User-generated Content and Social Media[1]

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Abstract:

This paper documents what economists have learned about UGC and social media. A growing body of evidence suggests that UGC on platforms ranging from Yelp to Facebook has a large causal impact on economic and social outcomes ranging from restaurant decisions to voting behavior. These findings often leverage unique data sets and methods ranging from regression discontinuity to field experiments, and researchers often work directly with the companies they study. I then survey the factors that influence the quality of UGC. Quality is influenced by factors including promotional content, peer effects between contributors, biases of contributors, and self-selection into the decision to contribute. Nonpecuniary incentives, such as "badges" and social status on a platform, are often used to encourage and steer contributions. I then discuss other issues including business models, network effects, and privacy. Throughout the paper, I discuss open questions in this area.

keywords: user-generated content, social media, economics of information, design economics

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1. Introduction

Imagine that a hypothetical employee at an encyclopedia company in the year 1980 pitches the following idea to her boss:

I think we can cut most of our expenses and produce more content than ever before. All we have to do is allow anyone to visit our office and write encyclopedia entries on the topics they think know something about. Forget about the experts we typically hire. We can validate the content by having other unvetted visitors correct their entries and hope that it all comes out in the wash. Don't worry, we can still have editors. The best contributors can become editors, but here's the beauty: let's not pay any of them. Let them volunteer to write encyclopedia entries. Oh, and I think we should stop selling encyclopedias and just run on donations.

It's safe to say that in 1980, this employee would likely not have been long for her job. Situated in a different time and place, the conceptual framework of one of the most popular social media sites of the early 21st Century seems like an absurd proposition. Yet that site, Wikipedia, has thrived, even as traditional encyclopedias (produced with content generated and edited by paid professional writers and editors) have sped toward obsolescence.

The concept of user-generated information has spread well beyond encyclopedias. Consumers now turn to Yelp to find new restaurants, TripAdvisor to plan a vacation, Rotten Tomatoes to find a movie, AngiesList for contractors, ZocDoc to check on physicians' reputations, and Amazon reviews when purchasing anything ranging from a book to a vacuum cleaner to cat food. With the click of a button, consumers can share experiences, information, and recommendations about product quality for nearly any product imaginable. Table 1 provides a sample of popular platforms covering different industries as of 2014.

Table 1-1 – Sample Platforms with User Reviews (as of 2014)

Industry	Sample Platforms with UGC	Most Popular (Unique Monthly Visitors)[3]
Restaurants	Yelp, Zagat, Urbanspoon, OpenTable, Chowhound	Yelp (52 million)
Movies	Rotten Tomatoes, Yahoo! Movies, IMDB, Metacritic	Rotten Tomatoes (400,000)
Hotels and Rooms	TripAdvisor, Expedia, Orbitz, Hotels.com, Airbnb, HomeAway	TripAdvisor (10.8 million)
Physicians	Healthgrades, ZocDoc, Vitals, RateMDs	Healthgrades (4.9 million)
Consumer goods	Amazon, eBay, Target, Walmart, Target	Amazon (80 million)

The sheer number of products that consumers, relative to other information sources, are able to review is striking. To take one example, Figure 1 shows the percentage of restaurants covered by different review systems in select urban areas. The consumer review website Yelp contains reviews of 70% of the restaurants in Seattle, while Zagat covers roughly a 5% sample of Los Angeles restaurants (Jin and Leslie 2009). *The Seattle Times*, the local newspaper, contains even fewer restaurants, and *Food & Wine* magazine reviews even fewer. Looking at numbers like these, it is clear that online consumer reviews and recommendations have become important sources of information.

The way consumers receive news has changed just as quickly. People read news and commentary via blogs and Tweets, which supplement—and in some cases replace—more

[3] These figures are obtained from the most recent month with data available on Quantcast. All figures are from 2014.

traditional media. Even the fabric of our day-to-day interactions is changing, with online social networks such as Facebook, LinkedIn, and WhatsApp complementing, and at times replacing, offline networks. Clearly, in the digital age, how we interact with friends and family, learn about products, services, and jobs, and think about news, politics, and religion are dramatically changing.

