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Platform Versus Creator Provision of Generative AI on Creator Platforms

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Abstract

Generative AI is changing not only how content is created on digital content platforms but also who provides the AI used to create it. Platforms may offer generative AI using data pooled across creators, whereas creators may provide AI services based on their own content. Understanding how these provision regimes affect creators' investment incentives and the value generated by AI is therefore important. We develop a game-theoretic model in which human-generated content competes with AI-generated content while contributing to AI learning. The results show that platform provision can induce higher human-generated content quality than creator provision when AI learning effectiveness lies within a certain range and the platform's pooled-data advantage is limited. A stronger pooled-data advantage can make creator provision more favorable for sustaining human-generated content quality. Platform provision can nevertheless generate higher AI-generated content quality even when creator provision induces higher human-generated content quality, provided that the pooled-data advantage is sufficiently strong. We further find that AI value sharing can encourage or discourage quality investment under platform provision, while its effects on regime preferences and preference alignment depend on market conditions. Thus, the provision regime preferred by the creator need not be the one that sustains higher human-generated content quality.

Keywords: generative AI; creator platforms; AI provision mode; content quality

1. Introduction

Digital content platforms provide an important channel for content distribution and monetization by connecting creators with consumers [1,2]. Video creators, musicians, and artists publish their work on these platforms, providing a continuing source of content [3]. One type of digital content platform monetizes content primarily through advertising and similar channels. Consumers can typically access content free of charge, and the platform shares a portion of the associated revenue with creators. The YouTube Partner Program illustrates this business model, as eligible creators receive a share of the advertising revenue generated by their videos [4]. Under this model, creators invest time, expertise, and creative resources to improve content quality, and the returns on these investments depend on both consumers' content choices and revenue-sharing arrangements. Sustaining creators' incentives to invest in quality is therefore an important concern for platforms seeking to maintain a continuing supply of appealing content.

Advances in generative AI are changing content supply and consumer choice on digital content platforms [5–7]. As AI becomes capable of generating images, text, audio, and video, human-generated and AI-generated content compete for consumer attention, potentially affecting demand for creators' content and their payoffs. A study of Pixiv finds that some

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incumbent illustrators reduced their uploads following the emergence of generative AI and documents evidence of shifts in consumer attention and competition from AI-generated content [8]. This competition is further complicated by AI's ability to improve by learning from human-generated content. Creators' investments in content quality may therefore make their own work more appealing while also improving the quality of competing AI-generated content. The resulting improvement in AI quality can, in turn, affect demand for human-generated content and the returns on creators' quality investments.

In commercial applications, platforms and creators can play different roles in providing AI services, with corresponding differences in how content resources are used and how returns are allocated. Under platform provision, the platform pools content to provide a centralized AI service to users. For example, an early commercial model of Adobe Firefly was trained on Adobe Stock images, openly licensed content, and public-domain content. Adobe also provides Firefly bonuses to eligible content contributors [9]. Under creator provision, creators use their own work to build personalized AI models and offer content generation services to users through the platform. For example, Fiverr Go allows creators to build AI Creation Models using their own images, text, or audio, and customers can purchase the resulting AI-generated outputs [10]. Although these examples primarily involve creative asset licensing and transactions for customized services, they illustrate differences in who provides AI services, how content resources are used, and how platforms and creators earn revenue.

For creator platforms that depend on creators for a continuing supply of content and monetize content consumption, alternative AI provision modes may have different implications for creator incentives and platform profit. Pooling content from multiple creators can give platform provision a potential advantage in AI capability. How creators share in the value generated by AI may affect their willingness to continue investing in high-quality content. By contrast, creator provision connects personalized AI services more directly to the creator's own work and economic returns, while AI capability depends more heavily on that creator's accumulated content. At the same time, competition between AI-generated and human-generated content may give rise to different economic consequences under these arrangements. It is therefore unclear in advance whether creator platforms should provide AI themselves or rely on creator provision. We accordingly address two research questions. How do alternative AI provision modes affect the creator's investment in human-generated content quality, AI-generated content quality, the creator's payoff, and platform profit? Under what conditions does the platform choose each AI provision mode, and does its choice align with the creator's preferences?

To address these questions, we develop a game-theoretic model with a creator platform, a creator, and consumers. We consider three regimes, namely no AI, platform provision, and creator provision. We characterize the equilibrium outcomes under each regime and compare human-generated content quality, AI-generated content quality, the creator's payoff, and platform profit. We then examine how the pooled-data advantage and AI value sharing affect equilibrium outcomes, identify the conditions under which the platform chooses each regime, and assess whether the creator's and the platform's preferences align.

Our results show that the provision mode yielding higher human-generated content quality need not also yield higher AI-generated content quality. Although the platform's pooled-data advantage can enhance AI's potential generative capability, it may also weaken the creator's incentives to invest in human-generated content quality, leading the two provision modes to perform differently across the two types of content. Payoff comparisons further show that the creator's and the platform's preferences depend jointly on the pooled-data advantage and the level of AI value sharing. When the pooled-data advantage is substantial and the level of AI value sharing is high, both parties are more likely to prefer

platform provision. When the pooled-data advantage is limited and AI learning effectiveness is high, both may prefer creator provision. Moreover, under certain conditions, both parties prefer the no-AI regime, indicating that AI adoption does not necessarily benefit both the platform and the creator.

This study makes three contributions. First, we examine AI adoption on creator platforms by explicitly considering who provides the AI service. Within a unified framework, we examine platform provision of centralized AI services and creator provision of personalized AI services, systematically analyzing their effects on human-generated content quality, AI-generated content quality, the creator's payoff, and platform profit. This extends research on AI adoption and operational decisions on digital content platforms. Second, we advance understanding of the relationship between content production incentives and AI capability development in the presence of generative AI. Building on prior research on learning and competition between human-generated and AI-generated content, we examine how the pooled-data advantage and value-sharing arrangements associated with different AI providers affect the creator's quality investment decisions. The analysis shows how AI provision modes can have different effects on human-generated and AI-generated content quality, clarifying the relationship between technological advantages, creator incentives, and content quality. Finally, we provide managerial guidance for AI provision mode choice on creator platforms. By identifying the conditions favoring each mode and examining whether platform and creator preferences align, we show that a provision mode that maximizes platform profit does not necessarily yield both a higher creator payoff and higher content quality. These findings suggest that platforms should evaluate AI provision modes by considering their data advantages, creators' incentives to invest in quality, and the economic interests of the participants.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the model. Section 4 characterizes the equilibrium outcomes under the three regimes. Section 5 compares content quality and regime preferences across the alternative AI provision regimes. Section 6 presents three model extensions. Section 7 concludes with the main findings and managerial implications. Proofs and key threshold expressions are provided in the Appendix.

2. Literature Review

This study relates to two streams of research. The first examines content provision on digital platforms, including how platforms incentivize creators, source external content, and provide first-party content. The second focuses on generative AI in digital content creation, particularly its effects on creative production, creator behavior, and platform design.

2.1. Content Provision on Digital Platforms

Research on content provision examines how platform policies shape creators' participation, content supply, and incentives to invest in quality. Jain and Qian [11] study advertising revenue sharing among competing content producers and show that greater producer competition can induce higher compensation and better content quality. Bhargava [1] examines how revenue sharing and platform design influence heterogeneous creators' participation and supply decisions, thereby shaping the scale of the creator ecosystem. Ren [12] studies how advertising levels affect viewers' consumption and competition among creators, showing that their effect on equilibrium content quality can be nonmonotonic. Platforms also influence creation incentives through the allocation of consumer attention. Qian and Jain [13] show that biased recommendations can encourage creators to produce higher-quality content. Ren [14] examines paid content promotion and the allocation of views

based on content quality and promotional spending, showing how these policies shape creators' quality and promotion decisions.

A related body of research examines platforms' acquisition, distribution, and monetization of externally supplied content. Hagiu and Lee [15] show that exclusive distribution and multihoming depend critically on whether content providers retain control over consumer pricing. Jiang et al. [16] examine content production and acquisition when consumers can purchase services from multiple distributors, showing that the effect of consumer multipurchase on new content production depends on distributors' existing content differentiation. Amaldoss et al. [17] analyze how competition among content suppliers shapes media platforms' allocation of space between content and advertising and their choice of revenue sources. Wei et al. [18] study exclusive contracts on advertising revenue-sharing platforms, showing that exclusivity alleviates crowding among providers on each platform and weakens the role of revenue sharing in attracting providers from competing platforms.

Research also examines platforms' provision of their own offerings alongside those supplied by third parties. In the related context of application platforms, Huang et al. [19] compare quality regulation through the exclusion of low-quality complementors, subsidies to high-quality complementors, and the development of first-party applications. Focusing on user-generated content (UGC), Amaldoss and Shin [20] show that platform-provided content can attract more consumers and increase aggregate UGC provision, allowing the two sources of content to function as strategic complements. Qin et al. [21] examine first-party original content production by competing media distributors. They show that greater overlap in existing content can strengthen production incentives when subscription prices are fixed but weaken them when prices can adjust flexibly.

This literature shows how platforms' content provision and monetization decisions affect the incentives of third-party content providers. We extend this perspective to the provision of generative AI services, where the platform chooses between providing a centralized AI service and allowing creators to provide creator-specific AI services. This choice affects not only the allocation of AI-generated value but also the content resources available for AI learning, linking the provision decision to creators' incentives to invest in human-generated content quality.

2.2. Generative AI in Digital Content Creation

Generative AI can reshape creative performance and competition by changing how creators develop content and translate their expertise into output. In an advertising copywriting experiment, Chen and Chan [22] find that using large language models as sounding boards improves nonexperts' performance, whereas using them as ghostwriters reduces experts' performance, with textual evidence linking this deterioration to anchoring on AI-generated drafts. Hou et al. [23] distinguish between ideation and implementation. Generative AI improves creativity during ideation across expertise levels, but during implementation, designers with greater expertise spend more time without achieving higher creativity, while those with less expertise continue to benefit. Analytical studies extend this discussion to production choices and market competition. In content commerce, Zhao et al. [24] examine competing creators who also sell products, showing how the cost of AI-assisted creation and consumers' greater trust in human-created content shape their creation strategies. Zou et al. [7] study content-creation technologies such as generative AI and show that improvements in lower-quality content can divert consumption from higher-quality content and discourage its production when consumers must search for content.

At the platform level, research examines how generative AI integration and related policies affect creator participation and contributions. Liu et al. [25] find that the introduction of an AI drawing tool on LOFTER reduces work sharing by drawing-category

creators relative to novel-category creators, with evidence supporting a protective response to perceived copyright infringement threats. Huang et al. [5] emphasize the role of platform stance signaling, documenting reduced creator activity following LOFTER's introduction of an AI image generator and increased activity following Graffiti Kingdom's prohibition of AI-generated artwork. Cui et al. [26] report increased original content contributions following the integration of a generative AI illustration tool, alongside a shift in contributions from designers' primary domains toward less-affected creative areas. Drawing on a qualitative study of an educational content platform, Mayer et al. [27] examine generative AI as a boundary resource and explain how resistance and accommodation between the platform owner and complementors shape the evolution of governance mechanisms and power relations.

The dependence of generative AI on human-created content links platforms' provision and pricing decisions to their incentives to sustain human contributions. Luo et al. [28] study AI-generated news summaries that help readers assess article relevance but can also substitute for full-article consumption. They show how summary accuracy and reading costs affect consumption patterns and the benefits accruing to the platform and news providers. Yuan et al. [6] examine a platform that offers generative AI tools to heterogeneous creators. Free access can intensify competition and induce high-ability creators to leave, weakening the training data available to generative AI; charging for access can help retain these creators and improve platform revenue. Our study is particularly related to Luo et al. [29] and Moosavi et al. [30]. Luo et al. [29] examine pricing and compensation for creators' contributions to the fine-tuning of platform-integrated generative AI, whereas Moosavi et al. [30] investigate how creator compensation and algorithmic promotion affect human-content investment and AI learning under alternative monetization designs. Building on these studies, we examine a different platform decision: whether generative AI is provided by the platform or by individual creators. The two provision modes differ in their access to pooled content and in how the value generated by AI is allocated to creators. Because investment in human-generated content quality also improves the quality of competing AI-generated content, these differences alter the creator's returns to quality investment and the resulting equilibrium outcomes. We further characterize the platform's choice among no AI, platform provision, and creator provision, and examine when its preference aligns with that of the creator.

