Data privacy, service addictiveness, and pricing in online markets*

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Abstract

This paper analyzes a model of an online host platform with a service provider and a group of users, examining the interplay between users' data privacy—determined by the host's data disclosure policy—and the service provider's choice of service addictiveness. The service provider's decision involves a trade-off between advertisement revenue from user attention and revenue from the admission price. When the host platform receives a share of the admission price, I show that it benefits from a restrictive privacy policy. Under such a policy, the service provider chooses a lower addictiveness level and a higher admission price compared to a policy with greater data disclosure. Furthermore, when network effects among users are sufficiently strong, this leads to a positive level of addictiveness even when the host's policy fully restricts advertisement revenue.

Keywords: digital platforms; addiction; attention; privacy; network effects

JEL-Codes: D42; L12; L86

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1 Introduction

Online service providers and users interact on a host platform. iOS, Apple's operating system that powers the iPhone, connects the providers of digital services, or apps, with potential users, and is used by approximately 1.3 billion people (Curry, 2023). In April 2021, Apple rolled out a privacy update introducing App Tracking Transparency (ATT), making it difficult for app providers to generate user profiles based on third-party data unless users actively permit tracking.[1] Nevertheless, the majority of users still do not allow tracking (e.g., Wetzler, 2023). As a consequence, the app providers' capabilities for targeted advertisement have been restricted by the introduction of ATT, and advertisement revenues have dropped.[2] In order to boost user attention that can be monetized via targeted advertisements, app providers may adopt addictive design features that potentially harm users (e.g., Alter, 2018; Newport, 2019; Allcott et al., 2022). Examples include feeds that allow endless scrolling, the use of social pressure via read notifications, and the implementation of gambling elements such as loading spinners or loot boxes (e.g., Montag et al., 2019; Scott Morton et al., 2019).

This paper examines how a host platform's data disclosure policy, which restricts advertisement revenue for online service providers, impacts these providers' subsequent pricing and service design decisions, especially considering the implementation of potentially user-harming addictive design features.

For this purpose, the paper presents a simple theoretical framework that captures features of online markets, where a service provider faces a homogeneous group of users on a two-sided host platform. First, the host commits to a policy regime dictating a level of data disclosure. The service provider then chooses an admission price and a level of addictiveness, representing the service design. Lastly, each user simultaneously decides if she makes use of the service and how much attention she spends on it. The

[1]For an overview of ATT and its implications, see, e.g., Jerath (2022) and Kourinian (2021).

[2]Advertisement generates a large share of today's online businesses' revenues. For instance, Alphabet Inc. (2023) announces that roughly 80 percent of its revenues originate from Google and YouTube ads services. Referring to a study by Lotame, McGee (2021) shows that ad revenues of the largest online platforms dropped significantly after the introduction of ATT. Following the ATT rollout, Snap, Facebook, Twitter, and YouTube have lost nearly $10bn in ad revenues in the last two quarters of 2021. See also, e.g., Bergan (2022).

payoff of each active user is the utility from the service itself combined with network effects, net of attention cost and the admission price. The service provider's payoff consists of the revenue generated from collecting admission fees and from monetizing user attention through targeted advertisements, with the latter possibly being restricted due to the host's policy. Following Ichihashi and Kim (2023), the choice of addictiveness is associated with a trade-off between advertisement revenue through user attention and the admission price. The host receives an exogenous share of the admission fees.

The main contribution of this paper is the endogenization of the data disclosure policy of a host platform and the investigation of its effect on the service provider's pricing and addictiveness decisions. The analysis reveals that the host prefers a restrictive privacy policy because this induces the service provider to set an addictiveness level that maximizes the users' willingness to pay for service usage. This level of addictiveness is strictly below the addictiveness levels the service provider would choose under less restrictive policies. In fact, privacy-focused policies yield higher prices and superior service quality through reduced addictiveness in equilibrium compared to disclosure-oriented policies. Furthermore, the paper investigates two countervailing effects of increasing the level of service addictiveness on the service provider's revenues: the attention monetization effect and the price effect. Increasing service addictiveness results in an increase in user attention but may respectively decrease users' willingness to pay. The first effect, which describes the increase of revenue from targeted advertisement due to an increase in user attention, is always positive as long as users make use of the service. Interestingly, I find that the latter effect can be ambiguous when network effects are considered. On one hand, an increase in addictiveness corresponds to a loss in service utility, resulting in a lower willingness to pay and, therefore, a decreasing price. On the other hand, it boosts user attention which, in turn, leads to a utility and therefore price increase due to network effects. I provide conditions under which network effects result in positive levels of addictiveness even when advertisement revenues are fully restricted. Under these conditions, the service provider chooses a combination of strict positive prices and a strict positive level of addictiveness under each policy regime. I further demonstrate that the equilibrium level of addictiveness increases with stronger network effects. In addition, it increases with a higher share that the service provider must give to the host when the host cannot fully restrict advertising revenue.

The remainder of this paper is organized as follows: In Section 2, I position the paper within the existing literature. The model setup is described in Section 3. In Section 4, I derive the equilibrium. A brief comparative statics analysis is presented in Section 5. After a discussion of model assumptions and possible extensions in Section 6, Section 7 concludes.

2 Related Literature

This paper contributes to the literature on online markets. A closely related work is by Ichihashi and Kim (2023), who introduce addictiveness as a choice variable in an oligopoly model where competing online platforms make profits from capturing the attention of a multi-homing user. Referring to a three-period habit formation model with a time-inconsistent consumer, based on Gruber and Köszegi (2001), the authors assume that platforms face a trade-off: platforms can increase their addictiveness to capture more attention but at the cost of reducing user utility, which can deter users from joining. In scenarios where platforms sell access to their services instead of making profits from attention, this leads to zero addictiveness. Building upon their framework, I introduce a game stage in which a host platform commits to a data disclosure policy, determining whether a service provider (platform) can profit from user attention through advertisements alongside selling service access. Additionally, I incorporate network effects, demonstrating that positive network effects can lead the service provider to implement addictive design features even in the absence of advertisement revenue. While Ichihashi and Kim focus on competition and attention limitations, this paper examines the endogenous privacy policy of a superordinate platform and its impact on online service providers' pricing and addictiveness strategies.

Zennyo (2024) investigates the business model choice of an app provider in a mobile app market with endogenous commissions from an app and an ad platform. Similar to the present model, the app provider generates profits from admission prices and advertisements. In contrast, the present work considers a data disclosure policy that endogenously determines the feasibility of advertisement revenues. Furthermore, it examines the implementation of addictive features to enhance user attention at the expense of service quality and network effects, elements not included in Zennyo's model.

Another relevant article, Fainmesser et al. (2023), studies how user data collection and protection are influenced by an online business's revenue model, providing regulatory recommendations. Going one step further, I examine the incentives of the platform on which service providers and users interact, where this platform can determine the possible revenue model of the service provider.

This work is related to literature regarding the effects of online services on users. Mainly in the context of social media, recent literature points out the negative effects of digital features on user well-being (e.g., Allcott and Gentzkow, 2017; Allcott et al., 2020; Mosquera et al., 2020; Bhargava and Velasquez, 2021; Allcott et al., 2022; Montag and Elhai, 2023). Features that boost attention can harm users (e.g., Alter, 2018; Newport, 2019; Scott Morton et al., 2019; Rosenquist et al., 2021). Throughout this paper, I adopt a framework in which a service provider may sacrifice service quality and therefore user utility for attention and show that a higher level of privacy corresponds to less implementation of user harming features.

The article is also connected to the literature about the implications of privacy policies. Acquisti et al. (2016) and Goldfarb and Que (2023) provide overviews of the tradeoffs connected with privacy. Scholars investigate the implications of a privacy-centered environment on online advertisement. Johnson et al. (2022) name research avenues relevant from a marketing perspective. An environment with limited tracking capabilities may raise issues related to advertisement campaign strategy (e.g., Blake et al., 2015; Schwartz et al., 2017; Goldfarb and Tucker, 2011), ad targeting (e.g., Neumann et al., 2019; Rafieian and Yoganarasimhan, 2021; Ada et al., 2022), and ad measurement (e.g., Bruce et al., 2017; Lin and Misra, 2022). More specific, Johnson et al. (2020) and

Ravichandran and Korula (2019) show that advertising revenues are positively connected to the ability for third-party tracking. Referring to Apple's ATT update, Aridor et al. (2024) provide evidence for decreasing ad effectiveness and advertisement revenues as a consequence of Apple's policy change. De Cornière and De Nijs (2016) analyze the impact of privacy policies in an advertisement slot auction setting and consider precisely targeted advertisement as utility enhancing. Throughout this work, I adopt their notion and distinguish between a Privacy and a Disclosure policy. The focus of this work lies not on governmental policies that influence the possibilities of data usage (e.g. Xu et al., 2025), like, e.g., the European Union's General Data Protection Regulation (GDPR), but on the restrictions that may arise from the corporate side and their implications (e.g., Baye and Sappington, 2020). In a recent study, Kesler (2023) examines the impact of privacy policy on business models based on the example of Apple's ATT. He empirically analyzes the market for mobile applications and investigates business models of apps and developers before and after the introduction of Apple ATT. In the course of this, he shows that, following ATT, apps from Apple's App Store become more often chargeable and are more likely to include in-app purchases. While an increase in the number of apps with in-app payments seems to be an industry-wide phenomenon, there is evidence that the increasing adoption of paid business models is exclusive to apps affected by ATT. The results of the current paper may help explain these recent observations.