Social media platforms such as YouTube, Wikipedia, Yelp, WhatsApp, and Twitter enable users to interact with each other through the generation and sharing of content. The common thread across these platforms is that they contain *user-generated content*. User-generated content (UGC) is material that a platform sources from its own end users. Part of the crowdsourcing movement, UGC ranges from videos on YouTube to posts on Wikipedia to reviews on Yelp. All social media platforms contain UGC. However, not all UGC is contained on traditional social media platforms. Virtually all online platforms—ranging from online newspapers to online marketplaces—rely to some extent on UGC. UGC is dramatically transforming the media landscape. In addition to producing unprecedented amounts of information, UGC raises a variety of new intellectual and practical questions and challenges.

UGC grew dramatically over the past ten years. From 2001-2006, a number of major social media platforms sprang up, including Wikipedia (2001), LinkedIn (2003), MySpace (2003), Facebook (2004), Yelp (2004), YouTube (2005), and Twitter (2006). UGC now spans a vast swath of the Internet, from user-provided pictures to videos to comments on news stories and blogs. Table 2 presents an overview of different types of UGC and a sampling of prominent platforms that display it, including the world's largest social network (Facebook) and the world's most trafficked video site (YouTube).

Table 1-2 – Popular User-generated Content Platforms

Types of User-generated Content	**Prominent Platforms**
Pictures	Instagram, Pinterest, Snapchat, Flickr
Personal Updates and Networking	Twitter, FourSquare, Facebook, LinkedIn
Reviews for Products and Services	Yelp, Rotten Tomatoes, ZocDoc, Amazon
Encyclopedia and Reference Sites	Wikipedia, Wikia
Videos	YouTube, Vine
Comments on News Articles	NY Times Online, WSJ Online
Crowdfunding	Crowdrise, Kickstarter, IndieGoGo
Sharing Platforms	Uber, Airbnb, Couchsurfing
Social Payments	Venmo, Square
Discussion / Question and Answer	Reddit, Quora, StackOverflow
Blogs	Tumblr, WordPress

There are several types of actors on any given UGC platform. First, there are contributors who provide content. Second, there are consumers of content. In traditional media, these are typically two different sets of actors. A novel feature of UGC is that a platform's end users are both contributors and consumers. Because *users* are producing content, the amount of content and its value to any given user depends on the number of total users. There are significant network effects on all UGC platforms, and the value of the platform depends on the number of users. Of course, some users will primarily produce, while others will primarily consume. You may prefer to watch YouTube videos, for example, yet have a friend who posts them but rarely watches them.

A third set of actors is the set of *advertisers*—people and organizations that are trying to reach users. For example, Facebook earns four billion dollars per year through advertising,[4] with major clients including Ford, Disney, Walmart, and Microsoft. Advertising is also a central source of revenue for Yelp and many other UGC platforms. In addition to advertisements that are displayed on UGC webpages, advertisers sometimes use other channels to influence content. For example, there have been reports of staffers being paid to maintain Wikipedia pages for politicians.

Fourth, UGC platforms have *bystanders*—people or organizations that are essentially the subjects of content. A person being discussed on Twitter is a bystander, as is a restaurant being reviewed on Yelp. Bystanders may or may not be users, and in some cases are not allowed to be. They are sometimes advertisers as well, and May more generally try to shape the content users create – through both legitimate and illegitimate means.

Finally, every UGC platform has a *designer* who sets the rules that shape contributions and interactions on the platform. Ultimately, the designer decides which users are allowed to interact on the platform and the incentives the users will face. The designer creates the market for advertisements to be sold, and decides whether the platform should intervene at the request of a bystander. Ultimately, these choices determine the impact and quality of UGC.

While social media platforms and the content generated on them will continue to evolve, a set of principles and intellectual questions underlies UGC platforms. A growing body of research investigates the ways in which social media and user-generated content platforms are affecting the world around us. The goal of this chapter is to summarize the main areas of this

[4] http://www.businessinsider.com/the-30-biggest-advertisers-on-facebook-2012-9

research and to identify areas in which this emerging field can progress, focusing on issues such as why people provide content, the degree to which this content matters in making decisions, and the information design challenges and choices that platform designers face.

The chapter proceeds as follows. Section 2 surveys the effect of user-generated content on user and market behavior. Section 3 discusses these challenges to the quality of content and mechanisms that improve quality. Section 4 discusses incentive design for user-generated content. Section 5 provides a brief discussion of several related issues. Section 6 offers a conclusion.