3. Model

3.1. Model Setting

We consider a creator platform that connects a focal creator with a unit mass of consumers. The creator supplies human-generated content and chooses its quality, denoted by $q_H \geq 0$. Higher quality requires greater creative investment. We capture this investment cost by the convex cost function $C(q_H) = \frac{q_H^2}{2}$, where the marginal cost coefficient is normalized to one.

We consider a no-AI benchmark and two AI provision regimes. Under the no-AI benchmark, denoted by N, only human-generated content is available. Under platform provision, denoted by P, the platform provides a centralized generative AI service that learns from the creator's content together with a broader pool of training data available to the platform. Under creator provision, denoted by C, the creator provides a creator-specific AI service through the platform, and the AI learns from the creator's own content.

Let $Q \geq 0$ denote the baseline generative AI capability that is independent of the creator's quality choice, and let $\lambda \in (0,1)$ denote AI learning effectiveness, which measures the extent to which higher human-content quality improves AI quality. Under platform provision, the centralized AI additionally benefits from access to a broader pool of training

data. We capture the resulting incremental capability by the pooled-data advantage $b \geq 0$. AI quality under the two AI provision regimes is therefore $q_A^P = Q + b + \lambda q_H^P$, and $q_A^C = Q + \lambda q_H^C$. Thus, b captures the additional AI capability enabled by the broader data pool available under platform provision.

The two AI provision regimes also differ in how AI-generated value is shared with the creator. Under platform provision, let $\mu \in [0,1)$ denote the AI value-sharing parameter, defined as the fraction of AI-generated value allocated to the creator before the platform commission is applied. The platform retains the residual fraction $1 - \mu$. Under creator provision, AI-generated value is generated through the creator-specific AI service, and we normalize the creator's share of that value before commission to one. Accordingly, the two provision regimes differ in both the scope of data available for AI development and the share of AI-generated value allocated to the creator.

The sequence of events is as follows. First, the platform selects N, P, or C. Second, after observing the platform's choice, the creator chooses human-content quality q_H. Third, consumers observe the available content qualities and make their consumption choices. The notation is summarized in Table 1.

Table 1. Main notation.

Symbol	Definition
$r \in \{N,P,C\}$	Regime: no AI, platform provision, or creator provision
q_H^r	Human-content quality under regime r
q_A^r	AI-generated content quality under AI $r \in \{P,C\}$
Q	Baseline generative AI capability, $Q \geq 0$
b	Pooled-data advantage under platform provision, $b \geq 0$
λ	AI learning effectiveness, $0 < \lambda < 1$
μ	AI value-sharing parameter under platform provision, $0 \leq \mu < 1$
ρ	Platform commission rate, $0 < \rho < 1$
t	Consumer mismatch cost, $t > 0$
v	Baseline consumption utility, $v > 0$
D_H^r	Demand for human-generated content under regime r
D_A^r	Demand for AI-generated content under regime r
U_H^r	Creator payoff under regime r
Π^r	Platform profit under regime r

3.2. Consumers and Demand

Consumers have unit demand and are uniformly distributed on the Hotelling interval $x \in [0,1]$. Location x captures horizontal heterogeneity in consumers' relative fit with AI-generated and human-generated content. Consumers closer to 0 are better matched with AI-generated content, whereas consumers closer to 1 are better matched with human-generated content. Let $t > 0$ denote the unit mismatch cost and v the baseline utility from consuming content. Under an AI provision regime $r \in \{P,C\}$, a consumer located at x obtains utility $u_H^r = v + q_H^r - t(1 - x)$ from human-generated content and $u_A^r = v + q_A^r - tx$ from AI-generated content. The consumer chooses the option that yields the higher utility, with an outside option normalized to zero. To focus on how alternative AI provision modes affect demand allocation between human-generated and AI-generated content, we consider a fully covered market in which every consumer selects one of the available content options. Specifically, we assume that the baseline consumption utility v is sufficiently large to ensure that all consumers choose one of the available content types. Furthermore, we restrict attention to the case where both content types receive positive demand, which requires the equilibrium qualities to satisfy $|q_H^r - q_A^r| < t$ for $r \in \{P,C\}$. The consumer who is indifferent between the two content types satisfies $u_H^r = u_A^r$ and is located at $x_r = \frac{t + q_A^r - q_H^r}{2t}$. Hence, for

$r \in \{P,C\}$, $D_A^r = \frac{t+q_A^r-q_H^r}{2t}$, $D_H^r = \frac{t+q_H^r-q_A^r}{2t}$, with $D_A^r + D_H^r = 1$. Under the no-AI benchmark N, only human-generated content is available. Given full market coverage, $D_H^N = 1$.

3.3. Creator Payoff and Platform Profit

The platform monetizes consumer attention through channels such as advertising. Higher-quality content can sustain greater consumer engagement and thereby generate more revenue per consumer. To capture this relationship, we adopt a reduced-form specification in which gross revenue per consumer is proportional to content quality, with the proportionality coefficient set to one. Thus, content of quality q with demand D generates total revenue qD before revenue sharing. A linear relationship between content quality and revenue per consumer is also used in [30,31].

Let $\rho \in (0,1)$ denote the platform's commission rate, so that the creator retains a fraction $1-\rho$ of the value allocated to her. Under the no-AI benchmark, the creator earns only from human-generated content. Her payoff is $U_H^N = (1-\rho)q_H^N - \frac{(q_H^N)^2}{2}$. Under platform provision, the creator earns from her human-generated content and receives a share μ of the value generated by platform-provided AI. Her payoff is $U_H^P = (1-\rho)\left[q_H^P D_H^P + \mu q_A^P D_A^P\right] - \frac{(q_H^P)^2}{2}$. Under creator provision, the value generated by both human-generated and AI-generated content is attributed to the creator before the platform commission is applied. Her payoff is $U_H^C = (1-\rho)\left[q_H^C D_H^C + q_A^C D_A^C\right] - \frac{(q_H^C)^2}{2}$. For each regime $r \in \{N,P,C\}$, the creator chooses quality to maximize her payoff.

The platform earns commission revenue from the value allocated to the creator and, under platform provision, the platform additionally retains the portion of AI-generated value not allocated to the creator. Under the no-AI benchmark, platform profit is $\Pi^N = \rho q_H^N$. Under platform provision, the platform earns commission revenue from human-generated content. For AI-generated content, it directly retains the fraction $1-\mu$ and receives commission on the fraction μ allocated to the creator. Platform profit is therefore $\Pi^P = \rho q_H^P D_H^P + [1-(1-\rho)\mu] q_A^P D_A^P$. Under creator provision, the value generated by both human-generated and AI-generated content is allocated to the creator before the platform commission is applied, and the platform earns commission on both sources of value. That is, $\Pi^C = \rho\left(q_H^C D_H^C + q_A^C D_A^C\right)$. The platform selects its regime anticipating the creator's equilibrium quality response.

Throughout the analysis, we assume $t > max\left\{(1-\rho)(1-\lambda)(1-\mu\lambda), \frac{(Q+b)(1-\mu)}{1-\mu\lambda}, \frac{(Q+b)(1+\mu-2\mu\lambda)}{1+\mu\lambda}, \frac{2Q(1-\lambda)}{1+\lambda}\right\}$. This restriction ensures that the creator's payoff function is strictly concave and that equilibrium investment in human-generated content is positive under both AI provision regimes. Together with the interior-demand condition specified in Section 3.2, it also guarantees the global optimality of the equilibrium quality choices, including against deviations to corner-demand outcomes. This assumption is consistent with creator-platform markets in which consumers exhibit sufficiently differentiated preferences for human-generated and AI-generated content, allowing both content types to attract demand despite differences in quality.

4. Equilibrium Analysis

4.1. No-AI Benchmark

In the no-AI benchmark N, the creator chooses human-content quality to maximize her payoff. The equilibrium human-content quality is $q_H^{N*} = 1-\rho$, and the corresponding creator payoff and platform profit are $U_N^* = (1-\rho)^2/2$ and $\Pi_N^* = \rho(1-\rho)$, respectively. A higher platform commission reduces the creator's share of the value generated by human content and therefore weakens her incentive to invest in human-content quality.

4.2. Regime P

Under regime P, the creator chooses the quality of human-generated content while the platform provides the AI service. Higher human-content quality increases the value generated from the creator's human content and also improves AI quality through learning. However, the creator receives only a share μ of the value generated by AI. The creator's quality choice therefore reflects the returns from both human-generated and AI-generated content. The resulting equilibrium is summarized in Lemma 1.

Lemma 1. *Under regime P, the creator's equilibrium human-content quality and the resulting AI quality are given by*

$$q_H^{P*} = \frac{(1-\rho)\Phi_P}{2\Gamma_P},\ q_A^{P*} = Q + b + \frac{\lambda(1-\rho)\Phi_P}{2\Gamma_P}.$$

The corresponding equilibrium demands are

$$D_H^{P*} = \frac{2\Gamma_P(t-Q-b) + (1-\rho)(1-\lambda)\Phi_P}{4t\Gamma_P},\ D_A^{P*} = \frac{2\Gamma_P(t+Q+b) - (1-\rho)(1-\lambda)\Phi_P}{4t\Gamma_P}.$$

The creator's equilibrium payoff is

$$U_H^{P*} = \frac{(1-\rho)\mu(Q+b)(Q+b+t)}{2t} + \frac{(1-\rho)^2\Phi_P^2}{8t\Gamma_P},$$

and the platform's equilibrium profit is

$$\Pi^{P*} = \frac{\begin{array}{c}\rho(1-\rho)\Phi_P[2\Gamma_P(t-Q-b) + (1-\rho)(1-\lambda)\Phi_P] \\ +[1-(1-\rho)\mu][2(Q+b)\Gamma_P + \lambda(1-\rho)\Phi_P][2\Gamma_P(t+Q+b) - (1-\rho)(1-\lambda)\Phi_P]\end{array}}{8t\Gamma_P^2},$$

where $\Gamma_P = t - (1-\rho)(1-\lambda)(1-\mu\lambda)$, $\Phi_P = t(1+\mu\lambda) - (Q+b)(1+\mu-2\mu\lambda)$.

The creator's equilibrium human-content quality decreases with the pooled-data advantage, i.e., $\frac{\partial q_H^{P*}}{\partial b} < 0$. A stronger pooled-data advantage enhances AI capability independently of the creator's quality investment, making AI-generated content more competitive and reducing the marginal return to improving human-generated content. Although human-content investment also contributes to AI quality through learning, this benefit does not fully offset the reduced incentive to invest in human-generated content. The resulting decline in human-content quality, in turn, weakens the contribution of AI learning to equilibrium AI quality. Consequently, the net effect of data pooling on AI quality depends on the relative strength of the direct capability gain and the indirect loss from reduced human-content investment. Specifically, $\frac{\partial q_A^{P*}}{\partial b} > 0$ when $t > \frac{(1-\rho)[2-\lambda(1+\mu)]}{2}$, as the direct capability gain outweighs the reduction in AI quality resulting from lower human-content investment. Conversely, $\frac{\partial q_A^{P*}}{\partial b} < 0$ when $t < \frac{(1-\rho)[2-\lambda(1+\mu)]}{2}$, as the indirect negative effect dominates. Regardless of its effect on equilibrium AI quality, a stronger pooled-data advantage increases the relative attractiveness of AI-generated content, leading to $\frac{\partial D_A^{P*}}{\partial b} > 0$ and $\frac{\partial D_H^{P*}}{\partial b} < 0$. Thus, data pooling affects equilibrium outcomes through both direct AI capability enhancement and the creator's endogenous quality investment.

