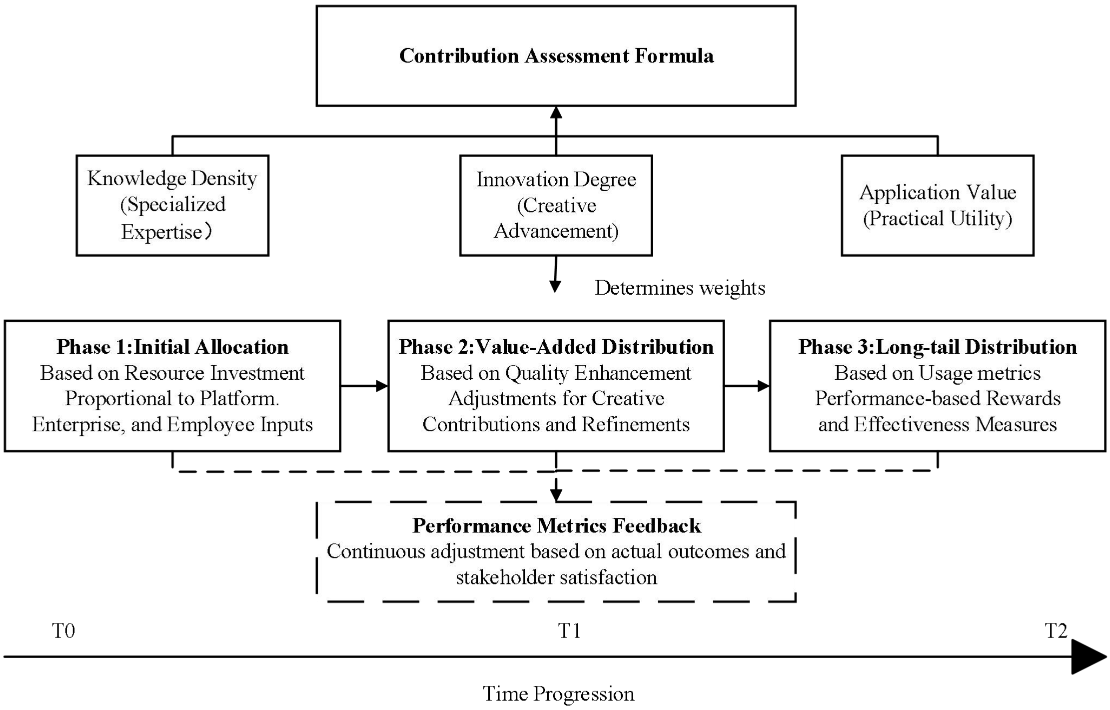

Figure 2: Dynamic Value Distribution Model Based on Contribution Assessment

Figure 2 illustrates the dynamic nature of value distribution, where the contribution assessment formula

$$C = \alpha \cdot D_k \times \beta \cdot D_i \times \gamma \cdot V_a \tag{1}$$

generates weighted scores that determine initial allocations, with D_k representing knowledge density reflecting specialized expertise embedded in content, D_i denoting innovation degree measuring creative advancement beyond existing materials, and V_a indicating application value capturing practical utility in training contexts, while α , β , and γ serve as calibrated weighting coefficients. Subsequent phases adjust distributions based on actual performance metrics and usage data, creating an adaptive system that aligns incentives with value creation throughout the content lifecycle, ensuring that all stakeholders receive compensation commensurate with their actual contributions rather than predetermined contractual arrangements.

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3.2 Modernizing Service Invention Regulations for the AI Era

The expansion of what have historically been technical inventive channels into the broader category of "occupational intellectual outputs," such as knowledge products, training materials, and other creative works that arise from human-AI authorship in the workplace, is a significant development in the law of intellectual property. This is due to the change in the service invention rules to account for AI-assisted invention creation. The guidance for AI-assisted inventions issued so far across jurisdictions reaffirms that human intervention is still a critical factor for securing IP protection; however, the existing frameworks for service inventions do not properly accommodate necessary recognition or compensation tools for employees who contribute expertise, creativity, and domain knowledge to the AI-generated training examples [27]. This gap necessitates a reevaluation of the theoretical foundations of service inventions, moving away from a limitation on patentable technical inventions and toward a broad definition that includes all forms of intellectual creation that benefit the organization, regardless of whether they qualify for one of the more conventional forms of intellectual property protection.