2. The Impact of User-generated Content

According to Wikipedia, the 2010 edition of the Encyclopedia Britannica – the last to be printed – was "written by about 100 full-time editors and more than 4,000 contributors, including 110 Nobel Prize winners and five American presidents." While there is a certain irony to this Wikipedia entry, it raises a question that is central to the study of UGC: How will UGC affect existing media markets and the economy more generally?

In contrast with the Encyclopedia Britannica, Wikipedia (and other UGC platforms) have a self-organizing authority and do not rely on the standard institutional arrangements for assigning authority, such as credentialing or restrictions on resources. Critics often argue that the grass roots, unvetted nature of UGC leads to content that is too unreliable to meaningfully change the world, beyond perhaps the case of Wikipedia. In this view, platforms such as Yelp and TripAdvisor (which consist of a non-representative sample of amateur reviews, with no way to eliminate all fake reviews) might have limited impact on the market as a whole. Comments on news articles may simply be entertainment for a small niche of readers with no discernable influence on how news is produced or digested. Similarly, YouTube videos of cats riding Roombas may simply be procrastination material for bored students, posing little threat to traditional media.

Yet, an alternative possibility is that UGC participants amount to millions of Davids, relative to the small number of Goliaths in competing media outlets. According to this view, UGC might influence markets despite its challenges. This would have the potential to reshape the way media is consumed and produced on a mass scale.

A priori it is unclear which of these views is more representative of the world we inhabit, and under which conditions each is more likely to dominate. In this section, we survey the literature on the impact of UGC. After discussing the unique data and challenges involved in this area of research, we look at how UGC influences the behavior and structure of markets, and highlight potential areas for future research. Ultimately, estimates of the extent and types of impact UGC has on markets offers important insights for policymaking, strategic decisions of UGC and traditional media outlets, design of online platforms, and welfare calculations.

2.1. Data and Identification Challenges

Data is a central challenge to the study of UGC. Most of the papers cited in this chapter began with a researcher (or team of researchers) constructing a novel dataset that had not previously been analyzed. For papers that study phenomena happening within a UGC platform, researchers often gather data on their own, working directly from the platform. More recently there has been a movement toward researchers working directly with companies, including Yelp, Facebook, Airbnb, eBay, and oDesk. This trend gives researchers greater access to data, as well as the ability to run field experiments.

Data from a given UGC platform alone is sometimes insufficient to measure the impact of UGC on a market. For example, suppose that a researcher wants to study the impact of Facebook posts on demand for Diet Coke. One option would be to look at the number of users who "like" Diet Coke's Facebook page and/or read its posts. Yet this method would provide an incomplete picture of Facebook's overall impact on Diet Coke demand. An approach of potentially greater value would be to obtain sales data from Diet Coke—which Facebook would not have to estimate the effect of UGC on sales. At the same time Coca-Cola would not have all of the data that Facebook would have – which highlights that partnerships between multiple organizations might be valuable in this situation.

When studying UGC, there are two key barriers to constructing the optimal data set. The first is data collection, which can be difficult due to the proprietary nature of much of the data in this realm. One challenge to this is that many for-profit companies consider their data to be a competitive advantage and choose not to share it for research. Others view sharing as a strategic choice. Still others attempt to be generally open with data. I expect partnerships between companies and researchers to grow in this area on academic research papers that produce findings that are valuable for the partner companies. While this is valuable in many situations, researchers should consider the extent to which their objective aligns with those of the firm when choosing a data collection strategy. There are times when *not* partnering with an organization is the optimal strategy, even if the organization is interested in cooperating.

The second data challenge involves the actual merging and preparation of datasets. In this field, datasets are often large (consider, for example, the number of words written on Wikipedia), and hence unwieldy and time-consuming to analyze. In contrast with merging different pieces of a carefully constructed survey with unique identifiers, two datasets from different field sources are almost certain to have different labels and formats. While this problem is typically surmountable, it can be complicated, requiring researchers to make subjective decisions about which data to keep and which to drop. In many settings, a match rate of 85-90% is considered very high.

