Opt-In to Innovation? The Effects of Apple's App Tracking Transparency Policy on Complementor Innovation

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Abstract

Platform operators face a continuous trade-off in governance decisions between addressing user interests and preserving incentives for complementor innovation. One highly debated area of platform governance involves protecting user privacy by limiting targeted advertising, which, however, is vital to many complementors' value capture models. In this paper, we seek to understand the implications of such stricter privacy governance on complementor innovation. To do this, we examine how mobile app developers adjust their innovation activities in response to Apple's App Tracking Transparency (ATT) policy. Using a quasi-experimental difference-in-differences framework, we compare the innovation outcomes for apps affected by the policy with those unaffected, both before and after the policy announcement. We measure innovation as the frequency of updates that introduce new features or extend content. To accurately identify these updates, we use a new AI-based approach that classifies all update release notes of an app with a fine-tuned GPT-3.5 model. Our results indicate that although both affected and unaffected apps showed an overall decline in feature updates after the policy announcement, the reduction was less pronounced—or even reversed—for affected apps. This suggests that developers reliant on targeted advertising may have increased their innovation efforts to offset the reduced effectiveness of their primary value capture model. We discuss that while stricter privacy governance may initially seem to negatively affect complementor innovation, its nuanced effects can also serve as strategic catalysts to reshape their innovation activities.

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1 Introduction

Innovation in complements is central to the value of platform-based ecosystems (Gawer and Cusumano, 2002; Jacobides et al., 2024; Parker and Van Alstyne, 2005). Typically, the platform operator defines the operational scope for complementors through a set of governance policies (Tiwana et al., 2010; Wareham et al., 2014), which ultimately shape how innovation occurs within the ecosystem (e.g., Boudreau, 2010). A frequently observed development is that initially, while the platform operator is focused on growth, governance supports a broad complementor population and encourages wide-ranging innovation activities. Over time, as the platform operator's focus shifts to value capture, they often become more selective and focused on users (Rietveld et al., 2020). At this stage, complementors find it difficult to leave, even if they experience unfavorable changes to platform governance (Cutolo and Kenney, 2021; Rahman et al., 2024; Rietveld and Schilling, 2021). This has sparked great interest in exploring the behavior of complementors following such governance changes and the implications for ecosystem value.

One set of user-focused governance policies that has become subject of much debate centers on user privacy and targeted advertisement (Goldfarb and Que, 2023). Targeted advertisement involves personalizing ads displayed to users based on their behavioral, demographic, and location data. This form of advertising is central to many complementors' value capture models, especially in platform-based ecosystems like Apple's iOS and Google's Android, where products are often offered for free and users' willingness to pay is generally low (e.g., Casadesus-Masanell and Hervas-Drane, 2015). With stricter privacy governance, the availability of user data is limited, reducing the effectiveness of targeted advertising and requiring complementors to react. Recent findings by Kircher and Foerderer (2023) point to a substantial drop in overall innovation activities following Google's 2019 ban on targeted advertising in certain app categories on their Android platform. Considering that in other scenarios where complementors' value capture was threatened by a governance change, for instance by the selective promotion of competitors (Agarwal et al., 2023; Foerderer et al., 2021; Rietveld et al., 2019, 2021) or the platform operator's market entry (Foerderer et al., 2018; Shi et al., 2023; Wen and Zhu, 2019), a reorientation or even an increase in innovation efforts was documented, these results raise important questions on how privacy governance can be effectively designed without stifling innovation.

Our study seeks to contribute to these questions by investigating the implications of Apple's App Tracking Transparency (ATT) policy for complementors and the iOS ecosystem. In June 2020, Apple announced that it will introduce a privacy-preserving feature that requires explicit consent from users to track them outside of the app in the next large iOS 14 update. If consent is denied, this could exacerbate the personalized targeting and attribution of advertisements with negative effects for the app's advertisement revenue. After strong opposition from developers, Apple delayed the implementation of this policy as a part of the iOS 14.5 update in April 2021. The ATT policy is intriguing for three major reasons. First, this setting allows us to study complementors' reactions to privacy governance that reduces their value-capture opportunities. Targeted advertising is the primary revenue source for most mobile apps. Requiring users to opt-in to activity tracking now renders the complementors' opportunities to capture value from their apps directly dependent on that consent. In fact, the ATT policy has reduced revenue streams from app advertisements significantly (Kraft et al., 2023). Second, ATT is not a full ban of (targeted) advertising but promises to provide insights on the implications of less strict opt-in policies. Third, the policy announcement serves as a suitable setting to be studied in a quasi-experimental design. The announcement was exogenous to Apple's developer ecosystem, rather unexpected to the third-party app developers, and the policy loomed to be implemented quickly. Also, it is unlikely that other events coincided with the policy announcement.

We use comprehensive app- and developer-level data from the iOS App Store to track complementor innovation and ecosystem implications over time. Apps are the key complements to a mobile platform like iOS. After launching their apps on the platform, developers typically continue development efforts. Alongside bug fixes and technical adaptations, this involves releasing new features and content in order to keep the app attractive. We model complementor innovation as the monthly frequency of updates that introduce new features and content to an app. To operationalize this measure, we analyze each update's release notes using a GPT-3.5 model, which we fine-tuned for this purpose. We compare apps affected by the ATT policy to those unaffected, before and after the policy's announcement. Our strategy for distinguishing between affected and unaffected apps involves a close examination of the software development kits (SDKs) they have used. Specifically, we posit that apps integrating SDKs from advertising networks are likely designed to capture value through the monetization of advertisement spaces and rely on user data for targeted advertising, thus requiring compliance with the ATT policy. Conversely, apps devoid of advertising network SDKs are presumed to be unaffected.

Our results suggest a general decline in updates that release new features or content for affected and unaffected apps. However this decrease was less pronounced for affected apps or even reversed the negative trend. A small fraction of apps show descriptive patterns towards a change in monetization after the announcement of the ATT policy. These changes are positively related to feature updates. When apps change their way to capture value, further development efforts might be required as the value proposition needs to be transformed.

2 Related Literature

Our research contributes to a growing literature that examines digital platforms as systems in which a wide range of external complementors independently contribute to a generative infrastructure provided and orchestrated by a platform operator (Bhargava, 2022; Parker and Van Alstyne, 2018; Tiwana et al., 2010). This literature attributes a key role to the platform operator in attracting new complementors to the platform and encouraging existing complementors to continuously improve their value propositions in a way that benefits the entire ecosystem.

