Digital Platforms 2.0: Emerging Topics, Opportunities, and Challenges

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Abstract

Platform-based digital ecosystems form the backbone of our interactions with the Internet. Over the past decade, they have witnessed significant growth, both in terms of industry footprint and academic research. Yet, the challenges associated with their operations, governance, and regulation continue to evolve. Our paper aims to aid researchers in better understanding these developments, such that they can contribute more effectively to active debates and open questions in this space. We structure our paper in two parts. First, we lay out emerging challenges in research topics related to platforms, both from an internal (platform design) and external (platform regulation)

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perspective. Then, we complement this by presenting challenges inherent in conducting empirical research in platform markets, both with and without the collaboration of the platforms themselves. Our insights highlight the importance of multidisciplinary and multi-method approaches to the study of digital ecosystems to get a full grasp of the value they create for firms and consumers.

Keywords: online markets, platform design, platform regulation, data acquisition strategies

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1 Introduction

Many of today's most valuable companies are platform businesses (Cusumano et al., 2020; Parker and Van Alstyne, 2018). The top five players alone (Apple, Microsoft, Alphabet, Amazon, and Meta) represent $13.08 trillion in market value as of January 2025. Broadly, platforms act as intermediaries that facilitate interactions between two or more distinct agent groups. Governance rules set the terms of participation, and these interactions often generate direct or indirect externalities (Sriram et al., 2015; Parker et al., 2024).

Platforms have gained significant public and media attention over the years.[1] In tandem with the increasing importance of the platform economy, research on platforms has also grown significantly across a broad range of disciplines.[2] Platform businesses operate across many markets, but penetration in certain categories has grown faster than others, and profitability (or lack thereof) displays even greater heterogeneity. Between 2020 and 2023, e-commerce, the dominant category, witnessed over 150% growth, followed by food and beverage, travel, and education.[3] However, many platforms continue to remain unprofitable.

Such growth and performance heterogeneity have led to three challenges. The first challenge concerns *internal* platform dynamics: determining how to monetize, curate, disclose, and rank content so the platform serves users effectively and in turn remains profitable. The second challenge, involving *external* platform dynamics, concerns regulation—how to curb platforms' preferential treatment of their own offerings, safeguard data privacy, and prevent discrimination. Finally, a third set of challenges relates to practical constraints around platforms research: what *data acquisition* strategies allow researchers to study these issues rigorously, and when is collaboration with the platforms themselves indispensable? Drawing on recent multi-disciplinary work, we map the frontier along these three axes, highlight open questions, and offer a practical resource for scholars (especially those new to the field) seeking to navigate both the substantive and logistical complexities of platform research.

Recent efforts have provided a broad framework for studying online platforms (e.g., Rietveld and Schilling (2021); Cheng et al. (2023); Sen et al. (2025)). We distinguish our work in two key ways. First, rather than summarizing existing work, we focus primarily on highlighting emerging challenges in platform related research topics (both in the domain of platform design and regulation), and also proposing appropriate data acquisition strategies that can optimize various trade-offs researchers face in this domain. Given the rapid developments

[1]Based on data from Factiva, there has been over a sixfold increase in the number of mentions of the top nineteen platform businesses, (as defined by https://ec.europa.eu/commission/presscorner/detail/en/IP_23_2413) in major news and business sources over the past decade

[2]See https://platformpapers.com/data-visualizations/. Last retrieved 1 February 2025.

[3]See https://a16z.com/marketplace-100/. Last retrieved in February 2025.

in platform research, we view this as a key contribution towards mapping the evolution of future work and helping researchers better understand and navigate the complexities in this area. Second, our objective is to highlight how addressing many of these challenges requires a multidisciplinary and multi-method lens. From a disciplinary perspective, we highlight how emerging platforms research across economics, management, marketing, operations and information systems is deeply intertwined and complementary.[4] From a methods perspective, we highlight insights from both theoretical and empirical research, while paying special attention to data acquisition related considerations in an empirical setting.

Our framework has limitations. Our aim is not to provide a comprehensive bibliometric analysis of every aspect of digital ecosystems, but to showcase a collection of key topics and themes at the frontier of platforms research. We also intend for the paper to be a complement, rather than a substitute, to existing reviews of the work on digital platforms. Our discussion is intentionally current and forward looking–notably, the majority of cited papers were circulated after 2020.

1.1 Structure of the Paper

Our paper consists of two main components: research topics and data acquisition strategies. First, we review emerging research topics to chart out lingering open questions and challenges. We do this from an internal perspective in Section 2, specifically focusing on two key within-platform design choices: monetization and information flows. Additionally, in Section 3, we consider platform regulation from an external perspective, emphasizing the role of interactions with off-platform entities such as policymakers and other platforms in shaping two crucial elements: consumer protection and competition. Next, in Section 4, we introduce a broad data acquisition framework to carry out efficient empirical research on online platforms for both types of research topics. Figure 1 illustrates the structure of the paper.

[4] Appendix A lays out our approach to choose articles to include in this paper.

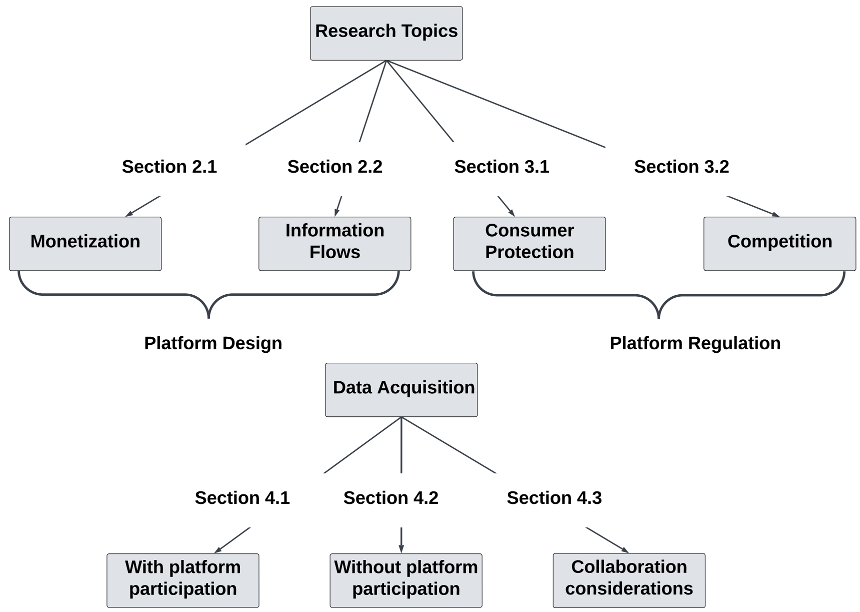

Figure 1: A Schema of the Paper

1.2 Digital Platforms 1.0 vs 2.0

In this paper, we focus on new and emerging themes related to online platforms, as previously mentioned. However, it's important to note the progression of platform research over time. We view this research as encompassing four separate 'eras', each characterized by unique questions and limitations. Using insights from three recent review articles (Rietveld and Schilling, 2021; Cheng et al., 2023; Sen et al., 2025), we outline this progression and emphasize the distinct aspects of "Digital Platforms 2.0" (Eras 3 and 4) compared to earlier ones, thus justifying our focus on these emerging topics in the rest of the paper.

Era 1 (pre-2000) scholarship was almost entirely conceptual. Because bandwidth, payment rails, and ad-serving technology were rudimentary, successful platforms (e.g., newspapers, credit-card networks, online service providers such as AOL, and early dial-up marketplaces) relied on subscription or per-transaction fees for revenue. Empirical evidence was thin, drawn mainly from small samples in financial services or proprietary online portals (e.g., Kauffman et al. (2000)); user reviews and open reputation systems were still in their infancy.

Era 2 (2000–10) capitalised on the Web 2.0 boom: platforms such as Google AdWords, eBay, and Facebook monetised attention at scale via sponsored search and auction-based ads. The same boom generated an explosion of user reviews on Amazon, Yelp, and TripAdvisor, shifting research toward the mechanics of reputation systems (e.g., Dellarocas (2003)). Research also expanded on the fundamentals of two-sided-market pricing and network-effect signalling, laying out 'chicken-and-egg' models that explained why getting at least one side of the market to critical mass was decisive (e.g., Rochet and Tirole (2003); Parker and Van Alstyne (2005)). Further, scholars began to study competitive dynamics among platforms, which were intensified by customers' multi-homing behaviour, for example, many users listed or shopped on multiple platforms at once (Caillaud and Jullien (2003)). Together, eras 1 and 2 established the baseline questions—pricing, network effects, reputation, and early advertising models.

