Infinite Scroll: Addiction by Design in Information Platforms

Hemant K. Bhargava,[*]

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Abstract

Digital platforms, particularly those focused on information dissemination, have been criticized for their social and economic dominance, as well as for amplifying harmful information and fostering addictive behaviors. Such platforms predominantly use indirect business models where user attention and engagement are raw materials to be monetized through advertising or the sale of personal data. In this paper we examine the extent to which attention-driven platforms prioritize content investment vs. addictive design as drivers for user engagement. We then compare competition between a free platform that relies on these monetization models and a hypothetical "for-fee" platform that prioritizes user well-being and is funded through user fees. Our analysis reveals that the for-fee platform can compete with the free platform under standard conditions, but it faces significant challenges when network effects drive users' utility. The paper proposes a potential solution to this problem by introducing an engagement tax that recirculates revenue collected from the free platform into subsidies for the for-fee platform's subscription fees. This solution could potentially incentivize users to switch to the for-fee platform while still ensuring that the free platform can continue to operate. The findings could have significant implications for policymakers, platform operators, and users, as they navigate the complex landscape of digital platforms and their impact on society. By shedding light on the economics of digital addiction, this paper contributes to a more nuanced understanding of the trade-offs involved in the design and operation of digital platforms.

[*]Graduate School of Management University of California Davis

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1 Introduction

There is broad concern in society today about the deleterious effects of digital platforms on account of their reach, financial prowess, extensive data collection, and deep influence (Lehdonvirta, 2022; Moore & Tambini, 2018; Zuboff, 2015). These concerns affect several types of platforms: those that enable innovation ecosystems around products (e.g., Apple's iOS and Google's Android), those used for commerce and shopping (e.g., Amazon), and those that control how information is disseminated and propagated across populations today. This last category includes social communication platforms like Facebook and Twitter, and crowd-sourced content and entertainment platforms like YouTube, Instagram and Tik Tok. For convenience in exposition, we shall refer to these "information propagation platforms" as IPPs, because these platforms' algorithms influence how people receive, consume, process, and share information. They are also considered addictive, with users indulging in excessive and compulsive use that interferes with daily life activities, such as work, relationships, and physical health, and considered a threat to human cognition (Rosenquist et al., 2021). For instance, data from the Pew Research Center shows that in 2021, over 70% of Americans used mobile devices and social media, with the average American spending over hours per day. This article examines how the revenue strategy of IPPs influences their design features that promote user addiction, analyzes the extent to which competition mitigates negative effects, and offers an economic intervention for improving design outcomes.

Part responsibility for digital addiction lies on users' lack of self-control against huge content and recommendation algorithms (Allcott et al., 2022), reliance on social media for affirmation and validation (Andreassen et al., 2016), a fear of missing out (FOMO) or a craving for dopamine release (Kuss & Griffiths, 2017). Humans have underlying limitations such as "negativity biases" which make negative information more attractive and more contagious than positive information

(Rozin & Royzman, 2001). Common examples are stories, images, or videos about racism, death threats, bullying, suicide or assisting suicide, violence, genocide, vaccine skepticism, flat earth, conspiracy theories, etc. Not only are many people drawn to sensational, hyperbolic, and extreme content that is visibly fake, but technologies such as photoshopping, deepfake videos, and AI-generated content, can inexpensively generate content that has a veneer of authenticity.

Substantial blame for digital addiction is also placed on platforms for deliberate design choices that promote addiction, and for exploiting—and possibly even amplifying or manufacturing—human cognitive weaknesses. Digital platforms are populated by smart and talented technology professionals, powered by massive amounts of data and sophistical algorithms, and are financially flourishing. They possess technological and financial capabilities for countering addictiveness, detecting fake accounts and bots and harmful content, and reducing kinds of content that bind users to their devices and social media. Platforms can tune their technical and governance dials to limit such content and its propagation. It is their strategic design *choice* whether or not (or how hard) to do so. *Addictiveness* in platform design represents its choices in content, algorithms or user interface designs, that exploit users' self-control problems and emphasize prolonged engagement or attention over quality, user well-being or welfare (Ichihashi & Kim, 2022).

Many researchers argue that IPPs choose to be addictive, taking deliberate actions to exploit users' cognitive limitations and help harmful content flourish in order to prolong usage (Bhargava & Velasquez, 2021; Hari, 2022; Montag et al., 2019; Rosenquist et al., 2021). Reflecting the idea "if it [content] is enraging, it is engaging," their algorithms promote content that titillates, shocks, enrages, divides, or is harmful yet not illegal, with the goal of getting users to open their device as often as possible and to scroll as long as possible (Hari, 2022). A plausible reason is that platforms employ attention-driven revenue models rather than charge users, turning them into the "product" that advertisers seek. These models drive platforms to not only host harmful information, but to deliberately seek such content and rapidly amplify it, with algorithms that actively exploit humans' limitations. Paraphrasing Edward Tufte in the *Netflix* documentary "The Social Dilemma," IPPs (and software, generally) stand only with the illegal drug industry in referring to their customers as "users."

Does the use of an advertising-driven revenue model necessarily drive platforms to adopt aggressive addictive designs? For many social scientists, addictiveness is an axiomatic choice for attention-driven platforms: their reliance on advertising or data monetization places them in the business of harvesting attention (Hari, 2022).[1] Borwankar et al. (2022)'s work supports this view, finding that Twitter's Birdwatch program, which implemented "crowdsourced" monitoring and controls, hurt Twitter's advertising revenues, because deleted posts led to less engagement and less production. A counterpoint to this belief is in Liu et al. (2022)'s finding, based on a theoretical model of monetization, that pressure from advertisers is a stronger force for investment in content moderation technology than user subscription fees. Zhang et al. (2022) empirically evaluate social media platforms' content-moderation tactics such as restricting or banning content from certain mal-participants, or glorifying desirable ones. Some platforms such as Twitter and Meta have tried to link account authenticity to user payments (for verification badges), but with mixed results, including a temporary fiasco with Twitter's experiment in 2022.[2].

The interplay between design for addictiveness and platform monetization models leads to several interesting questions. In markets dominated by attention-based business models, how would market entry by a "benign" fee-based platform, which sacrifices addictive design in return for user fees, change design choices of attention-based platforms? Alternately, if a content market initially had firms that chose fee-based business models, what is the impact of market entry by a platform that offers free service in exchange for attention-based monetization? Further, if platforms competed with alternate business models, could a benign but fee-based platform offer formidable competition to a free, but addictive and manipulative, platform? Data privacy is cited as a positive

[1] See also *Center for Humane Technology, https://www.humanetech.com/key-issues*

[2] Switching to payment, vs. organic validation, for a blue check led to a flood of fake accounts and posts, with significant losses to investors in the affected impersonated companies such as Lockheed Martin and Eli Lilly. https://www.nbcnews.com/tech/crypto/twitters-subscription-service-not-available-impersonators-flourish-rcna56730

example for competition, where firms with stronger privacy-protection can charge higher prices and capture more quality-sensitive consumers (Elvy, 2017). Could competition produce similar results in IPP markets?

This paper models an IPP's design problem with respect to both direct business models (charging user fees) and *indirect* ones which turn user attention into revenue (e.g., they monetize user eyeballs or data rather than charge usage fees). We show that platforms which rely on indirect monetization adopt overly addictive designs, choosing content, creators, recommendation algorithms, and interface features that prolong user time on the platform. The consequent user harm and potential backlash creates space for an alternative platform which constraints addictiveness in return for charging user fees. We develop an economic model to study how an IPP's design addictiveness is influenced by its revenue model, and the extent to which design extremes can be mitigated by competition. Further, we examine the impact of network effects on the effectiveness of competition, and propose an economic intervention to improve the effects of competition in the presence of network effects.

