Digital Platforms 2.0: Emerging Topics, Opportunities, and Challenges

Shrabastee Banerjee*[1], Ishita Chakraborty[2], Hana Choi[3], Hannes Datta[4], Remi Daviet[5], Chiara Farronato[6], Minkyung Kim[7], Anja Lambrecht[8], Puneet Manchanda[9], Aniko Öry[10], Ananya Sen[11], Marshall Van Alstyne[12], Prasad Vana[13], Kenneth C. Wilbur[14], Xu Zhang[15], and Bobby Zhou[16]

[1,4,] *Tilburg University, Dept of Marketing*
[2,5] *Wisconsin School of Business, University of Wisconsin-Madison*
[3] *Simon Business School, University of Rochester*
[6] *Harvard Business School*
[7,10] *Tepper School of Business, Carnegie Mellon University*
[8,15] *London Business School*
[9] *University of Michigan, Ross School of Business*
[11] *Heinz College, Carnegie Mellon University*
[12] *Questrom School of Business, Boston University*
[13] *Tuck School of Business, Dartmouth University*
[14] *University of California, San Diego*
[16] *Robert Smith School of Business, University of Maryland*

Abstract

Digital platforms increasingly influence most online markets and ecosystems, creating substantial value for their customers, owners, and other partners. Yet, the challenges associated with platform operations, governance, and regulation continue to evolve. This paper aims to help researchers understand the extensive platform literature to facilitate effective academic contributions. First, we lay out emerging challenges in research topics related to platforms, both from an internal (platform design) and external (platform regulation) perspective. Then, we compare techniques for acquiring and using platform data, both with and without the collaboration of the platforms themselves, to facilitate

** = shrabastee.b@tilburguniversity.edu; corresponding author, address: Tilburg University, Warandelaan 2, 5037 AB Tilburg, The Netherlands.

empirical platform research. Our insights highlight the importance of multidisciplinary and multi-method approaches in studying digital platform policies, value chains and regulation.

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

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1 Introduction

Digital platforms have become central to public debate. The five largest platform companies alone (Apple, Microsoft, Alphabet, Amazon, and Meta) account for \$13.08 trillion in market value as of January 2025, and many more platforms rank among the world's most valuable firms (Cusumano et al., 2020; Parker and Van Alstyne, 2018). Formally, platforms are intermediaries that facilitate interactions among two or more distinct groups (e.g., consumers, advertisers, creators). Through governance choices, platforms shape participation and generate direct and indirect network externalities that determine value creation and capture (Sriram et al., 2015; Parker et al., 2024). These features help to explain why platforms attract so much attention: they not only command enormous economic value, but also orchestrate the interactions that shape modern markets and user experiences.

Academic research on platforms has evolved significantly across a broad range of disciplines.[1] Prior to 1999, scholarship was almost entirely conceptual and the few empirical papers drew from small samples in financial services or proprietary online portals (e.g., Kauffman et al., 2000). Between 2000 and 2010, theoretical research established the fundamentals of two-sided-market pricing and network-effect signalling, showing how customer single-homing on one side could lead to markets 'tipping' on both sides (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 using multiple platforms at once (Caillaud and Jullien, 2003). The early empirical research focused primarily on two areas, including markets for consumer attention that were financed via advertising (e.g., Rysman, 2004; Wilbur, 2008; Ghose and Yang, 2009), and the explosion of user reviews, which offered the first reputation systems to help reduce information asymmetries and improve trust (e.g., Dellarocas, 2003). Together, this early work established the baseline questions in platform research.

The decades from 2010 onwards marked a decisive acceleration in the evolution of digital platforms. Whereas the earlier period centered on building and scaling platform ecosystems which we label "Platforms 1.0", research after 2010 shifted toward studying what we call "Platforms 2.0": namely, how data-intensive practices–such as targeted advertising and pricing, algorithmic matching and ranking, and data-driven governance–jointly determine value creation and extraction for modern platforms. Cheaper data storage, the widespread availability of smartphones, and new advertising technologies made it possible to track behavior at fine granularity and experiment at scale, enabling personalized recommendation systems, large-scale randomized tests, and more precise measurement of network effects (e.g., Goldfarb and Tucker, 2011a; Ghose et al., 2014; Chu and Manchanda, 2016; Taylor and

[1] See https://platformpapers.com/data-visualizations/.

Eckles, 2018). Since 2020, advances in large-scale machine-learning systems have pushed this trajectory further, into an era of "hyper-personalisation" in which algorithms infer user traits, tailor content and prices, and filter or amplify different types of offerings (e.g., Mitkina et al., 2022; Zhu et al., 2025; Zou and Zhou, 2025). These developments have intensified debates about market power, transparency, discrimination, and privacy (e.g., Hylton, 2019; Johnson et al., 2020; Luca and Zervas, 2016) and prompted new regulatory responses, such as data-protection and privacy rules (including GDPR and CPRA), the EU's Digital Markets Act, and emerging algorithmic-audit mandates (Kaushal et al., 2024).

This research evolution coincides with a marketplace in which platform performance varies dramatically across sectors. Between 2020 and 2023, e-commerce, the dominant sector, witnessed over 150% growth, followed by food and beverage, travel, and education.[2] However, many platforms continue to struggle financially: of 100 startups worth more than $1 billion, 64% were unprofitable[3].