In Era 3 (2010–2020), the smartphone boom, cheap cloud storage, and real-time-bidding (RTB) exchanges unlocked a wave of programmatic display advertising, native ad formats, dynamic-surge pricing and in-app purchases (e.g., Goldfarb and Tucker (2011a); Fisher et al. (2018)). At the same time, this era is characterized by an influx of granular data, both collected by researchers and made available by firms. Driven by this, platforms moved from rule-based merchandising to machine-learning recommendation engines that personalised feeds (e.g., Ghose et al. (2014)), and large-scale randomized experiments started to pick up (Taylor and Eckles, 2018). Ubiquitous clickstream and auction logs also enabled micro-panel analyses, letting scholars quantify network effects with unprecedented precision (e.g., Chu and Manchanda (2016b)), and thus extend early theoretical work in this domain. Advances in measurement also paved the way for discussions of market power and antitrust law (e.g., Hylton (2019)). Rising societal concern about data use triggered the GDPR and early algorithmic-fairness debates, so consumer-protection research added transparency, bias and privacy to its toolkit while still wrestling with review manipulation and misinformation (Johnson et al. (2020); Luca and Zervas (2016)).

Era 4 (post-2020) builds on many elements of Era 3, with continued availability of large scale data and analysis toolkits (Lee et al., 2023). Large-scale machine learning models have pushed platforms into an era of personalization, with hyper-tuned ad loads and context-aware pricing that update in real time (Cheng et al., 2023). E-commerce platforms now feature demographic-signal labels (e.g., Mitkina et al. (2022)), automated fake-review detection, and AI-curated feeds, all of which raise new questions about disclosure and equity (Cheng et al. (2023)). Policy attention has followed suit: the impact of GDPR (and California's equivalent CPRA), EU's Digital Markets Act, a flurry of antitrust suits, and emerging algorithmic-audit mandates have moved competition and consumer-protection research to rethink governance and cross-platform accountability metrics (Kaushal et al., 2024) - scholars now blend theoretical models of industrial organisation models with data and legal scholarship to study such interventions and algorithmic self-preferencing (e.g., Johnson (2022); Farronato et al. (2023b)). Concerns have also been raised about market concentration and 'rich-gets-richer' dynamics triggered by various platform policies (e.g., Zhu et al. (2025); Zou and Zhou (2025)).

Grouping the first two eras as "Platform 1.0" and the latter two as "Platform 2.0" highlights a clear transition. Whereas 1.0 centred on building and scaling platforms, 2.0 asks (i) how different instruments interact with each other to supercharge platforms' value creation and extraction, which is only possible with micro-level data availability and (ii) what checks and balances can mitigate potential harm and winner-take-all dynamics. Scholars now have the ability to finetune complex algorithms to optimise platform objectives, but are also concerned with how such algorithms can be monitored, constrained, and redesigned to meet societal goals such as fairness and transparency.

These shifts have allowed empirical research to test, extend and inform theory development, thanks to rich click-streams, auction logs, and user-level panels that support causal inference and structural estimation. For example, earlier theory work in Eras 1 and 2 focused on value creation and extraction by the platform through various pricing instruments (e.g., transaction fees, commission fees), while recent theory work in Eras 3 and 4, guided by developments in platform design, delves deeper into non-pricing tools such as seller/position prominence, ranking and personalized recommendations, where asymmetry among players within one side is carefully accounted for (e.g., Donnelly et al. (2023)). Furthermore, recent empirical work can quantify the welfare effects of major regulatory policies, enriching earlier theory work's discussion on the potential effects of regulation (e.g., Johnson et al. (2023)). Large-scale data availability has also expanded empirical research on self-regulation, extending prior work that mostly focused on government regulation (e.g., Huang et al. (2022)). The resulting feedback loop—regulation shaping platform design and vice versa—creates a new research agenda that this paper seeks to highlight.

In Table 1, we frame this historical narrative through the same lenses of platform design (monetization, information flows) and regulation (consumer protection, competition) introduced in Section 1.1 and used in the rest of the paper.

	Era 1: Network effects on Platforms (pre-2000)	Era 2: Platform growth and monetization (2000–2010)	Era 3: Personalization and its consequences (2010–2020)	Era 4: Data, algorithms and regulation (post-2020)
Monetization	Newspaper ads; Subscription / licence fees; per-transaction fees; early display ads	Sponsored-search advertising; listing fees; paywalls & freemium; auction-based ads	Programmatic / display ads; in-app purchases; subscription bundles; dynamic or personalized pricing	Hyper-personalised ad loads; algorithmic pricing; creator / publisher revenue sharing; hybrid affiliate approaches
Information Flows	Network-effect signalling; rudimentary star ratings	Online-review boom & word-of-mouth; cold-start strategies; reputation-system inception	Unstructured data; personalised recommendation & ranking algorithms; content-curation dashboards; platform endorsements / badges; review-selection & polarity effects	Badges and labels; fake-reviews; reciprocity effects in online reviews; privacy-sensitive personalisation; bias-corrected ranking experiments; AI-driven curation
Consumer Protection	Tackling information asymmetry; early reputation cues	Nascent privacy rules; platform-governance frameworks; first regulatory interventions	Algorithmic-fairness debates; GDPR/CPRA spotlight; transparency initiatives; disinformation	Consumer-data-rights enforcement; misinformation mitigation; safety / verification features; advanced review-fraud detection
Competition	Circulation spiral; winner-take-all theories; early ecosystem orchestration	Two-sided-market theory; network effects; multi-homing	Market power; antitrust; native advertising	Self-preferencing; Extending governance/regulation to algorithms via DMA / antitrust actions; winner-take-all empirics

Table 1: Dominant Platform-Research Topics by Era

2 Internal Dynamics: Platform Design Challenges

Platforms utilize a variety of design tools to optimize their operations. These tools influence agent behaviors through monetary incentives and offered services. In addition, platforms manage the information flow among participants through mechanisms such as disclosure rules, rating systems, and content curation. This section explores challenges and open questions related to optimal strategies for platform monetization and information flows in platform design within the Platform 2.0 paradigm.

2.1 Monetization

We explore key platform monetization strategies—including transaction fees, advertising, freemium models, in-app purchases, subscriptions, and affiliate marketing—to better understand trade-offs and open research questions in this space.

Transaction Fees We begin with the direct monetization model, where a platform generates revenue by charging transaction fees using various pricing formats. In traditional N-sided platforms (e.g., Rochet and Tirole (2006)), the side of the market that is less sensitive to price changes typically faces higher fees. This approach can lead to a skewed pricing structure. In some cases, one side of the market might even be paid to participate—for instance, credit card users may receive rewards or benefits without incurring any fees. Recent research has shown that these forces play a key role in how value is created and distributed across the platform ecosystem. For example, research by Zhang et al. (2025) shows that hospitals that attract more consumers to join an online healthcare platform capture a larger share of the platform's economic value. Expanding beyond direct network effects, Zhu et al. (2025) finds that introducing a flat fee to promote books on Goodreads can inadvertently reduce the diversity of books in the marketplace, diminishing the platform's value, especially for consumers who value titles from smaller publishers. In a similar vein, Bhargava et al. (2022) demonstrate that a differential revenue-sharing design, tailored to benefit small businesses, can lead to improvements in both total welfare and output, as observed on the Apple App Store. These insights suggest that incorporating network effects—whether through personalized access fees or by applying fees to both sides of the market—could enhance overall welfare and profitability.

Advertising Platforms also commonly monetize through advertising. Ad-supported monetization requires careful matching of eyeballs with advertisers. The matching process must account for advertiser willingness to pay, consumer willingness to attend to the ad, and consumer likelihood to take the advertiser's desired conversion action. Effective matching involves optimizing ad selection, format, creative, placement, quantity, pricing, and the right balance between paid and organic listings (Wilbur et al., 2013; Choi and Mela, 2019; Chu et al., 2020; Long et al., 2022; McGranaghan et al., 2022). Recent work has also examined how ad load may affect content consumption (Rajaram et al., 2024; Goli et al., 2024).

The choice of search ranking algorithms also affects the ability to monetize via ads. Prominent ad placements may not align with consumer preferences, potentially hindering search efficiency and reducing transaction-based revenue. However, this may prompt sellers to bid for prime advertising spots, increasing ad revenue. These dynamics should be considered when developing search-ranking algorithms aimed at optimizing business objectives (Ursu (2018); Ursu et al. (2024); Dinerstein et al. (2018)).