2 A Model of Addiction by Design

One or more information platforms exist in a market, bringing a bundle of information (social media feeds, news, videos, images, etc.) to consumers. Let $\mathcal{Q}$ represent the magnitude of the bundle, and let $v(\mathcal{Q})$ be the bundle value from a platform user's perspective. This framing of $\mathcal{Q}$ abstracts out the details of content inside the bundle, and avoids any value judgements of what content is more valuable or harmful than the other. Users visit the platform for content, and engage more if there's more or better content, for instance because they value variety or flexibility (Bhargava, 2020). Thus, higher $\mathcal{Q}$ indicates higher value. Without loss of generality, we use the identity function to set $v(\mathcal{Q}) = \mathcal{Q}$. The model is built around the following crucial concepts summarized in Table 1 and elaborated on in this section. The aim is to set up a model which is suitable with respect to the key research questions, hence should cover three analysis scenarios: i) a monopoly IPP (with either fee-based or attention-based monetization) and its level of investment in content, ii) competition between platforms with the two revenue models, and iii) IPPs with network effects.

Platform's Decision Variables	$\mathcal{Q}$	measure of users' value from content (quality and quantity)
	a	degree of aggressiveness in designing for addiction when users engage with content.
User Attitudes	κ	societal propensity for addictive design, the fraction of users who engage more as a increases.
	δ	societal distaste for addictive design, rate at which engagement (among the $1-\kappa$ fraction) dissipates as a increases.
Monetization	μ	strength of demand for attention (ability to monetize attention)
	λ	difficulty in leveraging higher a into higher monetization of unit attention, e.g., platform's algorithms and laws related to data and advertising.
	c	cost of acquiring content to monetize

Table 1: Summary of key elements in model.

2.1 Addictive Design and User Attitudes

Platforms make technological and other design choices that govern what information is presented or promoted to users, and also the feedback users receive about their actions. Given content $\mathcal{Q}$, a platform can manipulate user engagement with $\mathcal{Q}$ through its user management, content moderation policies, and content steering algorithms. Let the strategic design variable a represent technical features, discovery and steering mechanisms, or other interventions that the platform can do, or not do, that promote greater engagement at the cost of user well-being and health. One example is adoption of filters for deepfake videos, prevention of fake accounts and misinformation, and promotion of sensational acts and violence. Another example is feedback mechanisms embedded in platforms (such as "like" buttons, or email alerts about when someone engages with a user's content), which aim to exploit users' craving for validation. Benign designs that improve both user engagement and welfare pose no strategic tension with respect to our research focus. Instead, our conceptualizaton and measurement of addiction starts at the point where such tension occurs, involving manipulative designs that seek greater engagement and addiction at the cost of well-being, truth, or normalcy. Therefore, our operationalization of $\mathbf{a}$ and its "zero point" is that increasing $\mathbf{a}$ for $\mathbf{a} < 0$ is beneficial, but that increasing $\mathbf{a}$ for $\mathbf{a} > 0$ causes at least some users to consider the design harmful, although other users might then engage more.

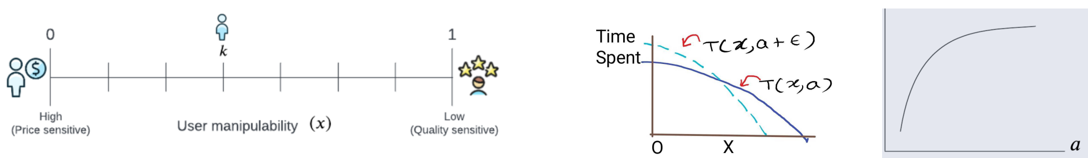


Figure 1: Heterogeneous user attitudes towards platform's addiction design (those to the left of κ prefer higher $\mathbf{a}$, those to the right prefer lower $\mathbf{a}$), and effect on engagement and per-user monetization.

Individual users' characteristics affect how they respond to a platform's addictiveness design. Users may be heterogeneous in such attitude, desiring or tolerating different levels of extremity. This is the feature the model shares with Liu et al. (2022). Going beyond users' participation decision, the model allows for heterogeneity in how design affects their level of engagement. Some users are seduced by higher $\mathbf{a}$ into spending more time on the platform (even if, perhaps, it causes them long-term harm), while others are put off and reduce time spent or (at the margin) even abandon the platform. Let the index variable x capture user attitude to platform design, specifically their vulnerability to manipulation by the platform (see the left panel). It is normalized as $x \in [0, 1]$. $U(x, \mathbf{a}, \mathcal{Q})$ denotes user x's utility for platform with addictiveness $\mathbf{a}$, while $T(x, \mathbf{a}, \mathcal{Q})$ represents engagement level (middle panel). Low x (close to 0) represents inclination towards addictive content and vulnerability to addictive design, whereas higher x indicates strong preference for quality and aversion to extreme content or addictive design. In the middle are users with moderate responsiveness, with κ being the user who is indifferent (i.e., has constant utility for given $\mathcal{Q}$ regardless of $\mathbf{a}$). Thus, users in $[0, \kappa]$ increase their engagement when the platform increases $\mathbf{a}$, while those in $(\kappa, 1]$ $[0, \kappa]$ reduce it (the x=1 user has the highest drop). Collectively, these requirements capture the tradeoff inherent in a platform's choice of $\mathbf{a}$: a more addictive design leads to greater engagement and monetization (see the right panel), but risks a reduction in platform demand. The requirements are formalized below, and captured in Fig. 1.

Requirement 1. Users' attitudes towards content $\mathcal{Q}$ and addictive design $\mathbf{a}$ satisfy the following.

1. More content increases user utility (i.e., $\frac{\partial U(x,\mathbf{a},\mathcal{Q})}{\partial \mathcal{Q}} > 0$) and platform demand ($\frac{\partial D(\kappa,\mathbf{a},\mathcal{Q})}{\partial \mathcal{Q}} > 0$).
2. Heterogeneous response to addictiveness: higher $\mathbf{a}$ increases utility for a fraction $\kappa \in (0,1)$ of users (i.e., $x \leq \kappa$), and lowers it for the rest ($x > \kappa$). Formally, $\frac{\partial U(x,\mathbf{a},\mathcal{Q})}{\partial \mathbf{a}} > 0$ for $x < \kappa(\mathbf{a})$, and $\frac{\partial U(x,\mathbf{a},\mathcal{Q})}{\partial \mathbf{a}} < 0$ for $x > \kappa(\mathbf{a})$.
3. Increase in addictiveness reduces the platform's user base, $D(\kappa, \mathbf{a}, \mathcal{Q})$: $\frac{\partial D(\kappa,\mathbf{a},\mathcal{Q})}{\partial \mathbf{a}} < 0$.
4. Higher $\mathbf{a}$ increases average (per-user) engagement among remaining users ($\frac{\partial T(x,\mathbf{a})}{\partial \mathbf{a}} > 0$ for $x < \kappa$ and $\frac{\partial T(x,\mathbf{a})}{\partial \mathbf{a}} < 0$ for $x > \kappa$), increasing per-user attention-monetization $m(\kappa, \mathbf{a}, \mathcal{Q})$.