The proposed expansion introduces differentiated recognition criteria based on three intersecting dimensions that determine the nature and extent of employee rights in AI-assisted creation: work task relevance measuring the degree to which content creation aligns with assigned responsibilities, enterprise resource utilization assessing the extent of organizational assets employed in development processes, and personal creative contribution evaluating the substantive intellectual input provided by individual employees. These factors combine to produce a complex classification scheme that can handle the entire range of AI-assisted creation scenarios, from highly inventive inventions that go beyond job requirements to strictly mechanical executions of organizational instructions. By introducing graduated reward mechanisms linked to these classification criteria, incentive structures are created that promote employee participation in AI-enhanced knowledge creation while safeguarding legitimate enterprise interests in work-related outputs. This ensures that compensation reflects the value generated as well as the relative contributions of various stakeholders. To systematically implement these expanded criteria in organizational contexts, a comprehensive recognition matrix has been developed that maps the intersection of relevance, utilization, and contribution dimensions, as shown in Table 4.

Table 4: Occupational Intellectual Output Recognition Matrix

Work Task Relevance	Enterprise Resource Utilization	Personal Creative Contribution	Ownership Attribution	Reward Mechanism
High	High	Leading	Enterprise	Standard reward + 5% revenue share
High	High	Participating	Enterprise	Standard reward only
High	High	Supporting	Enterprise	Basic reward only
High	Medium	Leading	Enterprise (Primary)	Enhanced reward + 10% revenue share
High	Medium	Participating	Enterprise	Standard reward + bonus
High	Medium	Supporting	Enterprise	Standard reward only
High	Low	Leading	Shared (70:30)	20% revenue share
High	Low	Participating	Enterprise	Enhanced reward
High	Low	Supporting	Enterprise	Standard reward
Medium	High	Leading	Enterprise (Primary)	Enhanced reward + 8% revenue share
Medium	High	Participating	Enterprise	Standard reward + bonus
Medium	High	Supporting	Enterprise	Standard reward
Medium	Medium	Leading	Shared (60:40)	15% revenue share
Medium	Medium	Participating	Shared (80:20)	8% revenue share
Medium	Medium	Supporting	Enterprise	Standard reward
Medium	Low	Leading	Employee (Primary)	25% revenue share
Medium	Low	Participating	Shared (50:50)	12% revenue share
Medium	Low	Supporting	Enterprise	Enhanced reward
Low	High	Leading	Shared (50:50)	15% revenue share
Low	High	Participating	Enterprise	Enhanced reward
Low	High	Supporting	Enterprise	Standard reward
Low	Medium	Leading	Employee (Primary)	30% revenue share
Low	Medium	Participating	Shared (40:60)	15% revenue share
Low	Medium	Supporting	Enterprise	Standard reward
Low	Low	Leading	Employee	Full ownership rights
Low	Low	Participating	Employee	80% ownership rights
Low	Low	Supporting	Shared (30:70)	10% revenue share

Table 4 shows how attribution and reward levels are systematically configured across the twenty-seven cells in the matrix, and that combined high work relevance, high resource utilization, and leading creative contribution results in enterprise ownership with standard rewards plus 5% revenue sharing, while combined low work relevance, low resource utilization, and leading creative contribution is enough to warrant full employee ownership rights – indicating that flexible attribution mechanisms can effectively reconcile the organization's investment with the individual innovation in AI-assisted training content development, in that the co-occurrence of these three dimensions creates subtle scenarios necessitating differential treatment rather than binary ownership decisions.

The distinction between one-time rewards and continuous revenue-sharing is because contributions and value creation patterns for the numerous training content types are different, where commoditized content should provide fixed remuneration while new and impactful content should integrate long-term value streams. The design principles for such reward structures incorporate numerical metrics, such as the frequency of training deployments, and subjective judgments about the level of innovation in the materials and with the strategic use of the materials, and as such, are objective and sensitive to the range of contributions.