The methodology and pricing of ad sales differ considerably. Ad sales can be priced per impression, click, or action, and sold at a fixed rate in advance with broad targeting criteria or through real-time bidding with more granular targeting options (Sayedi, 2018). They can also use first-price or second-price auctions with various reserve prices (Despotakis et al., 2021; Choi and Mela, 2023).[5] Each of these choices can affect advertising revenue as well as the relevance and quality of the winning ads served to users.

Freemium and In-App Purchases Model Many digital platforms, including media firms, mobile apps, and online games, employ freemium strategies—offering basic services for free while charging for premium content or features. One of the main challenges in this case is to calibrate an optimal level of freemium content that draws consumers in while not cannibalizing demand. Wang et al. (2024a) highlights that firms must balance three key effects—cannibalization, consumption expansion, and competition—to determine the optimal amount of free content to offer. Kamada and Öry (2020) show that platforms may benefit from subsidizing a broad base of lower-valuation users to generate demand from higher-valuation users. Lambrecht and Misra (2017) analyze the trade-offs between subscription and advertising revenues and demonstrate that firms can benefit from countercyclically increasing the amount of free content at times of higher demand.

The balance between paid and free content also depends on content quality (Li et al., 2019) as well as the extent of network effects provided by the free ('low end') vs paid ('high end') versions of the product (Shi et al., 2019). Appel et al. (2020) presents a broader framework for mobile app monetization, showing how uncertainty and satiation considerations affect the prevalence of each. More recently, Deng et al. (2023) investigate the spillover effects between the free version and the paid version of the same app and find that the launch of a free version increases the demand for the paid version of the app. Relatedly, Li (2022) studies the factors influencing the conversion of free users to paid subscribers in the Software-as-a-Service (SaaS) industry, finding that more frequent free-trial usage encourages conversion, but exploring a greater variety of software leads to a lower conversion rate.

[5]See Choi et al. (2020) for details of display advertising sales.

Subscription Model Services such as Netflix and Spotify utilize subscription-based models, charging users a recurring fee for access to premium content or features. This approach ensures a steady revenue stream and often includes tiered pricing to cater to different user preferences. Considerations similar to the freemium model may also emerge here. For instance, Mai and Hu (2023) examine the optimal strategies for free-to-play (F2P) multiplayer games that offer premium subscriptions, showing the benefits of monetizing early player-based growth through aggressive advertising while delaying the introduction of premium subscriptions. In a study of competing platforms that produce integrated content and host independent developers—all paying fixed subscription fees—Lin et al. (2020) find that, under competition with an installed base, seller fees remain the same for all bundling strategies, while mixed bundling emerges as the dominant equilibrium when integrated content's intrinsic worth declines or the installed base grows. Platforms can also take a more user-centric approach to set subscription prices. For instance, Chou and Kumar (2024) develop a method to estimate the distribution of consumers' willingness to pay (WTP) through variation in consumer usage behavior, providing insights into optimal pricing strategies for subscriptions.

Affiliate Marketing and Sponsored Content and Partnerships Content platforms and blogs may earn commissions by promoting third-party products or services. When users make purchases through affiliate links, the platform receives a percentage of the sale. Social media platforms and influencers often collaborate with brands to create sponsored content, receiving payment for promoting products or services to their audience. Lin et al. (2022) examine how subscription-based crowdfunding (SBC) creators use earnings concealment and private postings as information control strategies, which positively impact creators' backer base and fan engagement and foster long-term performance through authenticity.

In a recent editorial, Peres et al. (2024) propose research questions focusing on creators, consumers, firms, and platforms, and examine their implications for the marketing function within organizations. A key insight is that, while content creators may seem like independent individuals, their collective activity generates emergent patterns that can be strategically monitored, monetized, and managed. Achieving this requires developing appropriate metrics, methodologies, and adapting established marketing constructs. Responding to this editorial, Bleier et al. (2024) explores the role of social media platforms in the creator economy, highlighting their key functions in connecting actors, supporting content creation, and facilitating monetization. Further, Hofstetter and Gollnhofer (2024) discusses the authenticity vs. monetization trade-off faced by content creators.

Hybrid monetization strategies Monetization methods are often not mutually exclusive; many platforms integrate multiple strategies. For example, Amaldoss et al. (2021) analyze media platforms' content provision and pricing strategies when they interact with three sides: content suppliers, consumers, and advertisers. Platforms can also implement voluntary payments by counting on social norms. Kim et al. (2023) identify a positive impact of a norm message on tipping behavior on an online freelancing platform. Huang et al. (2022) compare two-sided platforms' quality self-regulation strategies, and find that both subsidization and first-party application strategies render the platform owner better off, but only subsidization always improves social welfare.

Deciding on the most appropriate monetization model requires platforms to understand consumer preferences (Cong et al., 2024). Future work could develop a unified framework that optimizes these interdependent choices in light of overarching business goals. Table 8 in the Appendix distills the literature along two dimensions—revenue source (selling the service vs. selling attention) and tariff structure (pay-per-use, subscription, freemium)—noting that hybrid strategies can blend elements of both. Another unresolved issue is value capture: how much surplus accrues to the platform versus its users and partners? Information monetization remains under-explored; studies on selling data (e.g., cookies) (Bergemann and Bonatti, 2015; Bergemann et al., 2018) and charging third parties for API access (Benzell et al., 2024) offer some insights, yet the long-run benefits and risks of relying on such channels as primary revenue streams are still unclear. Table 2 outlines these and other avenues for future research.

2.2 Information Flows

As granular data availability has exploded in the Platform 2.0 paradigm, platforms must carefully consider which types of information to collect from users, which information to disclose back to users, and how to utilize this information. We now highlight research and open questions pertaining to sub-categories of information design, namely online word of mouth, content curation and platform endorsements.

Online word of mouth User generated reviews and ratings are ubiquitous across online platforms. However, different platforms present online review information in different ways. For instance, Tripadvisor provides comprehensive distributions of reviews, including ratings related to specific attributes (such as location for hotels) and the count of reviews by satisfaction level. In contrast, Airbnb offers only aggregated measures such as review counts and average ratings. A significant challenge scholars in this domain have explored is that the aggregated information may not capture the subtleties of product quality. For instance,

Topic	Open Questions
Direct and Hybrid Monetization	1. What are the consequences of increasingly personalized and dynamic monetization policies on firm outcomes? 2. How can firms effectively monetize consumer attention as information overload becomes rampant? 3. How can platforms monetize data and how would it affect platform users?
Advertising	1. How do ad ranking choices impact user satisfaction and overall revenue? 2. What is the "optimal" quantity of advertising for a platform, such that revenue and user satisfaction can be balanced?
Affiliate Marketing	1. How do affiliate strategies affect consumer trust and creators' authenticity? 2. What metrics can platforms use to evaluate long-term growth from affiliate collaborations? 3. Are there negative spillovers for the platform that shovels its traffic to others e.g., could this lead to lowering the quality of the content and focusing more traffic generating "clickbaity" content?

Table 2: Open Questions in Monetization Research

Dai et al. (2018) proposes an alternative method that takes into account the variations in reviewers' accuracy, stringency, and social incentives, leading to more informative and nuanced assessments of quality. Chakraborty et al. (2022b) suggests considering how reviewers self-select attributes to write about. Aziz et al. (2023) demonstrates how platforms' rating display rules can impact user behavior, benefiting platforms through rating inflation, while also affecting user trial and sales concentration among popular sellers.

Another dimension of selection is that the decision of potential future reviewers to purchase a good is driven by the information available at the time of purchase (Acemoglu et al. (2022)). This can lead to a cold start effect where new entrants to the platform may struggle if they are unlucky to receive a negative review. This can affect the long-run composition of platform participants (Vellodi (2018)) - Vana and Lambrecht (2021) also demonstrate that individual reviews have a strong effect on consumer purchase decisions even after accounting for a product's average rating. To make ratings more representative, an important consideration for the platform is to create incentives for agents to generate valuable content. For example, Chakraborty et al. (2022a) provide a theoretical framework for conditions under which consumers write reviews, which can help develop such incentive structures. However, Karaman (2025) uses a randomized review solicitation instrument to show that posting a review causally reduces future spending on the reviewed brand, especially among dissatisfied but loyal customers, suggesting that review solicitation can backfire if not targeted thoughtfully.