There is research on the valuation of privacy from the user's perspective, where privacy serves as a protective instrument against the disclosure of one's personal type. For instance, Taylor (2004), Acquisti and Varian (2005), and Hann et al. (2008) introduce models in which privacy acts as a tool to avoid price discrimination. Other studies investigate how user data can be used for personalized pricing and targeted advertising (e.g., Villas-Boas, 1999; Villas-Boas, 2004; Zhang and Krishnamurthi, 2004). I contribute to this body of literature by providing a theoretical model that, to the best of my knowledge, is the first to link privacy policies with business model choices in the context of addictive service design. This allows me to demonstrate that the value of privacy for consumers encompasses a new dimension. A higher level of privacy results in higher service quality.

Lastly, this article contributes to the general discussion about antitrust in connection with privacy policies and online platforms. Sticking to the example from above, there are some recent antitrust issues against Apple in connection with ATT brought up by France, Germany, Italy, and Poland (e.g., McGee, 2023). This article highlights potential benefits of privacy policies for users. It contributes to the discussion by providing evidence that a restrictive data disclosure policy leads to higher service quality and therefore, user satisfaction. In the context of social media, Montag and Elhai (2023) state that actual problems can only be solved if the providing platforms change their business model away from data and therefore attention monetization. I show that this may be induced by the implementation of privacy policies by superordinate platforms such that the user-harming free and addictive models are becoming less profitable.

3 The model

I consider a model in which a provider of an online service interacts with a homogeneous group $\mathcal{I}$ of potential users on a host platform. $\mathcal{I}$ is of measure one, with each individual having a mass of zero.

Each user $i \in \mathcal{I}$ decides whether to use the service or not and how much attention $a_i \geq 0$ to spend on it. For access to its service, the service provider charges an admission price $p \geq 0$. Furthermore, it can implement potentially user harming addictive design features to boost attention. Examples of these features include endless scrolling feeds, read notifications, loading spinners, or loot boxes (Montag et al., 2019). The variable $d \geq 0$ represents the implementation of these features, with a higher d indicating a higher level of service addictiveness.

If user i makes use of the service, her payoff is

$$U_i(a_i, d, p, A_{-i}) = u(a_i, d) + \kappa \cdot b\left(A_{-i}\right) - c\left(a_i\right) - p, \tag{1}$$

where $u(\cdot)$, $b(\cdot)$ and $c(\cdot)$ represent service utility, network effects and attention costs, respectively. Otherwise, her payoff is normalized to zero.

Each user i enjoys utility from making use of the service. Since users are assumed to be homogeneous, one can write service utility as $u(a_i, d)$. For all $a_i \geq 0$ and $d \geq 0$, $u(a_i, d)$ is twice-differentiable and $u(0, 0) \geq 0$. Service utility is increasing and marginal service utility of attention is decreasing in attention, i.e., for all $a_i \geq 0$ and $d \geq 0$, $\partial u/\partial a_i|_{(a_i,d)} > 0$ and $\partial^2 u/\partial a_i^2|_{(a_i,d)} < 0$. Following Ichihashi and Kim (2023), for all $a_i \geq 0$ and $d \geq 0$, a higher level of addictiveness corresponds to a lower level of utility, $\partial u/\partial d|_{(a_i,d)} < 0$, and a higher level of marginal utility of attention, $\partial^2 u/(\partial a_i \partial d)|_{(a_i,d)} > 0$. Thus, with a higher level of addictiveness, a user who uses the service will spend more attention on it but might be willing to pay less for access due to its lower utility.[3] Furthermore, assume that the disutility of addictiveness increases, such that $u(\cdot)$ is concave in d, $\partial^2 u/\partial d^2|_{(a_i,d)} < 0$.[4]

In addition, each user i gains utility from interacting with others due to network effects and therefore benefits from the attention other users spend on the online service, $A_{-i} = \int_{j \in \mathcal{I} \setminus i} a_j \, \mathrm{d}j$. Examples for such online services include social media platforms, multiplayer games, recommendation services, digital maps with live traffic information, and marketplaces. The function $b(A_{-i})$ represents network effects. It is twice differentiable, and monotonically and concavely increases in attention, i.e., for all $A_{-i} \geq 0$, $\partial b/\partial A_{-i}|_{(A_{-i})} > 0$ and $\partial^2 b/\partial A_{-i}^2|_{(A_{-i})} < 0$. Further, $b(0) = 0$. $\kappa > 0$ is a parameter that scales the extent of network effects. It represents various factors, such as the size of the network, mechanisms that enhance network effects, or other relevant attributes.[5]

Spending attention incurs a cost $c(a_i)$ for each user i, which represents, for instance, the opportunity cost of allocating attention to an online service. $c(a_i)$ is monotonously

[3]Ichihashi and Kim (2023) motivate the service utility specification based on a three-period model with habit formation of a time-inconsistent dual-self consumer. A consumer first chooses a set of service platforms to join (long-run self) and, second, an allocation of attention across them (short-run self), prior to being addicted. Third, the consumer again chooses an allocation of attention over the joined platforms, where prior attention spending negatively affects consumer utility. This negative impact is associated with service addiction, and the consumer consequently needs to increase attention in the last period to ensure the same payoff as in the second. The extent of this negative impact is scaled by an addictiveness parameter, i.e., d, with a higher value corresponding to a greater harm on the consumer in the last period.

[4]A simple function that satisfies the assumptions is $u(a, d) = \ln(a - d + 1)$ for $d < 1 + a$.

[5]This is in line with the modeling of Chen et al. (2009), where the network effects monotonically increase in platform specific variables. In this model, network effects are assumed to be independent of a user's own attention level. It is also possible to allow for dependence on a user's own attention level, as in, e.g., Candogan et al. (2012) and Fainmesser et al. (2023), by representing effects via a function $\kappa \cdot b(A_{-i}) \cdot a_i$. I have found that this feature does not alter the results, so, I omit it for reasons of simplicity.

increasing, convex, and twice differentiable, i.e., for all $a_i \geq 0$, $\partial c/\partial a_i|_{(a_i)} > 0$ and $\partial^2 c/\partial a_i^2|_{(a_i)} > 0$, and $c(0) = 0$.

In order to ensure a positive attention level in equilibrium, assume that $\partial u/\partial a_i|_{(0,0)} - \partial c/\partial a_i|_{(0)} > 0$. Further, assume that there exists a level of addictiveness such that $\max_{a_i} (u(a_i, d) + \kappa \cdot b(A_{-i}) - c(a_i)) < 0$ for $A_{-i} = \arg\max_{a_i} (u(a_i, d) - c(a_i))$ to ensure that users do not make use of the service if the addictiveness level is too high.[6]

The host platform sets a data disclosure policy γ. A more restrictive data disclosure policy may prevent the service provider from collecting user data, resulting in less effective targeting and, consequently, less profitable monetization of attention through targeted advertising. For tractability, consider γ as dichotomous. Either data usage is fully restricted (privacy policy), $\gamma = 0$, or there is full disclosure (disclosure policy), $\gamma = 1$.[7]

If the service is used, the service provider's payoff is

$$\Pi_S = (1 - \lambda) \cdot P + \gamma \cdot v(A). \tag{2}$$

If not, the payoff is zero. All costs of the service provider are normalized to zero, such that the payoff consists of two streams of revenues. There are payments that flow directly between the users and the service provider. A user may pay in advance for access to a service platform, for subscription to or to unlock additional features of a service. Throughout this work, focus on an admission price representative for payments between the users and the service provider. $\mathcal{I}_S \subseteq \mathcal{I}$ is the set of users that pay the admission price in order to gain access to the service, such that the total revenue from this stream is given by $P = \int_{i \in \mathcal{I}_S} p \, \mathrm{d}i$. From this revenue, the service provider must give an exogenous share $\lambda \in (0, 1)$ to the host to receive permission to operate.[8]

[6] The second assumption rules out trivial situations in which it is always profitable for the service provider to increase the level of addictiveness.

[7] I discuss the implications of a positive γ under privacy in Section 6.1. Furthermore, I contend that assuming γ is dichotomous is not critical in Section 6.2.

[8] The standard commission on all revenues generated via the App Store, which every app provider must pay to Apple, is 30%. For example, Baggott (2023) provides a detailed overview of Apple App Store fees. A meaningful examination of the endogenous choice of λ would need to involve factors that are not investigated here. For instance, one might consider λ as a market price determined by competition among host platforms, which is beyond the scope of this paper.