Once data are in hand, there are a variety of identification challenges to understanding the impact of UGC. For example, consider a researcher who wishes to estimate the impact of a movie's Rotten Tomatoes rating on ticket sales. The researcher may begin by regressing the movie's ticket sales on its Rotten Tomatoes rating. But note that while social media content can influence demand (the topic of this section), it can also *reflect* demand. Buzz can make movies popular, but popular movies also tend to generate more buzz. Because of the reflection problem (Manski 1993), it is difficult to interpret this type of regression as being causal.

Researchers have implemented a variety of empirical approaches to support a causal interpretation in this context, ranging from difference-in-differences across platforms to regression discontinuity taking advantage of platform quirks to pure field experiments. Next, I briefly describe the three distinct types of methodologies discussed throughout the rest of the chapter.

2.1.1 Cross-platform Comparisons

One approach to identifying an outcome of interest on a particular platform is to compare outcomes across platforms, as done by Chevalier and Mayzlin (2006), Wang (2010), Zhu and Zhang (2010), and Mayzlin, Dover, and Chevalier (2014). Essentially, each of these papers looks at institutional features or content on a given platform that is different on other platforms, and uses this as variation in the feature or content of interest.

Properly implemented, this would represent a difference-in-differences approach – with variation across platforms representing one of the differences. For example, Mayzlin et al. (2014) compare the difference between ratings for hotels with a single unit and hotels with multiple units (first difference) across TripAdvisor and Expedia (second difference).

There are empirical challenges to implementing this flavor of identification strategy. The key conceptual challenge is detecting whether other factors could be driving the same outcome. One important econometric challenge is deciding on the unit of observation and how to cluster standard errors. In particular, researchers may run into the issue of a small number of clusters; see Bertrand et al. (2004) for a discussion of standard errors in difference-in-differences estimation.

2.1.2 Platform Quirks

A second approach has been to exploit institutional details within a single UGC platform, or essentially to look for platform "quirks." For example, Luca (2011) and Anderson and Magruder (2012) exploit the fact that ratings on Yelp are rounded before they are displayed to users, which creates exogenous variation between the true rating and the displayed rating. This idiosyncratic institutional detail allows the researchers to estimate the causal effect of ratings on their outcome of interest. This approach has now been used on other platforms such as TripAdvisor (Ghose et al 2012).

Many platforms have the feature of rounded ratings, but one can imagine a variety of similar approaches by identifying and exploiting unique features across UGC platforms.

Leveraging this type of platform quirk achieves two goals. First, it allows researchers to better understand the causal impact of UGC. Second, it provides insight into the behavioral foundations of how people behave on a platform. For example, in the average rating case, it is clear that readers are very inattentive, paying attention to coarse summaries of existing information. This could potentially be used to inform the large literature on limited attention. Other identification strategies would likely yield other behavioral insights.

2.1.3 Field Experiments

A third approach has been to run experiments directly on platforms, as Bond et al. (2012) and Aral and Walker (2012) did in field experiments on Facebook. A powerful tool, field experiments on online platforms are becoming increasingly common, allowing researchers and organizations to answer questions in a simple, straightforward manner. In fact, the main challenge to implementing a field experiment may be finding areas of mutual interest between the organization and the researchers. As discussed above, one challenge is that a firm's goals and a researcher's goals do not overlap entirely. Thus far, some firms have been open to researchers pursuing topics outside of the narrow short run needs of the firm. Other firms with privacy concerns, such as Google, restrict access to data. Others with strategic concerns, such as Amazon, also restrict access.

2.2. Impact of UGC on Demand: Data, Methods, and Results

An abundance of evidence now reinforces a causal link between user-generated reviews and product demand in areas ranging from book sales (Chevalier and Mayzlin 2006) to restaurants (Luca 2011) to hotels (Ghose et al. 2012). As briefly introduced in the previous section, three types of approaches have been used to causally identify the impact of reviews on sales.

The first approach, first offered by Chevalier and Mayzlin (2006) is to look at reviews across two different platforms to determine the effect of a review on both sites' sales. Using Amazon and Barnes and Noble's platforms, the authors show the differences in a book's sales following three points in time at which a review was posted on one of the company's websites. By using this difference-in-differences approach, the authors can isolate the effects of the review on one site by assuming parallel book sales trends absent the review. They find that, depending on the specification, many review-related variables influence book sales, including the number of reviews, average review rating, fraction of one-star reviews, and fraction of five-star reviews. Looking at only one platforms, it is easy to imagine that an OLS regression of sales on review variables would be biased due to the omission of unobservable product and firm-level quality variables, which affect both sales and reviews. The difference-in-differences method of Chevalier and Mayzlin (2006) allows them to include book-time fixed effects, and book-site fixed effects, enabling them to isolate the causal effect of reviews on sales.