The work on platform governance has studied various decisions that platform operators make to shape complementors' incentives and activities in contributing to the platform. As the platform emerges and grows, these decisions focus on building an attractive complement pool und include decisions on pricing choices (Hagiu, 2006; Parker and Van Alstyne, 2005), partnership programs (Ceccagnoli et al., 2012), boundary resources (Ghazawneh and Henfridsson, 2012; Miric et al., 2022), access control (Casadesus-Masanell and Hałaburda, 2014; Zhang et al., 2022), performance investments (Anderson et al., 2014), opportunities for interfirm exchange (Foerderer, 2020), and property rights (Miric and Jeppesen, 2020). As the platform matures, the operator's focus shifts to value capture from platform usage and governance decisions concentrate primarily on users' perception of the platform. Such decisions can include, for instance, the selective promotion of complements (Agarwal et al., 2023; Claussen et al., 2013; Foerderer et al., 2021; Rietveld et al., 2019, 2021), algorithmic management (Curchod et al., 2019; Farronato et al., 2023; Huang and Xie, 2023; Möhlmann et al., 2021), and entering complementary markets (Foerderer et al., 2018; Gawer and Henderson, 2007; Huang et al., 2013; Shi et al., 2023; Wen and Zhu, 2019; Zhu, 2018; Zhu and Liu, 2018). Although these governance decisions may threaten complementors' ways of value capture by reducing expected rents from their contributions to the platform, they find it difficult to leave the platform (Cutolo and Kenney, 2021; Rahman et al., 2024). As such, complementors often still contribute to the platform and may reorient or even enhance their contributions. Platform operators use such governance policies strategically to steer the value proposition in ways that they consider important for overall ecosystem value (Rietveld et al., 2019).

We contribute to this literature by focusing on a widely debated but less studied platform governance decision: enforcing stricter user privacy. Empirical work in this area is still nascent. In the research that relates closest to ours, Kircher and Foerderer (2023) investigate the impact of Google's ban of targeted advertising in Android children's games on app development, revealing that the ban reduced the release of feature updates, particularly for games of young, undiversified, and ad-dependent firms. An increase in development efforts has been only detected for high-quality and high-demand games. The drop in development efforts is intriguing as it raises questions about how such governance decisions should be introduced in broader roll-outs without stifling the ecosystem's innovation activities and overall viability. We address this issue by investigating the effects of Apple's ATT policy. The ATT-policy differs from the ban in three important ways that allow us to contribute additional insights to this line of research: (i) ATT is not a full ban of (targeted) advertising—it requires users to actively opt-in to tracking and thereby reduces revenue streams, but targeted advertising is not forbidden in general; (ii) ATT does not only affect a niche in a genre but a great share of the iOS platform given that a large share of apps engages in targeted advertising; (iii) developers can't simply switch development efforts to "unaffected" apps but they would have to switch to their IAP-financed apps or other monetization models if these seem beneficial.

Notably, recent working studies have provided first empirical insights of the ATT policy's impact. Kesler (2022) examines the shift in app monetization models due to ATT, revealing a modest increase in paid apps on Apple and a trend towards more in-app payments, particularly among apps relying heavily on Apple and tracking. Cheyre et al. (2023) findings indicate a rapid recovery in the number of apps on the Apple App Store following an initial decline after ATT's implementation. They also observe shifts in app components, with a decrease in the use of Monetization- and Ad Mediation- and an increase in Authentication- and Payment-related components. This suggests developers adapted their strategies to align with the new privacy framework, rather than withdrawing from the market. Kraft et al. (2023) analyze the ATT policy using ad impression data across various countries. In line with conceptual arguments of Sokol and Zhu (2021), they demonstrate that ATT significantly reduced the trackable Apple traffic in the U.S. and led to a decrease in ad revenue for publishers. Our study differs from this research. We focus on developers' product development choices to understand how they adjust their innovation activities in response to the ATT policy. Furthermore, we argue that a differentiated perspective within the iOS ecosystem might be necessary, as many apps do not primarily monetize through advertising and may therefore be less affected by the policy than is often assumed when treating the entire ecosystem as uniformly impacted. By offering this more nuanced view, our study aims to deepen the understanding of the policy's implications on innovation and to shed light on the potential mechanisms that influence the behavior of affected developers.

Our study also contributes to the literature on decentralization of decision rights in digital platforms. So far, this literature has studied governance elements that allocate decision rights to external platform participants in settings in which decentralized structures are already established by design, such as blockchain-based platforms (Chen et al., 2020; Hsieh et al., 2018; Lumineau et al., 2021). The implications of decentralizing decision rights in platforms with a priori centralized structures have received limited attention, and when studied, it is typically in contexts where complementors are granted decision rights (e.g., Chen et al., 2021), rather than users. A notable exception is research on rating and review systems, which illustrate cases where users are indirectly empowered to shape complementors' value capture, thereby incentivizing desirable complementor contributions to the platform (Klein et al., 2016; Leyden, 2021; Xu et al., 2023). However, it remains unclear how complementors' respond when users are directly empowered to shape complementors' value capture models.

Last, given that we study a platform's privacy-enforcing initiative, our study is also related to the research that is concerned with understanding the economic consequences of privacy initiatives. This strand of literature considers data to be valuable for firms, for instance, by leveraging it as an input into innovation, enabling targeted advertisement, or creating a direct revenue stream through selling the data to third parties. Initiatives to regulate access to these data by increasing user privacy have been studied across a variety of contexts, revealing their impact on market structure and competition (Campbell et al., 2015; Casadesus-Masanell and Hervas-Drane, 2015; Johnson et al., 2023; Peukert et al., 2022), diffusion of technology (Miller and Tucker, 2018), product use (Goldberg et al., 2024; Sun et al., 2023), advertising effectiveness (Goldfarb and Tucker, 2012; Johnson et al., 2020), and innovation (Janssen et al., 2022; Jia et al., 2021), among others. It is important to note, that these studies have been concerned with government-imposed privacy regulations. But firms might have also reason to protect consumer privacy, even in the absence of public regulation (Goldfarb and Que, 2023). For instance, addressing users' privacy concerns can affect business model choices of firms (Gopal et al., 2018) and be a lever to mitigate competition (Lee et al., 2011)—aspects that are also in the interest of platform operators. Investigating the effects of non-regulatory privacy initiatives empirically remains an open question, particularly with first empirical work pointing to negative consequences on firm innovation (Kircher and Foerderer, 2023).