The type of interactions that are permissible between agents on a platform also influences the kind of content users generate and determines who remains active on the platform. For example, historically, review platforms only permitted one-way feedback from reviewers.[6] Nowadays, many platforms have expanded to incorporate multi-sided dialogues, like Q&As (Banerjee et al., 2021; Banerjee and Sudhaharan, 2025), and allow businesses to reply to online critiques (Chevalier et al., 2018; Proserpio and Zervas, 2017). The impact of these multi-sided conversations is mixed. For instance, Chevalier et al. (2018) find that responding to reviews can make future reviews more negative whereas Proserpio and Zervas (2017) find that responding makes future reviews more favorable. Karaman et al. (2024) study response styles and their differential impact on future reviews and sales, showing that firms should consider the impact of response strategies over and above the binary decision of responding itself.

Content Curation The selection and presentation of displayed information can impact participation as well as the value generated for participating agents. An example of how platform-curated cues can affect behavior comes from vacation rental platforms, which use historical price information on listings to decide what kinds of price estimates to display when incomplete search information is provided. Banerjee et al. (2025) show in a field experiment that the decision to display lower 'From' prices has a positive effect on engagement, even though these prices are closer to the 'true' price consumers would have to pay. Another class of design issues emerge with regard to ranking algorithms. As an example, Donnelly et al. (2023) find that personalized rankings increase consumer searches and purchases, and despite the ranking algorithm putting positive weight on profitability, these rankings still significantly enhance consumer welfare. Similarly, Pachali and Datta (2024) show that users have strong preferences for playlists curated by Spotify. Ichihashi (2020) demonstrates the interplay between information disclosure by consumers and its impact on the quality of subsequent recommendations on the platform. Although the consumer benefits from accurate recommendations, the seller may use the information to price discriminate.

Platform endorsements Recently, platforms have increasingly introduced aggregate quality signals by incorporating not only review information but also a broad spectrum of product information. One prominent example is platform endorsements like Amazon's Choice and Etsy's Picks. Bairathi et al. (2025) demonstrate that exposure to platform endorsement increases user search and purchases not only for endorsed services, but also for unendorsed services due to an increase in the overall perceived platform quality. Furthermore, focusing

[6] https://reviewinc.com/2021/09/07/a-history-of-online-reviews/

on an online healthcare platform, Zhan et al. (2024) finds that platform endorsements could motivate doctors to provide more services. Paridar et al. (2023) explore the often nuanced and different effects between endorsements from platforms and those from other users, as well as the distinction between monetary and non-monetary incentives. Platform endorsements can also have an effect on reviewer behavior on e-commerce platforms. For instance, Yazdani et al. (2024) show how Top Reviewer badges awarded by platforms like Amazon can make reviewers more critical in a drive to differentiate themselves from other reviewers, while Tamaddoni et al. (2023) explore the asymmetric effects of status gain ("Elite" reviewer) vs loss on reviewing activity in the context of Yelp. Finally, on the seller side, Zhou and Zou (2023) show that sellers strategically adjust prices to compete for an online marketplace's personalized product recommendations.

Many open questions remain relating to platform information flows. Specifically, the active role of platforms in holding information is understudied and future research may require novel market definitions for different platform participants and the platform itself. Information design may also interact with issues such as disintermediation, i.e, preventing off-platform interactions between agents so that the platform continues to remain profitable (e.g., Hagiu and Wright (2023)). Likewise, research on content spillovers (e.g., Song and Manchanda (2025)) and interactions like retweets/shares on social platforms (e.g., Wang et al. (2024b)) is understudied. Other pertinent open questions are highlighted in Table 3.

Topic	**Open Questions**
Online word-of-mouth	1. How can platforms use advanced review aggregation (e.g., using LLMs) to surface nuanced quality signals in real time? 2. In what ways can algorithmic aggregation ensure transparency and address challenges like rating inflation, reviewer bias, and the cold start problem?
Content curation	1. How can platforms design ranking algorithms to balance seller outcomes and buyer retention? 2. What long-term impacts occur if platforms optimize curation only for short-term clicks?
Platform endorsements	1. How can platforms balance endorsement frequency and transparency—building provider trust without inviting strategic manipulation or undermining the integrity of the system? 2. How can platform endorsements be designed to promote a more equitable distribution of attention and avoid "rich-get-richer" dynamics, including the abuse of market power?

Table 3: Open Questions in Information Flows Research

3 External Dynamics: Platform Regulation Challenges

Existing regulation does not always directly apply to markets where new platforms have emerged (Einav et al., 2016). Building on Farronato (2025), we discuss how the regulatory environment is adapting to the growth (and dominance) of digital platforms in the 2.0 paradigm, and critical open questions and trade-offs. In the first part, we discuss regulation concerning consumer protection. In the second part, we focus on competition and antitrust.

3.1 Consumer Protection

Platforms intermediate exchanges between buyers and sellers. User safety concerns may prevent participation in the platform activity in the first place, giving rise to a market breakdown (Akerlof, 1970). We discuss emerging topics in consumer protection, including dimensions where societal and profit objectives may not be aligned.

Asymmetric Information Despite platform-led consumer protection efforts, many digital platforms intermediate services traditionally provided by professionals who are subject to government-mandated regulatory screening and monitoring, such as occupational licensing or ongoing health and safety inspections. While such regulations aim to ensure quality and safety, they can also increase entry barriers, reducing consumer options and raising prices (Farronato et al., 2020). The challenge lies in determining when the benefits of such policies outweigh the costs, particularly in sectors where service quality can be objectively measured. For instance, Athey et al. (2019) leverage telemetry data in the ride-sharing market to demonstrate that Uber drivers provide higher-quality services than traditional taxi drivers, due to a combination of platform incentives and better alignment with consumer preferences.

These examples illustrate that, in certain circumstances, the objectives of external regulators—protecting consumers from risky transactions—align with those of the platform, which seeks to maintain a high level of trust. This alignment is crucial for sustaining user activity and, consequently, the platform's revenue. In this context, platform design and government regulation can function as substitutes. Effective platform mechanisms that reduce information asymmetries may diminish the need for government intervention to ensure consumer safety. A limited set of work has explored the extent to which reviews can substitute for existing regulation. While there are dimensions of quality for which that may be the case – for example, quality dimensions that are directly observable to the consumer – Farronato and Zervas (2022) find that monitoring by regulators is still needed for many dimensions of quality relevant for consumer safety.

Fake reviews undermine customer protection by damaging platform credibility and creating deception, resulting in sub-optimal purchase decisions (Pocchiari et al., 2025). As a result, more stringent policies against review fraud have recently been proposed by the Federal Trade Commission. Recent work has shown that an active online market for fraudulent reviews exists, where businesses compensate customers to purchase selected products and leave positive reviews (He et al., 2022b,a). Such instances will likely increase as sophisticated fake reviews generated using AI tools make detection more difficult.

While platforms and regulators share broadly aligned objectives regarding certain aspects of consumer protection, their focus often differs due to jurisdictional boundaries. Platforms typically prioritize the safety and well-being of their users (e.g., travelers and hosts on Airbnb), whereas regulatory bodies are primarily concerned with protecting the residents within their local jurisdiction (e.g., residents of a city). For example, as Yu et al. (2020) highlight, the entry of on-demand ride-hailing platforms like Uber and DiDi can disrupt traditional industries. This entry could drive taxis out of the market, which may trigger regulatory intervention to protect the interests of local taxi drivers. A similar tension exists for short-term accommodations: even if travelers and hosts benefit from transacting on Airbnb (Farronato and Fradkin, 2022), local residents may be worse off as a result via, for example, increased rents (Barron et al., 2021; Calder-Wang, 2021).

Discrimination Platforms may reduce information asymmetry between participants by enabling access to personal details, such as race or gender, before engaging in transactions. At the same time, this transparency can sometimes lead to discriminatory practices. For example, Chan (2023) reveals discrimination against minority doctors.

Platforms have a unique capacity to mitigate biases through the data they collect on consumer preferences and provider performance. In the context of Airbnb, Cui et al. (2020) demonstrate that credible positive reviews can diminish discrimination. Similarly, Chan (2023) finds that providing information about doctors' quality can help reduce bias. However, recent studies by Bairathi et al. (2023) and Teng et al. (2023) highlight a limitation: reviews themselves can reflect biases against minorities, potentially undermining their role in combating discrimination and even exacerbating it in some cases.

Further, the complexity of decisions in the context of platforms that involve algorithms and mulitple economic actors means there is the potential for outcomes that may unintentionally disadvantage some dmeographic groups. Lambrecht and Tucker (2019) demonstrate that in the context of display advertising, an algorithm that simply optimizes cost-effectiveness in ad delivery may deliver ads that were intended to be gender neutral in an apparently discriminatory way, because of crowding out. This is a result of advertisers' valuations for consumer's eyeballs varying across different demographic groups. In the context of search advertising, Lambrecht and Tucker (2024) demonstrate that when algorithms need to overcome a 'cold-start problem' by swiftly learning whether content engages users, individuals in minority groups are proportionately more likely to be test subjects for experimental content – including undesirable content – that may ultimately be rejected by the platform.