The requirements on user utility are captured by defining $U(x, \mathbf{a}, p) = \mathcal{Q} - \delta\mathbf{a}(x-\kappa) - p$, where p is an access price for the platform (possibly 0), δ measures preference or dislike for higher $\mathbf{a}$, and κ is the indexed user who is indifferent to $\mathbf{a}$. The parameter κ is interpreted as a societal or population-level characteristic, indicating a fraction of the population that lacks self-control or is otherwise predisposed towards addictive design and content. This framing allows for both addictiveness-seeking users (who get higher utility from higher $\mathbf{a}$, ones in $x \in [0, \mathbf{a})$) and addictiveness-averse ones ($x \in (\mathbf{a}, 1]$. This heterogeneous treatment generalizes the view of addictiveness in Ichihashi and Kim (2022), who model utility of a single representative consumer. It similarly goes beyond (Liu et al., 2022) who cover only "extremeness aversion" (albeit with different threshold levels for different users), and no users experience utility gain as the platform becomes more extreme.[3]

2.2 Monetization and Costs

The final requirement on how addictiveness in design affects user engagement motivates the adoption of a per-user monetization function that monetization rate increases with $\mathbf{a}$ but decreases with

[3]We model utility from "content consumption" only, whereas Liu et al. (2022) also cover users' utility from posting content.

the difficulty in exploiting attention (λ). Hence the function must satisfy

$$\frac{\partial m}{\partial \mathbf{a}} > 0, \frac{\partial m}{\partial \mu} > 0, \frac{\partial m}{\partial \lambda} < 0.$$

In the exposition below, we predominantly use the monetization function $m(\mathbf{a}) = \mu\,\mathrm{e}^{\frac{-\lambda}{\mathbf{a}}}$ (see the third panel of Fig. 1), where λ affects how quickly this potential is reached as $\mathbf{a}$ is increased. To examine the interplay between a platform's addictiveness design and content, I assume that achieving content $\mathcal{Q}$ requires a cost $c(\mathcal{Q})$, which can be captured as a convex cost function $c\mathcal{Q}^2$. The model is agnostic to whether the content is "user generated" or sourced from a smaller set of more professional creators. For the platform's decision making, we employ the sequence ($\mathcal{Q} \rightarrow \mathbf{a}$), i.e., that the platform arranges $\mathcal{Q}$ and designs $\mathbf{a}$ with respect to its inventory of $\mathcal{Q}$.

$$m(\mathbf{a}) = \mu\,\mathrm{e}^{\frac{-\lambda}{\mathbf{a}}}; \quad c(\mathcal{Q}) = c\mathcal{Q}^2. \tag{1}$$

2.3 Platform Demand and Competition

I examine the effect of competition by examining the choices of two platforms which have access to identical content $\mathcal{Q}$, but compete for users with sharply different monetization models. Platform $\mathcal{B}$ respects user well-being and health, promoting healthy digital behavior by abjuring addictiveness (sets $\mathbf{a}$ to 0). Its product is an information platform with a responsible and ethical design, for which it charges (and optimizes) users a subscription fee p. Platform $\mathcal{A}$ forfeits user fees, and its product is its users (or user attention) for which it sets $\mathbf{a}$ to maximize revenue from an attention-driven business model.[4] Let $D_{\mathcal{A}} = D_{\mathcal{A}}(\mathbf{a}, p)$ be platform $\mathcal{A}$'s adoption level when it sets design $\mathbf{a}$ while platform $\mathcal{B}$ sets price p; likewise, $D_{\mathcal{B}} = D_{\mathcal{B}}(\mathbf{a}, p)$ is platform $\mathcal{B}$'s demand. While this setup directly captures duopolistic competition between a fee-based high-quality platform vs. a free and attention-driven addictive one, the monopoly demand cases $D_A(\mathbf{a})$ and $D_B(p)$ can be obtained by

[4] A mnemonic: $\mathcal{A}$ is attention-driven, addictive, seeks advertising; $\mathcal{B}$ is better, benign, promotes well-being.

setting the other platform's choice parameters to extreme values that yield it zero adoption. Hence, faced with the two platforms $\mathcal{A}$ and $\mathcal{B}$, user x evaluates the following two utilities

$$U_{\mathcal{A}}(x, \mathbf{a}, p) = \mathcal{Q}_{\mathcal{A}} - \delta\mathbf{a}(x - \mathsf{\kappa}) \tag{2a}$$

$$U_{\mathcal{B}}(x, \mathbf{a}, p) = \mathcal{Q}_{\mathcal{B}} - p. \tag{2b}$$

Resolving $U_{\mathcal{A}}(x, \mathbf{a}, p) = U_{\mathcal{B}}(x, \mathbf{a}, p)$ yields the marginal or indifferent user ($\mathsf{X} = \frac{\mathcal{Q}_{\mathcal{A}} - \mathcal{Q}_{\mathcal{B}} + p}{\delta\mathbf{a}} + \mathsf{\kappa}$) who perceives identical net utility from the two platforms (with the requirement that $U_{\mathcal{A}}(\mathsf{X}, \mathbf{a}, p) = U_{\mathcal{B}}(\mathsf{X}, \mathbf{a}, p) \geq 0$). Further, users in $[0, \mathsf{X}]$ pick $\mathcal{A}$ while those in $[\mathsf{X}, 1]$ pick $\mathcal{B}$. For the fee-based platform $\mathcal{B}$, users' heterogeneity in their adoption decision is driven by how they perceive the outside option, platform $\mathcal{A}$. For platform $\mathcal{A}$ the pursuit of attention-driven monetization presents the following tension: it loses some users as it increases $\mathbf{a}$, but gets higher per-user monetization rate because remaining users engage more. With this framework, the demand and profit functions of the two platforms are

$$D_{\mathcal{A}} = \frac{\mathcal{Q}_{\mathcal{A}} - \mathcal{Q}_{\mathcal{B}} + p}{\delta\mathbf{a}} + \mathsf{\kappa}; \quad D_{\mathcal{B}} = 1 - \frac{\mathcal{Q}_{\mathcal{A}} - \mathcal{Q}_{\mathcal{B}} + p}{\delta\mathbf{a}} - \mathsf{\kappa} \tag{3a}$$

$$\Pi_{\mathcal{A}} = \mu\, \mathrm{e}^{\frac{-\lambda}{\mathbf{a}}} \left(\frac{\mathcal{Q}_{\mathcal{A}} - \mathcal{Q}_{\mathcal{B}} + p}{\delta\mathbf{a}} + \mathsf{\kappa} \right) - c{\mathcal{Q}_{\mathcal{A}}}^2; \quad \Pi_{\mathcal{B}} = p \left(1 - \frac{\mathcal{Q}_{\mathcal{A}} - \mathcal{Q}_{\mathcal{B}} + p}{\delta\mathbf{a}} - \mathsf{\kappa} \right) - c{\mathcal{Q}_{\mathcal{B}}}^2. \tag{3b}$$

With this construction, for platform $\mathcal{A}$, market conditions are more favorable when the market has more addicts (high $\mathsf{\kappa}$) and when there's weak aversion for addictive design among $\mathcal{B}$-type users (low δ), or when λ is low.

3 Analysis

Analysis of design choices by a single platform provides a good starting point, and a comparative benchmark, for examining how competition would affect these choices. In both cases, it is useful to separate the outcomes into the following three regimes and corresponding data scenarios.

3.1 Monopoly Platform

The benchmark case of a monopolist platform $\mathcal{B}$ (i.e., it charges a price p) is set to be a vacuous one, defined for comparative purpose. Here, all users are homogeneous in their content valuation ($U_{\mathcal{B}}(x) = \mathcal{Q}_{\mathcal{B}}$), and the platform can set $p^* = \mathcal{Q}_{\mathcal{B}}$ and capture profit $\mathcal{Q}_{\mathcal{B}}$. Further, after considering the cost of content, it would be optimal to set ${\mathcal{Q}_{\mathcal{B}}}^* = \frac{1}{2c}$.