The second approach, which has been used by Luca (2011), Anderson and Magruder (2012), and Ghose et al (2012), leverages a common institutional detail of review platforms. These papers exploit the fact that many review platforms choose to round the rating that they display to users. For example, consider two restaurants on Yelp—one with 3.24 stars and the other with 3.25 stars. The 3.24 star restaurant will be displayed as 3 stars, while the 3.25 star restaurant will be displayed as 3.5. This variation in displayed ratings is unrelated to underlying quality and other market forces that could be driving demand. These papers then implement regression discontinuity designs around these rounding thresholds.

Combining restaurant ratings from Yelp with sales data for every restaurant that operated in Seattle over a six-year span, Luca (2011) shows that a one-star increase in Yelp rating leads to roughly a 5% increase in sales for an independent restaurant, but has no impact for chains. This result is consistent with the idea that consumers have more information about chains, and hence learn less about them through Yelp. Applying the same general approach to restaurant reservation data from Opentable, Anderson and Magruder (2012) show that that increases in Yelp ratings increase the probability that a restaurant will be fully booked on a given night. Ghose et al (2012) also follow this general approach to identify the causal effect of TripAdvisor ratings on hotel bookings.

The third approach involves using UGC platforms as a field site for randomized control trials. For example, Aral and Walker (2012, 2014) use a Facebook application to send notifications of a user's "like" of an app to a random selection of his or her peers and measure the subsequent adoption of the app. Using this approach to determine the contagion of the "like," the authors found that final demand for the product increased 13% relative to the initial adopter cohort.

Every element of a business's online presence—from the length and distribution of reviews to the emotional content of Tweets—contains information. Identifying the factors that customers use is of direct managerial relevance and provides further evidence of the behavioral foundations of how users process information.

Ghose et al. (2012) also develop a structural model for estimating hotel demand based on hotel characteristics, as well as Travelocity and TripAdvisor review characteristics. Collecting review text and measures of review length, they use machine learning to assess readability, complexity, and subjectivity. The authors find that longer, easy to read reviews are associated with higher demand while word complexity and spelling errors are associated with lower demand. Though they do not make causal claims about review characteristics, they argue that since ratings influence demand (using the regression discontinuity approach discussed above), it seems plausible that these other factors are also causal. One novel feature of this paper is its use of machine learning and text analysis.

Similarly, Chevalier and Mayzlin (2006) find that one-star reviews affect book sales more than five-star reviews. This may be because a large majority of reviews are five-star, such that consumers expect books to have several five-star reviews and thus perceive five-star reviews to provide less new information than one-star reviews. This phenomenon is akin to reputation models, in which one piece of negative news is enough to ruin a good reputation.

The identity of the writer of a review may also matter. Through a laboratory experiment simulating online book reviews, Huang and Chen (2006) find that peer reviews affect subjects' book choices more than expert reviews. Looking at the impact of Yelp reviews on sales, Luca (2011) finds that reviews written by those with "elite" status (awarded by Yelp for high-quality reviews) are more influential than other reviewers.

Another widely studied review system is that of eBay, the popular auction website that tallied 115 million unique visitors in September 2014.[5] On this site, the main item of interest in

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[5] This figure is available on Quantcast.

reviews is the reliability of each party, not the quality of a good. Reliability ratings are conveyed through the numbers of positive and negative feedback reports that a user has received. The most documented effect of this review regime is the impact of a seller's overall rating (given by buyers) on the sale price. One particular challenge to estimating this effect is that goods sold on eBay vary in their condition, and in small (but significant) characteristics that are difficult to observe by the econometrician. For example, books of the same title might be heavily used, lightly used, or brand new; they might be a domestic or international edition; they might have highlighter marks or dog-eared pages. Looking at data from auctions of mint condition $5 U.S. gold coins (which are plausibly undifferentiated), Melnik and Alm (2002) find that seller ratings are significantly correlated with final price. Lucking-Reiley et al. (2007) obtain the same qualitative result. Looking at the dynamics of reputation, Cabral and Hortaçsu (2010) show that once a seller on eBay receives negative feedback, subsequent negative feedback arrives 25% more rapidly.