Such growth and performance heterogeneity have led to three classes of challenges for researchers, practitioners and policymakers, which emerge from the core ideas developed for Platforms 1.0 and the rapid technological shifts leveraged by Platforms 2.0. First, it has become increasingly important to understand how tools internal to the platform influence outcomes. These can be described as *platform design* challenges: determining (i) how to monetize (e.g., pay-per-use, freemium, affiliate marketing, advertising) and (ii) how to manage information flows so the platform serves users effectively and in turn remains profitable (e.g., decisions on how to curate, disclose, and rank content). Second, it is important to study what checks and balances can mitigate potential harm and winner-take-all dynamics. This can most effectively be addressed through the lens of external *platform regulation*, addressing concerns of (i) consumer protection (e.g., safeguarding data privacy, preventing discrimination) and (ii) competition (e.g., reducing self-preferencing). Third, despite widespread data availability, researchers face significant barriers accessing secure, representative, and relevant data needed to study high-value questions. This creates a research infrastructure challenge: how to conduct rigorous empirical work in an era defined by confidential algorithms, strict privacy and liability rules, and shifting data-access policies.

Against this background, our contributions are twofold. We first synthesize emerging research topics and open questions in platform design (Section 2) and platform regulation (Section 3), emphasizing developments most salient to Platforms 2.0. We then discuss data acquisition strategies for empirical platform research, both with and without direct

[2] See https://a16z.com/marketplace-100/.

[3] Based on startups which successfully completed an initial public offering since 2010. See https://www.businessinsider.com/tech-companies-worth-billions-unprofitable-tesla-uber-snap-2019-11.

collaboration, and outline methodological trade-offs that shape feasibility and credibility (Section 4). Rather than providing an exhaustive review, we complement existing surveys (e.g., Sen et al., 2025; Cheng et al., 2024; Rietveld and Schilling, 2021) by offering a forward-looking perspective grounded in recent work. From a disciplinary perspective, we highlight how emerging platform 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.

2 Recent Topics in Platform Design Research

Platforms utilize a variety of design tools to optimize their operations. These tools influence agent behaviors in two ways: (1) through monetization strategies (e.g., pay-per-use, advertising, freemium, subscriptions) and (2) through information flows within the platform ecosystem (e.g., online word-of-mouth and platform endorsements). This section highlights research related to these internal dynamics of platform design. We conclude the section by proposing open questions and active areas of debate in Table 1.

2.1 Monetization

Research on Platforms 1.0 framed platform monetization through the lens of two-sided markets and network effects: to solve the chicken-and-egg problem of attracting both buyers and sellers in markets like credit cards and media, platforms adopted highly skewed pricing structures that subsidized the more price-sensitive side and charged higher fees to the less elastic side (e.g., Rochet and Tirole, 2006), sometimes even pricing below cost or paying users to participate (for instance, rewarding credit card holders). Classic theory highlighted how optimal price structures, rather than price levels, drive participation across sides and described how network externalities may dictate such choices (Parker and Van Alstyne, 2005; Cheng et al., 2024).

While this work established the foundational pricing logic (who pays, who's subsidized), it did not anticipate the full breadth of modern platforms' monetization strategies. Research on Platforms 2.0 quantifies causal effects of more complex pricing and advertising models

[4] To ensure a selection consistent with this goal, we reviewed an initial list of articles within the broad domains of platform design and regulation based on our own research and domain expertise. We then selected working papers across disciplines (SSRN, arXiv) and published papers from marketing (e.g., *Marketing Science*, *IJRM*, *JMR*), management (e.g., *Management Science*), economics (e.g., *AER*, *AEA Proceedings*, *RAND*), operations and information systems (e.g., *ISR*, *Production and Operations Management*), and law and general interest science journals (e.g., *Journal of Law and Innovation*, *Nature Human Behavior*).

using experiments and large observational datasets. In particular, recent research has shifted toward empirics and design questions, e.g., the optimization of "free vs. fee" over demand cycles (Lambrecht and Misra, 2017) and spillover effects of digital paywalls (Pattabhiramaiah et al., 2019), reflecting the broader empirical turn in platform studies (Sen et al., 2025).

2.1.1 Main Focus Areas

We explore key platform monetization strategies for Platforms 2.0 (pay-per-use, freemium and in-app purchases, subscriptions, advertising, affiliate marketing and hybrid strategies) to better understand trade-offs and open research questions in this space.

Pay-per-use A platform using a direct "pay-per-use" monetization model generates revenue by charging transaction fees using various pricing formats. Recent research has shown how network effects continue to play an important 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) find 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 to readers, especially those who most 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 alignment between pay-per-use pricing and value creation can influence both short-run and long-run welfare and profitability.

Freemium and In-App Purchases 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 (Rietveld, 2018). One of the main challenges in this case is to calibrate an optimal level of freemium content that draws consumers without cannibalizing payments too much. Wang et al. (2024) highlight 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) demonstrate that a media firm can increase overall revenue by offering more free content in high demand periods, through increased advertising sales.

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) present 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 free-trial usage frequency encourages conversion, but free-trial variety leads to lower conversion.