AI value sharing affects the creator's quality investment by allowing her to internalize a larger share of AI-generated revenue. From Lemma 1, we obtain $\frac{\partial q_H^{P*}}{\partial \mu} = \frac{(1-\rho)t}{\Gamma_P}\left(\lambda D_A^{P*} - \frac{(1-\lambda)q_A^{P*}}{2t}\right)$. λD_A^{P*} captures the marginal benefit of improving AI quality through learning, whereas $\frac{(1-\lambda)q_A^{P*}}{2t}$ reflects the revenue loss from shifting demand away from AI-generated content. Thus, an increase in AI value sharing encourages human-content

quality investment when $\lambda D_A^{P*} > \frac{(1-\lambda)q_A^{P*}}{2t}$, but discourages it when the inequality is reversed. This result highlights how the creator's internalization of AI-generated value interacts with AI learning and demand competition to shape quality investment incentives.

4.3. Regime C

Under regime *C*, the creator provides a creator-specific AI service and chooses the quality of human-generated content. Higher human-content quality increases the value of the creator's human content and also improves AI quality through learning. Because the value generated by the creator-specific AI service is allocated to the creator before the platform commission is applied, the creator internalizes the returns to quality from both human-generated and AI-generated content. The resulting equilibrium is summarized in Lemma 2.

Lemma 2. *Under regime C, the creator's equilibrium human-content quality and the resulting AI quality are given by*

$$q_H^{C\star} = \frac{(1-\rho)\Phi_C}{2\Gamma_C},\ q_A^{C\star} = Q + \frac{\lambda(1-\rho)\Phi_C}{2\Gamma_C}.$$

The corresponding equilibrium demands are

$$D_H^{C*} = \frac{1}{2} - \frac{Q}{2t} + \frac{(1-\rho)(1-\lambda)\Phi_C}{4t\Gamma_C},\ D_A^{C*} = \frac{1}{2} + \frac{Q}{2t} - \frac{(1-\rho)(1-\lambda)\Phi_C}{4t\Gamma_C}.$$

The creator's equilibrium payoff is

$$U_H^{C*} = \frac{(1-\rho)Q(Q+t)}{2t} + \frac{\left(1-\rho\right)^2{\Phi_C}^2}{8t\Gamma_C},$$

and the platform's equilibrium profit is

$$\Pi^{C*} = \frac{\rho Q(Q+t)}{2t} + \frac{\rho(1-\rho)(\Gamma_C+t)\Phi_C^2}{8t\Gamma_C^2},$$

where $\Gamma_C = t - (1-\rho)(1-\lambda)^2$, $\Phi_C = t(1+\lambda) - 2Q(1-\lambda)$.

Similar to the effect of the pooled-data advantage under regime *P*, an increase in baseline generative AI capability under regime *C* reduces the creator's investment in human-content quality, i.e., $\frac{\partial q_H^{C\star}}{\partial Q} < 0$, as stronger AI capability lowers the marginal return to human-content investment. The resulting reduction in investment partially offsets the direct improvement in AI quality through the learning channel. Consequently, $\frac{\partial q_A^{C\star}}{\partial Q} > 0$ when $t > (1-\rho)(1-\lambda)$, whereas $\frac{\partial q_A^{C\star}}{\partial Q} < 0$ when $t < (1-\rho)(1-\lambda)$. In either case, AI-generated content gains a greater share of demand relative to human-generated content, with $\frac{\partial D_A^{C*}}{\partial Q} > 0$ and $\frac{\partial D_H^{C*}}{\partial Q} < 0$.

AI learning effectiveness affects the creator's investment incentives through a distinct mechanism. Under regime *C*, the creator receives revenue from both content types after the platform commission. Stronger AI learning improves the contribution of human-content investment to AI quality, but also weakens its ability to attract demand toward human-generated content. These opposing effects determine the creator's investment response. Specifically, $\frac{\partial q_H^{C*}}{\partial \lambda} = \frac{(1-\rho)\left[t+2Q-4(1-\lambda)q_H^{C*}\right]}{2\left[t-(1-\rho)(1-\lambda)^2\right]}$. Thus, stronger AI learning effectiveness increases human-content quality investment when $t + 2Q > 4(1-\lambda)q_H^{C*}$, but decreases it when the inequality is reversed.

5. Comparison Across Regimes

In this section, we compare the three regimes to characterize content-quality outcomes and regime preferences. We first compare platform provision and creator provision in terms of human-generated content quality and AI-generated content quality, and then examine the creator's payoff and the platform's profit across the alternative regimes to identify their respective and joint preferences.

5.1. Quality Incentives

Comparing the equilibrium human-content quality under regimes P and C, we obtain the following proposition.

Proposition 1. *Regime P induces higher human-content quality than regime C, i.e., $q_H^{P*} > q_H^{C*}$, if and only if $\underline{\lambda}_H < \lambda < \lambda_H$ and $b < \overline{b}_H$. Otherwise, $q_H^{P*} \leq q_H^{C*}$.*

Regime P can induce higher human-generated content quality than creator provision because the creator internalizes the competitive effect between her human-generated content and AI-generated content to different degrees across the two provision modes. Under regime C, improving human-content quality also improves AI quality through learning, but because human-content quality increases more strongly than AI quality, some demand shifts from AI-generated to human-generated content. The creator therefore faces a loss in AI-generated value when investing in higher human-content quality. When AI learning effectiveness lies within the range identified in Proposition 1, this demand-side loss can outweigh the additional AI value created through learning, giving the creator an incentive to moderate her investment in human-content quality. Under regime P, the creator receives only a share of AI-generated value, so she internalizes less of this loss and may therefore invest more in human-generated content.

This advantage of regime P, however, depends on the pooled-data advantage remaining sufficiently limited. A stronger pooled-data advantage raises AI quality independently of the creator's own quality investment and increases the relative attractiveness of AI-generated content. As a result, the creator's return from further improving human-generated content under platform provision declines. Once the pooled-data advantage becomes sufficiently strong, this effect outweighs the weaker self-cannibalization under platform provision, and creator provision yields higher human-generated content quality. Proposition 1 therefore shows that the relative quality incentives under the two provision modes are jointly shaped by AI learning from creator content and the additional capability generated through data pooling.

From a managerial perspective, Proposition 1 cautions against assuming that creator provision necessarily leads to stronger human-content investment. The provision mode associated with higher human-generated content quality depends on both the platform's advantage from pooled data and how effectively creator content improves AI quality. Platforms seeking to preserve high-quality human content should therefore assess the incentive consequences of alternative AI provision modes directly, rather than inferring them simply from who provides the AI or from the technological advantage of platform-level data aggregation.

Corollary 1. *A larger share of AI-generated value allocated to the creator makes regime C more likely to induce higher human-generated content quality than regime P, i.e., $\frac{\partial \overline{b}_H}{\partial \mu} < 0$.*

A larger creator share of AI-generated value under platform provision makes the creator internalize more of the reduction in AI-generated value that occurs when higher

human-content quality shifts demand toward human-generated content. Platform provision therefore becomes more similar to creator provision in the extent to which the creator bears this self-cannibalization effect. As a result, its relative advantage in encouraging human-content investment diminishes, and creator provision can generate higher human-content quality at a lower level of pooled-data advantage. This result implies that increasing the creator's share of AI-generated value does not necessarily strengthen the case for platform provision when preserving human-content quality is a priority. Value-sharing design and AI provision choice should therefore be considered jointly rather than as independent decisions. Notably, when the pooled-data advantage is absent, i.e., $b = 0$, the two AI provision regimes have identical technological conditions. As the creator's share of AI-generated value under platform provision increases, the difference in equilibrium human-generated content quality between the two regimes narrows, but which regime induces higher quality is independent of the value-sharing parameter. Thus, increasing the creator's revenue share may either encourage or discourage investment in human-generated content under platform provision, depending on AI learning effectiveness and market conditions.

We next compare the equilibrium AI-content quality under regimes P and C. The result is summarized in the following remark.

Remark. *When regime P induces higher human-generated content quality than regime C, it also induces higher AI-generated content quality. When regime C induces higher human-generated content quality, regime P yields higher AI-generated content quality if and only if* $b > \lambda\left(q_H^{C*} - q_H^{P*}\right)$.

When platform provision induces higher human-generated content quality, it benefits from both the pooled-data advantage and the higher quality of creator content available for AI learning. The two effects therefore reinforce each other, leading to higher AI-generated content quality under platform provision. When creator provision induces higher human-generated content quality, by contrast, the two effects work in opposite directions. Creator provision benefits from the higher quality of creator content transmitted to AI through learning, whereas platform provision retains the direct capability advantage generated by pooled data. Platform provision therefore produces higher AI quality only when its pooled-data advantage is large enough to offset the AI-quality gain associated with higher human-content quality under creator provision.

This result shows that the ranking of AI quality cannot be inferred directly from the ranking of human-content quality. Platform provision may still generate higher AI quality even when it provides weaker incentives for human-content investment, provided that its pooled-data advantage is sufficiently strong. For platforms concerned with AI performance, evaluating provision modes therefore requires considering both the quality of creator content available for AI learning and the independent capability gains from data pooling.

5.2. Regime Preferences

We first examine the creator's preference between regimes P and C. Comparing the creator's equilibrium payoffs under the two regimes yields the following proposition.

Proposition 2. *There exists a threshold* b_U *such that the creator prefers regime P when* $b > b_U$ *and regime C otherwise.*

Proposition 2 shows that the creator's preference between the two AI provision modes depends on whether the capability gain from data pooling is large enough to offset the smaller share of AI-generated value she receives under platform provision. When the pooled-data advantage is limited, creator provision is more attractive because the AI-generated value is allocated to the creator before the platform commission is applied. As

the pooled-data advantage increases, platform-provided AI gains a stronger capability advantage, increasing the value generated under platform provision. Once this advantage becomes sufficiently strong, it outweighs the creator's smaller share of AI-generated value, making platform provision more attractive. The threshold therefore captures the level of pooled-data advantage required for the creator's preference to shift from creator provision to platform provision.

Figure 1 illustrates the creator's preference shift characterized in Proposition 2 and further shows how AI value sharing affects the relative attractiveness of the two provision modes. A larger share of AI-generated value allocated to the creator under platform provision increases the creator's relative payoff from platform provision, as $\frac{\partial(U_H^{P*}-U_H^{C*})}{\partial \mu} > 0$. Platform provision therefore becomes more attractive to the creator as AI value sharing increases, and the preference switch occurs at a lower level of pooled-data advantage. This result also complements Corollary 1. Greater value sharing makes platform provision more attractive to the creator, while making it less likely to induce higher human-generated content quality than creator provision. Thus, the provision mode preferred by the creator need not be the one that better sustains human-content quality. In particular, when the pooled-data advantage is absent, the creator always prefers regime C because she receives a larger share of AI-generated revenue under this regime. Although increasing the creator's share of AI-generated value under regime P narrows the payoff gap between the two regimes, it is insufficient to make regime P more attractive to the creator.

This finding is related to recent studies showing that compensating creators for the use of their content can strengthen creator incentives and improve outcomes in generative AI-enabled content markets [32]. Ref. [32] shows that creator compensation can encourage the production of high-value human-generated content. Our result complements this study by showing that value sharing also affects creators' preferences over how AI is provided. A larger creator share of AI-generated value makes platform provision more attractive to the creator. Importantly, however, this stronger preference for platform provision does not necessarily imply stronger human-content investment. Together with Corollary 1, the result shows that value sharing can improve the creator's relative payoff from platform provision while making platform provision less likely to generate higher human-content quality than creator provision. Relatedly, Cohen et al. [33] find that operators prefer a serial human–automation design even though it reduces independent checking and increases expected accident risk relative to a parallel design. Although their study focuses on safety monitoring, it similarly highlights a potential divergence between preferences over automation arrangements and their effects on human effort.

Given the analytical complexity of comparing the platform's equilibrium profits under the two AI provision regimes, we conduct extensive numerical experiments to examine its regime preference. To assess how the results vary across market and technological conditions, we examine the effects of the pooled-data advantage, AI learning effectiveness, and AI value sharing under different combinations of baseline AI capability ($Q \in [0.05,0.20]$), content differentiation ($t \in [0.7,1.3]$), and the platform commission rate ($\rho \in [0.3,0.8]$). We retain only parameter combinations that satisfy all the equilibrium conditions established in Section 3. The platform's preferred regime is then determined by comparing the equilibrium profits calculated from the analytical expressions under the two regimes. Figures 2 and 3 present representative results, with the main findings summarized in Observation 1.