Restricted and Illegal Content Consumer protection is a particularly delicate goal when platforms deal with restricted or even illegal content. In these contexts, evidence on the efficacy of regulations has been mixed. For instance, Zeng et al. (2022) examine the impact of shutting down two major commercial sex advertising sites on prostitution arrests and violence against women. They find that targeting a small number of prominent sex advertising portals is unlikely to be effective in combating sex trafficking, given the fluidity of online markets for illegal activity. Vana and Pachigolla (2021) focus on dark web marketplaces that facilitate transactions of illegal goods such as drugs, weapons, and counterfeits. Their key finding is that after a law enforcement intervention, economic activity increased in adjacent dark web marketplaces.

Privacy Consumer privacy is a key dimension of consumer protection online. Regulating privacy has been difficult because individuals often claim to value privacy, though few behave in accordance with these preferences (Johnson et al., 2020). Some research has suggested these patterns may relate to the way in which digital platforms design interfaces for user consent over data collection and usage (Lin and Strulov-Shlain, 2023; Farronato et al., 2025). The value of specific data to firms is sometimes difficult to quantify (Bergemann et al., 2022; Galperti et al., 2023), which complicates any market for the exchange of data and, because collecting data is rarely costly, may lead firms to err on the side of collecting too much. Building on this challenge, Ponte et al. (2024) develop a privacy-utility framework showing that deep-learning–generated synthetic data can preserve analytical value while formally protecting individual identities, even revealing cases where larger datasets lower re-identification risk.

A wealth of empirical work highlights that data in the aggregate is valuable to individual firms, especially first-party data. Sun et al. (2023), for example, conduct a large-scale field experiment to quantify the losses incurred when a platform cannot use personal consumer data for product recommendations. Their results emphasize that these losses are unequally distributed, disproportionately affecting niche sellers and consumers who would otherwise benefit most from e-commerce. Similar positive values of personal data have been found in news consumption (Peukert et al., 2023) and advertising (Goldfarb and Tucker, 2011b).

While first-party data has demonstrated significant value, evidence suggests that third-party data sourced from brokers often falls short in fulfilling its intended purpose (Neumann et al., 2019). Moreover, such data can exacerbate societal inequities by delivering uneven prediction accuracy across demographic groups (Tucker, 2023; Neumann and Tucker, 2021). To address these challenges, Bergemann and Bonatti (2023) advocate for privacy-focused data governance strategies, such as federated learning, which can enhance consumer welfare by reducing platforms' informational dominance and limiting excessive data collection. These approaches aim to balance the scales in bargaining power between platforms and users. In contrast, Fainmesser et al. (2023) explore the relationship between platforms' revenue models and their data practices, showing that data-driven platforms are more likely to collect and safeguard consumer information compared to usage-driven models. Their analysis also warns against regulatory frameworks that prioritize data protection without considering broader implications, as such measures could unintentionally reduce consumer benefits and overall welfare.

Given the value data provides to companies, it is not surprising that studies looking at the effect of the European Union's General Data Protection Regulation (GDPR), passed in 2018 to require user consent when collecting their data, have found that privacy regulation tends to hurt firms' performance and innovation, limit competition and increase market concentration (Johnson, 2022; Peukert et al., 2022; Johnson et al., 2023). Quantifying these economic stakes further, Miller and Skiera (2024) estimate that limiting tracking-cookie lifespans to one year would cut European publishers' advertising revenues by roughly 9%, highlighting the tension between stronger privacy and marketplace viability. On the positive side, GDPR has heightened consumer awareness regarding corporate data practices and enhanced individuals' sense of control over their personal information. Johnson (2022) presents a comprehensive review of the literature on GDPR. Since GDPR, other regulators, including in China and California, have passed legislation to limit the collection of consumer data and ask for explicit consent from consumers. Such policies may also have unintended consequences - for instance, Aridor et al. (2024) show that Apple's App Tracking Transparency (ATT) privacy policy reduces clickthrough rates of Meta ads by 37%, with smaller e-commerce firms being most affected.

There are several open questions relating to consumer protection. An important rapidly evolving challenge is that of managing toxic content, including misinformation and hate speech, on social media platforms. Findings by Beknazar-Yuzbashev et al. (2022) suggest that at least in the short run, lowering exposure to negative content reduces advertising impressions on the platform, time spent, and other measures of engagement. At the same time, Ahmad et al. (2024) demonstrate that users decrease their demand for a company's products or services upon learning about its role in monetizing misinformation via online ads. Advertisers worrying about brand safety and suitability can create incentives for platforms to police toxic content (Griffin, 2023). Recent studies propose interventions such as subtle nudges to reduce misinformation (Arechar et al., 2023).

An important broader question is what role platforms, especially social media platforms, have in moderating harmful user-generated content (Van Alstyne, 2024). Should it be governments, platforms themselves, users, or another party altogether? Additionally, open questions remain about balancing free speech rights with the harms caused by false or toxic content, and how moderation by platforms versus independent parties affects user satisfaction and platform profits. Other open questions are summarized in Table 4.

Topic	**Open Questions**
Asymmetric information and illegal content	1. What are the potential biases in AI-driven content filtering mechanisms (e.g fake reviews), and how can they be mitigated? 2. How do fraudsters adapt to the shutdown of illegal sites, and what countermeasures can regulators implement?
Privacy	1. How can online platforms best balance the collection of data to improve their services while respecting consumer preferences for privacy (which still need to be better understood)? 2. What methodologies can be developed to effectively measure the direct and indirect benefits of privacy protections for consumers? 3. How do different privacy regulations impact personalized advertising, product recommendations and in turn consumer trust, engagement, and long-term purchasing behavior? 4. How do consumers' privacy preferences shift when their data is used to train AI models, and what are the implications for platforms and regulators?

Table 4: Open Questions in Consumer Protection Research

3.2 Competition

Platforms often exhibit structural features that favor the growth and dominance of large firms (Scott Morton et al., 2019), including low marginal and distribution costs, enabling scalability without significant incremental expenses, and increasing returns to data. Moreover, platforms are bolstered by both own-side and cross-side network effects (Chu and Manchanda, 2016a), where the value of the platform increases as more users join on the same side (e.g., more buyers or sellers) and across different sides (e.g., interactions between buyers and sellers). These dynamics have the potential to create barriers to entry for smaller competitors and reinforce the market dominance of established players. Because of this, scrutinizing the market power of digital platforms has recently come into policy focus.

Hylton (2019), among others, has argued that the market power challenges emerging from digital platforms are nothing unusual and can be tackled without a reform of antitrust. Farronato et al. (2023a) highlight that reliance on network effects as a justification for large platforms may be overblown. Below we address three areas at the interface of platforms and other market participants that have attracted the attention of regulators: self-preferencing and defaults, native advertising and the role of gig economy workers.

Self-Preferencing and Defaults When platforms offer products in direct competition with alternatives sold by third-party sellers (e.g., Amazon selling its own brands, or Google offering its own Shopping app), platforms may have incentives to engage in self-preferencing, that is giving an advantage to their own products or services when surfacing them to consumers. The theoretical trade-offs of self-preferencing have been explored by Long and Amaldoss (2024), among others. Empirically, recent work is emerging on how to detect self-preferencing (Reimers and Waldfogel, 2023), especially in the context of Amazon (Farronato et al., 2023b; Jürgensmeier and Skiera, 2023; Raval, 2022; Lam, 2023; Lee and Musolff, 2021). Kittaka et al. (2023) offers a broad review of the existing literature.

Regulating or banning self-preferencing has nuanced consequences. Zou and Zhou (2025) analyze the possible impact of the Digital Markets Act's 2022 self-preferencing ban,[7] and show that search neutrality may harm consumers by weakening price competition between the platform and third-party sellers. Dubé (2022) suggests that self-preferencing regulations on Amazon could reduce consumer welfare, based on the ample evidence that exists about the benefits of private labels in the offline world. Hagiu et al. (2022) highlight that preventing vertical integration altogether can harm consumer welfare even after taking into account the risk of self-preferencing. In the extreme, a ban on private labels may lead the platform to stop catering to sellers and instead transform into a reseller (Anderson and Bedre-Defolie, 2022). Finally, Krämer and Schnurr (2018) argue that there is no sufficient basis for a general ex-ante neutrality regulation for online platforms, and that instead requiring transparency on various platform practices is a necessary first step to evaluate the potential effects of market power.