The service provider further makes revenue from monetization of user attention. This revenue is generated from a third party, typically by targeted advertisement. The service provider basically sells user attention to advertisers and its revenue from it is positively related to the total amount of attention users spend, denoted as $A = \int_{i \in \mathcal{I}_S} a_i \, \mathrm{d}i$. The function $v(A)$ represents the advertisement revenue and increases in the total attention the platform receives, i.e., for all $A \geq 0$, $\mathrm{d}v/\mathrm{d}A|_{(A)} > 0$.[9] The success of targeting depends on the service provider's capability to track and use user data, which is, in turn, determined by the host's data disclosure policy. To capture this, the revenue from targeted advertisement is scaled by γ.

All costs of the host are normalized to zero, such that the host's payoff equals its share of total admission fees, i.e.,[10]

$$\Pi_H = \lambda \cdot P. \tag{3}$$

The timing of the three-stage game is as follows:

1. The host commits to a data disclosure policy $\gamma \in \{0, 1\}$.
2. The service provider chooses an addictiveness level $d \geq 0$ and an admission price $p \geq 0$.
3. Each user $i \in \mathcal{I}$ simultaneously decides whether to use the service and, if so, determines an attention level $a_i \geq 0$.

The solution concept is a subgame-perfect Nash equilibrium (SPNE) in pure strategies, which I will refer to as the equilibrium.

4 Equilibrium

In this section, I derive the equilibrium using backward induction.

[9]This simplistic approach of modeling advertisement revenue is made for tractability. A characterization of advertisement strategy is beyond the scope of this paper.

[10]This model focuses on host revenues that are related to user attention and therefore to addictive service designs. Other sources of revenue include selling devices and offering services to users, such as iCloud or Apple Care, in the example of Apple.

4.1 User participation and attention

In what follows, I analyze the equilibrium participation and attention choices of the users. At the last stage, each user $i \in \mathcal{I}$ observes d, p and γ, and decides whether to use the service and how much attention to spend in order to maximize her payoff, as given by (1). Suppose i makes use of the service. Then she chooses her attention level according to the first-order condition $\mathrm{d}U_i/\mathrm{d}a_i = 0$, or rather,

$$\left.\frac{\partial u}{\partial a_i}\right|_{(a_i,d)} - \left.\frac{\partial c}{\partial a_i}\right|_{(a_i)} = 0. \tag{4}$$

The following proposition characterizes the equilibrium strategy of user i.

Proposition 1 *In the equilibrium of the last stage, each user $i \in \mathcal{I}$ makes use of the service and chooses a unique attention level $a_i = a_i^*(d)$ if $U_i(a_i^*(d), d, p, A_{-i}^*(d)) \geq 0$, where $A_{-i}^*(d) = a_i^*(d)$. Then, for all $d \geq 0$, $a_i^*(d) > 0$ and $\partial a_i^*/\partial d|_{(d)} > 0$. Otherwise, she does not use the service and $a_i = 0$.*

Proof. *See Appendix A.1.*

In equilibrium, user i chooses the unique payoff maximizing attention level $a_i(d) > 0$ (which solves (4)) when she makes use of the service, and, since users are homogeneous and rational, predicts that all other users behave like herself. Thus, each user i makes use of the service if spending attention $a_i(d)$ results in a weakly positive payoff given that all other users also spend this level of attention, i.e., $U_i(a_i^*(d), d, p, a_i^*(d)) \geq 0$.[11] Then, as in Ichihashi and Kim (2023), users tend to spend more attention when the service is more addictive, i.e., $\partial a_i^*/\partial d|_{(d)} > 0$. Nevertheless, a higher level of addictiveness decreases service utility, which may result in reduced willingness to use the service. When $U_i(a_i^*(d), d, p, a_i^*(d)) < 0$, users prefer to not use the service, corresponding to zero attention.

[11] One can think about a strategy of user i in which she does not use the service if she is indifferent. Following the backward induction argument, this will make the profit maximizing service provider choose a combination (d, p) in order to provide an infinitely small amount of positive utility to each user, and the service provider optimizes over an open set. Like in the standard bargaining game of Harsanyi (1961) (*Ultimatum game*), this makes it impossible to characterize an equilibrium strategy of the service provider. As a consequence, a strategy in which the user does not use the service if she is indifferent cannot be part of any equilibrium.

4.2 Admission price and addictiveness level

In this part, I examine the service provider's equilibrium strategy. At the second stage, the service provider observes γ and chooses a combination of the admission price and the addictiveness level. It chooses (d, p) to maximize its payoff (2) in anticipation of the users' equilibrium strategies, as given by Proposition 1.

First, observe that the service provider always receives a positive payoff as long as users participate, which makes it prefer users to make use of its service rather than not using the service at all. There exists a threshold $\overline{d} > 0$ such that users are indifferent between using the service and not using it when the service is free, i.e., $U_i(a_i^*(\overline{d}), \overline{d}, 0, a_i^*(\overline{d})) = 0$. Any addictiveness level $d > \overline{d}$ deters users from using the service and, therefore, cannot be part of any equilibrium.

For $d \leq \overline{d}$, users make use of the service if the admission price is not too high, and each user's optimal attention level is independent of the admission price. Hence, for a given $d \leq \overline{d}$, payoff maximization implies that the service provider sets a price $\overline{p} \geq 0$ such that users are indifferent between using the service and not using it, i.e., $U_i(a_i^*(d), d, \overline{p}, a_i^*(d)) = 0$. It is given by

$$\overline{p}(d) = u\left(a_i^*(d), d\right) + \kappa \cdot b\left(a_i^*(d)\right) - c\left(a_i^*(d)\right). \tag{5}$$

The service provider's problem boils down to the choice of the optimal level of addictiveness, which, in turn, determines the corresponding price according to (5). Note that, when $d \leq \overline{d}$, the total attention the service provider receives is $A^*(d) = a_i^*(d)$. The service provider solves

$$\max_{d\in[0,\overline{d}]} \Pi_S = \max_{d\in[0,\overline{d}]} \left[(1-\lambda)\cdot\left(u\left(a_i^*(d), d\right) + \kappa \cdot b\left(a_i^*(d)\right) - c\left(a_i^*(d)\right)\right) + \gamma \cdot v\left(a_i^*(d)\right)\right], \tag{6}$$

where the effect of increasing addictiveness on the service provider's payoff is given by

$$\begin{aligned}\frac{\mathrm{d}\Pi_S}{\mathrm{d}d} = (1-\lambda)\cdot \Bigg[& \left.\frac{\partial u}{\partial d}\right|_{(a_i^*(d),d)} + \kappa \cdot \left.\frac{\partial b}{\partial A_{-i}}\right|_{(a_i^*(d))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d)} \\ & + \left(\left.\frac{\partial u}{\partial a_i}\right|_{(a_i^*(d),d)} - \left.\frac{\partial c}{\partial a_i}\right|_{(a_i^*(d))} \right) \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d)} \Bigg] \\ & + \gamma \cdot \left.\frac{\partial v}{\partial A}\right|_{(a_i^*(d))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d)} .\end{aligned} \tag{7}$$

The term in square brackets captures the effect of an increase in addictiveness on the admission price, which we will call the *price effect*. It reflects how increasing addictiveness affects user utility, which is then extracted by the service provider. Recall that $a_i^*(d)$ solves (4). Hence, the price effect is given by

$$\psi(d) = \left.\frac{\partial u}{\partial d}\right|_{(a_i^*(d),d)} + \kappa \cdot \left.\frac{\partial b}{\partial A_{-i}}\right|_{(a_i^*(d))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d)} . \tag{8}$$

The sign of this effect can be ambiguous. On one hand, an increase in addictiveness reduces service utility, which may lower the (accepted) price. On the other hand, by Proposition 1, it increases attention. This, in turn, raises utility through network effects, potentially increasing the price.

The last term of (7) reflects the effect of increased addictiveness on the service provider's revenue from attention monetization. We will refer to this as the *attention monetization effect*, denoted by

$$\xi(d,\gamma) = \gamma \cdot \left.\frac{\partial v}{\partial A}\right|_{(a_i^*(d))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d)} . \tag{9}$$

This effect is weakly positive. As long as users make use of the service, increasing addictiveness stimulates attention, which, in turn, increases the revenue from attention monetization. Note that the host can restrict this revenue by setting $\gamma = 0$, such that $\xi(d,0) = 0$ for all d.

In any interior equilibrium, the service provider chooses d according to the first-order condition $\mathrm{d}\Pi_S/\mathrm{d}d = 0$, where the left-hand side is given by (7), i.e.,

$$(1-\lambda)\cdot\psi(d) + \xi(d,\gamma) = 0. \tag{10}$$

The following proposition describes the interior equilibrium strategy of the service provider and the corresponding existence conditions.