Subscriptions 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 Content platforms and blogs may earn commissions by promoting third-party products or services (Sun and Zhu, 2013). 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. Bleier et al. (2024) further explore 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) discuss the authenticity vs. monetization trade-off faced by content creators.

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; 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., 2025; Goli et al., 2025).

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; Choi and Mela, 2019; Ursu et al., 2025; Dinerstein et al., 2018).

Ads are priced, sold and targeted in many different ways. Ad sales can be priced per impression, per click, per action, or per incremental action, and may be sold at a fixed rate in advance with broad targeting criteria or through real-time bidding with more granular targeting options (Sayedi, 2018; Choi et al., 2020). Choi and Mela (2025) highlight the importance of incorporating practical constraints, such as advertisers' reach or budgets, when setting ad prices. Moreover, the platform's choice of pricing format, e.g., first-price or second-price auctions, influences not only welfare allocation but also the degree of market concentration among agents in the ecosystem (Despotakis et al., 2021; Choi, 2025). Increasingly, platforms offer automated services, such as Google P-Max or Meta Advantage+, which seek to automatically optimize advertisers' purchasing choices within a defined budget.

Hybrid Monetization Monetization methods are often not mutually exclusive; many platforms integrate multiple strategies (Chao and Derdenger, 2013).[5] For example, Amaldoss et al. (2021) analyze media platforms' content provision and pricing strategies when they

[5] Table 4 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.

interact with three sides: content suppliers, consumers, and advertisers. Platforms can also implement self-selected price discrimination by enabling consumers to make voluntary payments, such as directly requesting monetary tips (Kim et al., 2025), or enabling consumers to name their own price.

2.1.2 Open Questions

Deciding on the most appropriate monetization model requires platforms to understand consumer preferences (Cong et al., 2025), as well as factors like the availability of advertising space and user-platform match (Chen et al., 2016b). Future work could develop a unified framework that optimizes these interdependent choices in light of overarching business goals. For example, while video streaming platforms started out with subscription-based models, they are increasingly moving towards ad-supported tiers to deal with plateauing subscriber numbers. The optimal amount of advertising depends on the nature of advertising conveyed, balancing positive incremental ad reactions (e.g., conversions) with negative ones (e.g., decreased engagement due to ad clutter and nuisance). Structural models can help uncover relevant parameters such as ad elasticities and the disutility of interruptions in streaming to guide platforms. Another open question pertains to value capture: how much surplus accrues to the platform versus its users and partners? As platforms play an increasingly pivotal role in how consumers experience the Internet, it becomes important to determine how financial gains are distributed across different players such that the health of the ecosystem is preserved. 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 information monetization as primary revenue streams are still unclear. More granular micro-data over time coupled with either controlled or natural interventions (e.g., the staggered adoption of information monetization policies by a platform) are needed to answer such questions causally.

2.2 Information Flows

Early research on information flows was inspired by the long tail of products brought about by e-commerce (e.g., Brynjolfsson et al., 2003). Given unlimited shelf-space, designing optimal recommendation and feedback systems became critical for platform profitability and product discoverability. Platforms and consumers came to rely on product ratings and reviews to inform assortment and purchase decisions. Early empirical work established that feedback mechanisms reduce information asymmetries and shape demand: online reviews affected sales (Chevalier and Mayzlin, 2006), functioned as a new element of the marketing mix, and built trust that yielded price premia for reputable sellers (Dellarocas, 2003). Complementary design studies showed how recommendation agents and site features influence trust and choice (Wang and Benbasat, 2007). While this scholarship established the centrality of reviews and recommendations, newer research explores how algorithms and richer data shape word-of-mouth, content curation and direct product endorsements by platforms. Examples include managerial responses and externalities in review systems (Proserpio and Zervas, 2017), context-aware cart targeting (Panniello et al., 2016), sophisticated ranking algorithms (Donnelly et al., 2024), and platform badges/protections to orchestrate transactions (Hui et al., 2025).

2.2.1 Main Focus Areas

We now highlight research and open questions pertaining to three main sub-categories of information design particularly relevant for Platforms 2.0, 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, Dai et al. (2018) propose an aggregation approach that accounts for variations in reviewers' accuracy, stringency, and social incentives, leading to more informative and nuanced quality assessments. Chakraborty et al. (2022b) suggest how reviewers self-select attributes to write about. Aziz et al. (2023) demonstrate how platforms' rating display rules can impact user behavior, benefiting platforms through rating inflation, while also concentrating users and sales 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 average product ratings. One way platforms can incentivize high-quality reviews is to reward reviewers. For example, Chakraborty et al. (2022a) characterize the theoretical conditions that encourage consumer reviews, which can help develop such incentive structures. 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.

On-platform interactions between customers can facilitate review evaluation, thereby incentivizing further review generation and platform usage. 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 critical reviews (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. (2025) 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 (e.g., product page cues or platform recommendations) can impact participation as well as the value generated for participating agents (Oestreicher-Singer and Sundararajan, 2012). 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 emerges with regard to ranking algorithms. As an example, Donnelly et al. (2024) 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. Pachali and Datta (2025) show that users respond strongly to playlist promotions on Spotify's "Search Page". 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 introduced aggregate quality signals by incorporating not only review information but also their own quality certifications, e.g.,

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

"top rated" eBay sellers, Amazon's Choice and Etsy's Picks (Elfenbein et al., 2015). 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 on an online healthcare platform, Zhan et al. (2025) find that platform endorsements could motivate doctors to provide more services. Paridar et al. (2025) 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.