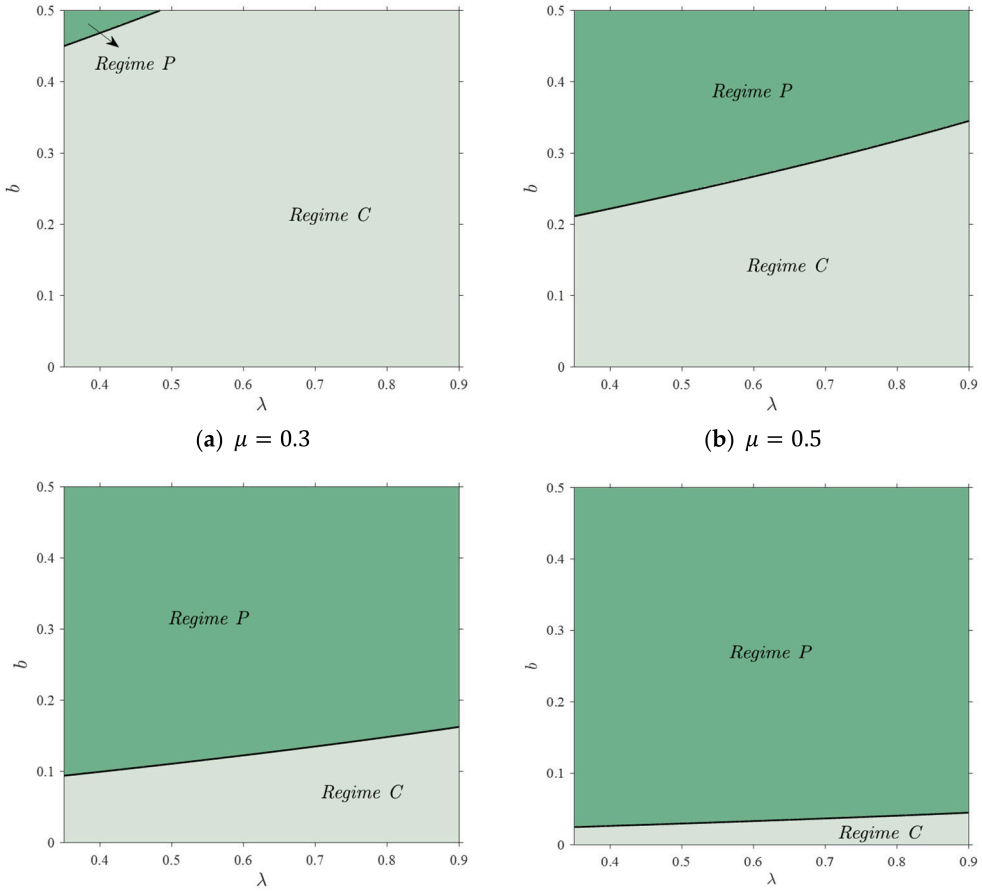


Figure 1. Creator preferences across AI provision regimes under different levels of AI value sharing. The AI value-sharing parameter μ takes values of 0.3, 0.5, 0.7, and 0.9 in panels (**a**), (**b**), (**c**), and (**d**), respectively. (The fixed parameters are $Q = 0.1$, $t = 1$, and $\rho = 0.6$. The shaded regions indicate the creator's preferred regime, and the solid black curves indicate indifference between the two regimes.).

Observation 1. *(i) The platform generally prefers regime P, whereas regime C becomes more attractive when the pooled-data advantage is limited and AI learning effectiveness is high. (ii) Greater AI value sharing can favor either regime. While it may strengthen the platform's preference for regime P, it can instead favor regime C when content differentiation and platform commission rates are low.*

The platform's regime preference reflects a trade-off between its direct capture of AI-generated value and the content quality induced by the creator's investment decisions. Under regime P, the platform earns additional AI-generated revenue beyond commission income, while the pooled-data advantage directly enhances AI capability. These factors favor platform provision. Under regime C, the creator captures a larger share of the returns from AI-generated content, which can strengthen incentives to invest in human-content quality. When the pooled-data advantage is limited and AI learning effectiveness is high, stronger human-content investment can also improve AI quality, generating additional content value that may outweigh the platform's direct revenue advantage under regime P.

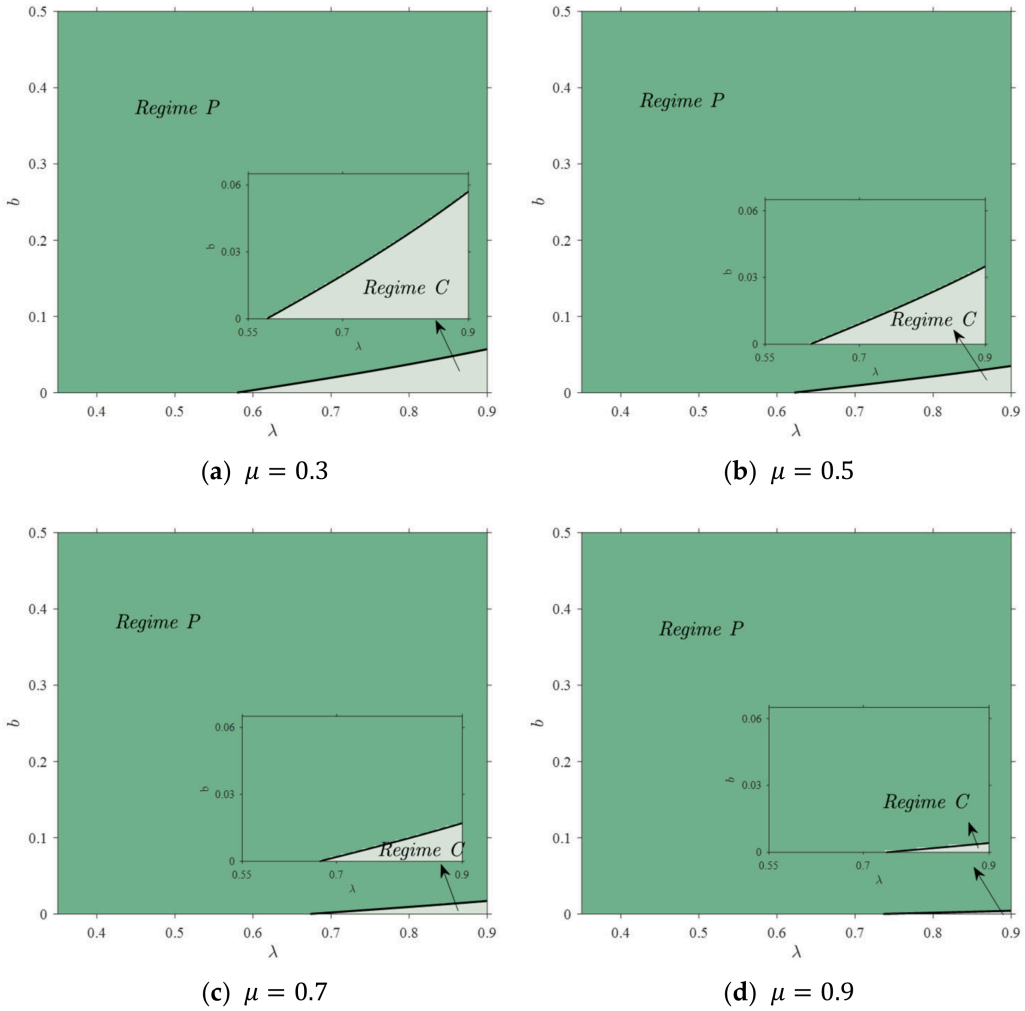
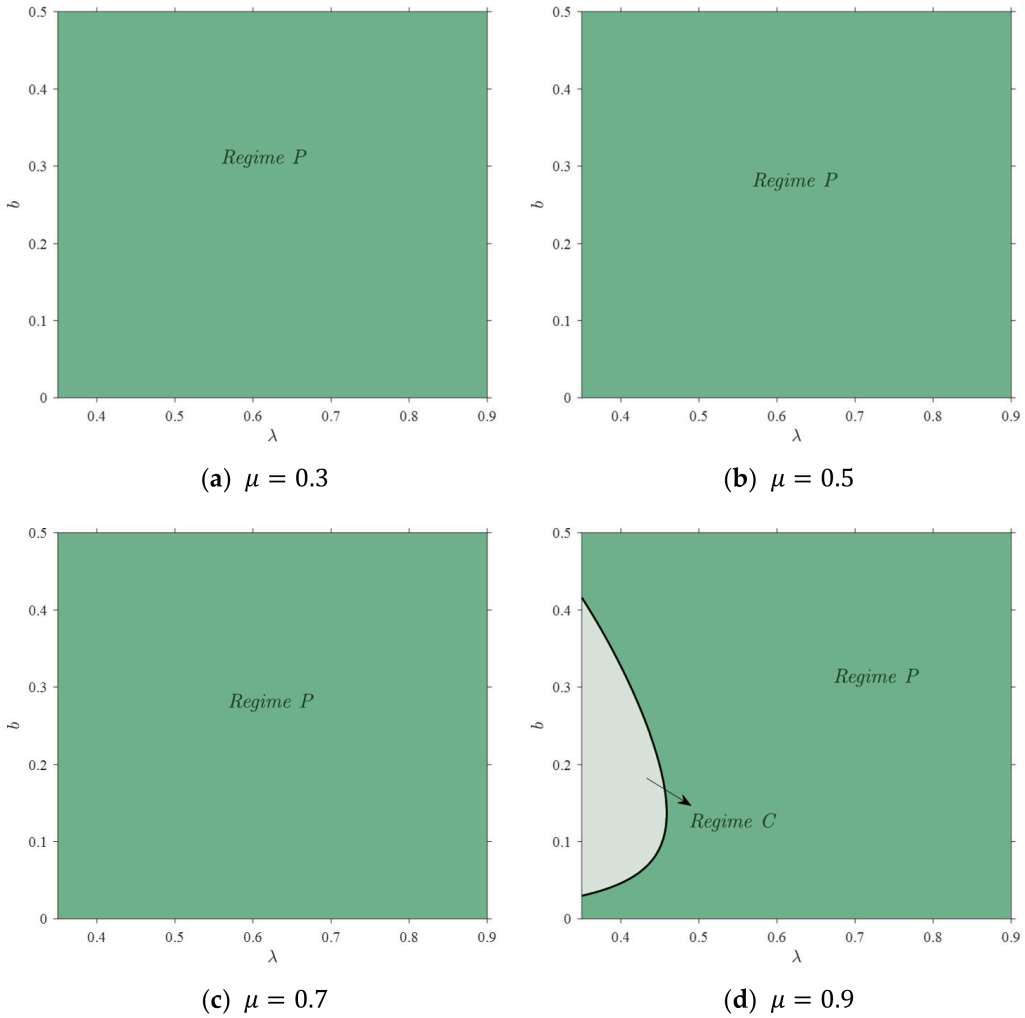


Figure 2. Platform preferences across AI provision regimes under different levels of AI value sharing. The AI value-sharing parameter μ takes values of 0.3, 0.5, 0.7, and 0.9 in panels (**a**), (**b**), (**c**), and (**d**), respectively. (The fixed parameters are $Q = 0.1$, $t = 1$, and $\rho = 0.6$. The shaded regions indicate the platform's preferred regime, and the solid black curves indicate indifference between the two regimes. The insets provide enlarged views of the regions where regime C is preferred.).

AI value sharing further affects the platform's regime preference through two channels: the AI-generated revenue it retains directly and the commission revenue associated with endogenous content quality and demand allocation. Increasing the creator's share reduces the former under regime P, while its effect on the latter depends on the creator's quality investment response. Under the baseline conditions (i.e., Figure 2), greater value sharing encourages human-content investment and enhances AI quality through learning. Near the regime-preference boundary, the resulting gains can offset the reduction in directly retained AI revenue, making regime P more attractive. This pattern can reverse when content differentiation and the commission rate are both lower (i.e., Figure 3). Lower content differentiation makes demand more responsive to relative quality, while a lower commission rate changes the platform's returns from quality improvements. In some parameter regions, greater value sharing even reduces the creator's quality investment under regime P, weakening both human-content and AI quality. Combined with the reduction in directly retained AI revenue, this can shift the platform's preference toward regime C. Considering the case where the pooled-data advantage is absent, Figure 2 shows that increasing the creator's share of AI-generated value may shift the platform's preference from regime C to regime P, even when the two regimes have identical technological conditions.