An alternative approach to observational data is to run a field experiment on eBay, with different seller characteristics. Resnick et al. (2006) worked with an established eBay user to sell a pair of matched postcards, offering them either on the seller's highly rated main account or on one of the seller's recently created accounts with few ratings. On average, buyers were willing to pay 8.1% more for a postcard from the established, highly rated account. While some of the effect may be attributed to the difference in ages between the user's main account and the accounts generated for the experiment, this supports the causal effect of ratings on prices.

2.3 Social Effects of Social Media

Thus far, I have focused on the impact of social media on market outcomes such as purchases. However, there are a variety of behaviors—from education to public health to voting—that can be influenced by social media and UGC.

Bond et al. (2012) examine the effect of different types of messages sent to more than 61 million adult Facebook members visiting the site on November 2, 2010, the date of the US midterm elections, on each member's probability of voting that day. The authors find that those who received a social message (one showing friends who had voted) were two percentage points more likely to click an "I voted" button than those who were merely shown an informational message about Election Day. Of course, the ultimate goal of this study is to look at voting behavior. Because voting records are public, the authors were able to merge voting records with data from Facebook on users. Looking at roughly six million records, the authors find that members who were sent a social message voted 0.39 percentage points more often than those who were shown an informational message or no message at all. The authors estimate that the direct and indirect effects of the Facebook messages increased the 2010 voter turnout by roughly 340,000 votes.

Facebook could potentially influence a variety of other behaviors as well. For example, in 2012 Facebook began allowing users to include an indicator for whether they were organ donors as part of their profiles. During the rollout of this, users were provided a link to their state donor registries; moreover, status updates were sent to friends of donors. Cameron et al. (2013) show that on the first day of this campaign, roughly 13,054 people registered as organ donors – relative to the baseline daily average of 616 per day. This suggests a role for Facebook in contributing to the social good. One can imagine social media playing an important role role in advancing a variety public health goals such as increasing childhood vaccination rates, and more generally in areas ranging from education to savings.

2.4. Other Findings and Open Questions

There are many open areas for future research on the impact of UGC. One possible direction is to investigate the impact of UGC on market structure. For example, Clemons et al. (2006) argue that information provided in reviews can help to grow demand for products with more differentiated products by increasing the quality of the match, and find generally consistent evidence when looking at reviews for beer and growth in demand. Bar-Isaac et al. (2012) theoretically show that introducing new information into a market will lead to a higher degree of product differentiation in markets. This suggests that the existence of platforms such as Yelp and TripAdvisor may lead to a greater variety of restaurants and hotels. Online reviews may also create incentives for businesses to change prices, as modeled by Li and Hit (2010), where the pricing incentives depend on whether the reviews take into account only quality or price and quality.

Second, UGC has the potential to displace more traditional media content. Much as Wikipedia has supplanted traditional bound encyclopedias, YouTube may replace traditional television content, Yelp may replace the professional restaurant critic, and blogs may replace traditional news media outlets. In addition to competing on content, one can imagine contributors aspiring to work at traditional media outlets. There are prominent examples of this, such as Nate Silver transitioning from his start as an anonymous blogger to a prominent employee at the New

York Times and then ESPN. An important area for future research is to explore these types of career dynamics.

Beyond direct competition in content, there are a variety of ways in which UGC platforms may affect more traditional media platforms. For example, there can be competition in advertising markets. Apartment and job listings on Craigslist directly compete with local advertisements in online newspapers (Kroft and Pope 2014). This, in turn, generates a reduced value from additional content (Seamans and Zhu 2014). See "Chapter [Chandra and Kaiser]" for further discussion on this. A fruitful area for future research would be to further investigate these effects, as well as the extent of competition and cooperation between traditional media and UGC platforms.

More generally, an important direction for future research would be to investigate the limits of UGC. For example, research has shown the value of Yelp and TripAdvisor for restaurants and hotels. Will user reviews become the norm for doctors and cars as well? Luca and Vats show that roughly 25% of New York City primary care physicians are reviewed on ZocDoc. Will this become an important information source? The answer to these questions likely depends on factors such as the number of products or services being evaluated and the extent to which specialized knowledge is required to evaluate that product or service. There may also be areas where UGC will never be feasible.