2.2.2 Open Questions

Many open questions remain relating to platform information flows. For instance, information design may interact with issues such as disintermediation, i.e., platform-facilitated interactions that lead to off-platform transactions between agents. As platform competition intensifies, disintermediation poses a clear threat to platform revenue, and may also harm user welfare by facilitating scams and withholding platform protections. Designing appropriate information flows to protect customers and retain revenue is an active area of research. For instance, users may be more likely to return if platforms provide trustworthy reviews and ratings and good matches between users and products in the form of recommendations. These questions are inherently difficult to study empirically, given disintermediation is hard to observe in most contexts. Thus, analytical models can provide boundary conditions for the amount of disintermediation platforms can withstand before they unravel, extending, e.g., upon papers like Hagiu and Wright (2024).

Another emerging topic that warrants more research focus is engagement incentives (e.g., Wang et al., 2025) and content spillovers (e.g., Song and Manchanda, 2025) between social platforms, given the fast pace at which our social media feeds are being transformed by AI generated content. For instance, can users accurately detect undisclosed AI generated content, and how does perceived detection affect engagement? While there is literature on algorithmic aversion in policy contexts (e.g., Longoni et al., 2023), it remains an open question how users on public communities like Reddit or StackOverflow engage with AI generated content, and the role of disclosure. These types of questions can best be studied with combinations of lab and field experiments, or by exploiting natural experiments such as the rollout of advanced LLMs.

Table 1: Open Questions in Platform Design

Topic area	Open questions
Monetization	**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., clickbait incentives)? **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? **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?
Information Flows	**Online Word-of-Mouth** 1. How can platforms use advanced review aggregation (e.g., LLMs) to surface nuanced quality signals in real time? 2. How can algorithmic aggregation ensure transparency and address challenges like rating inflation, reviewer bias, and cold start? **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 without encouraging manipulation? 2. How can endorsements promote equitable attention rather than reinforcing "rich-get-richer" dynamics?

3 Recent Topics in Platform Regulation Research

Existing regulation does not always directly apply to markets where new platforms have emerged (Einav et al., 2016). Building on Farronato (2025), we discuss the external dynamics of how the regulatory environment is adapting to the growth (and dominance) of Platforms 2.0, and critical open questions and trade-offs. In the first part, we address regulation concerning consumer protection, including asymmetric information, discrimination and privacy. In the second part, we focus on competition topics, including self-preferencing, native advertising and gig economy workers. We conclude by providing a set of pertinent open questions in Table 2.

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). Early work saw consumer protection primarily through the lens of information asymmetry and adverse selection, with feedback mechanisms presented as tools to increase trust (Ba and Pavlou, 2002). While this scholarship established reputation as a core protection lever, the evolution of Platforms 2.0 has brought forth new concerns, e.g., the emergence of fake reviews that can game the system (Luca and Zervas, 2016). As the volume of platform data has increased, new concerns have also emerged around algorithmic bias, data protection and privacy (Sen et al., 2025). In parallel, other forms of consumer protection policies have been studied, e.g., buyer protection policies that raise seller quality and market efficiency (Hui et al., 2016). Granular platform-level data and advances in measurement have enabled a methodological shift (from lab/surveys to field experiments and large-scale policy evaluations), allowing researchers to quantify more precise causal estimates of various facets of consumer protection and their consequences for the platform ecosystem.

3.1.1 Main Focus Areas

We discuss emerging topics in consumer protection within the areas of asymmetric information, discrimination, restricted and illegal content, and privacy, highlighting dimensions where societal and profit objectives may diverge.

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., 2024b). The challenges lie in determining when the benefits of such policies outweigh the costs, particularly in sectors where service quality can be objectively measured, and in ensuring that consumers are not misled. For instance, Athey et al. (2025) 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 also seeks to maintain a high level of trust. This alignment may be crucial for sustaining user activity and platform revenue, especially at an early stage before a platform matures. 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. However, 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 are another form of information asymmetry that undermines consumer protection by weakening trust in platforms and misleading users, which in turn leads to inferior purchase decisions (Pocchiari et al., 2025). As a result, the Federal Trade Commission has recently advanced stricter regulations targeting review fraud. Recent work has shown an active online marketplace for fraudulent reviews, in which firms orchestrate sting operations by instructing customers to buy specific products and post positive reviews in exchange for compensation (He et al., 2022b). At the same time, platforms can identify and roll back such deceptive review activity by applying clustering techniques in the joint product–reviewer space (He et al., 2022a). The generation and detection of fake reviews is thus a continual cat-and-mouse struggle that will be increasingly shaped by developments in natural language processing and generative AI tools.

While platforms and regulators share broadly aligned objectives regarding certain aspects of consumer protection, their focus could differ 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). More research is needed for a holistic evaluation of how platforms affect not only their immediate markets, but also their adjacent (indirect) markets and communities.