Defaults can play a similar role as self-preferencing. They have recently been the focus of heightened antitrust scrutiny[8] and likewise recevied academic attention. Allcott et al. (2024) quantify their pivotal role in shaping market dynamics and sustaining Google's market share.

[7] https://digital-markets-act.ec.europa.eu/index_en.

[8] https://www.justice.gov/opa/pr/justice-department-sues-monopolist-google-violating-antitrust-laws.

Native Advertising Online platforms' revenue models increasingly rely on advertising. The use of native advertising has led to the concern that advertised products cannot be distinguished from organic alternatives and might misguide consumers.[9] In social media, Ershov et al. (2025) find that the vast majority of influencer posts on X that include sponsorships are not disclosed as such. In a field experiment, Sahni and Nair (2020) find that while native advertising benefits advertisers, there is no evidence of consumer deception. Some countries have passed mandatory disclosure policies. In particular, Ershov and Mitchell (2024) study the implementation of mandatory disclosure in Germany and find that disclosure sizably increased post-implementation. Yet, the regulation also seems to have given influencers license to advertise, which led to a substantial increase in sponsored content.

Further, Yu (2024) examines sponsored product advertising and finds that advertising, to the extent that it substitutes for commission fees charged to all sellers, can be an efficient form of price discrimination, where sellers of low quality products must pay more (i.e., advertise) to be presented to consumers compared to sellers of high quality products.

Gig Economy Workers While most digital platforms rely on independent contractors or freelancers as service providers, some, particularly in ride-sharing, have faced criticism for their control over providers, such as setting prices, while not offering benefits. In these arrangements, providers retain full control over their schedules but shoulder all responsibility for delivering services. This flexibility can be valuable (Koustas, 2019; Garin et al., 2020), especially for those who prioritize control over their work hours (Hall and Krueger, 2018; Chen et al., 2019). However, this model also has drawbacks, including lower earnings for drivers. Fisher (2024) suggests that unionization could help address these issues. As alternative work arrangements continue to expand (Mas and Pallais, 2020), developing effective regulatory approaches will become increasingly critical.

An important emerging area of research is the role of algorithmic pricing in collusion, which brings the possibility of supra-competitive prices under certain conditions (e.g., Calvano et al. (2020); Hansen et al. (2021)). Recent developments in generative AI has also demonstrated similar patterns that merit more exploration in the future (Fish et al., 2024). It also remains an active area of research to determine how regulators can carefully balance the compliance costs of antitrust measures, such as potential reductions in innovation or increased operational burdens for platforms, against the societal and economic benefits of fostering competition. Sokol and Zhou (2024) underscores the importance of this tradeoff, advocating for regulatory frameworks that promote fairness and competition while minimiz-

[9]Native advertising has been extensively discussed by the FTC. See here for more details: `https://www.ftc.gov/business-guidance/resources/native-advertising-guide-businesses`

ing unintended consequences. Other open questions are presented in Table 5.

Topic	Open Questions
Self-preferencing	1. What is the equilibrium effect of self-preferencing by dominant platforms, considering market competition and consumer welfare?
Native Advertising	1. What kinds of disclosure rules are effective in helping consumers distinguish sponsored content from organic content? 2. How do platforms' native ad placement practices affect market fairness in the long term, and should there be greater accountability to prevent unfair advantages or discrimination?
General	1. What measures can regulate gig platforms power relative to workers without harming work flexibility? 2. Should and if so, what kind of new definitions of platform power are needed? Are methods available to measure this, or do new methods have to be developed?

Table 5: Open Questions in Competition Research

4 Data Acquisition for Empirical Platform Research

Our review of emerging platform-related research topics in Section 2 and Section 3 illustrates the interdependent nature of agent outcomes, and the wide array of market structures and equilibria. Data often complement theory in refining predictions and findings. In this part of the paper, our goal is thus to propose some guidelines to make researchers aware of benefits and drawbacks of various data acquisition strategies to conduct platforms research efficiently in the 2.0 paradigm.

In Section 4.1, we explore data acquisition in researcher-platform collaborations and their challenges, while Section 4.2 addresses similar issues without platform involvement. Section 4.3 then integrates these challenges with methodological factors to assess trade-offs in research development.

4.1 Data acquisition with platform participation

We group the data acquisition strategies with platform participation in three categories: (1) cooperating with a firm's internal research teams, (2) using publicly available data shared by firms, and (3) using a firm's API (application programming interface).

First, research is essential for platforms to innovate, improve services, and stay competitive, leading some to form dedicated internal research teams. Some teams have developed robust internal scientific cultures and participate in leading conferences (e.g., Gao, 2024). For example, Airbnb conducts research on online experimentation, measurement, and two-sided marketplaces,[10] while investing in education and infrastructure (Bion, 2016). Similarly, Microsoft's Economics and Computation group publishes on marketplace design[11] while Facebook and Yahoo have collaborated with academics on joint research (e.g., Gordon et al., 2019; Johnson et al., 2017). Many firms now have AI research teams, such as Meta's FAIR team, which is tasked with advancing machine learning (LeCun, 2018). However, external collaboration and publication vary between organizations and over time.

Apart from these larger platforms, many small and medium-sized platforms have also directly collaborated with academics on research projects, sharing data or enabling field experiments. Though initially rare, this approach has recently become more common. One such indicator is that, out of 70 working papers submitted to the 2023 Workshop on Platform Analytics, more than half were direct collaborations between academics and platforms.[12] One advantage of such an approach is that researchers may be able to study fine-grained user data that are otherwise not easily available. For example, Xie et al. (2022) used geolocation data from a transportation app to study driver propensity to disintermediate the platform (i.e., take transactions offline to avoid platform fees). Beyond data access, some collaborations formalize arrangements by setting up shared data lakes, allowing researchers and company teams to pursue larger research agendas and investigate emerging questions quickly, thus shortening the time to market for resulting papers (e.g., Wlömert et al., 2024). Additional benefits include access to proprietary internal information such as algorithms used and other features of the data generating processes; and the possibility to implement improvements to platform design based on research findings.

Second, some platforms have created public datasets that can be used for research, teaching, or other public purposes. Popular examples include the Yelp Open Dataset, the Expedia Hotel Recommendations dataset, and IMDbs Non-Commercial Datasets, which have been analyzed in numerous academic papers. These may be available directly from the platform[13] or through a data aggregator like Kaggle[14]. Open datasets may enable external innovations that the platform can then adopt and expand upon (Ursu, 2018; Compiani et al., 2024). Similar to commercial platforms, some non-profit platforms have shared data and practices with independent researchers upon request, continuing a long tradition of openness among non-profit organizations. For example, Vana and Lambrecht (2022) analyzed extensive data and the exact algorithm used by the nonprofit crowdfunding platform DonorsChoose to rank

[10] See https://medium.com/airbnb-engineering/tagged/experimentation

[11] See, e.g., https://www.microsoft.com/en-us/research/project/market-design-center/

[12] https://platformanalytics.org/

[13] See, e.g., https://business.yelp.com/data/resources/open-dataset/ and https://developer.imdb.com/non-commercial-datasets/

[14] See, e.g., https://www.kaggle.com/c/expedia-hotel-recommendations

projects in search results. This allowed the authors to evaluate the algorithm used in practice versus two competing algorithms. Agarwal and Sen (2022) also use data from DonorsChoose to address the role of digital platforms in bridging the political divide and providing resources for teachers, enabling better conversations about diversity and inclusion with students.

Third, some platforms enable external researchers to access platform data through Application Programming Interfaces (APIs). APIs can enable powerful, flexible, regular access to various platform data (Boegershausen et al., 2022). Some of the best-known platform APIs include Facebook, Reddit, X/Twitter, and YouTube. There are also numerous less famous APIs, such as those that enabled Lu (2023) to explore the video game industry, and Stourm and Stourm (2025) to estimate spatial demand patterns in the car-sharing market.

4.2 Data acquisition without platform participation

Academic researchers have developed diverse techniques to collect platform data without platform participation. Such approaches can be costly in terms of time and money but enable greater independence and credibility when research diverges from platform objectives. We group the data acquisition strategies into six categories: (1) platform business partners and aggregators, (2) scripted platform monitoring (scraping), (3) recruiting consumers, (4) on-platform interventions, (5) creating synthetic platforms, and (6) market research studies.