In addition, an important intersection between UGC and social goods that has been under-examined. While the areas of voting and organ donation are clearly important, virtually every action we take is now potentially influenced by social media platforms. It is possible that UGC data will have effects on outcomes such as improving high school graduation rates, reducing teen pregnancies, and reducing bankruptcy rates.

3. The Quality of User-Generated Content

Because UGC creates a positive externality, underprovision of content is a standard prediction of models of UGC (Avery, Resnick, and Zeckhauser 1999; Miller, Resnick, and Zeckhauser 2005). Because network effects are central to social media platforms (Zhang and Zhu 2011), this can be exacerbated in new platforms and in areas where UGC is not yet popular. Theoretically, this can lead to multiple equilibria, in which some platforms are filled with excellent content and other equally good platforms are virtual ghost towns. In a world with little to no payment for content, generating an optimal *quantity* of content is a major challenge in the digital age. Che and Hörner (2014) theoretically demonstrate that it can be optimal to over-recommend a product early after its release in order to encourage more experimentation. One productive area for research is to further explore mechanisms to solve the underprovision problem as well as factors that cause one platform to succeed and another – often very similar – platform to fail.

Even when incentives are put in place to generate a high quantity of content, it is also important to understand the quality of content. Overall, there is evidence that online reviews are generally consistent with expert reviews (Dobrescu et al. 2013, Cao et al 2015). However, every type of media and information source has unique challenges and biases to the quality of content.[6] This section highlights several main challenges to the quality of content that are especially important in the UGC context.

[6] For example, see "Chapter [Prat]" for a discussion on media capture.

3.1. Promotional Content

Celebrities such as Khloe Kardashian and Jared Leto reportedly earn $13,000 for writing a single sponsored Tweet (Kornowski 2013). Bloggers often link to each other in an implicit quid pro quo, gaining additional viewers for both blogs in the process (Mayzlin and Yoganarasimhan 2012). Businesses often leave reviews about themselves or competitors (Mayzlin, Dover, and Chevalier 2014, Luca and Zervas 2015). Politicians, including Vice President Joe Biden, have been known to have their paid staff edit their Wikipedia pages to make them more favorable (Noguchi 2006). These are all attempts for businesses or individuals to promote themselves using social media or user-generated content. While there is a small literature beginning to emerge on these issues, the extent and implication of this type of content across different UGC platforms is largely an open question.

There are many methods of promoting a business online, such as advertising, maintaining a business profile, or responding to customer comments. Many of these are honest attempts to provide information and incentives to customers. Yet there are also misleading (and sometimes illegal) approaches to promoting a business online. For example due to the semi-anonymous convention of online handle names, businesses can attempt to create promotional content that will blend in with the general population of non-promotional contributors in a misleading way.

Perhaps the most frequently cited concern about UGC platforms is that they could become overrun by fraudulent or misleading operators seeking to boost their own reputations or plug their own products. After all, with the click of a button, virtually anyone can leave an anonymous review, post a video, write a Wikipedia entry, or indicate that they “like” a product or service. Promotional content arises in virtually every form of user-generated content.

The remainder of this section discusses the literature on promotional reviews (a term coined by Mayzlin, Chevalier, and Dover 2014). The focus on reviews reflects the fact that promotional content has been an especially salient issue in this area, and also the fact that there has been relatively more research in this area relative to other types of promotional content.

Concerns abound about firms providing fake positive reviews to boost their own reputations and providing fake negative reviews to harm their competitors’ reputations. Noting that reviews influence demand, neoclassical economists might be tempted to suggest that promotional content will litter social media sites. However, behavioral economists and social psychologists have documented the fact that people are generally uncomfortable with lying, even when they can get away with it (Gneezy 2005, Hurkens and Kartik 2009, Fischbacher and Föllmi-Heusi 2013). Moreover, as quickly as businesses find ways to manipulate content, platforms find ways (discussed below) to mitigate these concerns. Hence, the extent of fake reviews and promotional UGC is a priori unclear.

Consider a business that is managing its online reputation. Because it has the potential to increase revenue by leaving fake reviews, it has high-powered incentives to game the system. To blend in with authentic reviewers, the artful fake reviewer will try to disguise his or her review as an outside observer’s true experience. For example, here are two reviews—one fake and the other real—for dental services:

Review A

“I was in need of teeth whitening and my friend referred me to Southland Dental. Pain or no pain, it was very much worth it. I can’t stop staring at my bright smile in the mirror.”