The comparative benchmark for the design decision of a monopoly platform $\mathcal{A}$ is obtained by setting the missing $\mathcal{B}$'s strategic variable at a level it becomes irrelevant (i.e., $p = \mathcal{Q}$, so that no users are interested in platform $\mathcal{B}$). Then, $U_{\mathcal{A}}(x, \mathbf{a}) = \mathcal{Q}_{\mathcal{A}} - \delta\mathbf{a}(x - \kappa)$, and the platform covers $\mathsf{X} = \frac{\mathcal{Q}}{\delta\mathbf{a}} + \kappa$ share of users if $\mathbf{a} > \frac{\mathcal{Q}}{\delta(1-\kappa)}$ (otherwise $\mathsf{X} = 1$). As with price optimization, if the inverse demand function for attention is strong enough (high $\mathcal{Q}$, low λ, δ), then it is optimal to set $\mathbf{a}$ to cover the whole market, otherwise $\mathbf{a}^*$ is an interior solution with $D_{\mathcal{A}} < 1$ where the platform sets $\mathbf{a}$ so high that some users abandon it even at zero price. The full market coverage level is $\mathbf{a}_{\text{min}} = \frac{\mathcal{Q}}{\delta(1-\kappa)}$, and setting $\mathbf{a}$ lower would simply reduce monetization with no gain in market share. Thus, $\mathbf{a}^*$ is either $\mathbf{a}_{\text{min}}$ (with $D_{\mathcal{A}}$=1) or higher with $D_{\mathcal{A}}$=$\left(\frac{\mathcal{Q}}{\delta\mathbf{a}} + \kappa\right) < 1$. Finally, if distaste for addictive design among the $1-\kappa$ fraction is too high, the platform chooses to forfeit them and then concentrate on the κ fraction of manipulable users and then set $\mathbf{a}$ to the maximum level permitted by legal or other constraints. Lemma 1 states these branches formally.

Lemma 1 (Addictiveness Design for Monopoly Platform)**.** A monopoly platform with attention-based monetization sets

$$\mathbf{a}^* = \begin{cases} \frac{\mathcal{Q}}{\delta(1-\kappa)} & \text{for (a) } \mathcal{Q} \geq \lambda\delta, \quad \text{with } D_{\mathcal{A}} = 1, \quad m(\mathbf{a}, \kappa, \mathcal{Q}) = \mu\, \mathrm{e}^{-\frac{\lambda\delta(1-\kappa)}{\mathcal{Q}}} \\ \frac{\lambda\mathcal{Q}}{(\mathcal{Q}-\lambda\delta\kappa)} & \text{for (b) } \mathcal{Q} \in (\lambda\delta\kappa, \lambda\delta), \quad \text{with } D_{\mathcal{A}} = \frac{\mathcal{Q}}{\lambda\delta} \in (\kappa, 1), \quad m(\mathbf{a}, \kappa, \mathcal{Q}) = \mu\, \mathrm{e}^{-\left(1-\frac{\lambda\delta\kappa}{\mathcal{Q}}\right)} \\ \mathbf{a}_{\text{max}} & \text{for (c) } \mathcal{Q} \leq \lambda\delta\kappa, \quad \text{with } D_{\mathcal{A}} = \kappa + \frac{\mathcal{Q}}{\delta\mathbf{a}_{\text{max}}}, \quad m(\mathbf{a}, \kappa, \mathcal{Q}) = \mu. \end{cases}$$

Does access to better content lead the platform to be less (or more) aggressive in use of addictive design tactics? Lemma 1 provides useful insights, and the effect is depicted in Fig. 2. In

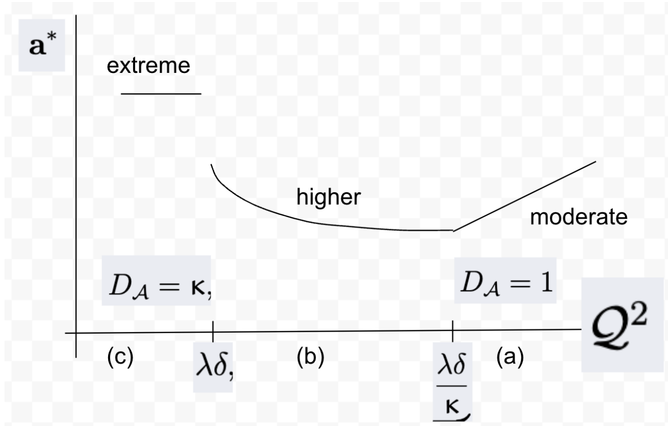


Figure 2: Effect of Content Quality on Degree of Addictive Design

general, the platform's addictiveness design encapsulates a tradeoff between being amenable to more users vs. more intense monetization of the remaining and more manipulable users. A higher $\mathcal{Q}$ or lower δ makes it easier for the platform to attract the more quality-sensitive segment of users. When market conditions favor an attention-driven model (low λ, low δ) then higher $\mathcal{Q}$ induces more addictive for and higher monetization, because there is little room to increase market share. Otherwise, the reverse logic applies: when content alone is not good enough to attract the most quality-sensitive users, then the platform uses a more aggressive design as a substitute mechanism to draw more engagement from users. To see this, consider the tradeoff perceived by a platform with weaker content (i.e., perceived as relatively low utility by users), or which operates in a market with low susceptibility to addictive design (low κ or high δ). Under these conditions, attracting $\mathcal{B}$-type users (x closer to 1, which requires setting $\mathbf{a}$ quite low) is too costly, imposing substantial revenue sacrifice due to lower $\mathbf{a}$. Hence, such a platform would forfeit the "right" side of the market, instead concentrating on high monetization of the addiction-prone segment. As market conditions get slightly more favorable (lower δ, higher $\mathcal{Q}$), a less manipulative design (lower $\mathbf{a}^*$) becomes more productive because the higher $\mathcal{Q}$ helps attract quality-sensitive customers. Proposition 1 summarizes.

Proposition 1. A monopoly IPP with an attention-based monetization model a) leverages higher $\mathcal{Q}$ into an increasingly aggressive addictive design when societal conditions are favorable (low λ, low δ), otherwise b) it uses addictive design to compensate for good content: lower $\mathcal{Q}$ induces higher $\mathbf{a}$ when $\lambda\delta$ is moderately high. In both cases, $\mathbf{a}$ increases with κ.

The two market outcome scenarios presented in Proposition 1 not only affect the relationship between content quality and addictiveness design, but will underlie other analyses including the platform's level of investment in content. For the present, the key insight is that when societal conditions towards addictive design are not too favorable (case (b)), the platform sets $\mathbf{a}^*$ to forego the more quality-sensitive users due to the high "cost" of attracting them (i.e., the loss in engagement and monetization with a low $\mathbf{a}^*$); then, increase in $\mathcal{Q}$ reduces this cost and it becomes optimal for the platform to reduce $\mathbf{a}^*$. Conversely, when market conditions are favorable enough (case (a))—that is, when its revenue-maximizing addictive design nevertheless enables it to retain most or all users—good content encourages more aggressiveness in addictive design. This is because, since the platform is already able to entice all users, then better content allows it to increase addictiveness (and therefore engagement and monetization) without sacrificing users.

Does this mean that an attention-based platform would invest more heavily in content and have stronger content (than a $\mathcal{B}$ type platform)? Or, would it instead design algorithms that manipulate users into spending more time, perhaps by promoting harmful content? To examine this formally, we consider the first stage of the platform's decision problem, its choice of $\mathcal{Q}$, under the two monopoly platform scenarios.