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 (2024) 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 (2024) 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, algorithmic decisions may lead to incidental, but still harmful, discrimination against some groups. Lambrecht and Tucker (2019) demonstrate that in the context of display advertising, an algorithm that simply optimizes cost-effectiveness in ad delivery may serve 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 consumers' 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 disproportionately 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 very difficult because individuals often claim to value privacy, but revealed preferences often tell a different story (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., 2024), 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., 2024) 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 et al., 2024). To address these challenges, Bergemann and Bonatti (2024) 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 transaction-driven platforms are more likely to collect and safeguard consumer information compared to attention-driven platforms. Their analysis also warns against regulatory frameworks that prioritize data protection without considering broader implications, because 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, 2023; 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 (2023) 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. (2025) show that Apple's App Tracking Transparency privacy policy reduces click-through rates of Meta ads by 37%, with smaller e-commerce firms being most affected.

3.1.2 Open Questions

An important, evolving challenge in consumer protection is that of managing harmful content, including misinformation and hate speech, on social media platforms. Findings by Beknazar-Yuzbashev et al. (2025) suggest that lowering short-run exposure to negative content reduces advertising impressions on the platform, time spent, and other measures of engagement, while 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. Griffin (2023) argues that advertisers worrying about brand safety can incentivize platforms to police toxic content. Arechar et al. (2023) propose interventions such as nudges to reduce misinformation. This stream of research demonstrates the relationship between online content, brand safety and revenue. The fact that harmful content is difficult to classify at scale and that user and advertiser responses may change over time further demonstrates the complexity in studying this topic empirically.

To tackle these challenges, researchers can combine large-scale field experiments with quasi-experimental designs around policy or algorithm changes, use text-as-data and machine learning to measure exposure and toxicity, and draw on models from platform economics and behavioral economics to formalize the trade-offs between engagement, advertising revenue, and consumer welfare.

Another important broader question is what role social platforms have in moderating harmful user-generated content (Van Alstyne, 2024). Should moderation be the responsibility of governments, platforms, users, or another party altogether? This question has received substantial media attention, and has a direct impact on various stakeholders (regulators, users, and advertisers). Yet it is hard to answer, since responsibility, legitimacy, and accountability are contested, and the relevant harms and benefits are diffuse and often long term. Moreover, counterfactual governance regimes cannot be directly observed. While this question is difficult to study empirically, progress may come from exploiting variation in moderation and liability regimes across jurisdictions or over time. Such variation can be leveraged using natural experiments, or to build structural models that map how different allocations of moderation authority affect platform behavior and welfare. Lab or field experiments can also be utilized by manipulating who is perceived to oversee moderation and measure consequences for perceived legitimacy, compliance, and user participation.

3.2 Competition

Early work on platform competition mainly studied multi-homing (Caillaud and Jullien, 2003), network effects (Armstrong, 2006) and frameworks on entry barriers (e.g., Boudreau, 2010). Drawing mainly on technology-based platforms such as software, operating systems, and early e-commerce marketplaces, these studies established baseline expectations about how exclusivity and access rules shape participation and platform success. These insights were derived almost entirely from formal theory and a small set of case-based studies, with systematic, large-sample empirical tests of platform rivalry and entry only beginning to appear in the late 2000s (Cheng et al., 2024).

Building on this early scholarship, Platforms 2.0 research tracks platform power inside ecosystems. Modern 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. These dynamics have the potential to create barriers to entry for smaller competitors and reinforce the market dominance of established players. Therefore, scrutinizing the market power of digital platforms has recently come into policy focus. For instance, a platform may both operate the market and compete asymmetrically in the same market by selling its own branded products (self-preferencing), which has sparked intense debates among politicians and regulators (Cheng et al., 2024). Market power also extends to questions of native advertising and disclosure (Sahni and Nair, 2020a) and to gig-economy labor - quantifying the value of flexibility for drivers on ride-hailing platforms (Chen et al., 2019). On the other hand, 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. (2024a) highlight that network effects, by themselves, may not fully explain the size and dominance of large platforms.

3.2.1 Main Focus Areas

Below we address three areas at the interface of platforms and other market participants that have attracted the attention of regulators: self-preferencing, native advertising and the role of gig economy workers.

Self-Preferencing 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., 2023; Jürgensmeier and Skiera, 2023; Raval, 2022; Lam, 2023; Lee and Musolff, 2021). Kittaka et al. (2023) offer 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 (2024) 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 received academic attention. Allcott et al. (2025) quantify their 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/Twitter that include sponsorships are not disclosed as such. In a field experiment, Sahni and Nair (2020b) 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 (2025) 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 a 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.

3.2.2 Open Questions

An important emerging area of research within platform competition 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 have also demonstrated similar patterns that merit more exploration in the future (Fish et al., 2024). Algorithmic and AI-based pricing tools are rapidly diffusing in many markets, often with limited transparency, which raises concerns for consumer welfare and enforcement. This question is challenging to answer because pricing algorithms are

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

often opaque even to their designers, and regulators rarely observe the full set of actions, counterfactuals, and design choices that shape potential collusive outcomes.[10] To tackle this, researchers can conduct computational experiments that benchmark different learning algorithms in simulated markets, or in an ideal scenario, collaborate directly with platforms for access to transaction-level data and documented changes in pricing tools.