3 The iOS App Platform and Apple's App Tracking Transparency Policy

We empirically study complementors' responses to stricter privacy governance in the context of Apple's iOS app platform and their implementation of the ATT policy. The iOS app platform is integral to mobile application development and distribution. Developers can enter the platform by building their apps on top of the provided general infrastructure by Apple and thus contribute value to the platform. To keep users engaged with an app, developers devote continuous innovative effort to introducing new features and improving user experience.

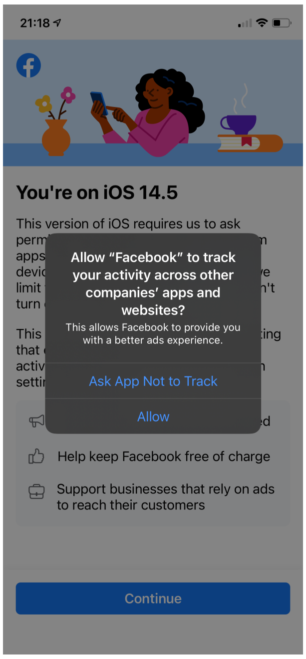
To capture value from an app and its extensions, developers have several options. Direct value capture involves charging an upfront price for the app download or integrating in-app purchases (IAP). In-app purchases enable users to buy content, features, or digital goods either through single purchases or subscriptions within the app. Indirect value capture involves collecting user data such as usage patterns, purchase history, identifiers, and location, and leveraging this information to sell in-app advertisement spaces through networks like Google AdMob or Facebook Ads (Audience Network). These ad networks aggregate digital ad spaces from various apps and broker them to advertisers, with personalized advertisements delivering the most significant returns (Sharma et al., 2019). Hybrid or so-called freemium approaches, in which a basic version is offered for free and additional features or content can be purchased, can combine both approaches. As digital goods such as apps are experience goods and thus charging an upfront price can be challenging (e.g., Casadesus-Masanell and Hervas-Drane, 2015), freemium approaches and ad-based models are predominant in app markets. For instance, while around 12% of all iOS apps in our sample charged an upfront price in January 2020[1], 17.0% followed freemium model with in-app-purchasing elements and 46.5% were connected to advertisement networks, with with a growing trend towards the latter.

On June 22nd 2020, Apple announced at its developer conference that the App Tracking Transparency (ATT) policy will be an integral part of the following iOS 14 update.[2] After discussions with developers, the implementation was postponed until "early 2021" and finally implemented on April 26th 2021 with the launch of iOS 14.5. This policy mandates that app developers integrate an opt-in consent prompt into their apps, if they want to track users' activities outside the app. The consent prompt appears when the user opens an already downloaded or newly downloaded app for the first time after updating to the new iOS version, unless they have already opted out of tracking in their general settings. Importantly, apps cannot base their functionality on the user's consent decision. Users can continue utilizing the app regardless of their consent decision. If consent is denied, the app is unable to obtain the user's Identifier for Advertising (IDFA). The IDFA is a random device identifier that works as an accurate means to track user behavior.

[1]This is also in line with external sources stating around 10% of paid apps in 2019 and early 2020. Differences might occur due to our sampling. See: https://www.statista.com/statistics/1020996/distribution-of-free-and-paid-ios-apps/ (Retrieved April 8, 2025).

[2]The press release from Apple published that day provided developers with detailed information about the upcoming tracking requirement, including the following: "All apps will now be required to obtain user permission before tracking. [...] This includes connecting information collected separately by other companies for targeted advertisements, for advertising measurement, or via data brokers." See: https://www.apple.com/newsroom/2020/06/apple-reimagines-the-iphone-experience-with-ios-14/ (Retrieved April 8, 2025).

Figure 1. Prompt for app-tracking authorization request



Note: This figure shows an exemplary consent prompt for the Facebook app.[3]

Denied consent makes it impossible to ascribe advertising success to the individual user or to enhance user ad profiles with personalized information from usage across apps.

Early predictions of tracking rates were as bad as 5% but did not prove to be true with an actual rate of around 16% in May 2021 which further increased over time, averaging at 34% in 2023. Interestingly, consent behavior differs across app genres as well as countries. The genre with highest ATT opt-in rates are Gaming (37%), Food and drink (36%) and E-commerce (34%). On the other extreme are Educational (7%) and Publications (15%). On the country-level, evidence so fars shows - not surprisingly - the lowest consent rates for Germany (20%) and Japan (22%). The United Arabic Emirates (49.6%) and Brazil (47%) show the highest ones on the other hand.[4]

The success of many apps' value capture strategy is directly dependent on that opt-in rate. The price for trackable ad impressions in the United States is 51% higher than for non-trackable ad impressions. With a reduction of 55 percentage points from April 2021 before ATT with an average of 73% trackable ad impressions to 18% trackable ad impressions in March 2022, this reflects a 21% decrease in advertising revenue (see Kraft et al., 2023 for a comprehensive study of the economic effects of ATT).

[4]See https://www.adjust.com/blog/app-tracking-transparency-opt-in-rates/ or https://maf.ad/en/blog/att-opt-in-rates-boost/ (Retrieved April 8, 2025).

4 Data and Methods

4.1 Research Framework

We analyze the effects of Apple's ATT policy in a quasi-experimental difference-in-differences approach. In our analysis, we compare the innovation outcomes of complementors' apps affected and unaffected by the ATT policy, both pre and post the policy's announcement. Our identification strategy involves a close examination of the SDKs the apps are based on. An SDK comprises a suite of software tools and libraries provided by vendors to developers, facilitating the development of applications for specific platforms or devices. SDKs typically include a documentation, code samples, processes, and guides necessary to develop and test applications for a specific software framework, hardware platform, or operating system. Apps that rely on SDKs from advertising networks are likely to collect user data for targeted advertising purposes and are thus affected by the ATT policy. Apps that do not rely on advertising network SDKs are likely to be not affected. Although some advertising networks can technically be integrated server-side without an SDK, the substantial cost savings from using the SDKs encourage most developers to adopt them directly.