3.3 Local Implementation Pathways and Pilot Programs

Translation of theoretical models into practical instruments necessitates well-thought-out pilot projects validating and calibrating policy instruments while creating stakeholder confidence and building evidence for further scale-up. One legislative model to increase transparency of AI training is the Generative AI Copyright Disclosure Act. However, disclosure is not sufficient to answer key ownership questions, and a coherent system of allocation and distribution of rights and value must accompany disclosure directives [28]. In response to international legal advances and learning from international experience, the envisaged policy implementation strategy is introduced as a stepwise approach, focusing initially on selected economic sectors and geographical areas where regulatory slackness and entrepreneurial skills provide suitable conditions for policy trial and error.

Pilot program selection criteria are based on industry sectors with a high rate of AI adoption, a high investment in training, and established intellectual property management in place. This ensures that meaningful insights can be gained from the early adoptions with minimal risk of disruption. Tech sector pilots target technical skills development in industries where AI-aided assistance is already prevalent. Technology sector pilots are in technical skill development where there is already AI support; financial services pilots are around compliance training where regulatory clarity is needed; manufacturing pilots are concerned with practical skill transfer where content standardization can bring efficiency gains. Geographic stratification allows parallel testing of different models, from first-tier cities practicing an all-encompassing operation model, to emerging economic centers operating on certain priorities, and to small and medium cities running pilot experiments based on local industry demand. The sequential nature of officer rollouts, depicted in Figure 3, provides an opportunity for iterative improvement at each step and for national framework development to evolve steadily using the weight of an accruing evidence base.

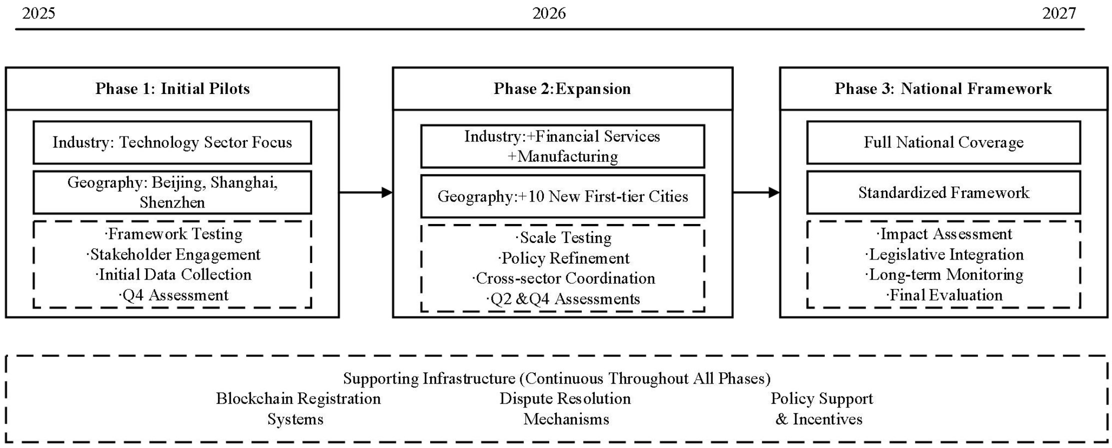

Figure 3: Phased Implementation Roadmap for Local Pilot Programs

Figure 3 illustrates a three-phased empirical process by which the pilots deliver in 2025, expand in 2026, and are potentially rolled out nationally by 2027. As part of an adaptive implementation process that can handle emerging issues while staying strategic in the framing of the overall framework, there are quarterly touchpoints to adjust for empirical data, stakeholder feedback, and emerging technologies.

4. Discussion

China's Three-Tier Rights System provides a new perspective on the binary rights models, yielding realistic insights for the moral and governance dimensions of

AI application. Although modern ethical guidelines focus on the protection of stakeholders, it is difficult to translate these principles into scalable ownership structures [29]. This implementation gap is due to the framework's multi-layered allocation of rights over resource holding, processing, and operation, the allocation in which aligns rights with the contributions made by stakeholders, thereby permitting a much fairer distribution than what is permitted under traditional IP systems.