Proposition 2 *Suppose that the following existence conditions hold:*

$$\lim_{d\to 0}\left(\psi(d)\right) > 0 \tag{11}$$

$$\lim_{d\to \overline{d}}\left((1-\lambda)\cdot\psi(d) + \xi(d,1)\right) < 0 \tag{12}$$

Then the service provider chooses a unique combination of the addictiveness level $d = d^*(\gamma)$ *and the admission price* $p = \overline{p}(d^*(\gamma))$ *in the equilibrium of the second stage, where* $d^*(\gamma)$ *solves* (10) *and* $\overline{p}(d^*(\gamma))$ *is given by* (5)*. Further, for all* $\gamma \in \{0,1\}$*, it holds that* $0 < d^*(\gamma) < \overline{d}$ *and* $\overline{p}(d^*(\gamma)) > 0$*.*

Proof. *See Appendix A.2.*

The proposition characterizes conditions under which the service provider's equilibrium strategy involves levels of addictiveness such that $0 < d^*(\gamma) < \overline{d}$, where $d^*(\gamma)$ solves (10), and positive prices, $\overline{p}(d^*(\gamma)) > 0$. The existence condition (11) ensures that the payoff maximizing level of addictiveness is positive, $d^*(\gamma) > 0$, even when the service provider cannot monetize attention via targeted advertisements. Then, starting from $d = 0$, each user's additional benefit from network effects exceeds the marginal loss in service utility, implying that introducing a positive level of addictiveness increases the accepted admission price. The existence condition (12) ensures that prices are positive under each policy. In other words, it rules out the scenario where it would always be profitable to forego the revenue from admission prices to maximize attention, corresponding to $d = \overline{d}$ and $p(\overline{d}) = 0$. Thus, when (12) holds, $d^*(\gamma) < \overline{d}$, resulting in $\overline{p}(d^*(\gamma)) > 0$.[12]

[12] Service providers for which (12) does not hold are, for instance, those offering free and highly addictive online games that are financed exclusively through advertising revenue.

4.3 Data disclosure policy

In what follows, I consider the equilibrium data disclosure policy, focusing on scenarios in which the existence conditions (11) and (12) hold. At stage one, the host chooses γ in order to maximize its payoff (3) in consideration of the users' and the service provider's equilibrium strategies, as given by Proposition 1 and Proposition 2, respectively. The host receives an exogenous share from the service provider's admission price revenue, such that it chooses its policy in order to solve

$$\max_{\gamma \in \{0,1\}} \left[\lambda \cdot \overline{p}(d^*(\gamma))\right]. \tag{13}$$

The following proposition characterizes the equilibrium strategy of the host.

Proposition 3 *When* (11) *and* (12) *hold, the host sets* $\gamma = 0$ *in the unique equilibrium.*
Proof. *See Appendix A.3.*

Under the conditions of Proposition 2, it holds that $\overline{p}(d^*(0)) > \overline{p}(d^*(1))$. Therefore, the host strictly prefers the privacy policy, $\gamma = 0$, as it yields the highest admission price (from which the host receives a share). By contrast, under disclosure policy the service provider designs its service to balance admission price revenue with revenue from selling user attention through targeted advertising. Then it becomes profitable for the service provider to sacrifice some admission fees in order to increase revenue from targeted advertising. Since revenue from targeted advertising increases with user attention, and by Proposition 1 a more addictive service generates more user attention than a less addictive one, disclosure policy distorts the service provider's decision away from price maximization. Specifically, under disclosure policy, the service provider implements a level of addictiveness that exceeds the price-maximizing level, $d^*(1) > d^*(0)$. By setting a privacy policy, the host restricts targeted advertising revenue, and the service provider maximizes its payoff by maximizing the admission price. In this case, the host's and the service provider's incentives are aligned. Overall, a privacy policy yields a less addictive but higher-priced business model than a disclosure policy. By Proposition 1, users spend

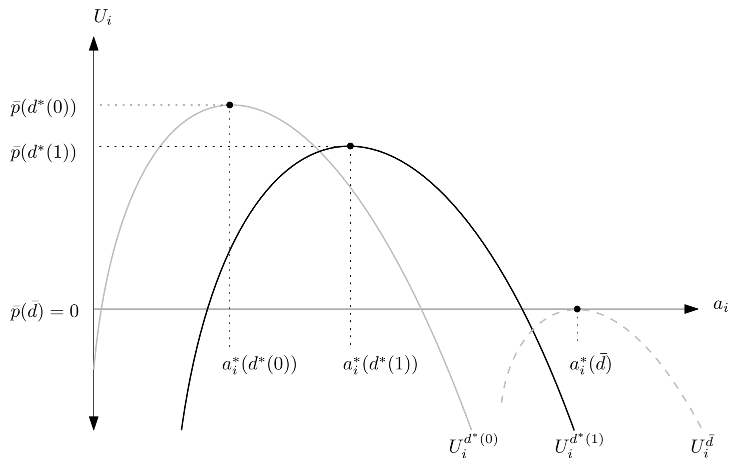

Figure 1: User utility under varying addictiveness levels.

less attention under privacy than under disclosure policy, i.e., $a_i^*(d^*(0)) < a_i^*(d^*(1))$.[13]

Figure 1 illustrates Proposition 3. The curves $U_i^{d^*(0)}$, $U_i^{d^*(1)}$ and $U_i^{\overline{d}}$ show the utility $U_i(a_i, d, 0, a_i^*(d))$ of user i as a function of her attention level, for addictiveness levels $d^*(0)$, $d^*(1)$ and $\overline{d}$, respectively.

The following corollary describes the effect of the data disclosure policy on the service utility a user experiences in the equilibria of the subgames for $\gamma = 0$ and $\gamma = 1$, i.e., $u(a_i^*(d^*(\gamma)), d^*(\gamma))$.

Corollary 1 *Privacy policy increases service utility compared to disclosure policy if*

$$\left.\frac{\partial u}{\partial a_i}\right|_{(a^*(d^*(0)),d^*(0))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d^*(0))} + \left.\frac{\partial u}{\partial d}\right|_{a^*(d^*(0)),d^*(0))} > 0.$$

The inequality $d^*(0) < d^*(1)$ suggests that service utility is higher under privacy than under disclosure policy for a given level of attention. In other words, the privacy policy corresponds to superior service quality. However, a higher level of addictiveness induces a higher level of attention. Therefore, the overall effect of the privacy policy on service utility depends on the balance between the utility gain from decreased addictiveness and the utility loss from decreased attention.

[13] In Section 6.4, I demonstrate that the main results of the paper also hold in scenarios where (11) and (12) are not satisfied, i.e., when the service provider may choose $d = 0$ or $d = \overline{d}$ in equilibrium.

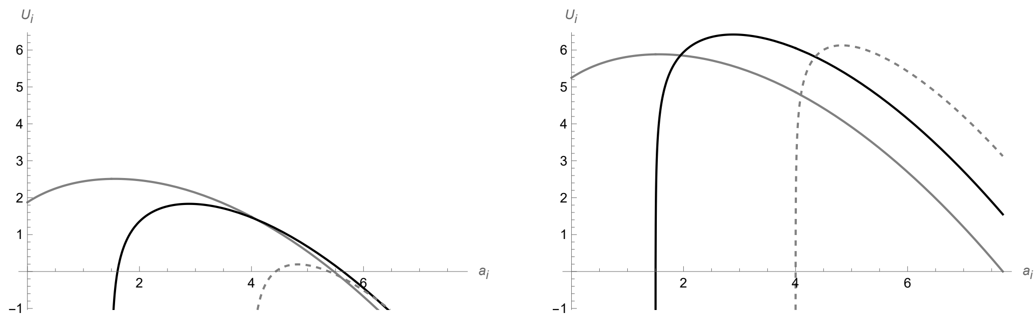

Figure 2: User utility under varying addictiveness levels for (a) $\kappa < \underline{\kappa}$ and (b) $\kappa > \underline{\kappa}$.

5 Comparative-statics results

In this section, I demonstrate how a stronger extent of network effects and an increase in the host's share of admission prices affect the equilibrium.

5.1 Extent of network effects

Online services differ in the extent of their network effects. For instance, users of online games strongly benefit from other users' activity (i.e., attention), because it improves matchmaking and the overall experience. In contrast, online education services rely less on user networks, since their primary value stems from the available content rather than user interaction. In what follows, I investigate how an increase in the extent of network effects, represented by an increase in κ, affects the equilibrium level of addictiveness.

The service provider sets the addictiveness level to maximize the admission price. Recall that user attention increases with addictiveness. Under positive network effects, $\kappa > 0$, users benefit from the attention of others, and the utility gain from increased attention by other users may outweigh the service utility loss caused by higher addictiveness. By Proposition 2, this occurs when (11) holds, implying that a positive level of service addictiveness maximizes the accepted admission price. Holding all else constant, there is a threshold $\underline{\kappa} > 0$ such that $\psi(0) = 0$, and (11) is satisfied for $\kappa > \underline{\kappa}$. Note that for $\kappa \leq \underline{\kappa}$, the service provider would always choose $d = 0$ in equilibrium. Overall, network effects alter the price-attention trade-off associated with increasing addictiveness and, when sufficiently strong, lead to positive levels of addictiveness in equilibrium.