Lemma 2 (Optimal Content and Revenue Model)**.** A monopoly platform with a fee-based revenue model, and with cost of content $c\mathcal{Q}^2$, would set $\mathcal{Q}_{\mathcal{B}}{}^* = \frac{1}{2c}$. The optimal content choice of an attention-based monopoly platform is

$$\mathcal{Q}_{\mathcal{A}}{}^* = \begin{cases} Sol.\left(\mu e^{-\frac{\lambda\delta(1-\kappa)}{\mathcal{Q}}}\frac{\lambda\delta}{\mathcal{Q}^2}(1-\kappa) = 2c\mathcal{Q}\right); \text{(a) with } (\mathcal{Q}>\lambda\delta), \left(\frac{\mu\,(1-\kappa)}{e^{1-\kappa}} > 2c(\lambda\delta)^2\right) \\ \\ Sol.\left[\frac{\mu e^{\frac{\lambda\delta\kappa}{\mathcal{Q}}}}{\lambda\delta e}\left(\frac{(\lambda\delta\kappa)^2}{\mathcal{Q}^3}\right) = 2c\mathcal{Q}\right]; \qquad \text{(b) with } \lambda\delta\kappa<\mathcal{Q}<\lambda\delta \end{cases} \tag{4}$$

When is $\mathcal{Q}_{\mathcal{A}}{}^* > \mathcal{Q}_{\mathcal{B}}{}^*$? Once again, the model formulation embeds a straightforward choice for platform $\mathcal{B}$: it has marginal cost $2c\mathcal{Q}$ per unit $\mathcal{Q}$ and marginal revenue 1, yielding optimal

${\mathcal{Q}_{\mathcal{B}}}^* = \frac{1}{2c}$. Hence the result depends on platform $\mathcal{A}$'s choice, which depends on societal conditions towards addictiveness (κ, δ), monetizability of attention (λ, μ), and the cost of content c. The parameter space separates out into the two cases that form the subtext for $\mathcal{A}$'s choice of $\mathbf{a}^*$. Recall that case (a) in Proposition 1 emerges when $\mathcal{Q}_{\mathcal{A}}$ is high (relative to λ, δ), i.e., content costs are low. Within this case, if c is very low then although $\mathcal{Q}_{\mathcal{A}}$ is high, $\mathcal{B}$ has even stronger incentives to invest in content (because its marginal revenue exceeds marginal cost substantially), so that ${\mathcal{Q}_{\mathcal{A}}}^* < {\mathcal{Q}_{\mathcal{B}}}^*$. However, as content gets moderately expensive (due to which both platforms get less of it), $\mathcal{B}$'s incentives towards content diminish faster than platform $\mathcal{A}$'s which can monetize attention, whereas $\mathcal{B}$ can only monetize the diminishing content. This is the region where ${\mathcal{Q}_{\mathcal{A}}}^* > {\mathcal{Q}_{\mathcal{B}}}^*$. Significantly higher costs push $\mathcal{Q}_{\mathcal{A}}$ low and into case (b) with high $\mathbf{a}^* > \mathbf{a}_{\text{min}}$ such that $D_{\mathcal{A}} < 1$. Here again, ${\mathcal{Q}_{\mathcal{A}}}^* > {\mathcal{Q}_{\mathcal{B}}}^*$ is more compatible with moderately high c, but when content becomes too expensive then platform $\mathcal{A}$ targets its design $\mathbf{a}^*$ to the κ segment of addiction-prone users and then pays less attention to content. The vital take-away from this analysis is summarized below.

Proposition 2 (Addiction Design and Weaker Content)**.** Content investment by an attention-driven monopoly platform can exceed that of a potential fee-driven one, both when the attention-driven prefers an aggressive design which forfeit some quality-sensitive customers and when it prefers a milder design to cover all customers.

3.2 Competitive Equilibrium

Now consider competition between two IPPs in the same market but pursuing alternative revenue models. Platform $\mathcal{A}$ picks its addictiveness level $\mathbf{a}$ while platform $\mathcal{B}$ sets a per-user price p. To isolate the role of revenue model on addictiveness design and the effect of competition on this design, first suppose that both platforms have the same content $\mathcal{Q}$. Recall that a segment κ of customers is addiction-friendly, hence is captive to the free platform $\mathcal{A}$, hence competition between $\mathcal{A}$ and $\mathcal{B}$ is for the remaining $1-\kappa$ segment. On one hand, competition should cause the two firms to fight harder for users, hence each should drop its "tax" on users: platform $\mathcal{B}$ should reduce price p while $\mathcal{A}$ should become less addictive. On the other hand, $\mathcal{A}$ should have cause to increase $\mathbf{a}$

because in the competitive market its market share is more dominated by the addiction-prone user segment! Fixing $\mathcal{Q}$ to be the same across both platforms, Proposition 3 presents the net effect of these two forces.

Proposition 3 (Competition between an $\mathcal{A}$ and $\mathcal{B}$ platform, identical $\mathcal{Q}$)**.** When $\mathcal{Q} > \frac{\lambda\delta}{2}(1+\kappa)$, competition causes platform $\mathcal{A}$ to lose half the non-captive $1-\kappa$ segment to platform $\mathcal{B}$, and impose a less addictive design (with $p^* = \frac{\lambda\delta}{2}(1+\kappa), \mathbf{a}^* = \frac{\lambda(1+\kappa)}{1-\kappa}$). The presence of the addiction-prone market segment gives the $\mathcal{A}$ platform a market share advantage.

Competition has the expected effect of causing both platforms to throttle back i.e., $\mathcal{A}$ has lower $\mathbf{a}^*$ and $\mathcal{B}$ has lower p^*. At this equilibrium, platform $\mathcal{B}$ captures half the customers in the $(\kappa, 1]$ segment, but (with $p > 0$ and $\mathbf{a} = 0$) it has no chance of attracting the $[0, \kappa)$ segment who have higher utility for platform $\mathcal{A}$'s zero-price and more addictive offering. Although platform $\mathcal{A}$'s user base is now more weighted towards addiction-friendly users, nevertheless its desire to capture some users in the other segment pushes it to work harder for them, thereby lowering its $\mathbf{a}^*$. This occurs when $\mathcal{Q}$ is high enough to cause the platforms to compete for the middle users; otherwise, the monopoly outcomes are obtained when $\mathcal{Q} < \frac{\lambda\delta}{2}(1+\kappa)$. Notably, the fee-driven platform is effective as a competitor to the attention-driven free platform.

We examine next whether this balanced competition, where $\mathcal{B}$ was able to capture half the non-captive $(\kappa, 1]$ segment, survives network effects. Specifically, if users' utility for either platform is increasing in the size of the platform's user base, does this make it harder for a fee-based $\mathcal{B}$ platform to compete against $\mathcal{A}$. The result follows quite intuitively. When $\kappa > 0$, then the standard equilibrium solution (without network effects) yields platform $\mathcal{A}$ a bigger user base than platform $\mathcal{B}$. Network effects then amplify the advantage for $\mathcal{A}$ and make it harder for $\mathcal{B}$ to compete.

Proposition 4 (Competition under Network Effects)**.** Network effects weaken the competitive position of a fee-driven platform competing for users against a free platform with an attention-based revenue model.