First, platform behaviors can often be observed by other platform companies (such as internet service providers or credit card companies) or data aggregators (e.g., Chartmetric). Simonov et al. (2023) studied consumer clickstream data from a market research firm to understand how display advertising affected subsequent consumer search. Kim and McCarthy (2023) used a large credit card expenditure dataset to understand how the entry of scooter-sharing platforms changed local restaurant demand. Taylor et al. (2025) use a similar dataset to study the effects of sports betting legalization on different types of consumer expenditures. Batikas et al. (2023) studied how the GDPR regulation changed apps' testing policies, using data collected by an experimentation-focused Software Development Kit (SDK) provider that was embedded within many apps. Some platforms record transaction data in distributed ledger systems, enabling public observation such as in the Uni/Sushi promotion analyzed by Liu et al. (2022). Pachali and Datta (2024) collect data on playlist followers for more than 1.2 million playlists, relying on data aggregator Chartmetric to retrieve data via the service's API.

Second, nonprofits, researchers, and other organizations have created panel datasets of platform behaviors by systematically crawling and monitoring digital platforms. For example, InsideAirBnB.com monitors AirBnB listings and provides archived data. Until recently, PushShift.io offered a similar service related to Reddit content (Baumgartner et al., 2020). Similarly, individual researchers or research groups create scrapers to collect data from platforms such as Amazon (Lam, 2023; Hou et al., 2024) and Google reviews (Troncoso et al., 2023), as well as from less commonly studied domains such as healthcare (Zhang and Zhang, 2024), and sometimes make them available to other researchers (Ni et al., 2019).

Third, platform data can be collected directly from consumers through various means. Allcott et al. (2022) created a smartphone app to track social media usage, recruited users via Facebook advertisements, and paid them to install it. Zeller (2023) analyzed data from trakt.tv, which allows consumers to self-monitor media consumption in exchange for personalized recommendations. Browser extensions have been used to track browsing behavior, manipulate browsing experience, and prompt additional tasks (Beknazar-Yuzbashev et al., 2022; Farronato et al., 2023b, 2025). One such browser extension has recently been open-sourced.[15]

Fourth, researchers have studied platforms by intervening directly in their environments, which requires navigating not only institutional review board (IRB) approvals but also key ethical considerations such as user privacy and informed consent (Mosleh et al., 2022). Privacy concerns arise when research exposes personally identifiable information, while obtaining informed consent can be difficult in online settings—though exemptions may apply in certain cases. For example, Toubia and Stephen (2013) created 100 synthetic Twitter profiles and randomly added them as followers of noncommercial Twitter accounts, finding that increasing audiences decreased posting frequency for most users. Jiménez Durán (2021) reported hateful posts using Twitter's on-platform tools, leading to increased post removals, no activity change by post authors, and increased subsequent activity by attacked profiles. Mosleh et al. (2022) provide a detailed discussion of how to balance ecological validity with ethical considerations when conducting field experiments on social media.

Fifth, some researchers build mock-up platforms to conduct platform interventions, typically in two ways. First, they use existing tools such as oTree, an open-source behavioral research and experimentation platform used in 1,500+ academic publications (Chen et al., 2016). It offers a large set of reusable templates, including online shopping environments [16]. More specialized applications include social media simulation software (Jagayat and Choma, 2024), which replicates the core functionalities of major social networking platforms, such as news feeds, user interactions, and content-sharing features, or even platform replicas. In other cases, researchers create new platforms to suit specific experimental needs. For example, researchers at the University of Minnesota, with National Science Foundation funding,

[15]See `https://www.webmunk.org/`.
[16]E.g., see `https://otree-more-demos.herokuapp.com/demo.`

developed the non-profit movie recommendation platform MovieLens.org, leading to a long series of publications, including multiple field experiments. Others have built realistic virtual shopping environments to study how advertising influences consumer search and purchase decisions (Morozov and Tuchman, 2022).

Finally, researchers have studied platform topics using realistic controlled settings. One approach is to use conjoint analysis with incentive-aligned designs, as has been done to study consumers' willingness to accept payment for personal data (Collis et al., 2021), data choice architecture effects (Lin and Strulov-Shlain, 2023), and efforts to debunk product misinformation (Fong et al., 2023).

4.3 Collaboration considerations

4.3.1 Balancing Data Control, Ecological Validity, and Speed

When acquiring data for academic research, researchers must consider three key factors: data control, ecological validity, and speed. Data control refers to the ability to influence what data is collected, how it is structured, and whether experimental interventions, such as field experiments, are possible. Ecological validity captures how well the data reflects real-world behavior, platform interactions, and market conditions. Speed determines how quickly researchers can access and analyze the data, likely depending on a negotiation about data access and signing of non-disclosure agreements (NDAs).[17] These dimensions shape the feasibility and impact of different data collection strategies. Table 6 provides an overview of the data collection methods discussed earlier, illustrating the trade-offs on these dimensions and helping researchers evaluate which approach best fits their study.

Data acquisition strategies are also dictated by the nature of the research question, as the feasibility of obtaining platform cooperation depends on the alignment between the research question and the platform's interests. Projects that study consumer behavior, interface design, or policies that affect profits are more likely to get support. Most of the questions listed in Table 3 fit this mold because platforms already have the tools and data to study them. By contrast, topics that involve inter-platform relationships (such as affiliate marketing in Table 2) or issues that could hurt consumers (see Table 4) face more pushback. Market-wide questions about power or antitrust, and broader issues of social welfare, regulation, or competition policy listed in Table 5 raise similar resistance: platforms fear reputational and

[17] Research collaborations with platforms typically require agreeing on a legal framework including NDAs or data usage agreements (DUAs), which are agreed upon between the researchers or university counsel and the partner company. Ensuring unambiguous terminology is important to reduce the risk of different interpretation between the parties. Within any such legal framework, a researcher or university should ensure upfront that they are guaranteed the unconditional right to publish results in academic journals.

Data Acquisition		Decision Criteria		
Method	Platform Cooperation	Data Control	Ecological Validity	Speed
Cooperate with a firm's internal research teams	Yes	+++	+++	+
Use public data dump	Yes	+	+++	+++
Use firm's API	Yes	++	+++	++
Platform business partners/aggregators	No	+	++	+++
Scripted platform monitoring (scraping)	No	++	++	++
Recruiting consumers	No	++	++	++
On-platform interventions	No	++	+++	++
Creating synthetic platforms	No	+++	+	++
Market research studies (e.g., conjoint)	No	+++	+	+++

Notes: Platform cooperation indicates whether the method requires direct collaboration with the platform. Data control refers to the ability to influence data collection, structure, and experimental design, with higher values (+++) indicating greater control. Ecological validity measures how well the data reflects real-world behavior and platform interactions, with higher values (+++) indicating stronger realism. Speed represents the time required to obtain and analyze data, where higher values (+++) indicate faster access, while lower values (+) suggest a slower process due to negotiations, approvals, or technical setup.

Table 6: Comparison of Data Acquisition Methods

legal risk, may refuse collaboration or insist on anonymity, and sometimes try to shape or suppress unfavorable findings, leaving readers unsure about research independence.

It is also possible to conduct long-term projects with platform collaboration (e.g., Brynjolfsson et al. (2024)). For instance, Question 2 under content curation in Table 3 could potentially be conducted with a platform, but would require sustained buy-in, as researchers need significant commitment to run a lengthy experiment or to keep data flowing over time. Without it, firms rely on short tests, and researchers must estimate long-run effects with outside data.

When cooperation isn't practical or takes too long, alternative methods come into play. Synthetic platforms and conjoint surveys give full control but may sacrifice ecological validity. Recruiting users—for example, through browser plug-ins—can bypass platform barriers but takes effort. Scraping or using data aggregators is fast but offers less control. Custom scrapers let researchers pick what to collect, while aggregators deliver pre-scraped files with limited flexibility. Unilateral interventions risk detection: researchers may face API shutdowns, higher fees, or legal threats. Scraped data must also comply with site terms, which change often and can be unclear. Regardless, researchers still need to satisfy IRB rules and any agreements with syndication partners.[18]

[18] Some journals require that any scraped data comply with a site's published terms of service. However, site terms change frequently, are often unclear, and can be unreasonably restrictive.

4.3.2 Why a Hybrid Approach is Ideal

More data typically improves an empirical study by providing fuller context. Therefore, the optimal approach is to both collaborate with a platform and collect as much relevant data as possible without the platform's participation, subject to a researcher's budget and skillset.