Our observation period spans from June 2019, one year before the announcement of Apple's ATT policy, to September 2021, thirteen months after the announcement. We use the date of the announcement on June 22, 2020 as a reference date for the pre- and post-periods. Apple introduced the ATT policy during the Worldwide Developers Conference (WWDC) and initially set compliance effective with the subsequent launch of iOS 14 in October 2020. Subsequent informal discussions with complementors led to a delay in implementation, with complementors being informed in October 2020 that the policy would be implemented in early 2021. Ultimately, the ATT policy was implemented at short notice in April 2021 with iOS 14.5. Using the announcement date as reference date allows us to cover direct reactions of complementors. Our comprehensive observation period also allows to cover subsequent late adjustments complementors made in response to the eventual implementation of the ATT policy.

4.2 Data Sources and Sample

This study draws on information from two data sources: First, we obtained the main data from MightySignal, a provider of app store analytics, that includes information on all apps in the Apple App Store. Our dataset is based on the time period from January 2018 to September 2021 and covers monthly snapshots of more than 3.7 million apps in total. For each app, we have most of the information that can be found on an app's store profile, such as the app name, developer, cumulative number of ratings, and average rating. Additionally, it includes information on the app genre, price to download the app and details about in-app-purchases if available, the description text, and the app's release date.

Second, we obtained complementary data from MixRank, a data provider for mobile apps and app SDKs. The SDK data contains all SDKs that free apps from the main data have installed or uninstalled, covering 96,876 unique SDKs and more than 125.5 million app-SDK-combinations. For each SDK, we have information on the SDK developer, date of installation and uninstallation in an app, description, and description-based tags indicating its usage purpose. The SDK data allows us to retrieve more detailed information about an app's connection to advertising networks. In addition, data on the entire update history of each app including release notes and changes of the installed SDKs allows us to retrieve detailed in-depth insights about an app's updating behavior.

For the construction of the core sample, we use the index of all listed apps on the iOS App Store as of January 1, 2020—six months prior to the announcement. This index comprises over 1.7 million listed apps. Given that our main variables depend on text-based measures, we limit our sample to apps with descriptions in English to ensure consistency in our analyses. As such, we excluded 37% of the apps, with 1,294,110 apps remaining. Although less common than in the Google Play Store, the Apple App Store also contains apps that are rarely downloaded, for instance when they were developed by hobbyists for private purposes. Since these apps mostly have no value capture objectives, we exclude them from our analysis. As such, we only retain apps that have received at least one rating, leading to a final sample of 588,068 apps.

4.3 Metrics of Interest

Ad-monetization: To identify apps that are affected by the ATT policy, we need to know whether an app collects the IDFA for individual users and engages in data-collecting and -sharing for targeted advertising purposes. As this information is not included in our main data we build our identification variable based on the SDK dataset. We classified an app as affected if it had integrated an SDK used specifically for advertising purposes before the announcement of the ATT policy (*ATT_affected*). Overall, 1,736 SDKs qualify as ad-related SDKs, whereby those of major "Big-Tech" ad-networks for ad-distribution and -analytics such as Google's "Admob" SDK as well as Apple's own frameworks to technically enable in-app-advertising being the most prevalent among apps with ad-related SDKs. It is important to note that information on apps' integrated SDKs is only available for apps that do not charge an upfront price for downloading. However, this limitation is not critical for our identification strategy, as these apps typically do not offer advertising spaces, nor do their value capture models primarily rely on them.

Innovation: The main outcome and measure of interest in our analysis is complementor innovation. Previous literature focusing on mobile app platforms used various metrics to measure innovation like entry of new apps (Janssen et al., 2022), frequency of app updates (Foerderer et al., 2018; Wen and Zhu, 2019), or the appearance in sales top rankings (Yin et al., 2014). Following Foerderer et al. (2018), we model innovation as complementors' efforts to further develop their app through new features or content. Hence, we focus on the updating frequency of apps and differentiate the type of update. That is, we differentiate the number of updates of an app per month into the number of feature updates and maintenance updates, whereby we understand feature updates as the introduction of new features or an extension of the app content. Maintenance updates such as pure bug fixes and performance improvements, simple adjustments to new iOS standards or security-related adjustments, are disregarded for the focal analyses.

To create the corresponding variables, we use data on all updates in the observation period and classify each individual update based on the corresponding release note. On the App Store, these release notes are displayed in a section titled "What's New" and limited to 4,000 characters. Since 2018, it is mandatory for developers to specify update details and avoid generic texts. For classification, we used the GPT-3.5-Turbo model (temperature = 0) which we fine-tuned based on a human-coded training sample of 2,000 randomly selected release notes (cf. Figure 2 for the exact prompt). Our classification includes six subcategories: (1) novel features; (2) content extensions; (3) support of new OS versions and hardware devices; (4) specific fixes constraining user experience; (5) privacy and security; and (6) general bug fixes and performance improvements. We derived these subcategories inductively (Gioia et al., 2012) and validated them in interviews with app developers.[5] Subcategories one and two indicate a *Feature Update (GPT)* and subcategories three to six indicate a *Maintenance Update (GPT)*. If several subcategories were present, the highest-priority category was selected. Out-of-sample validation with another sample of 1,000 randomly selected release notes showed an F1-Score of 0.959 for the identification of feature and maintenance updates. Three independent runs with the same deterministic setting (temperature = 0) achieved a 99.6% consistency rate across runs.

Figure 2. GPT Prompt for Update Classification

ONLY provide a number (1-6) in response.
Determine the category for the following app update text.
If multiple categories seem applicable, always choose the lowest category number (1<2<3<4<5<6).

(1) Novel features - Introducing or enhancing significant functionalities that modify user experience

(2) Extensions of app content - Additions to existing features/content

(3) Support of new iOS versions & hardware devices

(4) Specific fixes of bugs - Addressing distinct known issues

(5) Privacy & Security - Measures enhancing user safety

(6) General bug fixes and performance improvements

Update text: {update_text}

Note: The prompt is based on a task-specific prompting technique (Gao et al., 2021). Few-shot learning via prompting (Brown et al., 2020) was not required due to model fine-tuning.

[5] We continued the coding process until we reached thematic and meaning saturation and no new categories could be added. This coding scheme was then applied to code the training and validation samples, with no new categories emerging.