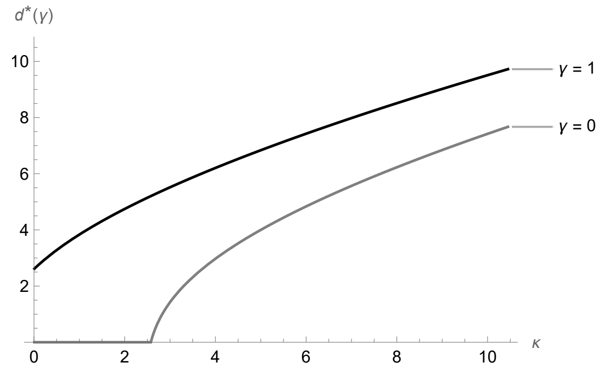

Figure 3: Optimal addictiveness levels under privacy and disclosure policy for varying κ.

Figure 2 illustrates this finding. Based on the numerical example from Appendix A.7, it shows the utility of a user who anticipates optimal attention spending of all other users for an admission price of zero. The gray solid line, black line, and gray dashed line represent utilities for $d_1 = 0$, $d_2 = 2.5$, and $d_3 = 5$, respectively. Figure (a) depicts a scenario in which $\kappa < \underline{\kappa}$ such that (11) does not hold. Then network effects are so weak that increasing the level of addictiveness always decreases the highest feasible utility level, i.e., the highest accepted admission price. Figure (b) illustrates the opposite case, $\kappa > \underline{\kappa}$. Then the effect of increasing addictiveness on the admission price is ambiguous. Increasing addictiveness from d_1 to d_2 increases the price, whereas increasing addictiveness from d_2 to d_3 decreases it.

Going one step further, the following proposition describes the effect of increasing the extent of network effects on the equilibrium addictiveness level for $\kappa \geq \underline{\kappa}$:

Proposition 4 *When $\kappa \geq \underline{\kappa}$, the equilibrium addictiveness level increases with κ.*

Proof. *See Appendix A.4.*

Increasing κ goes along with a stronger impact of network effects on overall user utility, and boosts the utility users gain from other users' attention. This, in turn, increases the price effect of addictiveness for any given d. Then it is beneficial for the service provider to implement a higher level of addictiveness in order to attract user attention, resulting in a higher equilibrium addictiveness level $d^*(0)$. Note that the payoff maximizing level of addictiveness under disclosure policy, $d^*(1)$, also increases in κ.

Figure 3 illustrates Proposition 4. Based on the numerical example an Appendix A.7, the graphs show the payoff maximizing addictiveness level for varying κ for $\gamma = 0$ and $\gamma = 1$. When $\kappa < \underline{\kappa} \approx 2.57$, it is profit maximizing to choose zero addictiveness under privacy policy. As κ increases, the impact of network effects outweighs the utility loss from addictiveness and (11) becomes satisfied. Then an increase of κ corresponds to an increase of equilibrium addictiveness levels under both policies.

5.2 Host's admission price share

I now investigate how an increase in the host's share λ of the revenue from admission prices affects the equilibrium.

Proposition 5 *When the host can fully restrict advertisement revenue, an increase of λ has no effect on equilibrium data disclosure, addictiveness level, admission price and attention.*

Proof. *See Appendix A.5.*

The host sets the privacy policy in equilibrium, corresponding to a full restriction of advertisement revenue. Accordingly, the service provider maximizes its share of revenue from admission prices. Since the service provider cannot affect the fraction it is allowed to keep, it maximizes its payoff by maximizing the accepted admission price. For $\gamma = 0$, the corresponding first-order condition (7) is independent of λ. Consequently, the equilibrium levels of addictiveness and the admission price are also independent of λ, and an increase in λ has no effect on the equilibrium when the host can fully restrict advertisement revenue.

6 Extensions and robustness

In this section, I discuss the effects of varying model assumptions on the results.

6.1 Limited restriction of advertisement revenue

In the model, it is assumed that setting a privacy policy fully restricts advertisement revenue. Proposition 5 implies that the host prefers a privacy policy combined with the highest possible value of λ in order to maximize revenue from admission prices and its share thereof. However, observed shares are intermediate, typically ranging between 30% and 50% (Ling, 2021). In what follows, I consider a scenario in which the host cannot fully restrict advertisement revenue by implementing a privacy policy, which leads to a trade-off regarding the choice of λ. To capture a limited restriction of advertisement revenue, let $\underline{\gamma}$ represent the privacy policy, with $0 < \underline{\gamma} < 1$. For example, in the case of iOS, a positive share of users chooses to opt in to tracking under ATT, corresponding to limited restriction of advertisement revenue. The following proposition describes the effect of λ on the equilibrium in this setting.

Proposition 6 *Let* (11) *and* (12) *hold and suppose that the host cannot fully restrict advertisement revenue,* $\gamma \in \{\underline{\gamma}, 1\}$ *with* $0 < \underline{\gamma} < 1$*. Then an increase in* λ *has no effect on equilibrium data disclosure, increases the equilibrium addictiveness level and attention, and decreases the equilibrium admission price.*

Proof. *See Appendix A.6.*

The host prefers privacy policy because a higher level of data disclosure leads to a lower admission price. Hence, the host sets $\gamma = \underline{\gamma}$ in equilibrium, independently of λ. The service provider then chooses an addictiveness level $d = d^*(\underline{\gamma})$ and a price $p = \overline{p}(d^*(\underline{\gamma}))$, balancing the price effect and the attention monetization effect of increasing addictiveness. It holds that $d^*(0) < d^*(\underline{\gamma}) < d^*(1)$ and $\overline{p}(d^*(0)) > \overline{p}(d^*(\underline{\gamma})) > \overline{p}(d^*(1))$. When the host cannot fully restrict advertising revenue, the service provider's equilibrium payoff comes from two sources, and only the revenue from admission prices is "taxed" by the host. As the share that must be given to the host increases (i.e., as λ increases), the service provider becomes more inclined to rely on advertising revenue, which can be increased by raising the level of addictiveness. Consequently, the equilibrium addictiveness level increases in λ, which in turn leads to a lower admission price and higher attention.

Proposition 6 suggests that the host faces a trade-off in choosing λ when it cannot fully restrict advertising revenue. On the one hand, a higher λ increases the share of admission-price revenue the host receives, which makes a higher value of λ attractive. On the other hand, a higher λ induces the service provider to increase addictiveness, which, in turn, lowers the admission price. Consequently, as λ increases, the host receives a larger share of a smaller revenue stream. Hence, Proposition 6 may provide an explanation for why observed revenue shares tend to be intermediate.[14]

6.2 Continuous data disclosure policy

In the model, the data disclosure policy is represented by a dichotomous variable that determines whether the service provider is able to generate advertising revenue or not. However, host platforms may set a degree of data disclosure rather than impose either full or no restrictions on advertising revenue. Thus, a more realistic approach is to model the data disclosure policy as a continuous choice variable, i.e., $\gamma \in [0, 1]$, where a higher value of γ corresponds to a less restrictive policy. When $\gamma \in [0, 1]$, the service provider chooses $d = d^*(\gamma)$ to solve (10) for any given level of γ. However, this level of addictiveness increases in γ, which in turn decreases the price. Consequently, the host prefers $\gamma = 0$, and thus the equilibrium is unchanged when the policy variable is continuous.

6.3 Network effects from participation

I assume that users benefit from the activity of other users, i.e., that network effects depend on the attention levels of other users. An alternative approach is to model network effects as depending on the presence of other users, i.e., as a function increasing in the mass of participating users. In equilibrium, the host sets the privacy policy and the service provider chooses an addictiveness level to maximize the admission price. When network effects depend on the mass of active users, rather than on their attention levels, increasing addictiveness always reduces user utility (existence condition (11) is not feasible to hold and the price effect is strictly negative) and therefore lowers the admission price. Consequently, when network effects depend on presence rather than attention, the service provider chooses zero addictiveness and a positive admission price in equilibrium.

[14] A comprehensive analysis is beyond the scope of this paper.

6.4 Existence conditions do not apply

The previous results apply to scenarios in which the existence conditions specified in Proposition 2 hold. In what follows, I show that the host weakly prefers privacy over disclosure policy when these conditions are violated.

Condition (11) rules out price maximization at zero addictiveness. If it is violated, equilibria may arise in which the service provider chooses an addictiveness level of zero under privacy and a weakly positive level under a disclosure policy. If strictness holds, i.e., if the (positive) attention-monetization effect outweighs the (negative) price effect for small levels of addictiveness, the host strictly prefers privacy over disclosure. Otherwise, the host is indifferent between the two policies. Taken together, even if (11) does not hold, the host never prefers disclosure over privacy.

Condition (12) excludes scenarios in which the attention-monetization effect always dominates the price effect. In such settings, the service provider maximizes its payoff under disclosure by setting an addictiveness level $\overline{d}$ with a corresponding price of zero. However, regardless of whether (12) holds, the service provider always maximizes a positive admission price under privacy. Hence, the host prefers the privacy over the disclosure policy even if (12) is violated.

7 Conclusion

This paper presents a theoretical model that captures key features of online markets in which a service provider and users interact on a host platform. It examines the relationship between the host's data disclosure policy and the pricing and service-design choices of a subordinate service provider. The host's policy determines whether the service provider can generate revenue from targeted advertising, while the service provider can sacrifice service quality in order to capture user attention by incorporating addictive design features.