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) highlight the importance of this tradeoff, advocating for regulatory frameworks that promote fairness and competition while minimizing unintended consequences. This question is pressing now because regulators worldwide are updating competition rules for digital markets, often under political and public pressure, with limited evidence on how different regimes affect innovation, entry, and platform behavior. It is difficult to answer since many effects are long term and general-equilibrium in nature, enforcement intensity and firm responses are endogenous, and the relevant counterfactual regulatory environments cannot be directly observed. Concrete progress is most likely to come from quasi-experimental evaluations of specific enforcement changes (e.g., staggered adoption of digital competition acts or merger-review thresholds across jurisdictions) linked to firm- and market-level outcomes, complemented by dynamic models that quantify how different enforcement intensities shift entry, investment, and pricing incentives.

Table 2: Open Questions in Platform Regulation

Topic area	**Open questions**
Consumer Protection	**Asymmetric Information** 1. What are the potential biases in AI-driven content filtering mechanisms (e.g., fake reviews), and how can they be mitigated? 2. How can platforms and local regulators coordinate consumer protection policies when the interests of platform users and local residents systematically diverge?

Continued on next page

[10]The question is particularly challenging when designing algorithms to set platform prices–as opposed to seller prices on platforms–as network externalities violate the stable unit treatment value assumption required for unsupervised learning experiments (Misra and Wilbur, 2026).

Topic area	Open questions
	Discrimination 1. How do systematic gaps in ratings, review tone, and user engagement between demographic groups shape whether information disclosure mitigates or amplifies discrimination on platforms? 2. What design principles for algorithmic learning (e.g., cold-start procedures, ad targeting) best protect disadvantaged groups in environments with biased feedback and heterogeneous user preferences, while preserving efficiency and user welfare? **Restricted and Illegal Content** 1. How do fraudsters adapt to the shutdown of illegal sites, and what countermeasures can regulators implement? 2. What unique challenges emerge for platform moderators regulating adult content (e.g., NSFW communities on Reddit)? **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?
Competition	**Self-Preferencing** 1. What is the equilibrium effect of self-preferencing by dominant platforms, considering market competition and consumer welfare? 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? **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? **Gig Economy Workers** 1. What measures can regulate gig platforms' power relative to workers without harming work flexibility? 2. How can gig platforms in emerging economies (e.g., India's instant-delivery platforms) design operational and incentive systems that preserve rapid service-level promises while improving worker welfare?

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 calibrating models to generate findings and predictions. Here, we survey a variety of strategies for researchers to get access to relevant data to help answer pressing questions in the area of platform research, including benefits and drawbacks. First, we explore data acquisition with and without platform involvement. Then, we integrate our discussions 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 platform's internal research teams, (2) using publicly available data shared by platforms, and (3) using a platform's API (application programming interface).

First, many large platforms maintain internal research teams to support innovation and experimentation. Some of these teams actively publish and collaborate with academics, particularly in areas such as experimentation, marketplace design, and machine learning. Examples include Airbnb's work on experimentation and two-sided markets,[11] Microsoft's research on market design,[12] and collaborations involving Meta, Yahoo, and other technology firms (e.g., Gordon et al., 2019; Johnson et al., 2017; LeCun, 2018). Such collaborations can provide access to granular behavioral data, proprietary algorithms, and controlled field experiments, enabling researchers to study mechanisms that are otherwise unobservable. More recently, sustained partnerships (sometimes involving shared data infrastructure) have allowed researchers to pursue broader agendas and reduce the time from project inception to publication (e.g., Wlömert et al., 2024).

Second, some platforms release public datasets for research and teaching. Prominent examples include the Yelp Open Dataset, the Expedia Hotel Recommendations dataset, and IMDb's non-commercial datasets, which have been widely used in academic research. These data may be accessed directly from platforms[13] or via aggregators such as Kaggle.[14] Open datasets can stimulate external innovation that platforms may later adopt or expand upon (Ursu, 2018; Compiani et al., 2024). Similar practices exist among nonprofit platforms,

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

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

[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

which often share data and algorithms with researchers. For example, Vana and Lambrecht (2022) analyze extensive data and the ranking algorithm used by the nonprofit platform DonorsChoose, while Agarwal and Sen (2022) use the same data to study how platforms can help bridge political divides in education.

Third, some platforms provide data access through Application Programming Interfaces (APIs), enabling structured and repeated data collection (Boegershausen et al., 2022). Well-known examples include APIs from Facebook, Reddit, X/Twitter, and YouTube. More specialized APIs have enabled studies such as Lu (2023) on the video game industry and Stourm and Stourm (2025) on spatial demand in car-sharing markets.

4.2 Data Acquisition Without Platform Participation

Academic researchers use several approaches to collect platform data without platform participation. Although these approaches can be time- and resource-intensive, they can increase independence and credibility, particularly when research questions diverge from platform objectives. We group these 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 through business partners (e.g., internet service providers, credit card issuers, software development kit providers) or data aggregators (e.g., Chartmetric). Such sources have been used to study advertising effects and subsequent search (Simonov et al., 2023), local demand impacts of platform entry and policy changes (Kim and McCarthy, 2024; Taylor et al., 2025), and how GDPR affected apps' experimentation policies using SDK-provider data (Batikas et al., 2023). Some platforms also record transaction data in distributed ledger systems, enabling public observation (e.g., Liu et al., 2022). Similarly, aggregator APIs can support large-scale measurement, such as playlist-following behavior for over 1.2 million playlists (Pachali and Datta, 2025).