However, Figure 3 shows that when content differentiation and the platform commission rate are lower, greater AI value sharing weakens the profit advantage of regime P but does not necessarily reverse the platform's regime preference.



(**a**) $\mu = 0.3$ (**b**) $\mu = 0.5$

(**c**) $\mu = 0.7$ (**d**) $\mu = 0.9$

Figure 3. Platform preferences under different levels of AI value sharing with lower content differentiation and a lower commission rate. The AI value-sharing parameter μ takes values of 0.3, 0.5, 0.7, and 0.9 in panels (**a**), (**b**), (**c**), and (**d**), respectively. (The fixed parameters are $Q = 0.1$, $t = 0.7$, and $\rho = 0.3$. The shaded regions indicate the platform's preferred regime, and the solid black curves, where present, indicate indifference between the two regimes.).

We further include the no-AI benchmark to examine the alignment of regime preferences between the platform and the creator. To this end, we conduct extensive numerical analyses under different market and technological conditions, comparing their equilibrium payoffs across the three regimes to identify whether their preferred regimes coincide. Figure 4 presents representative results illustrating how preference alignment and disagreement vary with the pooled-data advantage, AI learning effectiveness, and AI value sharing. The main findings are summarized in Observation 2.

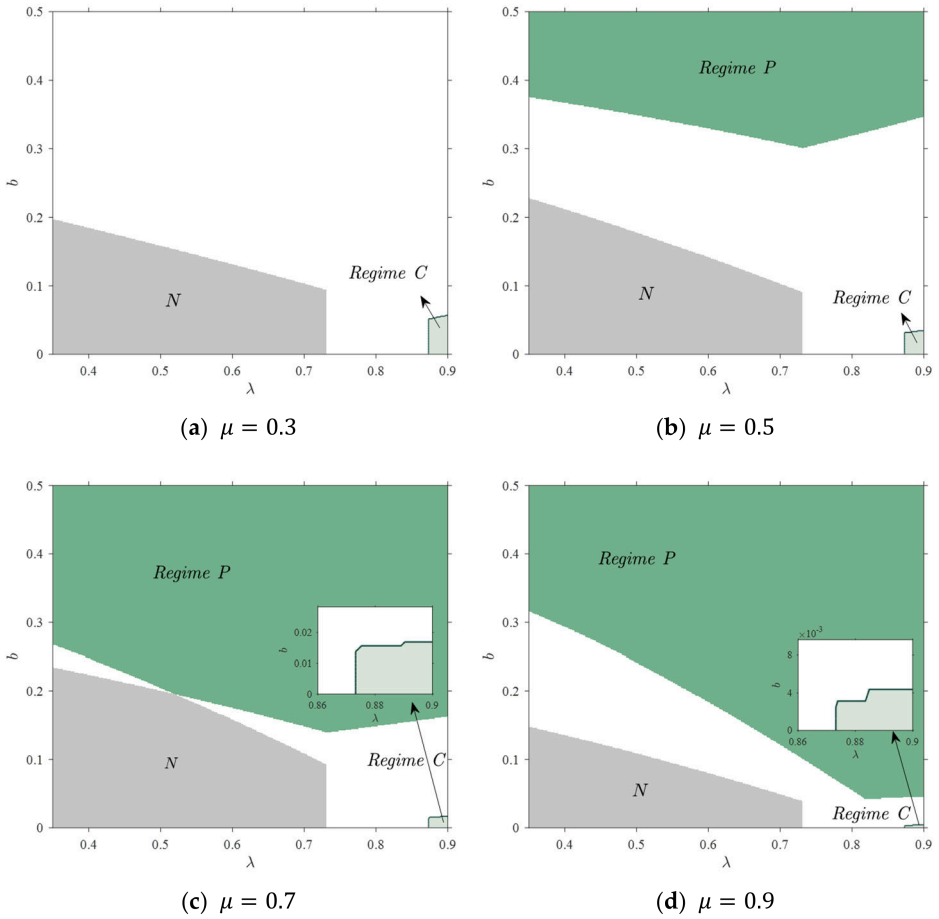


Figure 4. Preference alignment between the platform and the creator across AI provision regimes. The AI value-sharing parameter μ takes values of 0.3, 0.5, 0.7, and 0.9 in panels (**a**), (**b**), (**c**), and (**d**), respectively. (The fixed parameters are $Q = 0.1$, $t = 1$, and $\rho = 0.6$. The shaded regions indicate the regimes preferred by both the platform and the creator. The white regions indicate preference disagreement, where the platform and the creator prefer different regimes. The insets provide enlarged views of the narrow regime C preference-alignment regions.).

Observation 2. *(i) When both the pooled-data advantage and the learning effectiveness are low, the no-AI benchmark N is preferred by both parties. (ii) When the pooled-data advantage and AI value sharing are high, regime P is preferred by both parties. (iii) When the pooled-data advantage is very limited and the learning effectiveness is high, regime C is preferred by both parties. (iv) As AI value sharing increases, preference alignment between the platform and the creator may first improve and then deteriorate.*

The alignment of regime preferences depends on whether the benefits of AI provision are sufficient to improve the payoffs of both parties. When the pooled-data advantage and AI learning effectiveness are low, neither AI provision regime generates sufficient benefits for both parties to prefer it over the no-AI benchmark. A strong pooled-data advantage, by contrast, enhances AI capability under regime P and increases the value generated by AI content. For the creator, this additional value can compensate for receiving a smaller share of AI-generated revenue, particularly when AI value sharing is high. For the platform, the pooled-data advantage increases AI-generated revenue, part of which it retains directly. When the pooled-data advantage is limited but AI learning effectiveness is high, regime C may instead be preferred by both parties. Under this regime, the creator retains all AI-generated revenue after the platform commission, strengthening incentives to invest in

human-content quality. Higher human-content quality also enhances AI capability through learning, potentially generating sufficient returns for both the creator and the platform.

AI value sharing further influences the alignment of their preferences, although its effect is not necessarily monotonic. When value sharing is relatively low, the platform may prefer regime P because it retains a larger portion of AI-generated revenue, while the creator may prefer regime N or C. Increasing value sharing allows the creator to capture more AI-generated value and changes the incentives for quality investment, thereby expanding the conditions under which both parties prefer regime P. At higher sharing levels, however, the reduction in AI-generated revenue retained by the platform may weaken its incentive to provide AI. Consequently, the creator may continue to prefer regime P while the platform favors the no-AI regime, leading to renewed preference disagreement (as illustrated in Figure 4c,d). This explains why greater AI value sharing does not necessarily lead to stronger preference alignment. These findings suggest that AI provision and value-sharing arrangements should be considered together. Platforms with substantial pooled-data advantages may be better positioned to provide AI directly, while creator provision can be more attractive when AI capability depends strongly on learning from creator-specific content. Nevertheless, the alignment of platform and creator interests also depends on how AI-generated value is distributed, highlighting the importance of balancing creator incentives with the platform's returns from AI provision.

6. Extensions

6.1. Partial Market Coverage

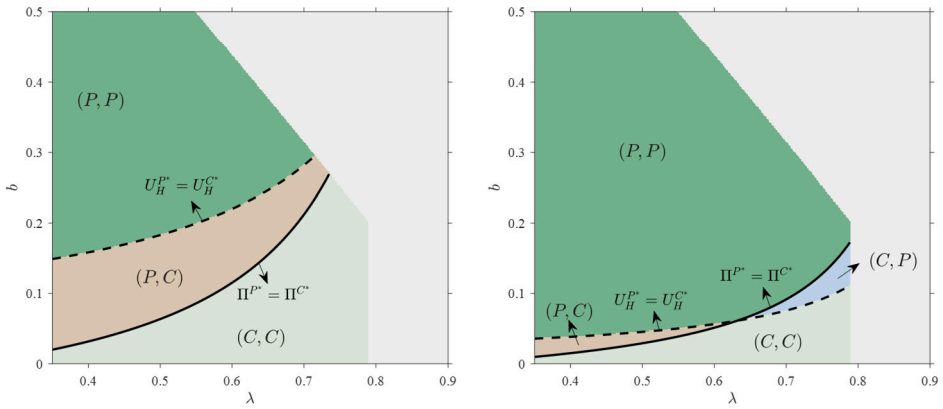
To assess the robustness of our findings, we relax the full market coverage assumption. Consumers may choose not to consume either type of content, with the utility of nonconsumption normalized to zero. All other model settings remain unchanged. We examine the implications for quality investment, equilibrium payoffs, and regime preferences. Based on the consumer utility functions in Section 3.2, the corresponding demand functions are given by $D_A^r = max\left\{0, min\left\{1, \frac{t+q_A^r-q_H^r}{2t}, \frac{v+q_A^r}{t}\right\}\right\}$, $D_H^r = max\left\{0, min\left\{1, \frac{t+q_H^r-q_A^r}{2t}, \frac{v+q_H^r}{t}\right\}\right\}$, where $r \in \{P,C\}$, and $D_H^N = max\left\{0, min\left\{1, \frac{v+q_H^N}{t}\right\}\right\}$. Restricting attention to the parameter region in which the market is partially covered under all three regimes, we derive the equilibrium outcomes summarized in Table 2. The corresponding parameter conditions and proofs are provided in Appendix B.

Table 2. Equilibrium under common partial market coverage.

Regime	Equilibrium Qualities	Creator Payoff and Platform Profit
N	$q_H^{N*} = \frac{(1-\rho)v}{t-2(1-\rho)}$	$U_H^{N*} = \frac{(1-\rho)^2 v^2}{2t[t-2(1-\rho)]}$, $\Pi^{N*} = \frac{\rho(1-\rho)v^2[t-(1-\rho)]}{t[t-2(1-\rho)]^2}$.
P	$q_H^{P*} = \frac{(1-\rho)[v+\mu\lambda(v+2Q+2b)]}{t-2(1-\rho)(1+\mu\lambda^2)}$	$U_H^{P*} = \frac{(1-\rho)\mu(Q+b)(v+Q+b)}{t} + \frac{(1-\rho)^2[v+\mu\lambda(v+2Q+2b)]^2}{2t[t-2(1-\rho)(1+\mu\lambda^2)]}$, $\Pi^{P*} = \rho q_H^{P*} D_H^{P*} + [1-(1-\rho)\mu] q_A^{P*} D_A^{P*}$.
C	$q_H^{C*} = \frac{(1-\rho)[(1+\lambda)v+2\lambda Q]}{t-2(1-\rho)(1+\lambda^2)}$	$U_H^{C*} = \frac{(1-\rho)Q(v+Q)}{t} + \frac{(1-\rho)^2[(1+\lambda)v+2\lambda Q]^2}{2t[t-2(1-\rho)(1+\lambda^2)]}$, $\Pi^{C*} = \rho\left(q_H^{C*} D_H^{C*} + q_A^{C*} D_A^{C*}\right)$.

The results in Table 2 show that a greater pooled-data advantage increases human-content quality under regime P when AI value sharing is positive, as $\frac{\partial q_H^{P*}}{\partial b} = \frac{2(1-\rho)\mu\lambda}{[t-2(1-\rho)(1+\mu\lambda^2)]} > 0$ when $\mu > 0$. This contrasts with the negative effect observed under full market coverage. Under partial coverage, improvements in AI quality attract previously unserved consumers without directly displacing demand for human-generated content. Through AI value sharing, the resulting increase in AI-generated revenue strengthens the creator's incentive to invest in human-content quality.