The analysis reveals that the host, which receives a share of the revenue from admission prices, prefers a restrictive data disclosure policy. Under such a policy, the service provider sets a higher admission price and a lower level of addictiveness compared to a policy allowing greater data disclosure. The service provider sets a price that absorbs all user surplus. Thus, a higher price reflects higher user utility, which also goes along with less attention spending. Network effects among users alter the price-attention trade-off associated with addictive online service design. If sufficiently strong, they induce the service provider to choose a positive level of addictiveness even when attention cannot be monetized through advertising (i.e., under a restrictive data disclosure policy). Moreover, stronger network effects increase equilibrium addictiveness. When the host cannot fully restrict advertisement revenue, addictiveness increases in the share of the revenue from admission fees that the service provider must give to the host.

These findings may help explain recent shifts in corporate privacy policies observed in online markets, such as Apple's ATT and Google's Privacy Sandbox, as these policies increase host platform profits. The results suggest that such shifts prompt app providers to raise prices, which is empirically supported by Kesler (2023), who finds that apps in Apple's App Store have increasingly become chargeable and include in-app purchases following the ATT update. The results also indicate a positive relationship between increased user privacy and improved service quality. While previous research has shown that privacy can protect users from price discrimination or harmful targeting (e.g., Villas-Boas, 1999; Taylor, 2004; Villas-Boas, 2004; Zhang and Krishnamurthi, 2004; Acquisti and Varian, 2005; Hann et al., 2008), this paper highlights an additional benefit: enhanced service quality for users. Given the adverse effects of online addiction, the findings suggest potential welfare gains from improved service quality and reduced negative externalities associated with addictive service design.

Taken together, the results imply that policymakers aiming to reduce online addictiveness may not need to regulate online markets proactively, as host platforms may have incentives to address these issues themselves. Nevertheless, this conclusion should be interpreted with caution, as the model specifically focuses on corporate data disclosure policies that restrict the data usage of third-party service providers.

A Appendix

A.1 Proof of Proposition 1

To prove the proposition, I argue that the payoff maximizing attention level of user $i \in \mathcal{I}$, $a_i^*(d) = \arg\max_{a_i} U_i$, uniquely solves the first-order condition (4) and describe her equilibrium strategy. Then, I demonstrate that $a_i^*(d)$ increases in d using the Implicit Function Theorem (IFT), and show that $a_i^*(d)$ is strictly positive.

Per assumption, $\lim_{a_i \to 0} \left(\partial u / \partial a_i |_{(a_i,0)} - \mathrm{d}c/\mathrm{d}a_i|_{(a_i)} \right) > 0$. Further, $u(a_i, d)$ and $c(a_i)$ are strictly concave and strictly convex in a_i, respectively. It follows that there exists a unique payoff maximum $a_i = a_i^*(d)$, i.e., a unique solution of (4), with $a_i^*(0) > 0$. If a user makes use of the service, she chooses $a_i^*(d)$. In anticipation of other users behaving like herself, i.e., $a_i^*(d) = a_j^*(d)$ for all $i, j \in \mathcal{I}$ with $i \neq j$, user i uses the service and spends attention $a_i^*(d)$ if $U_i(a_i^*(d), d, p, A_{-i}^*(d)) \geq 0$, where $A_{-i}^*(d) = \int_{j \in \mathcal{I} \setminus i} a_j^*(d) \mathrm{d}j = a_i^*(d)$ is the optimal attention level of all other users. (Recall that the set $\mathcal{I}$ has unit mass with atomic elements.) If $U_i(a_i^*(d), d, p, a_i^*(d)) < 0$, she does not use the service, corresponding to zero attention.

In order to investigate how changes in d affect $a_i^*(d)$, define for this proof $F(a, d) = \partial u / \partial a - \partial c / \partial a$, such that $F(a, d) = 0$ is equivalent to (4), and consider the IFT:

i.) The payoff of user i, as presented in (1), is a $\mathbb{C}^2$ function and concave in a. As a consequence, there exists an $a = a_0$ that uniquely solves the corresponding first-order condition (4) for a given $d = d_0$. Thus, $F(a_0, d_0) = 0$.

ii.) At the point $(a, d, F(a, d)) = (a_0, d_0, 0) = A$, we have

$$\left. \frac{\partial F}{\partial a} \right|_{(a_0, d_0)} = \left. \left[\frac{\partial^2 u}{\partial a^2} - \frac{\partial^2 c}{\partial a^2} \right] \right|_{(a_0, d_0)} < 0,$$

Thus, it holds that $\partial F / \partial a|_{(a_0, d_0)} \neq 0$.

iii.) Since i.) and ii.) hold, the IFT is applicable. In the neighborhood of A, a can be expressed as a function of d, such that $F(a(d_0), d_0) = 0$. Furthermore, we have

$$\left.\frac{\partial a}{\partial d}\right|_{(a_0,d_0)} = -\left.\frac{\frac{\partial F}{\partial d}}{\frac{\partial F}{\partial a}}\right|_{(a_0,d_0)} = -\left.\frac{\frac{\partial^2 u}{\partial a \partial d} - \frac{\partial^2 C}{\partial a \partial d}}{\frac{\partial F}{\partial a}}\right|_{(a_0,d_0)} = -\left.\frac{\frac{\partial^2 u}{\partial a \partial d}}{\frac{\partial F}{\partial a}}\right|_{(a_0,d_0)} > 0.$$

Since $\partial^2 u/\partial a \partial d > 0$ for all $d \geq 0$, this is true for arbitrary $d_0 \geq 0$. Changing the notation from a_0 to a_i^* and considering d as a variable, we have $\partial a_i^*/\partial d > 0$. That is, $a_i^*(d)$ increases in d.

Since $a_i^*(0) > 0$ and $a_i^*(d)$ is increasing in d, it follows that, for all $d \geq 0$, $a_i^*(d) > 0$.

■

A.2 Proof of Proposition 2

For each observed policy $\gamma \in \{0, 1\}$, the interior equilibrium d satisfies the first-order condition (10). To prove the proposition, I provide conditions that exclude corner solutions, specifically $d = 0$ and $d = \overline{d}$, for $\gamma = 0$ and $\gamma = 1$. Then, I demonstrate that there exist unique interior solutions to (10) under these conditions. Define, for this proof, from the left-hand side (LHS) of (10) the function

$$G(d, \gamma; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa) + \xi(d, \gamma),$$

such that $G(\cdot) = 0$ corresponds to (10).

Consider $\gamma = 0$. Since $\xi(d, 0) = 0$ for all d, $G(d, 0; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa)$. Then $d = 0$ can never be a solution to the service provider's payoff maximization problem if $\lim_{d \to 0} G(d, 0; \kappa, \gamma) > 0$, or rather

$$(1 - \lambda) \cdot \left(\left.\frac{\partial u}{\partial d}\right|_{(a_i^*(0),0)} + \kappa \cdot \left.\frac{\partial b}{\partial A_{-i}}\right|_{(a_i^*(0))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(0)} \right) > 0.$$

By Proposition 1, $\partial a_i^*/\partial d|_{(0)} > 0$, and it is feasible for this condition to be both satisfied and violated. Consequently, to exclude $d = 0$ as an optimal solution, it has to hold that

$$\psi(0; \kappa) > 0. \tag{A.1}$$

$d = \overline{d}$ cannot be a solution to the service provider's payoff maximization problem if $\lim_{d \to \overline{d}} G(d, 0; \kappa, \gamma) < 0$. Since the service provider can set a positive price by setting $d < \overline{d}$, this implies

$$\psi(\overline{d}; \kappa) < 0, \tag{A.2}$$

such that it cannot be optimal to choose $d = \overline{d}$.

Consider $\gamma = 1$, such that $G(d, 1; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa) + \xi(d, 1)$. Then $d = 0$ cannot be a solution to the service provider's maximization problem if $\lim_{d \to 0} G(d, 1; \kappa, \gamma) = (1 - \lambda) \cdot \psi(0; \kappa) + \xi(0, 1) > 0$. Proposition 1 implies that $\xi(0, 1) > 0$. Thus, the condition is not feasible to be violated if (A.1) holds. Consequently, if (A.1) is satisfied, $d = 0$ cannot be payoff maximizing. $d = \overline{d}$ cannot be payoff maximizing if $\lim_{d \to \overline{d}} G(d, 1; \kappa, \gamma) < 0$. Since $\xi(\overline{d}, 1) > 0$, (A.2) implies that the condition is feasible to be both satisfied and violated. Hence, to exclude $d = \overline{d}$ as a solution, it has to hold that

$$(1 - \lambda) \cdot \psi(\overline{d}; \kappa) + \xi(\overline{d}, 1) < 0. \tag{A.3}$$