Second, nonprofits, researchers, and independent organizations have created panel datasets by systematically crawling and monitoring platforms. Examples include InsideAirbnb.com and archival Reddit datasets such as PushShift.io (Baumgartner et al., 2020). Researchers further develop platform-specific scrapers (e.g., Lam, 2023; Hou et al., 2024 for Amazon; Troncoso et al., 2024 for Google reviews, Huang and Morozov, 2025 for Twitch and Zhang and Zhang, 2024 for healthcare marketplaces) and sometimes release these data for reuse (Ni et al., 2019).

Third, platform data can be collected directly from consumers via smartphone apps, browser extensions, or self-tracking services. For example, Allcott et al. (2022) built an app to track social media usage and recruited users via Facebook advertisements, while browser extensions have been used to track browsing behavior, manipulate exposure, and prompt additional tasks (Beknazar-Yuzbashev et al., 2025; Farronato et al., 2023, 2025).[15]

Fourth, researchers can intervene directly on platforms, subject to IRB approval and ethical constraints around privacy and informed consent (Mosleh et al., 2022). For instance, Toubia and Stephen (2013) used synthetic X/Twitter profiles to study how audience size affects posting, and Jiménez Durán (2021) examined outcomes from reporting hateful posts using platform tools. Mosleh et al. (2022) provide guidance on balancing ecological validity and ethics in social media field experiments.

The fifth approach is to build mock-up or synthetic platforms that enable controlled interventions. Researchers may use existing experimental infrastructures such as oTree (Chen et al., 2016a), which provides reusable templates including shopping environments,[16] as well as specialized simulation software for social platforms that replicates core functionalities such as news feeds, user interactions, and content-sharing features (Jagayat and Choma, 2024). Others create custom environments to suit specific research needs, including MovieLens.org and realistic virtual shopping settings to study advertising and search (Morozov and Tuchman, 2024).

Finally, researchers study platform-related questions using controlled market research designs such as incentive-aligned conjoint analysis, including work on willingness to accept payment for personal data (Collis et al., 2021), data choice architecture (Lin and Strulov-Shlain, 2023), and debunking product misinformation (Fong et al., 2024).

4.3 Collaboration Considerations

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 what 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, including negotiating data access and data use agreements.[17] Table 3 summarizes these trade-offs across the data acquisition methods discussed above to help researchers evaluate which approach might best fit their study objectives.

[15]Some of these tools are openly available for other researchers to use and adapt, see e.g., https://www.webmunk.org/.

[16]E.g., see https://otree-more-demos.herokuapp.com/demo.

[17]Researchers should ensure upfront that platform collaborations guarantee the unconditional right to publish scientific findings without censorship.

Table 3: Comparison of Data Acquisition Methods

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.

Feasibility also depends on whether the research question aligns with platform incentives. Projects focused on consumer behavior, interface design, or policies that can directly increase profits are more likely to receive support; questions like "How can algorithmic aggregation ensure transparency and address challenges like rating inflation, reviewer bias, and cold start?" and "How can platforms balance endorsement frequency and transparency without encouraging manipulation?" in Table 1 fit this mold. By contrast, topics involving inter-platform relationships (e.g., questions related to affiliate marketing like "Are there negative spillovers for the platform that shovels its traffic to others (e.g., clickbait incentives)?" in Table 1) or potential consumer harm and regulation (see Table 2) often face greater resistance, including reluctance to collaborate, demands for anonymity, or constraints that may raise concerns about research independence.

It is also possible to conduct long-term projects with platform collaboration (e.g., Brynjolfsson et al., 2025). For instance, content curation questions like "What long-term impacts occur if platforms optimize curation only for short-term clicks?" in Table 1 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 is not 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 (e.g., 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]

Towards a Hybrid Approach Combining platform collaboration with independent data collection can improve empirical inference by expanding context and reducing reliance on a single data source, subject to researcher budget and expertise. From a data access perspective, platform partnerships can provide access to comprehensive, context-rich datasets for empirical analysis, offering clear advantages in data control and ecological validity. At the same time, corporate policies and internal constraints may restrict the scope of admissible research questions, and access can be slow and limited. Platform datasets may also be incomplete due to selective data storage practices, internal compartmentalization, or undisclosed business constraints. For example, platforms may not record decision inputs such as unclicked recommendations or rejected bids if these are not operationally valuable (Shi et al., 2024). Platform-provided data may further lack competitive context, such as multihoming behavior, competitor pricing, or alternative algorithms, which limits market-level inference.

Beyond access, effective use of platform data depends on data integration and operational stability. Platform collaborations can complement external scraping with proprietary internal data and policies, but they are also vulnerable to project termination due to management changes. 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. These integration challenges are compounded by the fact that platform access may not persist indefinitely. Regulatory scrutiny, leadership changes, litigation, data breaches, public relations changes or strategic shifts can quickly change a platform's willingness to collaborate, even among historically open firms; complementary data sources can help protect against such risks.