For robustness checks, we create a second update variable employing the dictionary search (DS) approach of Kircher and Foerderer (2023), i.e. classifying an update based on the presence of at least one specific identifier keyword. An update is classified as *Feature Update (DS)* if its release note contains at least one of the words “new”, “added”, “upgrade”, or “major”. An update is classified as *Maintenance Update (DS)* if its release note contains at least one of the words “bug”, “minor”, “crash”, or “error”. To account for differences in text representation, we adopted several preprocessing steps. Initially, we tokenized the text and converted all words into lowercase. Subsequently, we removed punctuation, numbers, symbols, and all “stop words” common in the English language. Finally, we stemmed the texts, reducing each word to its stem or root form. We also applied the stemming to the keywords in the dictionary.

Feature-monetization: We construct several variables to track how apps directly monetize the content and features they offer. First, we deploy an indicator that takes the value 1 if a price for downloading is charged in a given month (*Paid Dummy*). Another indicator is employed that takes the value 1 if at least one in-app-purchase (IAP) element is offered in a given month (*IAP Dummy*). Beyond these binary indicators, we extend our analysis by quantifying the breadth of in-app monetization options. This involves counting the total number of *IAP Elements* available within the month.

Monetization-switches: To capture the dynamics of apps' value-capturing strategies, we construct a series of indicators designed to identify shifts in monetization models. These shifts include transitions from (1a) *free-to-paid*, indicating an app has started charging for downloads; (1b) *paid-to-free*, signifying the removal of a download charge; (2a) *non-IAP-to-IAP*, denoting the introduction of in-app purchases; (2b) *IAP-to-non-IAP*, reflecting the removal of in-app purchase options; (3a) *non-AD-to-AD*, capturing the initiation of ad-based monetization; and (3b) *AD-to-non-AD*, indicating the discontinuation of ad-based revenue models. For each of these transitions, a respective dummy variable is assigned the value 1 for the month in which the change occurs.

Other app and developer characteristics: We use further information in our dataset to construct several control variables, including the total number of *Ratings* and number of *New Ratings* of an app as proxies for app popularity, an app's *Average Rating*, the *App Age* measured by the difference in months between the policy announcement and release date, the developer experience measured by a developer's number of apps

(*Developer Apps*), the number of installed *SDKs* in an app, and an app's connections to (top) advertising networks (*AD SDKs* / *Top AD SDKs*).

Table 1 provides summary statistics for our main variables of interest, differentiated by ATT affected and unaffected apps.

Table 1. Summary Statistics

	Affected			Unaffected		
	Mean	**Median**	**N**	**Mean**	**Median**	**N**
App-Month level						
Updates	0.16	0.00	5,318,608	0.16	0.00	4,163,372
Feature Upd. (GPT)	0.07	0.00	5,318,608	0.08	0.00	4,163,372
Maintenance Upd. (GPT)	0.08	0.00	5,318,608	0.08	0.00	4,163,372
Feature Upd. (DS)	0.05	0.00	5,318,608	0.04	0.00	4,163,372
Maintenance Upd. (DS)	0.09	0.00	5,318,608	0.08	0.00	4,163,372
Paid Dummy	0.01	0.00	5,318,608	0.28	0.00	4,163,372
IAP Dummy	0.40	0.00	5,318,608	0.18	0.00	4,163,372
Ratings	4548.65	17.00	5,318,608	671.45	11.00	4,163,372
log(Ratings)	3.53	2.89	5,318,608	2.92	2.48	4,163,372
log(New Ratings)	0.78	0.00	5,318,608	0.48	0.00	4,163,372
Avg. Rating	3.94	4.30	5,318,608	3.88	4.20	4,163,372
Developer Apps	120.27	13.00	5,318,608	48.93	5.00	4,163,372
App Age	57.59	54.00	5,318,608	56.75	50.00	4,163,372
App level						
Updates	0.10	0.00	297,500	0.10	0.00	290,568
Feature Upd. (GPT)	0.04	0.00	297,500	0.05	0.00	290,568
Maintenance Upd. (GPT)	0.06	0.00	297,500	0.05	0.00	290,568
Feature Upd. (DS)	0.03	0.00	297,500	0.03	0.00	290,568
Maintenance Upd. (DS)	0.06	0.00	297,500	0.05	0.00	290,568
Paid Dummy	0.01	0.00	297,500	0.24	0.00	290,568
IAP Dummy	0.34	0.00	297,500	0.18	0.00	290,568
Ratings	3866.12	7.00	297,500	581.11	7.00	290,568
log(Ratings)	2.86	2.08	297,500	2.52	2.08	290,568
log(New Ratings)	0.48	0.00	297,488	0.32	0.00	289,786
Avg. Rating	3.91	4.30	297,500	3.86	4.30	290,568
Developer Apps	166.62	14.00	297,500	48.94	5.00	290,568
App Age	63.85	60.00	297,500	60.38	53.00	290,568

5 The Effect of ATT on Complementor Innovation

5.1 Econometric Specification

We employ a two-fold approach to evaluate the impact of the ATT policy on complementor innovation. First, we apply before-after regression models to evaluate the change in complementor innovation before and after the ATT announcement for both affected apps and unaffected apps. Our models take the following functional form:

$$I_{i,t} = \beta_0 + \beta_1 \text{After\_ATT}_t + X_{i,t} + \eta_i + \theta_i + \epsilon_{i,t}, \quad (1)$$

where the dependent variable $I_{i,t}$ represents the *Feature Updates* of app i in month t. Our coefficient of interest is β_1, and $After\_ATT_t$ is a binary indicator that equals 1 for periods following the announcement of ATT. This model includes control variables $X_{i,t}$, app-specific fixed effects η_i, and time-specific fixed effects θ_i to capture unobserved heterogeneity that is constant over time.

The second part of our empirical strategy extends the before-after comparison by a difference-in-differences (DID) estimation, directly including the affected apps within the regression model. By including both affected and unaffected apps in our analysis, this DID estimation allows us to control for external factors that are common to the entire iOS ecosystem. This method helps to isolate the specific impact of the ATT policy on complementor innovation. Our DID estimation takes the following functional form:

$$I_{i,t} = \beta_0 + \beta_1 \text{ATT\_affected}_i \times \text{After\_ATT}_t + X_{i,t} + \eta_i + \theta_i + \epsilon_{i,t}, \quad (2)$$

where $I_{i,t}$ continues to be the dependent variable indicating *Feature Updates* of app i in month t. The coefficient β_1 is of particular interest, representing the differential effect of the ATT policy between the affected and unaffected apps. $ATT\_affected_i$ is a binary variable indicating whether app i is primarily affected by the ATT policy, and $After\_ATT_t$ indicates the period after the announcement of ATT. Control variables $X_{i,t}$, app-specific fixed effects η_i, and time-specific fixed effects θ_i are included to account for other factors influencing complementor innovation.