4 A Proposal to Combat Digital Addiction

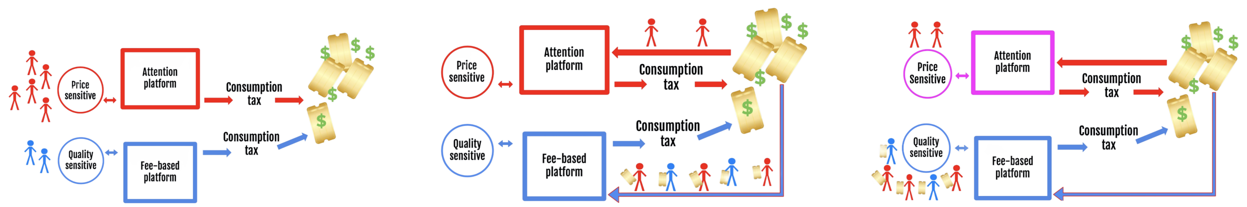
The failure of a competition market in IPPs to enable platforms with a fee-based, direct, monetization model, against a free platform which chooses an "addiction by design" approach adds to the cacophony of discussion around digital addiction. Rosenquist et al. (2021) make a powerful case for regulation of digital platforms, given the societal concerns around digital addiction, the role of platforms in enabling it, and the parallels with other addictive products (Rosenquist et al., 2021). Indeed, there are several proposals and methods for constraining the operations of digital platforms in order to combat digital addiction in society. These include the idea of a digital curfew (Ichihashi & Kim, 2022), limits on the amount or type of advertising,[5] bans on certain types of users (Zhang et al., 2022), holding platforms liable for harm resulting from information shared on it (Hua & Spier, 2021), and the Blackburn-Blumenthal bill[6] which places detailed restrictions on platform design.

Each of these proposals has merits with respect to its intended goal of curbing usage of digital platforms. However, each also faces challenges in its legal and social acceptability. For instance, while the concept of a digital curfew is feasible in China (Lindtner & Szablewicz, 2011), it might not be so in the US. Similarly challenged are proposals that require choosing or agreement between "good" vs "bad" or "socially harmful" vs not, or even "true" vs "fake" content. Each proposal appears challenging, if not impractical, in today's socio-political environment in the US. Based on the insights from the model of digital addiction, this paper proposes an alternate method based on economic incentives.

The proposed solution involves an economic transfer of money, collected by taxing the "bad" that one seeks to reduce (i.e., digital consumption), applying the tax to all platforms within some category (without *a priori* value judgements on their design or actions) as a function of their dig-

[5]https://www.booker.senate.gov/news/press/booker-announces-introduction-of-bill-to-ban-surveillance-advertising

[6]https://abcnews.go.com/Politics/senators-introduce-bill-limit-harmful-effects-social-media/story?id=82932781



(a) Consumption tax paid by all platforms based on total user hours.

(b) Tax revenue passed to users as vouchers to cover subscription fees.

(c) Users choose platforms to apply voucher to cover subscription fees.

Figure 3: A tax and distribution proposal to tilt an IPP market towards fee-based monetization, and away from dependence on maximizing user hours or addictive design.

ital consumption (user-hours spent per unit time) and distributed to platform users in the form of vouchers that can only be used to cover, at the user's choice, subscription fees to a platform in that category. Specifically, if platform i has n_i hours of consumption, it pays a fee $\tau(n_i)$ where $\tau(n)$ is an increasing function of n (and, potentially, progressively increasing). The aggregate fees $\sum_i \tau(n_i)$ are placed in a pot, of which fraction $((1-\gamma)\sum_i \tau(n_i))$ is returned to the user base. Thus, if there are N users (and with appropriate accommodations made for citizenship or eligible users) each user receives $\frac{(1-\gamma)\sum_i \tau(n_i)}{N}$, which can be used only to pay platform subscription fees to a platform of the user's choice (but only up to the level of subscription fees charged by the platform). The voucher acts as a subsidy that tilts user choice in favor of a subscription-driven and addiction-free (or low $\mathbf{a}$) platform. The intent is that marginal users shift from an $\mathcal{A}$ type platform to a $\mathcal{B}$ type platform, and this shift in competitive demand also alters (lowers) the $\mathbf{a}^*$ of platform $\mathcal{A}$.

In this proposal (see Fig. 3), all platforms pay a user engagement tax (see panel 3a), which can additionally be a progressive tax system, and hence tilted against platforms that have massive level of engagement. It makes no social judgements about what kind of content is "good vs bad" or true vs fake. The essential idea is that the recirculation method tilts the competitive field (between platforms) a little in favor of platforms that choose to monetize through subscription fees (and therefore pay more attention to quality, well-being) vs those reliant on "attention". The first-order consequence is that the voucher subsidy would cause some marginal users, who otherwise would have chosen the attention-based platform, to instead switch to the subscription fee platform (see panel 3b). The second-order consequence is that this shift in user behavior, and its effect on platform market share and revenues, would cause the attention-based platform to reduce the level of addictiveness (in order to reduce its loss of market share), or perhaps even induce some attention-based platforms to switch their revenue model to a fee-based one (see panel 3c). The intuition is that this rebalancing of competition will occur even if the tax rate is linear in the level of engagement, and will be more sharp under a progressive tax system. Further, a $\gamma > 0$ can be seen as a social tax on digital consumption, however the proposal is intended to work even with $\gamma = 0$.

5 Conclusion

Digital addiction is a 21^{st} century vice and threat to human society, blamed for hurting human memory and ability to focus on complex tasks, and implicated in loneliness and depression (Rosenquist et al., 2021). Addiction to digital devices and media allegedly occurs due to platforms' dependence on attention-driven revenue models which monetize user attention through sale of data or advertising. This paper develops an economic model to examine the interplay between addictive design, revenue model, and competition. Platforms pick a level of aggressiveness in addictive design as a trade-off between higher engagement vs. losing some quality-sensitive users. Competition with a quality-focused and fee-based platform can mitigate addictiveness, but this positive effect fails under network effects. With this limitation, the increasing tendency towards digital addiction can be partially countered by imposing a tax on digital consumption, similar to how society taxes other vices such as tobacco, alcohol, or gambling. The vital feature here is that the tax is applied to the thing which is considered a "bad," i.e., digital consumption. Tax revenue can be plugged back into the digital economy, returned to users in the form of vouchers that can be applied to cover subscription fees at digital platforms. This recirculation of revenue earned for attention, into a subsidy that is used to pay fees, tilts the competitive field towards quality-focused platforms, and also subdues addictive design in platforms that employ attention-based revenue models. It might be an more effective way, and more likely to be enforceable, than other proposals that require drastic and less-enforceable measures such as banning advertising or data sales, imposing digital curfews, or holding platforms liable for harm.

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A Technical Details and Proofs

Proof of Lemma 1 and Proposition 1. Recall that platform $\mathcal{A}$ captures the market when $\mathbf{a}$ equals $\mathbf{a}_{\text{min}} = \frac{\mathcal{Q}}{\delta(1-\kappa)}$, hence dropping $\mathbf{a}$ lower is never optimal (because per-user monetization rate increases with $\mathbf{a}$). Hence we optimize the profit function

$$\Pi_{\mathcal{A}} = \begin{cases} e^{\frac{-\lambda}{\mathbf{a}}}\left(\frac{\mathcal{Q}}{\delta\mathbf{a}}+\kappa\right) & \text{for } \mathbf{a} > \frac{\mathcal{Q}}{\delta(1-\kappa), \quad \text{but } \leq \mathbf{a}_{\text{max}}} \\ e^{-\frac{\lambda\delta(1-\kappa)}{\mathcal{Q}}} \cdot 1 & \text{if } \mathbf{a} = \frac{\mathcal{Q}}{\delta(1-\kappa)}. \end{cases}$$