Partial market coverage also affects the relative attractiveness of AI provision. Within the common partial-coverage region, the equilibrium payoffs satisfy $\Pi^{P*} > \Pi^{N*}$, $\Pi^{C*} > \Pi^{N*}$, $U_H^{P*} \geq U_H^{N*}$, $U_H^{C*} > U_H^{N*}$. These results indicate that AI provision benefits the platform under either provision regime by generating additional revenue from previously unserved consumers. The creator also benefits from AI provision under regime C and, when AI value sharing is positive, under regime P. We further conduct numerical analyses to examine the platform's and the creator's preferences between regimes P and C, with the results presented in Figure 5.



(**a**) $\mu = 0.3$ (**b**) $\mu = 0.7$

Figure 5. Platform and creator preferences between AI provision regimes under partial market coverage. The AI value-sharing parameter μ takes values of 0.3 and 0.7 in panels (**a**) and (**b**), respectively. (The fixed parameters are $Q = 0.1$, $t = 1.5$, $\rho = 0.6$, and $v = 0.1$. Each ordered pair indicates the preferred regimes of the platform and the creator, respectively. The curves represent their indifference boundaries. The excluded regions do not satisfy the common partial market coverage conditions.).

Figure 5 shows that a greater pooled-data advantage generally strengthens both parties' preferences for regime P, whereas regime C becomes more attractive when the pooled-data advantage is limited and AI learning effectiveness is high. AI value sharing further influences the positions and relative ordering of these preference boundaries. As shown in Figure 5a, when AI value sharing is relatively low ($\mu = 0.3$), a substantial disagreement region emerges in which the platform prefers regime P while the creator prefers regime C. As μ increases to 0.7, the region in which both parties prefer regime P expands, and the disagreement region observed at the lower sharing level contracts. In some regions with high AI learning effectiveness, however, the relative ordering of the two preference boundaries reverses, giving rise to a different type of disagreement in which the platform prefers regime C while the creator prefers regime P, as illustrated in Figure 5b. This occurs because greater AI value sharing strengthens the creator's incentives to invest in human-content quality under regime P while reducing the share of AI-generated revenue directly retained by the platform. These effects influence the payoffs of the two parties differently. Thus, although greater AI value sharing can improve preference alignment over a substantial

parameter region, it may also generate a different form of preference conflict under certain market conditions.

6.2. Heterogeneous AI Learning Effectiveness

The baseline model assumes identical AI learning effectiveness under platform and creator provision. However, platform-provided AI draws on pooled content data, whereas creator-provided AI primarily relies on creator-specific content. The data used for AI learning may therefore differ in scope and relevance, potentially leading to differences in learning effectiveness. Accordingly, we specify $q_A^P = Q + b + \lambda_P q_H^P$ and $q_A^C = Q + \lambda_C q_H^C$, where $0 < \lambda_P < 1$ and $0 < \lambda_C < 1$ represent AI learning effectiveness under regimes P and C, respectively. All other model settings remain unchanged. We then examine how differences in AI learning effectiveness interact with the pooled-data advantage to affect content quality, regime preferences, and preference alignment between the platform and the creator.

Following the backward induction procedure in the baseline model, the equilibrium outcomes under regime N remain unchanged. When $t > \max\{(1-\rho)(1-\lambda_P)(1-\mu\lambda_P), (1-\rho)(1-\lambda_C)^2, \frac{(Q+b)(1-\mu)}{1-\mu\lambda_P}, \frac{(Q+b)(1+\mu-2\mu\lambda_P)}{1+\mu\lambda_P}, \frac{2Q(1-\lambda_C)}{1+\lambda_C}\}$, the equilibrium human-content quality levels under regimes P and C are given by $q_H^{P*} = \frac{(1-\rho)[t(1+\mu\lambda_P)-(Q+b)(1+\mu-2\mu\lambda_P)]}{2[t-(1-\rho)(1-\lambda_P)(1-\mu\lambda_P)]}$, $q_H^{C*} = \frac{(1-\rho)[t(1+\lambda_C)-2Q(1-\lambda_C)]}{2[t-(1-\rho)(1-\lambda_C)^2]}$. We obtain the following proposition.

Proposition 3. *There exists a threshold $\tilde{b}_H$ such that (i) if $\tilde{b}_H \le 0$, regime C induces higher human-content quality than regime P, i.e., $q_H^{P*} \le q_H^{C*}$; (ii) if $\tilde{b}_H > 0$, regime P induces higher human-content quality than regime C when $b < \tilde{b}_H$, i.e., $q_H^{P*} > q_H^{C*}$, whereas the reverse holds when $b \ge \tilde{b}_H$, where $\tilde{b}_H = \frac{t(1+\mu\lambda_P)}{1+\mu-2\mu\lambda_P} - Q - \frac{[t-(1-\rho)(1-\lambda_P)(1-\mu\lambda_P)][t(1+\lambda_C)-2Q(1-\lambda_C)]}{(1+\mu-2\mu\lambda_P)[t-(1-\rho)(1-\lambda_C)^2]}$.*

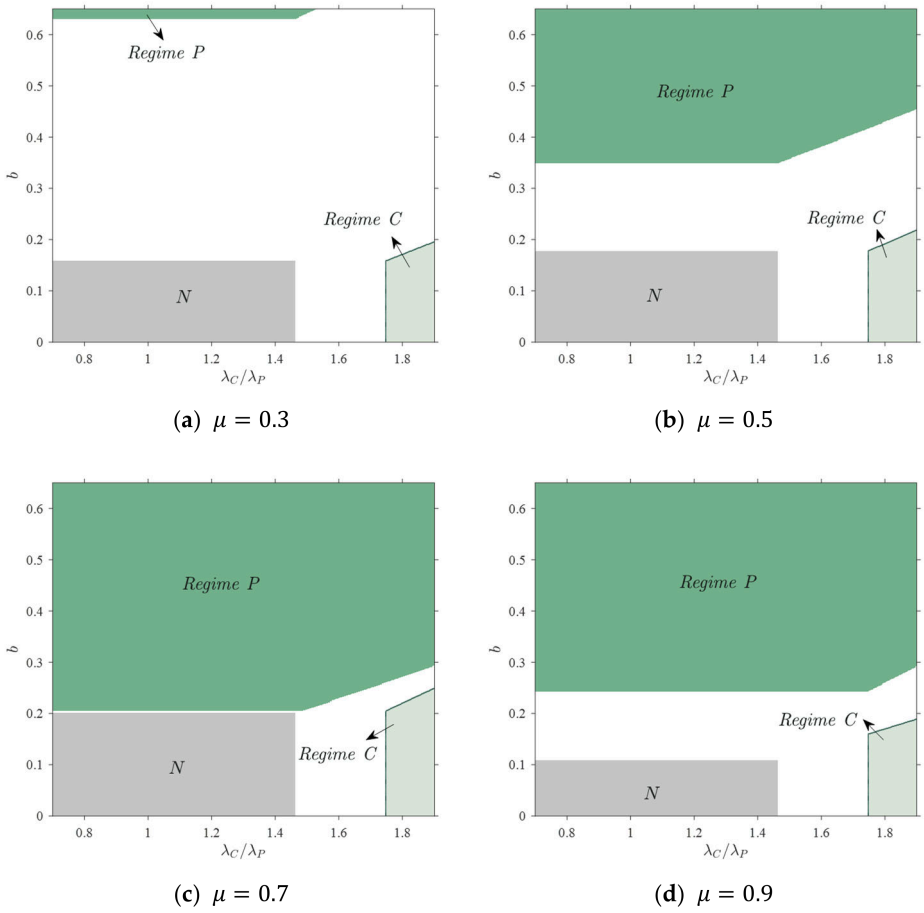
Proposition 3 shows that when regime P induces higher human-content quality, an increase in the pooled-data advantage weakens this advantage and may eventually reverse the quality comparison. This occurs because improvements in AI capability under regime P intensify the displacement of human-generated content, reducing the creator's marginal incentive to invest in human-content quality even after accounting for AI value sharing. In contrast, human-content quality under regime C is unaffected by the pooled-data advantage.

Differences in AI learning effectiveness further influence the creator's incentives to invest in human-content quality. Higher learning effectiveness allows improvements in human-content quality to translate more effectively into AI quality, although the resulting revenue gains and demand substitution effects differ across the two regimes. The effects on the quality-comparison threshold are given by $\frac{\partial \tilde{b}_H}{\partial \lambda_P} = \frac{\mu\left[t+2\left(Q+\tilde{b}_H\right)\right]}{1+\mu-2\mu\lambda_P} - 2q_H^{C*}$ and $\frac{\partial \tilde{b}_H}{\partial \lambda_C} = -\frac{D_H^{P*}}{(1+\mu-2\mu\lambda_P)D_C}\left[t + 2Q - 4(1-\lambda_C)q_H^{C*}\right]$.

Under regime P, greater AI learning effectiveness increases the creator's returns from AI-generated content through value sharing, but also intensifies the displacement of human-generated content. When the additional investment incentive from AI value sharing dominates, such that $\mu\left[t + 2\left(Q + \tilde{b}_H\right)\right] > 2(1 + \mu - 2\mu\lambda_P)q_H^{C*}$, an increase in λ_P expands the parameter region in which regime P induces higher human-content quality. Under regime C, the creator retains all AI-generated revenue after the platform commission, but stronger AI learning can also divert demand away from human-generated content. When $t + 2Q > 4(1-\lambda_C)q_H^{C*}$, the positive investment effect dominates, so increasing λ_C raises human-content quality under regime C and reduces $\tilde{b}_H$, narrowing the region in which regime P induces higher human-content quality.

Figure 6 illustrates how the pooled-data advantage and AI value sharing affect preference alignment between the platform and the creator under heterogeneous AI learning effectiveness. When the pooled-data advantage is limited, both parties tend to prefer regime

N, while regime C becomes more attractive as the relative learning effectiveness of creator-provided AI (λ_C/λ_P) increases. In contrast, a greater pooled-data advantage expands the region in which both parties prefer regime P. Even when creator-provided AI has higher learning effectiveness ($\lambda_C/\lambda_P > 1$), regime P may still be preferred by both parties. This suggests that the platform's pooled-data advantage can compensate for its disadvantage in AI learning effectiveness, with the relative strengths of these two technological advantages shaping regime preferences.



(**a**) $\mu = 0.3$ (**b**) $\mu = 0.5$

(**c**) $\mu = 0.7$ (**d**) $\mu = 0.9$

Figure 6. Preference alignment between the platform and the creator under heterogeneous AI learning effectiveness. The AI value-sharing parameter μ takes values of 0.3, 0.5, 0.7, and 0.9 in panels (**a**), (**b**), (**c**), and (**d**), respectively. (The fixed parameters are $Q = 0.1$, $t = 1$, $\rho = 0.6$, and $\lambda_P = 0.5$. The shaded regions indicate the regimes preferred by both the platform and the creator. The white regions indicate preference disagreement.).

AI value sharing further influences the conditions under which the preferences of the two parties align. As shown in Figure 6a–c, increasing μ from 0.3 to 0.7 substantially expands the region in which both parties prefer regime P, while reducing the white regions representing preference disagreement. Greater AI value sharing allows the creator to capture more AI-generated revenue under regime P, thereby strengthening its preference for platform provision. When μ increases further to 0.9, however, the preference-alignment region for regime P no longer expands appreciably, and preference disagreement increases, as illustrated in Figure 6d. Although greater value sharing improves the creator's returns from AI-generated content, it also reduces the AI-generated revenue directly retained by the platform, potentially creating divergent regime preferences. Thus, AI value sharing can promote preference alignment, but its effect is not necessarily monotonic.