In what follows, I use the Intermediate Value Theorem (IVT) to demonstrate that, if (A.1) and (A.3) hold, there exists a unique interior solution to the service provider's payoff maximization problem for each $\gamma \in \{0, 1\}$. By construction, $G(d, \gamma; \kappa, \lambda)$ is continuous over $d \in (0, \overline{d})$. (A.1) implies that the limit of $G(\cdot)$ at the lower border of its support is positive, i.e., $\lim_{d \to 0} G(d, \gamma; \kappa, \lambda) > 0$. (A.3) implies that the limit of $G(\cdot)$ at the upper border of its support is negative, i.e., $\lim_{d \to \overline{d}} G(d, \gamma; \kappa, \lambda) < 0$. According to the IVT, it follows that there exists at least one $d_c \in (0, \overline{d})$ such that $G(d_c, \gamma; \kappa, \lambda) = 0$. Denote the set of all these critical points as $\mathcal{D}_c = \{d_{c1}, d_{c2}, d_{c3}, \dots\}$. If $\mathcal{D}_c$ is a singleton, its element characterizes a unique global maximum, i.e., the unique addictiveness level in the equilibrium of the second stage for a given policy. If not, within the scope of the model, every element characterizes a critical point of the service provider's payoff function. Each critical point is either a local maximum or a local minimum. (A.1) and (A.3) imply that $\mathcal{D}_c$ consists of an odd number of elements, where every odd-numbered element of the set characterizes an argument that locally maximizes the payoff. Thus, the set of critical points that correspond to local maxima is $\mathcal{D}_{c,\max} \subset \mathcal{D}_c$, with $\mathcal{D}_{c,\max} = \{d_{c1}, d_{c3}, \ldots\}$. Since corner solutions are ruled out, the set of potential global maxima is $\mathcal{D}_{c,\max}$. Every global maximum characterizes an equilibrium level of addictiveness. In addressing the issue of multiplicity of equilibria, it is crucial to acknowledge that the presence of multiple equilibria depends on the existence of multiple global maxima. For each γ, there only exist multiple global maxima if there are local maxima $d_{ci}, d_{cj} \in \mathcal{D}_{c,\max}$, $i \neq j$ that result in the same payoff. However, scenarios featuring multiple global maxima are highly specific, requiring an exact alignment of parameters and functional forms. Furthermore, the fragile nature of these setups implies that even minimal variations in parameter values (e.g., marginal variation of κ) are sufficient to disrupt the existence of multiple global maxima, thereby eliminating the multiplicity of equilibria. Given the rarity and instability of such configurations, I choose to abstract from these cases in my analysis. Consequently, exactly one element of $\mathcal{D}_{c,\max}$ characterizes a global maximum, denoted by $d^*(\gamma)$.

Taken together, for every $\gamma \in \{0, 1\}$, there exists a unique $d^*(\gamma) \in (0, \overline{d})$ that maximizes the service provider's payoff if conditions (A.1) and (A.3) are satisfied. These conditions correspond to (11) and (12), respectively. It follows from $d^*(\gamma) < \overline{d}$ that the corresponding prices, as defined in (5), are strictly positive, i.e., $\overline{p}(d^*(\gamma)) > 0$.

■

A.3 Proof of Proposition 3

For profit maximization, the host solves (13), i.e., it chooses γ to induce the service provider to maximize the admission price. To prove the proposition, I first show that $\gamma = 0$ leads the service provider to maximize the admission price, and then demonstrate that $\gamma = 0$ is the unique maximizer when the existence conditions (11) and (12) hold.

For $\gamma = 0$, the service provider's payoff maximization problem at the second stage becomes a price maximization problem. It chooses $d_0 = \arg\max_{d \in [0, \overline{d}]} (1 - \lambda)\overline{p}(d) = \arg\max_{d \in [0, \overline{d}]} \overline{p}(d)$ and the corresponding price according to (5).

By Proposition 2, the service provider chooses $d = d^*(\gamma) \in (0, \overline{d})$ and $p = \overline{p}(d^*(\gamma)) > 0$

to maximize its payoff when (11) and (12) hold. In order to demonstrate that $\gamma = 0$ uniquely maximizes the admission price, compare the prices for $\gamma = 0$ and $\gamma = 1$. Recall from the proof of Proposition 2 that $d^*(0)$ is defined by $G(d, 0; \kappa, \lambda) = 0$, with $G(d, 0; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa)$, and that $d^*(1)$ is defined by $G(d, 1; \kappa, \lambda) = 0$, with $G(d, 1; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d, \kappa) + \xi(d, 1) = G(d, 0; \kappa, \lambda) + \xi(d, 1)$. Since $\xi(d, 1) > 0$ for all $d \in (0, \overline{d})$, it follows that

$$G(d, 0; \kappa, \lambda) < G(d, 1; \kappa, \lambda) \quad \forall\, d \in (0, \overline{d}),$$

such that $d^*(0) < d^*(1)$. Since $d^*(0)$ uniquely maximizes the service provider's payoff for $\gamma = 0$, i.e., it uniquely maximizes the admission price, and γ has no direct effect on the price, $d^*(0) \neq d^*(1)$ implies that $\overline{p}(d^*(0)) > \overline{p}(d^*(1))$. As a consequence, the host strictly prefers $\gamma = 0$ over $\gamma = 1$, such that the host's unique equilibrium strategy is $\gamma = 0$.

■

A.4 Proof of Proposition 4

In this proof, I investigate, for $\kappa \geq \underline{\kappa}$, the effects of increasing κ on equilibrium addictiveness. For $\kappa > \underline{\kappa}$, I show that the marginal effect of κ on $d^*(0)$ is positive, using the IFT. Then, I argue that the effect is also positive for $\kappa = \underline{\kappa}$.

For $\kappa > \underline{\kappa}$, the equilibrium level of addictiveness is implicitly defined by (7) for $\gamma = 0$. The corresponding LHS is equivalent to

$$G(d, 0; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa),$$

such that $G(d, 0; \kappa, \lambda) = 0$ corresponds to (7) being satisfied. Consider the IFT:

i. Denote, for this proof, the addictiveness level that solves the first-order condition under privacy policy as $d_0 = d^*(0)$. The function $G(d, 0; \kappa, \lambda)$ is $\mathbb{C}^1$, and according to Proposition 2, there exists a $d_0 \in (0, \overline{d})$ that solves $G(d, 0; \kappa, \lambda) = 0$ for any given κ_0 and λ_0, if conditions (11) and (12) are satisfied, which they are by assumption.

ii.) $\partial G/\partial d|_{(d_0,0;\kappa_0,\lambda_0)}$ is equivalent to the second-order condition of the service provider's profit maximization problem. d_0 characterizes a maximum. Hence, it holds that $\partial G/\partial d|_{(d_0,0;\kappa_0,\lambda_0)} < 0$, or rather $\partial G/\partial d|_{(d_0,0;\kappa_0,\lambda_0)} \neq 0$.

iii.) Points i.) and ii.) imply that the IFT is applicable. In the neighborhood of the point $(d, \kappa, \lambda, G(d, 0; \kappa, \lambda)) = (d_0, \kappa_0, \lambda_0, 0)$, d can be expressed as a function of κ, $d = g(\kappa, \lambda)$, such that $G(g(\kappa_0, \lambda_0), 0; \kappa_0, \lambda_0) = 0$. Furthermore, we obtain

$$\left.\frac{\partial g}{\partial \kappa}\right|_{(\kappa_0,\lambda_0)} = -\frac{\left.\frac{\partial G}{\partial \kappa}\right|_{(d_0,0;\kappa_0,\lambda_0)}}{\left.\frac{\partial G}{\partial d}\right|_{(d_0,0;\kappa_0,\lambda_0)}} = -\frac{\left.\frac{\partial b}{\partial A_{-i}}\right|_{(a_i^*(d_0))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d_0)}}{\left.\frac{\partial \psi}{\partial d}\right|_{(d_0;\kappa_0)}}.$$

By Proposition 1 and Proposition 2, $\partial g/\partial \kappa|_{(\kappa_0,\lambda_0)} > 0$. Changing notation, we obtain $\partial d^*(0)/\partial \kappa > 0$.

For $\kappa = \underline{\kappa}$, the sign of the marginal effect of an increase in κ on addictiveness is the same as for $\kappa > \underline{\kappa}$. This is because increasing κ from this level leads to a change from $\psi(0) = 0$ at $\kappa = \underline{\kappa}$ to $\psi(0) > 0$ for $\kappa > \underline{\kappa}$, which in turn raises the payoff-maximizing addictiveness level from $d = 0$ to $d = d^*(0) > 0$.

■

A.5 Proof of Proposition 5

The proof of the proposition is straightforward. By Proposition 3, the host chooses $\gamma = 0$ in equilibrium. The service provider maximizes the price as given by (5), which is independent from λ. Hence, $\partial d^*(0)/\partial \lambda = \mathrm{d}\overline{p}(d^*(0))/\mathrm{d}\lambda = 0$ for all $\lambda \in (0, 1)$.

■

A.6 Proof of Proposition 6

To prove the proposition, I first show that when $\gamma \in \underline{\gamma}, 1$ with $\underline{\gamma} \in (0, 1)$, the host chooses $\gamma = \underline{\gamma}$ in equilibrium, and that this decision is unaffected by changes in λ. Then, using the IFT, I show that equilibrium addictiveness increases in λ, while the equilibrium admission price increases and attention decreases.