5.2 Descriptive Trends

As displayed in the Summary Statistics in Table 1 there are minor differences in the innovativeness of app updates between affected and unaffected apps. However, clear statements about the effect of the ATT policy can only be made on closer examination of the course over time. For a first impression, Figure 3 shows the average number of feature updates and maintenance updates for affected and unaffected apps over time. While the group of unaffected apps had fewer feature updates at the beginning of our observation period, they exhibited a positive trend during the first year—surpassing the affected group—and then stagnated around the policy announcement in mid-2020 before showing a strong negative trend from the end of 2020 onward. The affected apps followed a comparable trend prior to the policy announcement, with the exception of a pronounced decrease in feature update releases at the end of 2019. After the policy announcement, their decline continued initially, but began to stabilize about six months later, at the end of 2020.

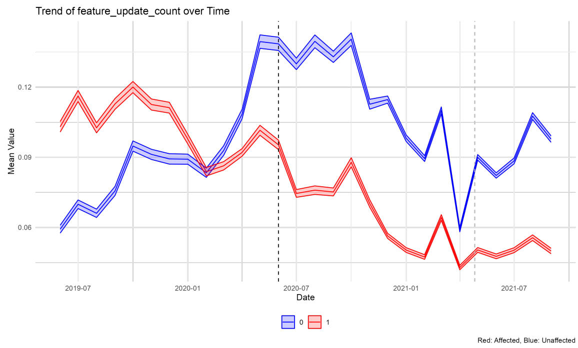
5.3 Average ATT Effects

The picture that emerges from the descriptive plots also continues in the before-after regressions reported in Table 2. On average, both affected and unaffected apps have a lower number of feature updates in the period following the ATT announcement compared to the period before. There is also a less pronounced feature update frequency in both groups for apps with more ratings, from developers with more apps and apps with a download price. Changes in an app's monetization model, such as shifting from IAP to no IAP or vice versa, are on average positively correlated with an increase in the frequency of feature updates.

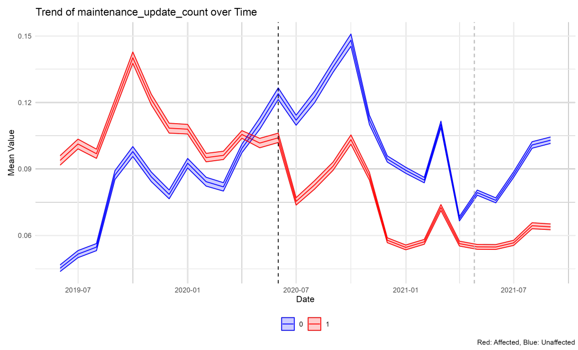
To estimate the specific effect of the ATT policy on complementor innovation, we use the difference-in-differences approach laid out in equation 2. This method allows us to compare the change in feature updates for both affected apps, i.e. our treatment group, as well as the unaffected apps as our control group before and after the ATT announcement. Table 3 presents the results of our main DiD analysis using different models: Column 1 presents our baseline model where the dependent variable is the GPT-based count of feature updates (*Feature Update (GPT)*). Column 2 uses the log-transformed version of this measure (*log(Feature Update (GPT)*) to further validate our findings. Given that we newly developed the GPT-based measure, column 3 reports results from an additional robustness check using the established dictionary search approach (*Feature Update (DS)*) described in Section 4.3. In all specifications, we include app and time fixed effects to

Figure 3. Update trends for affected and unaffected apps

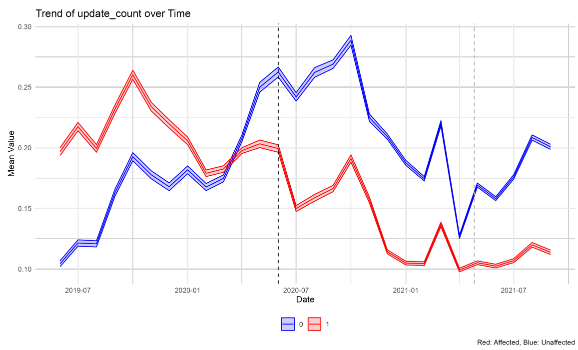
(a) Feature Updates (GPT)



(b) Maintenance Updates (GPT)



(c) Overall Updates



Notes: The figure shows the average monthly number of feature updates, maintenance updates and overall updates for affected and unaffected apps over the course of our observation period. Confidence intervals represent the 95%-intervals.

Table 2. Before-After Regression (Feature Updates (GPT))

	Affected	Unaffected
After_ATT	-0.01^{***}	-0.02^{***}
	(0.00)	(0.00)
log(Ratings)	-0.04^{***}	-0.03^{***}
	(0.00)	(0.00)
Avg. Rating	0.00^{***}	0.01^{***}
	(0.00)	(0.00)
log(Developer Apps)	-0.01^{***}	-0.01^{***}
	(0.00)	(0.00)
Paid Dummy	-0.01^{**}	-0.03^{***}
	(0.00)	(0.00)
IAP Dummy	-0.05^{***}	-0.02^{***}
	(0.00)	(0.00)
IAP Elements	-0.00^{***}	-0.01^{***}
	(0.00)	(0.00)
non-IAP-to-IAP Dummy	0.11^{***}	0.15^{***}
	(0.00)	(0.00)
IAP-to-non-IAP Dummy	0.01	0.09^{***}
	(0.02)	(0.02)
non-AD-to-AD Dummy	0.47^{***}	0.44^{***}
	(0.00)	(0.00)
AD-to-non-AD Dummy	0.05^{***}	0.02^{***}
	(0.00)	(0.00)
free-to-paid Dummy	0.03^{***}	0.04^{***}
	(0.01)	(0.01)
paid-to-free Dummy	0.02^{**}	0.06^{***}
	(0.01)	(0.01)
SDKs	0.00	-0.00^{***}
	(0.00)	(0.00)
AD SDKs	-0.00^{***}	-0.00^{***}
	(0.00)	(0.00)
Top AD SDKs	-0.00^{**}	-0.00^{***}
	(0.00)	(0.00)
R^2	0.01	0.02
N	5,318,608	4,163,258

Note: This table shows the results of our before-after regressions separated for affected (column 1) and unaffected apps (column 2). Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

control for time invariant app characteristics and common time trends that might affect overall developer behavior.