While collaborating with platforms offers strong advantages in data control and ecological validity, researchers still face challenges that are not immediately apparent. Getting access can take time, and platforms may set limits on how data can be used, narrowing the research. Even with direct access, datasets can be incomplete due to selective data storage practices, internal compartmentalization, or undisclosed business constraints. For example, platforms may not log certain decision-making inputs, like unclicked recommendations or rejected bids, if they are not deemed valuable for business operations (Shi et al., 2024). Platform-provided data often lacks competitive market context, such as multihoming behavior, competitor pricing, or alternative algorithms, which are crucial for studying market-level dynamics.

Even when a partnership is in place, internal inertia can slow data release. This is especially true when studying strategies aimed at increasing revenue but potentially compromising the user experience or content quality (e.g., issues discussed in Table 2). In such cases, data from third-party providers or directly recruited users as highlighted in Table 6 can be a useful substitute.

Platform partnerships also come with operational risks. Many platforms are relatively young firms with evolving data infrastructures, and their APIs, data schemas, and internal record-keeping practices may change without notice. Researchers working with platform data should request structured data retrieval scripts (e.g., SQL queries) alongside datasets to ensure transparency about data extraction methods and to allow verification of reproducibility over time. Without these scripts, researchers risk working with datasets that may not be consistent across retrieval periods, potentially leading to undetected errors in analysis.

Additionally, researchers should not assume platform access will last indefinitely. External events such as regulatory scrutiny, executive turnover, lawsuits, data breaches, or shifts in corporate strategy may suddenly alter a platform's willingness to collaborate. Even historically open platforms may become more restrictive due to competitive pressures, public controversies, or internal reorganizations. It is critical to consider alternative or complementary data collection strategies to avoid over-reliance on a single platform as a data source.

A particularly important issue when studying market-level effects is that competitor behavior often shapes platform outcomes. Researchers interested in market-level outcomes often have to collect data from multiple competitors (Farronato and Fradkin, 2022; Farronato et al., 2023a). Competitor changes may drive platform outcomes and therefore threaten to confound regression discontinuities in time (RDiT), or increase statistical noise and thereby make causal estimates from randomized controlled trials (RCTs) less precise.

RCTs, while often considered the gold standard of empirical evidence in digital platforms, also come with unique challenges in platform environments. A fundamental concern is interference or violations of the Stable Unit Treatment Value Assumption (SUTVA), which assumes that the outcome of any individual unit is independent of the treatment assignment of others. Potential SUTVA violations may accrue from improper RCT infrastructure, the type of experiment being run, or (perhaps most commonly) on-platform interactions between treated units (Goli et al., 2024; Holtz et al., 2025). Many large platforms address this issue through parallel experimentation infrastructure that minimizes interference between multiple A/B/n tests, but smaller platforms often lack such safeguards: individual consumers might end up being allocated into multiple simultaneous experiments. Cluster randomization techniques are often used to avoid SUTVA violations, such as randomizing treatments to geographies.

A hybrid approach, which combines different elements of Table 6, can overcome limitations in platform-based research. This may be supplementing internal platform data with web scraping, consumer surveys, or third-party aggregator data to capture external market forces. Another strategy is to conduct field experiments with platforms while gathering external behavioral data from consumers through browser plugins or direct recruitment, enhancing external validity by contextualizing findings within the broader digital ecosystem.

Hybrid strategies help researchers mitigate risks of change in platform cooperation. By maintaining external data sources, researchers can ensure continuity, even if access to internal platform data is revoked or restricted. Integrating multiple data streams provides flexibility in research design, allowing for robustness checks and alternative model specifications.

Researchers may not feel like they have both approaches available, and the exact combination of strategies used depends on many factors, notably researcher budget and expertise. Yet, it may be possible to generate platform collaboration opportunities by contacting platform executives via social media, university alumni networks, or mutual contacts. A compelling message delivered to the right executive may succeed, though corporate policies or other constraints may prevent collaborations. Similarly, collecting platform data from non-platform sources can be pursued with creativity and hard work, as demonstrated in the taxonomy of strategies in Section 4.2.

Ultimately, choosing between platform cooperation, independent data collection, or a hybrid approach depends on the specific research question and the trade-offs researchers are willing to accept. A hybrid model offers a middle ground, leveraging the strengths of platform collaboration while mitigating some of its constraints, ensuring greater robustness and broader applicability of research findings. Table 7 summarizes the benefits and drawbacks of collaborating with a platform, as discussed in this section.

Benefits	**Drawbacks**
Access to richer, more comprehensive data that provides fuller context for empirical studies.	Corporate policies and constraints may limit research questions.
Research that aligns with platform profit objectives can enhance research impact by influencing practice.	Potential bias: Platforms might try to censor inconvenient results, especially related to regulation or competition.
Opportunity to complement externally scraped data with proprietary internal platform data and policies.	Reliance on platform collaboration may lead to projects shutting down if management changes.
Enables policy interventions, such as field experiments, that may not otherwise be possible.	Generating collaboration opportunities can be challenging and may not be feasible for all researchers.

Table 7: Benefits and Drawbacks of Collaborating with Platforms

5 Conclusion

In this paper, we highlight emerging research topics and open questions in the domain of online platforms, and also present key considerations and best practices in terms of data acquisition and industry collaborations. We start by charting the evolution of platform related research topics over 4 “eras”, highlighting key defining features of digital platforms in the 2.0 paradigm, which is the focus of our article. Next, we review research topics within two broad domains: the internal dynamics of platform design and the external dynamics of platform regulation. Within the first domain, we review recent research and synthesize pertinent open questions and ongoing debates for topics related to monetization and information flows. For the second domain, we do the same for topics related to consumer protection and competition. Then, we propose a taxonomy of approaches to study platforms empirically for both types of domains. We highlight forces that dictate when and for what types of research questions platform collaborations (vs other modes of data collection) is the best approach. This practical advice aims to help researchers navigate empirical complexities associated with platform ecosystems, from data acquisition to managing bias and data privacy concern. We recommend that researchers start with the highest value research question and then assess whether to partner with a platform, considering collaboration opportunities and the costs and benefits of collecting supplemental data independently.

Overall, our paper underscores the importance of a multidisciplinary and multi-method approach to fully grasp the opportunities and challenges digital platforms pose for firms, consumers, and regulators. While our framework offers valuable insights, it also has its limitations. We do not claim to provide an exhaustive bibliometric analysis of all aspects of digital ecosystems. Instead, our goal has been to spotlight key topics and emerging themes that are at the frontier of platform research. As the digital platform landscape continues to evolve rapidly, we hope our forward-looking perspective will inspire further research and deepen our understanding of platforms and the role they will continue to play in the future.

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A Article selection

Given our aim is not to provide a comprehensive overview of platforms research, but to chart some very recent developments in platforms research along with open questions, we take an approach similar to conceptual papers such as Cennamo (2021). To ensure a well-rounded selection that is consistent with this goal, based on our own research and domain expertise, we reviewed an initial list of articles within the broad domains of platform design and regulation. We then selected papers to ensure a representative distribution of topics and subfields. Overall, we cite papers from marketing (Marketing Science, IJRM, JMR, etc), working papers across other disciplines (SSRN, arxiv), Management Science, economics journals (AER, AEA Proceedings, RAND), Information Systems, Operations and Strategy journals (ISR, Production and Operations Management), and a few from law and general interest science journals (e.g., Journal of Law and Innovation, Nature Human Behavior).

B Monetization strategies

Choice of tariff	Revenue source		
	Selling the service	Selling eyeballs	Others
Pay-per-use	Rochet and Tirole (2006); Zhang and Zhang (2024); Zhu et al. (2025); Dinerstein et al. (2018); Amaldoss et al. (2021)	Wilbur et al. (2013); Choi and Mela (2019); Chu et al. (2020); Long et al. (2022); McGranaghan et al. (2022); Ursu (2018); Ursu et al. (2024); Sayedi (2018); Despotakis et al. (2021); Choi and Mela (2023); Amaldoss et al. (2021)	
Subscription	Bhargava et al. (2022); Deng et al. (2023); Lin et al. (2020); Chou and Kumar (2024); Lin et al. (2022); Li (2022); Huang et al. (2022)	Goli et al. (2024); Wang et al. (2024a); Lambrecht and Misra (2017); Mai and Hu (2023)	
Freemium	Li et al. (2019); Shi et al. (2019); Kamada and Öry (2020); Appel et al. (2020); Deng et al. (2023); Li (2022)	Rajaram et al. (2024); Wang et al. (2024a); Lambrecht and Misra (2017)	
Others		Choi et al. (2020)	Peres et al. (2024); Bleier et al. (2024); Hofstetter and Gollnhofer (2024)

Table 8: Monetization Strategies: Revenue Source vs. Choice of Tariff