6.3. AI Provision Cost

The supply of AI-generated content entails costs associated with model access, technical configuration, and system operation and maintenance [34]. Because these costs are borne by different parties under alternative AI provision regimes, they may affect the creator's payoff, the platform's profit, and their respective regime preferences. Specifically, model configuration and system integration involve upfront expenditures, whereas certain licensing and computing-capacity charges are based on service periods or reserved capacity. For a given technical configuration and service capacity, such expenditures do not directly vary with content-viewing demand [34,35]. Accordingly, let $c_P \geq 0$ denote the AI provision cost borne by the platform under regime P, and let $c_C \geq 0$ denote the corresponding cost borne by the creator under regime C. These costs are independent of the creator's quality investment and consumer demand. Denote the platform's net profit and the creator's net payoff, after accounting for AI provision costs, by $\tilde{\Pi}^r$ and $\tilde{U}_H^r$, respectively, where $r \in \{P,C\}$. The payoff functions become $\tilde{U}_H^P = (1-\rho)\left(q_H^P D_H^P + \mu q_A^P D_A^P\right) - \frac{\left(q_H^P\right)^2}{2}$, $\tilde{\Pi}^P = \rho q_H^P D_H^P + [1-(1-\rho)\mu] q_A^P D_A^P - c_P$, $\tilde{U}_H^C = (1-\rho)\left(q_H^C D_H^C + q_A^C D_A^C\right) - \frac{\left(q_H^C\right)^2}{2} - c_C$, $\tilde{\Pi}^C = \rho\left(q_H^C D_H^C + q_A^C D_A^C\right)$. Because AI provision costs do not affect the marginal return to the creator's investment in human-generated content quality, equilibrium human-generated content quality remains unchanged under either regime.

AI provision costs nevertheless affect the comparison of the platform's and the creator's net payoffs. Let Π^{r^*} and U_H^{r*} denote the equilibrium profit and payoff, respectively, under regime r in the baseline model. The platform prefers regime P to regime C, and the creator prefers regime C to regime P, when the following respective conditions hold: $\Pi^{P*} - \Pi^{C*} > c_P$ and $U_H^{C*} - U_H^{P*} > c_C$. Thus, even if regime P yields a higher platform profit before AI provision costs, its advantage may be insufficient to cover c_P, making regime C more attractive to the platform. Similarly, if c_C exceeds the creator's original payoff advantage under regime C, the creator may instead prefer regime P. Because the costs are borne by different parties, they may also alter the alignment of the platform's and the creator's regime preferences. Relative to the no-AI regime N, c_P reduces the platform's net payoff advantage under regime P, while c_C reduces the creator's net payoff advantage under regime C. Hence, although these costs leave equilibrium content quality unchanged within each AI provision regime, they can affect payoff comparisons and the attractiveness of AI adoption.

7. Conclusions

The rapid development of generative AI has introduced new challenges for content provision on creator platforms. This study examines whether generative AI should be provided by the platform or by individual creators. We develop a game-theoretic model with a platform, a creator, and consumers and consider three regimes: no AI, platform provision, and creator provision. We characterize the equilibrium outcomes under the three regimes and compare how the two AI provision modes affect human-generated content quality, AI-generated content quality, and the payoffs of the creator and the platform. We further compare both AI provision regimes with the no-AI benchmark to identify when the creator and the platform prefer the same regime.

Our analysis yields four main findings. First, creator provision does not necessarily induce higher human-generated content quality. Platform provision can generate stronger human-content investment when AI learning effectiveness lies within an appropriate range and the pooled-data advantage is limited. As the pooled-data advantage becomes stronger, creator provision becomes more likely to sustain higher human-generated content quality. However, the effect of the pooled-data advantage on AI quality depends on its direct capability gain and the indirect effect of reduced human-content investment. Even when

creator provision induces higher human-generated content quality, platform provision can still generate higher AI quality if its pooled-data advantage is sufficiently strong. Second, the creator's preference between the two AI provision modes depends on the balance between the capability gain from data pooling and her share of AI-generated value. Greater AI value sharing may encourage or discourage human-content investment, while its effects on regime preferences and preference alignment depend on market conditions. Thus, the provision mode preferred by the creator need not be the one that better sustains human-content investment. Third, introducing AI is not always preferred by both the creator and the platform. Our numerical analysis further indicates that preference alignment between the two parties varies with the pooled-data advantage, AI learning effectiveness, AI value sharing, and market conditions. Fourth, under partial market coverage, a stronger pooled-data advantage can increase human-content investment when AI value sharing is positive. Furthermore, when AI learning effectiveness differs across provision modes, the platform's pooled-data advantage can compensate for lower learning effectiveness, affecting human-content quality and regime preferences.

These findings have several implications for creator platforms. The choice of AI provision mode should account not only for the technological advantage associated with broader data access, but also for how the provision mode changes creators' incentives to invest in human-generated content. A strong pooled-data advantage can support platform provision even when creator provision generates higher human-content quality, because the additional capability from data pooling can compensate for weaker creator investment. Value sharing should also be considered jointly with AI provision. Allocating a larger share of AI-generated value to creators can make platform provision more attractive to them, but this does not imply that human-content investment will increase accordingly. Platforms seeking to preserve high-quality human content should therefore distinguish between aligning creator preferences and strengthening creator quality incentives. More generally, the appropriate provision mode depends on whether AI capability is driven primarily by platform-level data pooling or by learning from creator-specific content. In practice, implementing AI provision modes may also involve considerations of creator consent and opt-out options for AI training, as well as the labeling of AI-generated content.

Several extensions could further develop this framework. First, future research could introduce heterogeneous creators who differ in content quality, creative capability, or the value of their content for AI learning and examine how competition among creators affects AI provision. Second, the AI value-sharing parameter is exogenous in the current model. Endogenizing value sharing, training-data compensation, or AI service pricing would allow the platform to jointly design the provision mode and the associated contractual terms. Third, a dynamic model could capture the accumulation of human-generated content over time, continued AI learning, and repeated creator investment or participation decisions.

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Appendix A

Proof of Lemma 1. Under regime P, the interior demands are $D_H^P = \frac{t-Q-b+(1-\lambda)q_H^P}{2t}$, and $D_A^P = \frac{t+Q+b-(1-\lambda)q_H^P}{2t}$. The creator chooses $q_H^P > 0$ to maximize $U_H^P = (1-\rho)\left[q_H^P D_H^P + \mu q_A^P D_A^P\right] - \frac{\left(q_H^P\right)^2}{2}$. Let $\Gamma_P = t - (1-\rho)(1-\lambda)(1-\mu\lambda)$, $\Phi_P = t(1+\mu\lambda) - (Q+b)(1+\mu-2\mu\lambda)$. Differentiating gives $\frac{\partial U_H^P}{\partial q_H^P} = \frac{(1-\rho)\Phi_P - 2\Gamma_P q}{2t}$, and $\frac{\partial^2 U_H^P}{\partial \left(q_H^P\right)^2} = -\frac{\Gamma_P}{t}$. If $t > (1-\rho)(1-\lambda)(1-\mu\lambda)$, then U_H^P is concave. The first-order condition yields $q_H^{P\star} = \frac{(1-\rho)\Phi_P}{2\Gamma_P}$, $q_A^{P\star} = Q + b + \frac{\lambda(1-\rho)\Phi_P}{2\Gamma_P}$. When $t > \frac{(Q+b)[1+\mu(1-2\lambda)]}{(1+\lambda\mu)}$, $q_H^{P\star} > 0$. The corresponding equilibrium demands are $D_H^{P\star} = \frac{2\Gamma_P(t-Q-b)+(1-\rho)(1-\lambda)\Phi_P}{4t\Gamma_P}$, $D_A^{P\star} = \frac{2\Gamma_P(t+Q+b)-(1-\rho)(1-\lambda)\Phi_P}{4t\Gamma_P}$. Substituting the optimal quality into the payoffs yields $U_H^{P\star} = \frac{(1-\rho)\mu(Q+b)(t+Q+b)}{2t} + \frac{(1-\rho)^2\Phi_P^2}{8t\Gamma_P}$ and

$$\Pi^{P*} = \frac{+[1-(1-\rho)\mu][2(Q+b)\Gamma_P + \lambda(1-\rho)\Phi_P][2\Gamma_P(t+Q+b) - (1-\rho)(1-\lambda)\Phi_P]}{8t\Gamma_P^2}.$$

To verify global optimality, consider the creator's payoff outside the interior-demand region. The two quality cutoffs are $q_L^P = \frac{Q+b-t}{1-\lambda}$, $q_U^P = \frac{Q+b+t}{1-\lambda}$. When $q_H^P \le q_L^P$, only AI-generated content has positive demand; when $q_H^P \ge q_U^P$, only human-generated content has positive demand. The corresponding creator payoffs are $U_{H,\mathrm{AI}}^P\left(q_H^P\right) = (1-\rho)\mu\left(Q+b+\lambda q_H^P\right) - \frac{\left(q_H^P\right)^2}{2}$, $U_{H,\mathrm{H}}^P\left(q_H^P\right) = (1-\rho)q_H^P - \frac{\left(q_H^P\right)^2}{2}$. These payoffs are continuous at the applicable cutoffs, and both have second derivative -1. At q_L^P, the difference between the right- and left-hand derivatives is $\left[\frac{\partial U_H^P}{\partial q_H^P} - \frac{\partial U_{H,\mathrm{AI}}^P}{\partial q_H^P}\right]_{q_H^P = q_L^P} = \frac{(1-\rho)[(Q+b)(1-\mu)-t(1-\mu\lambda)]}{2t} \le 0$, where the inequality follows from $t > \frac{(Q+b)(1-\mu)}{1-\mu\lambda}$. At q_U^P, $\left[\frac{\partial U_{H,\mathrm{H}}^P}{\partial q_H^P} - \frac{\partial U_H^P}{\partial q_H^P}\right]_{q_H^P = q_U^P} = -\frac{(1-\rho)[(Q+b)(1-\mu)+t(1-\mu\lambda)]}{2t} < 0$. Hence, the full payoff function is continuous, strictly concave within each demand region, and has no upward jump in its derivative at either cutoff. It is therefore strictly concave over $q_H^P > 0$. Since $q_H^{P\star}$ satisfies the first-order condition and lies in the interior-demand region, it is the unique global maximizer. □

Proof of Lemma 2. Under regime C, $q_A^C = Q + \lambda q_H^C$, and the interior demands are $D_H^C = \frac{t-Q+(1-\lambda)q_H^C}{2t}$ and $D_A^C = \frac{t+Q-(1-\lambda)q_H^C}{2t}$. The creator chooses $q_H^C > 0$ to maximize $U_H^C = (1-\rho)\left[q_H^C D_H^C + q_A^C D_A^C\right] - \frac{\left(q_H^C\right)^2}{2}$. Let $\Gamma_C = t - (1-\rho)(1-\lambda)^2$ and $\Phi_C = t(1+\lambda) - 2Q(1-\lambda)$. The first- and second-order derivatives are $\frac{\partial U_H^C}{\partial q_H^C} = \frac{(1-\rho)\Phi_C - 2\Gamma_C q_H^C}{2t}$, $\frac{\partial^2 U_H^C}{\partial \left(q_H^C\right)^2} = -\frac{\Gamma_C}{t}$. Thus, if $t > (1-\rho)(1-\lambda)^2$, then U_H^C is concave. The first-order condition gives $q_H^{C\star} = \frac{(1-\rho)\Phi_C}{2\Gamma_C}$, $q_A^{C\star} = Q + \frac{\lambda(1-\rho)\Phi_C}{2\Gamma_C}$. When $t > \frac{2(1-\lambda)Q}{(1+\lambda)}$, $q_H^{C\star} > 0$. The corresponding demands and the creator's equilibrium payoff are $D_H^{C\star} = \frac{2\Gamma_C(t-Q)+(1-\rho)(1-\lambda)\Phi_C}{4t\Gamma_C}$, $D_A^{C\star} = \frac{2\Gamma_C(t+Q)-(1-\rho)(1-\lambda)\Phi_C}{4t\Gamma_C}$, and $U_H^{C\star} = \frac{(1-\rho)Q(t+Q)}{2t} + \frac{(1-\rho)^2\Phi_C^2}{8t\Gamma_C}$. The platform's profit is $\Pi^{C*} = \frac{\rho Q(Q+t)}{2t} + \frac{\rho(1-\rho)(\Gamma_C+t)\Phi_C^2}{8t\Gamma_C^2}$.