Although our analyses separated by affected and unaffected apps revealed a general decline in feature updates for both groups, our main models consistently reveal a positive and significant interaction term (*After_ATT* × *ATT_affected*). This finding indicates that while both groups experienced declines in feature updates after the ATT announcement, the decline is less pronounced for affected apps. Specifically, model (1) indicates that apps affected by the policy have about 0.008 additional feature updates per month compared to unaffected apps. While this increase may appear small in absolute terms, it represents roughly an 11% increase considering the baseline mean of 0.07. In the log-transformed specification (model 2) the interaction term approximates the proportional difference in change rates between affected and unaffected apps. Here, a one-unit increase in the interaction term—that is, moving from being in the unaffected group pre-policy to being in the affected group in the post-policy—is associated with an approximate 0.56% increase in the outcome. The direction of these results remains consistent when using our alternative innovation measure derived from the dictionary approach (model 3), albeit with a slightly lower magnitude.

Our control variables cover a variety of aspects related to an app's monetization model and developer characteristics. Some interesting insights into their connection to the release of feature updates are the following: App popularity measured as the logarithm of the number of overall ratings is negatively associated with feature update release. This relationship might indicate that more established, popular apps have either lower innovation potential or reduced competitive pressure to introduce new features. Similarly, developer experience, indicated by the logarithm of the number of apps developed, also negatively correlates with feature update frequency. In contrast, a higher average rating (i.e., closer to five stars) is positively associated with the frequency of feature updates, suggesting that well-received apps might be incentivized to sustain user satisfaction through continuous innovation. For the monetization models of apps we find a negative correlation between feature update frequency and the presence of download prices or in-app-purchases. However, if there are changes in the monetization models in any direction, i.e. introducing or removing in-app-purchases, ad-based monetization or app prices, we see a positive correlation with the release of feature updates. This could indicate a need for innovative development efforts when the present way of value capture is changed, likely because shifts in value capture necessitate corresponding changes to the app's value proposition.

Table 3. DID Estimations of the Effects of ATT on Complementor Innovation

	(1)	(2)	(3)
After_ATT × ATT_affected	0.00768***	0.00556***	0.00223***
	(0.00076)	(0.00042)	(0.00060)
log(Ratings)	−0.0342***	−0.0195***	−0.0217***
	(0.00116)	(0.00060)	(0.00092)
Avg. Rating	0.00400***	0.00224***	0.000590
	(0.00112)	(0.00063)	(0.00088)
log(Developer Apps)	−0.00689***	−0.00431***	−0.00296***
	(0.00039)	(0.00024)	(0.00026)
Paid Dummy	−0.0197***	−0.0108***	−0.0145***
	(0.00341)	(0.00189)	(0.00278)
IAP Dummy	−0.0394***	−0.0238***	−0.0253***
	(0.00642)	(0.00334)	(0.00508)
IAP Elements	−0.00473***	−0.00267***	−0.00427***
	(0.00046)	(0.00024)	(0.00039)
non-IAP-to-IAP Dummy	0.128***	0.0703***	0.0854***
	(0.00432)	(0.00218)	(0.00354)
IAP-to-non-IAP Dummy	0.0531*	0.0250	0.0234
	(0.02517)	(0.01295)	(0.02388)
non-AD-to-AD Dummy	0.451***	0.287***	0.276***
	(0.00363)	(0.00202)	(0.00322)
AD-to-non-AD Dummy	0.0391***	0.0226***	0.0332***
	(0.00432)	(0.00245)	(0.00360)
free-to-paid Dummy	0.0351***	0.0197***	0.0210***
	(0.00469)	(0.00250)	(0.00345)
paid-to-free Dummy	0.0459***	0.0255***	0.0401***
	(0.00570)	(0.00305)	(0.00560)
SDKs	−0.000304***	−0.0000817***	−0.000101***
	(0.00004)	(0.00002)	(0.00003)
AD SDKs	−0.000951*	−0.000516*	−0.00139***
	(0.00039)	(0.00021)	(0.00035)
Top AD SDKs	−0.00169*	−0.00135***	−0.000262
	(0.00076)	(0.00040)	(0.00066)
Constant	0.223***	0.128***	0.143***
	(0.00597)	(0.00321)	(0.00474)
Month FE	*Yes*	*Yes*	*Yes*
App FE	*Yes*	*Yes*	*Yes*
R^2	0.374	0.374	0.323
N	9,468,404	9,468,404	9,468,404

Note: This table shows the results to our main analysis using difference-in-differences estimations that include both month and app fixed effects. Column 1 uses the number of feature updates based on our GPT-metric as a dependent variable (Feature Update (GPT)). Column 2 uses the logarithmized number of features updates based on our GPT-metric as a dependent variable (log(Feature Update (GPT)). Column 3 uses the alternative update measure employing the dictionary search approach of Kircher and Foerderer (2023) as a dependent variable (Feature Updates (DS)). Standard errors in parentheses. Standard errors are clustered by app. Month and App fixed effects included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Robustness Checks

6.1 Comparability of Groups

To address potential differences between the apps affected and unaffected by ATT, we apply coarsened exact matching (Kircher and Foerderer, 2023). Specifically, we match on *App Genre*, given that distinct app categories may exhibit varying levels of development effort and cater to different consumer demands (Rietveld and Eggers, 2018), the presence of in-app-purchases (*IAP Dummy*) to reflect variations in monetization models, and Log(*Ratings*) to account for differences in user feedback (Ghose et al., 2014). We further include *App Age* to capture app lifecycle variations (Boudreau, 2012) and the number of integrated *SDKs* to factor maintenance complexity.

We perform matches based on average pre-announcement values of these variables and apply quantile-based cutoffs for the continuous metrics. After implementing this procedure, the sample is reduced to 9,054,829 app-month observations. As shown in Table 4 (column 1), the estimation results from this refined sample closely align with our main analysis.