For the first case above, setting the derivative $\frac{\partial \Pi_{\mathcal{A}}}{\partial \mathbf{a}} = 0$ yields the first-order condition, $\frac{\lambda}{\mathbf{a}^2}\left(\frac{\mathcal{Q}}{\delta\mathbf{a}}+\kappa\right) = \frac{\mathcal{Q}}{\delta\mathbf{a}^2}$, simplified to $\lambda(\mathcal{Q}+\delta\mathbf{a}\kappa) = \mathbf{a}\mathcal{Q}$, and hence $\mathbf{a} = \frac{\lambda\mathcal{Q}}{\mathcal{Q}-\lambda\delta\kappa}$, provided $\mathcal{Q} > \lambda\delta\kappa$.[7] This solution is valid only when it exceeds $\mathbf{a}_{\text{min}}$, which occurs when $\lambda\delta > \mathcal{Q}$. Hence the platform sets

$$\mathbf{a}^* = \begin{cases} \frac{1}{\frac{\delta}{\mathcal{Q}}(1-\kappa)}, \text{ with } D_{\mathcal{A}} = 1, & \text{if } \mathcal{Q} \geq \lambda\delta \\[2ex] \frac{\lambda\mathcal{Q}}{\mathcal{Q}-\lambda\delta\kappa}, \text{ with } D_{\mathcal{A}} = \frac{\mathcal{Q}}{\lambda\delta} & \text{if } \underbrace{\lambda\delta\kappa < \mathcal{Q} < \lambda\delta}_{\text{weak content}} \left(\equiv \quad \underbrace{\kappa < \frac{\mathcal{Q}}{\lambda\delta}}_{\text{fewer addicts}} \quad \equiv \quad \underbrace{\delta > \frac{\mathcal{Q}}{\lambda}}_{\text{high distaste}} \right) \\[2ex] \mathbf{a}_{\text{max}}, \text{ with } D_{\mathcal{A}} = \kappa + \frac{\mathcal{Q}}{\delta\mathbf{a}_{\text{max}}} & \text{if } \mathcal{Q} \leq \lambda\delta\kappa. \end{cases}$$

The properties associated with Proposition 1 are obtained through comparative statics on $\mathbf{a}^*$. First note that $\mathbf{a}^*$ is in case (a) when $\lambda\delta$ is quite small relative to $\mathcal{Q}$. Then $\frac{\partial \mathbf{a}^*}{\partial \mathcal{Q}} > 0$ is trivial. Case (b) applies when $\lambda\delta$ exceeds $\mathcal{Q}$ and κ is small (so that $\mathcal{Q}$ exceeds $\lambda\delta\kappa$), then an increase in $\mathcal{Q}$ makes a decrease in $\mathbf{a}$ more productive because it helps attract quality-sensitive customers. ■

Proof of Lemma 2 and Proposition 2. Platform $\mathcal{B}$'s content investment decision is based on the profit function $\Pi_{\mathcal{B}} = \mathcal{Q} - c\mathcal{Q}^2$: the constant marginal revenue (1) and the marginal cost $c\mathcal{Q}$ yield ${\mathcal{Q}_{\mathcal{B}}}^* = \frac{1}{2c}$. To compute ${\mathcal{Q}_{\mathcal{A}}}^*$ for the attention-driven platform $\mathcal{A}$, plug in $\mathbf{a}^*$ from Lemma 1 into platform $\mathcal{A}$'s monetization and demand functions. When conditions are strongly against attention-based monetization (high $\lambda\delta\kappa$, $\mathbf{a} = \infty$ or $\mathbf{a}_{\text{max}}$), the platform will simply focus on the κ fraction of addiction-prone customers and minimize its investment in $\mathcal{Q}$. For the other two cases we have (after plugging in $\mathbf{a}^*$)

$$\Pi_A(\mathcal{Q}) = \begin{cases} \mu\, e^{-\frac{\lambda\delta(1-\kappa)}{\mathcal{Q}}} - c\mathcal{Q}^2 & \text{requires } (a) \quad \mathcal{Q} \geq \lambda\delta \\ \mu\, \frac{e^{\frac{\lambda\delta\kappa}{\mathcal{Q}}}}{e} \frac{\mathcal{Q}}{\lambda\delta} - c\mathcal{Q}^2 & \text{requires } (b) \quad \lambda\delta\kappa \leq \mathcal{Q} \leq \lambda\delta \end{cases} \qquad \text{with } \lambda, \delta > 0, \kappa \in (0,1).$$

Case (a) is the solution where the platform invests enough in content to cover the market and secure participation even of addiction-averse consumers. Its marginal cost is $2c\mathcal{Q}$, and writing

[7] When $\mathcal{Q} \leq \lambda\delta\kappa$ the first-order condition does not identify a critical point, and we get $\mathbf{a}^* = \mathbf{a}_{\text{max}}$, $D_{\mathcal{A}} = k$ and $m = \mu$, so that $\Pi^*_{\mathcal{A}} = \mu, \kappa$. And here it is optimal to set $\mathcal{Q}$ at the lowest possible level (hence less than $\mathcal{B}$'s level of $\frac{1}{2c}$).

$R = \mathrm{e}^{-\frac{\lambda\delta(1-\kappa)}{\mathcal{Q}}}$ (which is < 1) we get marginal revenue

$$\begin{aligned}\frac{\partial \mu R}{\partial \mathcal{Q}} &= \mu R \frac{\lambda\delta(1-\kappa)}{\mathcal{Q}^2} > 0 \\ \frac{\partial^2 \mu R}{\partial \mathcal{Q}^2} &= \mu R \lambda\delta(1-\kappa)\left(\frac{1}{\mathcal{Q}^2}\frac{\lambda\delta}{\mathcal{Q}}\frac{1-\kappa}{\mathcal{Q}} - \frac{2}{\mathcal{Q}^3}\right) < 0 \qquad \text{because } \frac{\lambda\delta}{\mathcal{Q}} < 1.\end{aligned}$$

Now ${\mathcal{Q}_{\mathcal{A}}}^*$ is simply where marginal cost intersects marginal revenue (if the intersection occurs in the feasible region), and we see (above) that marginal revenue is decreasing in $\mathcal{Q}$ throughout. Therefore, ${\mathcal{Q}_{\mathcal{A}}}^* > {\mathcal{Q}_{\mathcal{B}}}^* (= \frac{1}{2c})$ is equivalent to $\frac{\partial \mu R}{\partial \mathcal{Q}}\Big|_{\mathcal{Q}=\frac{1}{2c}} > 1$, and existence requires that $\frac{\partial \mu R}{\partial \mathcal{Q}} > 2c\mathcal{Q}$ at $\mathcal{Q} = \lambda\delta$, which yields $\mu\,(1-\kappa)\mathrm{e}^{-(1-\kappa)} > 2c(\lambda\delta)^2$. That is, λ, δ, κ and c should not be too large relative to μ. Returning to the main question, the condition for ${\mathcal{Q}_{\mathcal{A}}}^* > {\mathcal{Q}_{\mathcal{B}}}^*$ reduces to $4c^2\mu\mathrm{e}^{-2c\lambda\delta(1-\kappa)}\lambda\delta(1-\kappa) > 1$. This occurs when μ is large (increasing payoff from monetization), λ, δ are moderate (making the platform chase the right-side consumers), and c is large enough that a fee-based platform would invest even less in content. Tight examples are ($\mu = 4, \lambda\delta = 1.25, \kappa = 0.15, c = 0.4$, with $\mathcal{Q}_{\mathcal{B}} = 1.25$, $\mathcal{Q}_{\mathcal{A}} = 1.34$) and ($\mu = 1, \lambda\delta = 0.3, \kappa = 0.15, c = 1.5$ with $\mathcal{Q}_{\mathcal{B}} = 1/3$, $\mathcal{Q}_{\mathcal{A}} = 0.343$).