Hybrid designs can mitigate these access and integration limitations by supplementing

[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.

internal platform data with third-party providers, user recruitment, surveys, or scraping (see Table 3). Such approaches are particularly valuable when platforms are reluctant to study policies that increase revenue at the expense of user experience or content quality, including the types of monetization questions listed in Table 1. In these cases, alignment with platform goals may enhance the potential for practical influence, but it can also raise concerns about the risk of censorship when findings conflict with corporate interests. Hybrid strategies are also especially useful for studying market-level outcomes that depend on competitor behavior and multihoming, which often require data from multiple platforms (Farronato and Fradkin, 2022; Farronato et al., 2024a).

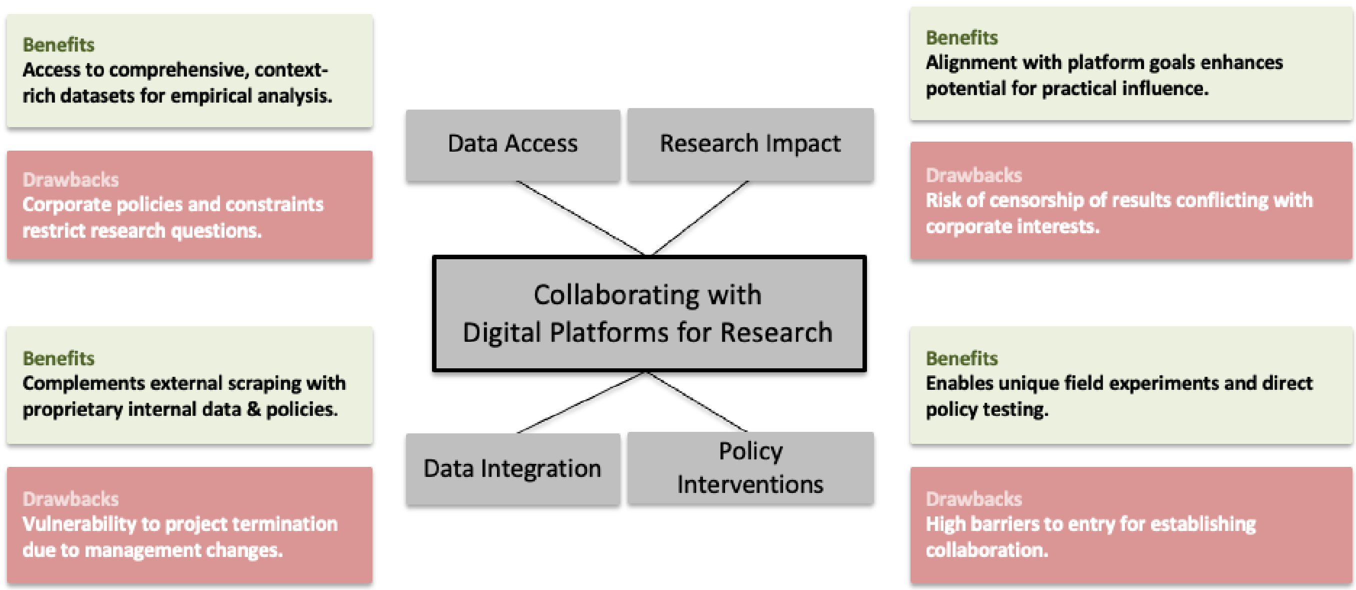
Finally, collaboration with platforms uniquely enables large-scale field experiments and direct policy testing, creating opportunities for high-impact policy interventions. At the same time, establishing such collaborations often involves high barriers to entry, and experimental designs face additional methodological challenges. Randomized controlled trials on platforms may suffer from interference and violations of the Stable Unit Treatment Value Assumption (SUTVA), particularly when outcomes depend on interactions between treated and untreated units (Goli et al., 2025; Holtz et al., 2025). While large platforms may mitigate these risks through cluster randomization and other practices, smaller platforms often lack such abilities. Combining internal experimentation with external measurement, such as recruiting users through browser plug-ins, can strengthen external validity and enable robustness checks when platform access changes.

Researchers may not feel that both collaborative and independent approaches are always available, and the exact combination of strategies depends on many factors, notably research objectives, budget and expertise. Ultimately, the choice between platform cooperation, independent data collection, or hybrid strategies depends on the research question and acceptable trade-offs. Hybrid approaches offer a practical middle ground by leveraging the benefits of platform collaboration while mitigating its drawbacks. Figure 1 summarizes these trade-offs on four dimensions: data access, data integration, research impact, and policy interventions.

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 reviewing 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

Figure 1: Benefits and Drawbacks of Collaborating with Platforms



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) are 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 concerns. 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 research on Platforms 2.0. 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 Monetization strategies

Table 4: Monetization Strategies: Revenue Source vs. Choice of Tariff

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. (2025); Sayedi (2018); Despotakis et al. (2021); Choi and Mela (2025); 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. (2025); Wang et al. (2024); 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. (2025); Wang et al. (2024); Lambrecht and Misra (2017)	
Others		Choi et al. (2020)	Peres et al. (2024); Bleier et al. (2024); Hofstetter and Gollnhofer (2024)