To see that the host chooses $\gamma = \underline{\gamma}$ in equilibrium, recall the proof of Proposition 3. As shown there, a higher level of data disclosure leads to a higher level of addictiveness and a lower admission price. Hence, in equilibrium, the host chooses the lowest possible level of data disclosure to induce price maximization, i.e. $\gamma = \underline{\gamma}$.

The service provider solves (7) for $\gamma = \underline{\gamma}$ to maximize its payoff. The corresponding LHS is equivalent to

$$G(d, \underline{\gamma}; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa) + \xi(d, \underline{\gamma}),$$

such that $G(d, \underline{\gamma}; \kappa, \lambda) = 0$ corresponds to (7) being satisfied for $\gamma = \underline{\gamma}$. Consider the IFT:

i. Denote, for this proof, the addictiveness level that solves the first-order condition for $\gamma = \underline{\gamma}$ as $d_0 = d^*(\underline{\gamma})$. The function $G(d, \underline{\gamma}; \kappa, \lambda)$ is $\mathbb{C}^1$, and according to Proposition 2, there exists a $d_0 \in (0, \overline{d})$ that solves $G(d, \underline{\gamma}; \kappa, \lambda) = 0$ for any given κ_0 and λ_0, if conditions (11) and (12) are satisfied, which they are by assumption.

ii.) $\partial G/\partial d|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}$ is equivalent to the second-order condition of the service provider's profit maximization problem. d_0 characterizes a maximum. Thus, $\partial G/\partial d|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)} < 0$, or rather $\partial G/\partial d|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)} \neq 0$.

iii.) Points i.) and ii.) imply that the IFT is applicable. In the neighborhood of the point $(d, \kappa, \lambda, G(d, \underline{\gamma}; \kappa, \lambda)) = (d_0, \kappa_0, \lambda_0, 0)$, d can be expressed as a function of λ, $d = g(\kappa, \lambda)$, such that $G(g(\kappa_0, \lambda_0), \underline{\gamma}; \kappa_0, \lambda_0) = 0$. Furthermore, we have

$$\left.\frac{\partial g}{\partial \lambda}\right|_{(\kappa_0, \lambda_0)} = -\frac{\left.\frac{\partial G}{\partial \lambda}\right|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}}{\left.\frac{\partial G}{\partial d}\right|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}} = \frac{\psi(d_0; \kappa_0)}{\left.\frac{\partial G}{\partial d}\right|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}}.$$

Recall Proposition 2 and the proof of Proposition 3. Linearity of $G(\cdot)$ in γ implies that $d^*(0) < d^*(\underline{\gamma}) < d^*(1)$. It follows that $\psi(d^*(1); \kappa_0) < \psi(d^*(\underline{\gamma}); \kappa_0)) = \psi(d_0; \kappa_0) < \psi(d^*(0); 0) = 0$. Consequently, $\partial g/\partial \lambda|_{(\kappa_0, \lambda_0)} > 0$. Changing notation, we obtain $\partial d^*(\underline{\gamma})/\partial \lambda > 0$.

Now consider the effect of λ on the equilibrium admission price. Since $\partial d^*(\underline{\gamma})/\partial\lambda > 0$, the sign of this effect is determined by the sign of $\psi(d^*(\underline{\gamma}))$. Hence, $\mathrm{d}\overline{p}(d^*(\underline{\gamma}))/\mathrm{d}\lambda < 0$. Moreover, by Proposition 1, $\partial d^*(\underline{\gamma})/\partial\lambda > 0$ implies that $\mathrm{d}a_i^*(d^*(\underline{\gamma}))/\mathrm{d}\lambda > 0$.

■

A.7 Numerical example

Suppose service utility is $u(a_i, d) = \ln(1 + a_i - d)$, network effects are $b(A_{-i}) = \sqrt{A_{-i}}$, attention costs are $c(a_i) = 1/8 \cdot a_i^2$, and attention can be directly monetized according to $v(A) = 3 \cdot \sqrt{1 + A}$. Furthermore, suppose $\kappa = 8$ and $\lambda = 0.3$ In the following, we construct the equilibrium.

At stage 3, each user i maximizes utility

$$U_i(a_i, d, p, A_{-i}) = \ln(1 + a_i - d) + \kappa \cdot \sqrt{A_{-i}} - \frac{1}{8} \cdot a_i^2 - p.$$

If she uses the service, the optimal attention level of user i is

$$a_i^*(d) = \frac{1}{2} \cdot \left(d - 1 + \sqrt{17 - 2d + d^2}\right). \tag{A.4}$$

Her participation constraint is

$$\begin{aligned} \ln\left(\frac{1}{2} \cdot \left(1 - d + \sqrt{17 - 2d + d^2}\right)\right) + \kappa \cdot \sqrt{A_{-i}} \\ -\frac{1}{32} \cdot \left(d - 1 + \sqrt{17 - 2d + d^2}\right)^2 - p \geq 0. \end{aligned} \tag{A.5}$$

At the second stage, for any $d \in [0, \overline{d})$, the price is determined by (A.5) holding with equality for $A_{-i} = A_{-i}^* = a_i^*(d)$ as defined in (A.4), and $\kappa = 8$, i.e.,

$$\begin{aligned} \overline{p}(d) = 4 \cdot \sqrt{2} \cdot \sqrt{d - 1 + \sqrt{17 - 2d + d^2}} - \frac{1}{32} \cdot \left(d - 1 + \sqrt{17 - 2d + d^2}\right)^2 \\ + \ln\left(\frac{1}{2}\left(1 - d + \sqrt{17 - 2d + d^2}\right)\right) \end{aligned} \tag{A.6}$$

Note that the conditions for the existence of an interior solution to the service provider's profit maximization problem, as presented in Proposition 2, are satisfied. Condition (11)

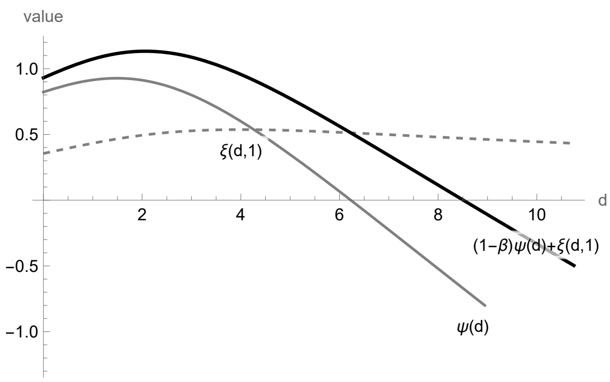

Figure 4: Service provider's first-order condition under disclosure policy (black), first-order condition under privacy policy / PE (gray), and AME (gray, dashed).

holds for $\kappa > \underline{\kappa} \approx 2.57$. Thus, the condition is satisfied for $\kappa = 8$. The maximum rationalizable level of addictiveness is $\overline{d} \approx 16.28$. Condition (12) is satisfied because $(1-0.3)\cdot\psi(16.28;8)+\xi(16.28,1) \approx -1.65 < 0$. Consequently, in the equilibria of both subgames, the service provider chooses addictiveness levels over the set $(0,\overline{d})$.

In the privacy subgame, i.e., for $\gamma = 0$, the service provider solves the first-order condition $\mathrm{d}\overline{p}/\mathrm{d}d = 0$, which is equivalent to $\psi(d) = 0$, or rather

$$\frac{1}{8}\left(1-d-\sqrt{17-2d+d^2}+\frac{16\sqrt{2}\sqrt{d-1+\sqrt{17-2d+d^2}}}{\sqrt{17-2d+d^2}}\right)=0. \tag{A.7}$$

$d^*(0) \approx 6.22$ solves (A.7). Plugging this value into (A.6) yields $\overline{p}(d^*(0)) \approx 14.69$. The corresponding attention level, as defined in (A.4), is $a_i^*(d^*(0)) \approx 5.90$.

In the disclosure subgame, i.e., for $\gamma = 1$, the service provider solves $(1-\lambda)\cdot\mathrm{d}\overline{p}/\mathrm{d}d + \mathrm{d}v/\mathrm{d}d = 0$, or rather

$$(1-0.3)\cdot\psi(d)+\frac{3\left(2+\frac{2(-1+d)}{\sqrt{17-2d+d^2}}\right)}{4\sqrt{2}\sqrt{1+d+\sqrt{17-2d+d^2}}}=0, \tag{A.8}$$

where $\psi(d)$ is equivalent to the LHS of (A.7). $d^*(1) \approx 8.51$ solves (A.8). Evaluating (A.6) yields the corresponding price $\overline{p}(d^*(1)) \approx 13.92$. The attention level of each user is $a_i^*(d^*(1)) \approx 8$, as defined in (A.4).

Figure 4 illustrates the effects of increasing d on the second stage. The solid and dashed gray lines depict $\psi(d)$ and $\xi(d,1)$, respectively. The black graph shows the interplay, i.e., $(1-\lambda)\psi(d)+\xi(d,1)$. Note that the roots of the solid gray and black lines characterize the addictiveness levels in the equilibrium of the privacy and disclosure subgame, respectively.

At the first stage, the host aims at price maximization. Thus, it follows from $\overline{p}(d^*(0)) > \overline{p}(d^*(1))$ that the host chooses $\gamma = 0$ in equilibrium.

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