For global optimality, the quality cutoffs are $q_L^C = \frac{Q-t}{1-\lambda}$, and $q_U^C = \frac{Q+t}{1-\lambda}$. The creator's payoffs in the AI-only and human-only regions are $U_{H,AI}^C\left(q_H^C\right) = (1-\rho)\left(Q+\lambda q_H^C\right) - \frac{\left(q_H^C\right)^2}{2}$ and $U_{H,H}^C\left(q_H^C\right) = (1-\rho)q_H^C - \frac{\left(q_H^C\right)^2}{2}$, respectively. All three payoff branches are continuous and strictly concave in their respective regions. At the cutoffs, the right-minus-left derivative differences are $\left[\frac{\partial U_H^C}{\partial q_H^C} - \frac{\partial U_{H,\mathrm{AI}}^C}{\partial q_H^C}\right]_{q_H^C = q_L^C} = -\frac{(1-\rho)(1-\lambda)}{2} < 0$, and $\left[\frac{\partial U_{H,\mathrm{H}}^C}{\partial q_H^C} - \frac{\partial U_H^C}{\partial q_H^C}\right]_{q_H^C = q_U^C} = -\frac{(1-\rho)(1-\lambda)}{2} < 0$. Thus, the creator's payoff is strictly concave over $q_H^C > 0$. The interior

stationary point $q_H^{C\star}$ is consequently the unique global maximizer, without an additional restriction for regime C. □

Proof of Proposition 1. $q_H^{P*} - q_H^{C*} = \frac{1-\rho}{2\Gamma_P\Gamma_C} F_H(b,\lambda)$, where $F_H(b,\lambda) = (1-\mu)\Xi_H - (1+\mu-2\mu\lambda)b\Gamma_C$, and $\Xi_H = -A_H\lambda^2 + B_H\lambda + C_H$, with $A_H = (1-\rho)(Q+2t) > 0$, $B_H = 2Q(1-\rho-t) + t[2(1-\rho)-t]$, $C_H = Q[t-(1-\rho)]$. □

Since $\Gamma_P > 0$, $\Gamma_C > 0$, and $1+\mu-2\mu\lambda \geq 1-\mu > 0$, $F_H(b,\lambda)$ is strictly decreasing in b. Hence, $F_H(b,\lambda) > 0$ for some feasible $b \geq 0$ only if $\Xi_H > 0$. Let $\Delta_H = B_H^2 + 4A_HC_H$, and, when $\Delta_H > 0$, define $\underline{\lambda}_H = \max\left\{0, \frac{B_H - \sqrt{\Delta_H}}{2A_H}\right\}$, $\bar{\lambda}_H = \min\left\{1, \frac{B_H+\sqrt{\Delta_H}}{2A_H}\right\}$. Because $A_H > 0$, $\Xi_H > 0 \Leftrightarrow \underline{\lambda}_H < \lambda < \bar{\lambda}_H$ whenever this interval is nonempty. Under this condition, solving $F_H(b,\lambda) > 0$ for b gives $b < \frac{(1-\mu)\Xi_H}{(1+\mu-2\mu\lambda)\Gamma_C} \equiv \bar{b}_H$. Therefore, $q_H^{P*} > q_H^{C*} \Leftrightarrow \underline{\lambda}_H < \lambda < \bar{\lambda}_H$ and $b < \bar{b}_H$. Otherwise, $q_H^{P*} \leq q_H^{C*}$. □

Proof of Corollary 1. $\frac{\partial \bar{b}_H}{\partial \mu} = -\frac{2(1-\lambda)\Xi_H}{\Gamma_C(1+\mu-2\mu\lambda)^2} < 0$. □

Proof of Remark. The difference between AI-content quality under the two regimes is $q_A^{P*} - q_A^{C*} = b + \lambda(q_H^{P*} - q_H^{C*})$. When $q_H^{P*} > q_H^{C*}$, $q_A^{P*} > q_A^{C*}$. When $q_H^{P*} < q_H^{C*}$, we have $q_A^{P*} > q_A^{C*} \iff b > \lambda(q_H^{C*} - q_H^{P*})$. □

Proof of Proposition 2. Define $\Phi_P^0 = t(1+\mu\lambda) - Q(1+\mu-2\mu\lambda)$. $U_H^{P*} - U_H^{C*} = \frac{(1-\rho)(A_2b^2+A_1b+A_0)}{8t\Gamma_P\Gamma_C}$, where $A_2 = \Gamma_C[4\mu t + (1-\rho)(1-\mu)^2] > 0$, $A_1 = 2\Gamma_C[2\mu\Gamma_P(2Q+t) - (1-\rho)(1+\mu-2\mu\lambda)\Phi_P^0]$, $A_0 = -4(1-\mu)Q(Q+t)\Gamma_P\Gamma_C + (1-\rho)\left[\Gamma_C\left(\Phi_P^0\right)^2 - \Gamma_P\Phi_C^2\right]$.

At $b = 0$, the two regimes have the same AI-quality technology, $q_A^P = q_A^C = Q + \lambda q_H$, and hence the same demands for any common q_H. Under the maintained interiority conditions and $\mu < 1$, we have $U_H^C(q_H;0) - U_H^P(q_H;0) = (1-\rho)(1-\mu)q_AD_A > 0$. Evaluating this inequality at $q_H^{P\star}(0)$ yields $U_H^C(q_H^{P\star}(0);0) > U_H^P(q_H^{P\star}(0);0) = U_H^{P*}(0)$. Since $q_H^{P\star}(0)$ is also feasible under regime C, $U_H^{C*}(0) \geq U_H^C(q_H^{P\star}(0);0) > U_H^{P*}(0)$. Since $U_H^{P*}(0) - U_H^{C*}(0) = \frac{1-\rho}{8t\Gamma_P\Gamma_C}A_0$ and the prefactor is positive, $A_0 < 0$.

Because $A_2 > 0$ and $A_0 < 0$, $\mathcal{D}_U > A_1^2 \geq 0$. Hence, $A_2b^2 + A_1b + A_0$ has two distinct real roots. Since $\frac{A_0}{A_2} < 0$, the two real roots have opposite signs. Hence its unique positive root is $\bar{b}_U = \frac{-A_1+\sqrt{A_1^2-4A_2A_0}}{2A_2} > 0$. Since the quadratic opens upward, for feasible interior equilibria, $U_H^{P*} \leq U_H^{C*}$ if $b \leq \bar{b}_U$, and $U_H^{P*} > U_H^{C*}$ if $b > \bar{b}_U$. □

Appendix B

The common partial coverage region is specified by

$$\begin{aligned} t &> 2(1-\rho)(1+\lambda^2), \\ 2v+Q+b &+ \tfrac{(1+\lambda)(1-\rho)[v+\mu\lambda(v+2Q+2b)]}{t-2(1-\rho)(1+\mu\lambda^2)} < t, \\ 2v+Q &+ \tfrac{(1+\lambda)(1-\rho)[(1+\lambda)v+2\lambda Q]}{t-2(1-\rho)(1+\lambda^2)} < t. \end{aligned} \tag{B.1}$$

The first inequality makes the denominators in Table 2 positive. The next two inequalities are exactly $2v + q_H^{P*} + q_A^{P*} < t$ and $2v + q_H^{C*} + q_A^{C*} < t$ after substitution of the equilibrium qualities. They imply $Q + b < t$ and $Q < t$.

For either AI regime, partial coverage occurs when $2v + q_H^r + q_A^r < t$. Consumers choosing AI occupy $\left[0, (v+q_A^r)/t\right]$, while those choosing human content occupy $\left[1-(v+q_H^r)/t, 1\right]$. The intervals are disjoint, and consumers between them choose the outside option. Uniform demand gives

$$D_H^r = \frac{v+q_H^r}{t}, \qquad D_A^r = \frac{v+q_A^r}{t}, \qquad D_0^r = 1 - \frac{2v+q_H^r+q_A^r}{t} > 0. \tag{B.2}$$

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Under N, $D_H^N = \min\{1, (v + q_H^N)/t\}$ and $D_0^N = 1 - D_H^N$. To verify that the N candidate also has partial coverage, note from Table 2 that $q_H^{C*} > q_H^{N*}$: its numerator is larger and its positive denominator is smaller. Therefore, $v + q_H^{N*} < 2v + q_H^{C*} + q_A^{C*} < t$.

Substituting (B.2) and the quality technologies into the original creator payoffs gives

$$\begin{aligned} U_H^N &= \tfrac{(1-\rho)q_H^N(v+q_H^N)}{t} - \tfrac{(q_H^N)^2}{2}, \\ U_H^P &= \tfrac{(1-\rho)q_H^P(v+q_H^P)}{t} - \tfrac{(q_H^P)^2}{2} \\ &\quad + \tfrac{(1-\rho)\mu(Q+b+\lambda q_H^P)(v+Q+b+\lambda q_H^P)}{t}, \\ U_H^C &= \tfrac{(1-\rho)q_H^C(v+q_H^C)}{t} - \tfrac{(q_H^C)^2}{2} \\ &\quad + \tfrac{(1-\rho)(Q+\lambda q_H^C)(v+Q+\lambda q_H^C)}{t}. \end{aligned} \tag{B.3}$$

Their derivatives satisfy

$$\begin{aligned} t\tfrac{\partial U_H^N}{\partial q_H^N} &= (1-\rho)v - [t - 2(1-\rho)]q_H^N, \\ t\tfrac{\partial U_H^P}{\partial q_H^P} &= (1-\rho)[v + \mu\lambda(v + 2Q + 2b)] \\ &\quad -[t - 2(1-\rho)(1+\mu\lambda^2)]q_H^P, \\ t\tfrac{\partial U_H^C}{\partial q_H^C} &= (1-\rho)[(1+\lambda)v + 2\lambda Q] \\ &\quad -[t - 2(1-\rho)(1+\lambda^2)]q_H^C. \end{aligned} \tag{B.4}$$

Under (B.1), each payoff is strictly concave in its quality choice. Setting the derivatives to zero gives the human qualities in Table 2, and the AI qualities follow from the technologies. Completing the square in (B.3) gives the optimized creator payoffs shown in the table. The platform profits follow by evaluating the original profit functions at these qualities and demands. In particular, $\Pi^{N*} = \rho q_H^{N*}(v + q_H^{N*})/t$, which gives the parameter expression in the N row.

The condition $t > 2(1-\rho)(1+\lambda^2)$ is necessary for a strictly partial-coverage optimum under regime C. Otherwise, the last derivative in (B.4) is strictly positive for all $q_H^C \geq 0$. This condition therefore identifies a coverage state that can arise in equilibrium.

The candidates in Table 2 remain optimal when quality choices can change the coverage state. Under regime N, the candidate lies below $t - v$. At $q_H^N = t - v$, the derivative falls by $(1-\rho)(t-v)/t$ as demand reaches one; it then decreases with slope -1. The payoff therefore remains decreasing beyond this boundary.

For regimes P and C, $Q + b < t$ and $Q < t$ rule out AI-only demand intervals. Once $2v + q_H^r + q_A^r = t$, the market becomes fully covered. While both types receive demand,

$$D_H^r = \frac{t + q_H^r - q_A^r}{2t}, \qquad D_A^r = 1 - D_H^r, \qquad r = P, C. \tag{B.5}$$

At the transition, the derivative of U_H^P falls by $(1-\rho)(1+\lambda)(q_H^P + \mu q_A^P)/(2t) > 0$, and the derivative of U_H^C falls by $(1-\rho)(1+\lambda)(q_H^C + q_A^C)/(2t) > 0$. These changes follow by differentiating the original creator payoffs using (B.2) and (B.5) on the two sides of the boundary. The derivatives are already negative there because the candidates lie strictly inside partial coverage. Under covered coexistence, the second derivatives are

$$\begin{aligned} \tfrac{\partial^2 U_H^P}{\partial (q_H^P)^2} &= -\tfrac{t-(1-\rho)(1-\lambda)(1-\mu\lambda)}{t} < 0, \\ \tfrac{\partial^2 U_H^C}{\partial (q_H^C)^2} &= -\tfrac{t-(1-\rho)(1-\lambda)^2}{t} < 0. \end{aligned} \tag{B.6}$$

Payoffs decrease under covered coexistence. Human-only demand starts at $q_H^P = (Q + b + t)/(1-\lambda)$ under regime P and at $q_H^C = (Q + t)/(1-\lambda)$ under regime C. Both exceed $t > 1 - \rho$. Beyond them, $\partial U_H^r/\partial q_H^r = 1 - \rho - q_H^r < 0$. Continuity at the transitions therefore establishes the equilibria in Table 2. □

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