The transparency objectives embodied in the proposed framework are stronger than the forms of transparency mechanisms proposed in regulation that primarily concern the documentation of training data but have little to say about downstream ownership [30]. Unlike current transparency frameworks that treat transparency as an end, the integrated management method disclosed herein ties transparency obligations directly to how value is distributed, such that value contribution visibility translates directly into customers' economic participation through the dynamic assessment formula that adjusts the realization of compensation to actual performance measurements rather than to static contractual provisions.

Recent regulatory developments in training AI models under various data protection regimes have highlighted the jurisdictional fragmentation that complicates multinational compliance efforts, yet these analyses have predominantly focused on input data governance rather than output ownership structures [31]. The local pilot program approach addresses this fragmentation through flexible implementation pathways that can adapt to regional variations while maintaining core principles of contribution-based allocation, contrasting with rigid regulatory frameworks that fail to accommodate local innovation ecosystems. This adaptive capacity becomes particularly relevant when considering the diverse impacts of AI on copyright law across different industrial contexts, where one-size-fits-all approaches have proven inadequate for addressing sector-specific ownership challenges [32].

The protection mechanisms for AI training stages proposed in comparative analyses of international frameworks have emphasized the distinction between commercial and non-commercial uses, yet such binary classifications fail to capture the hybrid nature of corporate training content that serves both internal capability building and potential external commercialization [33]. The occupational intellectual output framework transcends these limitations by recognizing training materials as a distinct category requiring specialized treatment that balances organizational investment with individual creativity, providing more nuanced protection than traditional copyright or patent paradigms allow. A growing number of legal and ethical frameworks for safeguarding intellectual property rights in AI-generated content have acknowledged the necessity of sector-specific strategies, confirming the framework's suggested differential treatment of different kinds of training content [34].

Given the mole-like pathways established in the law for evaluating machine creativity, the application of the originality test to copyright eligibility is also problematic in the context of AI, as its rejection will once more result in a copyright failure [35]. It does offer more objective standards than capricious court determinations of "creative height" by measuring originality along dimensions like the density of knowledge, the level of innovation, and the extent of applicability in the operation of the knowledge. The impact of generative AI on intellectual property extends beyond ownership concerns and challenges conventional human-centered content creation theories [36]. The current framework offers a solution to theoretical issues that come up in discussions of AI and intellectual property by addressing these implications through hybrid mechanisms of ownership that balance the advantages of knowledge sharing with the preservation of competitive advantage. This model brings scalable solutions for AI-generated content to an emerging reality by harmonizing with current understanding of technological capabilities and with legal frameworks aimed at human creators.

5. Conclusion

By putting forth an integrated strategy that makes use of China's Data Twenty Articles and updated service invention regulations to create distinct ownership structures in corporate training contexts, this study has filled a significant gap in intellectual property frameworks for AI-generated training content. A sophisticated alternative to binary ownership models, the three-tier rights architecture that includes data resource holding, processing, and operation rights allows for differentiated allocation mechanisms that mirror the intricate value chains present in AI-assisted content creation, where platforms, businesses, and employees all contribute different types of resources and expertise. The contribution assessment formula operationalizes value distribution through measurable metrics that match economic participation with actual stakeholder contributions, while the occupational intellectual output framework goes beyond conventional technical innovation paradigms to acknowledge knowledge products and training materials as valid forms of intellectual creation deserving of structured compensation mechanisms.

The phased implementation approach with local pilots provides a practical paradigm for policy evolution that balances the necessity for creating incentives for innovation while also providing proper protections for stakeholders, though several key areas for future development must be addressed for the deployment to be successful. Further research should be oriented towards the development of a uniform set of valuation methods for various training content types, defining interoperability protocols for cross-jurisdictional recognition of ownership structures, and the design of adaptive governance mechanisms, which could adapt to the fast technology evolution of generative AI capabilities. The framework's potential extension to other forms of AI-generated organizational knowledge, including strategic planning documents and operational procedures, warrants exploration as enterprises increasingly rely on AI systems for diverse knowledge production tasks beyond training materials, suggesting that the principles developed here may serve as foundations for broader intellectual property reforms in the age of artificial intelligence.

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Conflict of interest

The authors declare no conflict of interest.

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