In the case (b) solution the platform is willing to forfeit some quality-sensitive consumers in order to keep $\mathbf{a}$ higher and have high attention monetization. Here, write $R = \frac{\mathrm{e}^{\frac{\lambda\delta\kappa}{\mathcal{Q}}}}{\mathrm{e}}$, then

$$\begin{aligned}\frac{\partial \mu R}{\partial \mathcal{Q}} &= \mu R \frac{1}{\lambda\delta}\left(1 - \frac{\lambda\delta\kappa}{\mathcal{Q}}\right) > 0 \qquad \text{because } \frac{\lambda\delta\kappa}{\mathcal{Q}} < 1 \\ \frac{\partial^2 \mu R}{\partial \mathcal{Q}^2} &= \frac{\mu R}{\lambda\delta}\left[\frac{\lambda\delta\kappa}{\mathcal{Q}^2} - \frac{\lambda\delta\kappa}{\mathcal{Q}^2}\left(1 - \frac{\lambda\delta\kappa}{\mathcal{Q}}\right)\right] > 0.\end{aligned}$$

Here, marginal revenue is increasing in $\mathcal{Q}$ which creates the possibility of two values of $\mathcal{Q}$ such that marginal revenue equals marginal cost. An example where this design is optimal and leads to ${\mathcal{Q}_{\mathcal{A}}}^* > {\mathcal{Q}_{\mathcal{B}}}^*$ is ($\mu = 4.5, \lambda\delta = 1.6, \kappa = 0.2, c = 0.4$, with $\mathcal{Q}_{\mathcal{B}} = 1.25$, $\mathcal{Q}_{\mathcal{A}} = 1.305$) and ($\mu = 1, \lambda\delta = 0.3, \kappa = 0.15, c = 3$ with $\mathcal{Q}_{\mathcal{A}} \approx 0.2 > \mathcal{Q}_{\mathcal{B}} = 1/6$). ■

Proof of Proposition 3. We show that when $\mathcal{Q} > \frac{\lambda\delta}{2}(1+\kappa)$, $\mathcal{A}$ and $\mathcal{B}$ split the $1-\kappa$ segment, with $p^* = \frac{\lambda\delta}{2}(1+\kappa), \mathbf{a}^* = \frac{\lambda(1+\kappa)}{1-\kappa}$, lower than the monopoly level. Otherwise, there is no effective competition and $\mathcal{A}$ sets $\mathbf{a}^*$ as in case (b) of Lemma 1, while $\mathcal{B}$ follows with $p^* = \mathcal{Q}$. We elaborate below.

From Eq. 3 with identical $\mathcal{Q}$, and setting $U_{\mathcal{A}}(\mathsf{X}) = U_{\mathcal{B}}(\mathsf{X})$ (with the requirement that net utility be non-negative), $D_{\mathcal{A}} = \mathsf{X} = \frac{p}{\delta\mathbf{a}} + \kappa$, $D_{\mathcal{B}} = (1-\mathsf{X}) = (1-\kappa - \frac{p}{\delta\mathbf{a}})$. For platform $\mathcal{B}$, optimizing profit $\Pi_{\mathcal{B}}(p) = pD_{\mathcal{B}}$ involves two possible strategies: i) a "non-competitive" response $p^* = \mathcal{Q}$ wherein it captures exactly the user segment $(Y, 1]$ where $U_{\mathcal{A}}(Y, \mathbf{a}) = 0$, and ii) a best-response function $p = \delta\mathbf{a}(1-\kappa)/2$, indicating that $\mathcal{B}$ seeks to split the $1-\kappa$ segment with $\mathbf{a}$, and follows with a suitable price to achieve market share $\frac{1-\kappa}{2}$. For platform $\mathcal{A}$, $\Pi_{\mathcal{A}} = \mu\mathrm{e}^{-\frac{\lambda}{\mathbf{a}}}\left(\frac{p}{\delta\mathbf{a}} + \kappa\right)$ yields the best-response function $\mathbf{a} = \frac{\lambda p}{p-\lambda\delta\kappa}$. For $\mathcal{A}$ this is a dominant response which covers both of $\mathcal{B}$'s strategies.

Combining the response functions of $\mathcal{A}$ and $\mathcal{B}$ for the case of $p^* = \mathcal{Q}$ yields $\mathbf{a}^*{=}\frac{\lambda Q}{Q-\lambda\delta\kappa}$, $\mathsf{X}{=}\frac{\mathcal{Q}}{\lambda\delta}$, and $\Pi_{\mathcal{B}}{=}\frac{\mathcal{Q}^2}{\lambda\delta}$. In the second branch, the two best-response functions yield $p^*{=}\frac{\lambda\delta}{2}(1{+}\kappa)$, $\mathbf{a}^*{=}\frac{\lambda(1+\kappa)}{1-\kappa}$; this is easily seen to be lower than the lowest $\mathbf{a}^*{=}\frac{\mathcal{Q}}{\delta(1-\kappa)}$ in the monopoly case. In this case, with $D_{\mathcal{B}}{=}(1{-}\mathsf{X}){=}\frac{1-\kappa}{2}$, we have $\Pi_{\mathcal{B}}{=}\frac{\lambda\delta}{4}(1{+}\kappa)(1{-}\kappa)$. Hence $\mathcal{B}$ will pick a competitive response when this profit exceeds its profit in the non-competitive branch, i.e., when $\mathcal{Q} > \frac{\lambda\delta}{2}\sqrt{(1{+}\kappa)(1{-}\kappa)}$. There is also a second condition for this solution, i.e., that X (in the second branch) has non-negative net surplus, representing that $\mathcal{A}$ also finds a competitive solution better than a non-competitive one. This yields $\mathcal{Q} > \frac{\lambda\delta}{2}(1{+}\kappa)$ (which is a tighter condition that the one above), and when $p > \lambda\delta\kappa$ (which is automatically satisfied for $\kappa < 1$).

To sum it up, the competitive solution applies when $\mathcal{Q} > \frac{\lambda\delta}{2}(1{+}\kappa)$, and in this case $\mathbf{a}*$ is lower than the level chosen by a monopolist attention-driven platform; otherwise when $\mathcal{Q}$ is lower, a monopoly solution still emerges where platform $\mathcal{A}$ sets $\mathbf{a}^*$ to yield $D_{\mathcal{A}} = \mathsf{X}$ ($< \frac{1+\kappa}{2}$) while $\mathcal{B}$ can set $p^* = \mathcal{Q}$. ■

Proof of Proposition 4. Suppose that in the absence of network effects the two platforms have market share $D_{\mathcal{A}}$ and $D_{\mathcal{B}}$. With X defined as the user whose net utility for the two platforms is identical, we have $D_{\mathcal{A}} = \mathsf{X}$ (and $\mathsf{X} = \kappa + \frac{1-\kappa}{2}$). Hence $D_{\mathcal{A}} > D_{\mathcal{B}}$. By definition, at the equilibrium, $U_{\mathcal{A}}(\mathsf{X}) = U_{\mathcal{B}}(\mathsf{X})$.

Now, suppose there are network effects. That is a user's utility for platform $\mathcal{A}$ is increased by an amount that's a function of $D_{\mathcal{A}}$, with a corresponding increase for $\mathcal{B}$. Since $D_{\mathcal{A}} > D_{\mathcal{B}}$ it follows trivially that the new equilibrium indifferent user who separates the market (say Y) exceeds X, so that under network effects $\mathcal{A}$ has higher demand than before while $\mathcal{B}$ gets less. This direct effect is then compounded by the fact that this network effects advantage gives $\mathcal{A}$ more power in setting $\mathbf{a}^*$ and $\mathcal{Q}^*$.

Formal proof TBD. ■

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