6.2 ATT Enforcement and Compliance

A key assumption underlying our empirical strategy is that Apple's enforcement of its App Tracking Transparency (ATT) policy is robust and effective. Specifically, the credibility of our analysis rests on three conditions: (i) Apple consistently enforces its governance policies; (ii) the ATT technical framework effectively prevents the unauthorized collection of the Identifier for Advertisers (IDFA); and (iii) app developers comply with the requirements of the ATT policy.

First, Apple's iOS is a closed platform-based ecosystem with a long-standing reputation for rigorous review processes of new app releases and updates to already listed apps. Violations of Apple's policies are often met with strict penalties, which can even extend to the removal of apps from the App Store and the termination of developer accounts. A prominent example is the removal of Epic Game's Fortnite app and the termination of their developer account on the App Store, following Epic Game's attempt to circumvent Apple's payment system.[6] Second, empirical evidence supports widespread compliance

[6]See: https://www.theverge.com/2020/8/13/21366438/apple-fortnite-ios-app-store-violations-epic-payments or https://www.theverge.com/2020/8/28/21406013/apple-epic-

with ATT. Kollnig et al. (2022) demonstrate that, when correctly implemented at the technical level, the ATT framework effectively prevents the collection of the IDFA without user consent. Although some loopholes may still exist, Kesler et al. (2024) find that 87.4% of the iOS apps they examined did not collect device IDs for advertising without user authorization. Taken together, these results indicate strong enforcement and compliance, supporting the credibility of our empirical strategy.

6.3 Sample Validity

To assess whether our data filtering introduces coverage error, we estimate the DID model using the full sample of English-language iOS apps listed on January 1, 2020, without the requirement of at least one user rating. This broader sample covers approximately 63% of all iOS apps. As shown in Table 4 (columns 2 and 3), the results from this expanded dataset remain consistent with our primary findings, enhancing the generalizability of our conclusions.

`games-fortnite-developer-account-terminated-no-longer-available` (Retrieved April 8, 2025)

Table 4. DID Estimations of the Effects of ATT on Complementor Innovation with Matched Groups and Extended Sample

	(1)	(2)	(3)
After_ATT × ATT_affected	0.00818***	0.0104***	0.0112***
	(0.00076)	(0.00029)	(0.00030)
log(Ratings)	−0.0341***	−0.0119***	−0.0117***
	(0.00116)	(0.00036)	(0.00037)
Avg. Rating	0.00392***		
	(0.00114)		
log(Developer Apps)	−0.00716***	−0.00672***	−0.00734***
	(0.00040)	(0.00019)	(0.00020)
Paid Dummy	−0.0202***	−0.0118***	−0.0124***
	(0.00351)	(0.00168)	(0.00177)
IAP Dummy	−0.0393***	−0.0659***	−0.0650***
	(0.00645)	(0.00423)	(0.00429)
IAP Elements	−0.00472***	−0.00352***	−0.00350***
	(0.00046)	(0.00026)	(0.00026)
Top Rating Dummy		−0.269***	−0.269***
		(0.00053)	(0.00056)
non-IAP-to-IAP Dummy	0.138***	0.126***	0.138***
	(0.00481)	(0.00261)	(0.00297)
IAP-to-non-IAP Dummy	0.0534*	0.0389*	0.0409*
	(0.02567)	(0.01531)	(0.01591)
non-AD-to-AD Dummy	0.451***	0.459***	0.458***
	(0.00365)	(0.00190)	(0.00191)
AD-to-non-AD Dummy	0.0394***	0.0371***	0.0373***
	(0.00437)	(0.00290)	(0.00296)
free-to-paid Dummy	0.0373***	0.0217***	0.0241***
	(0.00492)	(0.00247)	(0.00270)
paid-to-free Dummy	0.0469***	0.0273***	0.0289***
	(0.00594)	(0.00297)	(0.00324)
SDKs	−0.000305***	−0.000639***	−0.000642***
	(0.00004)	(0.00002)	(0.00002)
AD SDKs	−0.000977*	0.00116***	0.00118***
	(0.00039)	(0.00030)	(−0.00013)
Top AD SDKs	−0.00168*	−0.00470***	−0.00474***
	(0.00076)	(0.00053)	(0.00052)
Constant	0.224***	0.116***	0.122***
	(0.00602)	(0.00116)	(0.00122)
Month FE	*Yes*	*Yes*	*Yes*
App FE	*Yes*	*Yes*	*Yes*
R^2	0.370	0.323	0.319
N	9,054,829	25,807,673	23,520,063

Note: The number of feature updates based on our GPT-metric is used as a dependent variable (Feature Update (GPT)). Column 1 presents the results with coarsened exact matching applied. Column 2 presents the results for the broader dataset including those apps without ratings. Column 3 presents the results for the broader dataset with coarsened exact matching applied. Standard errors in parentheses. Standard errors are clustered by app. Month and App fixed effects included.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

7 Conclusion

In this paper, we examined the implications of Apple's ATT policy on the innovation activities of mobile app developers. Drawing on comprehensive app- and developer-level data and employing a quasi-experimental research design, we found evidence consistent with previous research (Cheyre et al., 2023) that both affected and unaffected apps generally experienced a decline in the release of feature updates following the policy. However, our analysis revealed significant heterogeneous effects within the Apple's app ecosystem. Specifically, apps directly impacted by ATT not only mitigated the negative consequences but, in some cases, reversed this downward trend by increasing their innovation efforts.

These findings contribute to the broader discourse on platform governance in matured platform-based ecosystems (Kircher and Foerderer, 2023; Rietveld et al., 2019; Tiwana et al., 2010) by highlighting how privacy-oriented policy changes can prompt varied responses from complementors. While previous literature has often documented negative or neutral outcomes in innovation following restrictive governance policies, our results emphasize that complementors' reactions may not uniformly be negative when confronted with constraints on their value-capture mechanisms (Foerderer et al., 2018). Instead, certain developers appear to strategically leverage these policy shifts as opportunities to enhance their value propositions through intensified innovation activities.

Furthermore, our study underscores the importance of investigating heterogeneity in complementors' reactions. Future research should investigate the factors driving these varied responses, for instance, by examining the role of competitive dynamics, app categories, and different monetization models. A thorough understanding of these dynamics can enable platform operators to design privacy governance policies that more effectively balance user protection goals with sustained innovation in their ecosystem.

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