Review B

“Lorna Lally’s office does a great job with cleanings and treatments. The staff is also friendly and they send reminders before each appointment.”

While there are potential red flags with both reviews – for example, neither mentions specific details about the business and the information given could easily pertain to most dental offices – it is difficult to determine which is real. Here, the first is fake, and the second is real. The difficulty of telling the difference highlights the empirical, managerial, and policy challenges of fake reviews and promotional content.

It is hard to empirically separate legitimate from promotional content. To identify potential false reviews, a computer science literature has emerged designing algorithms to analyze review characteristics, such as text patterns and reviewer social networks (e.g. Akoglu et al. (2013)). One approach (taken by Ott et al. 2011) is to create a “gold standard” of known fake reviews by hiring workers from Amazon Mechanical Turk to write reviews about places they haven’t been. The researchers then compare the features of these reviews to features of reviews found on TripAdvisor, which are likely to include both real and fake reviews. Using machine learning, they then construct an algorithm that helps to identify the reviews that are most likely to be fake given these features that often include text, ratings, and characteristics of reviewers.

These classifiers allow companies to identify which reviews should be trusted the most and least. In practice, companies typically create their own algorithms using markers for promotional content such as the content’s origins, the patterns of contributions, and whether they can verify the content. For example, Yelp’s automated software places filtered reviews in a separate category that does not contribute to the aggregate star rating, whereas TripAdvisor adapts credit-card-detection algorithms used in the financial services world and uses them to scan for fake hotel, airline, and car rental reviews on its site (Williams (2013)).

How many fake reviews are there? Estimates inherently hinge on the analyst's ability to identify a fake. Investigating 316,415 reviews for 3,625 Boston-area restaurants, and using an algorithm developed by Yelp to identify suspicious reviews, Luca and Zervas (2013) find that Yelp identified 16% of restaurant reviews submitted to the site are flagged as suspicious. Per Yelp's filing, roughly 20% of reviews overall across categories and markets are filtered by its spam detection algorithm. Using the text of Yelp reviews, Ott, Cardie, and Hancock (2012) classify roughly 4% of reviews on Yelp as fake. One factor driving the difference between the two studies is the fact that Yelp has considerably more information about the reviews being written than researchers do, and hence, given an algorithm, it can more easily classify reviews as real or fake. For example, Yelp knows where a review has been written and the reviewers' detailed patterns of behavior on the platform. A second factor may be that Yelp prefers to be cautious and err on the side of removing a higher proportion of suspicious reviews.

What does a fake review look like? As discussed above, this is difficult to identify due to the fact that fake reviews are typically not directly observed. However, the literature using algorithmically identified fake and suspicious reviews has some insights into this question. For example, Ott et al (2012) find that a disproportionate amount of fakes are written by first- and second-time reviewers. Comparing suspicious (as identified algorithmically) and legitimate reviews submitted to Yelp, Luca and Zervas (2013) find that suspicious reviews are more extreme than real ones, and are more likely to be written by reviewers with little social capital on Yelp. Ott et al. (2011) note reviews that algorithmically identified suspicious reviews on

TripAdvisor tend to have positive textual descriptions in addition to high ratings. As these algorithms are developed, fake reviewers may learn to write reviews that won't be identified by the algorithm, highlighting the game theoretic nature of fake reviews.

While the computer science literature has primarily focused on markers of fake reviews, a small economics literature has focused on investigating the economic incentives and welfare effects of leaving fake reviews. Dellarocas (2006) develops a theoretical model of strategic manipulation of content and shows that although manipulation leads to a rat race and leads to wasted resources by all firms, the informational content may increase or decrease, depending on the relationship between the cost of manipulation and the true quality of firms.

To empirically investigate this question, Mayzlin, Dover, and Chevalier (2014) compare hotel reviews written on Expedia to those written on TripAdvisor. Because Expedia identifies people who have booked a hotel through its platform and then left reviews, it is more difficult to leave a fake review on Expedia than on TripAdvisor, which cannot verify whether users have actually stayed in a given hotel. Comparing the distribution of reviews within a hotel across the two platforms, the authors show that independent hotels (which have stronger incentives than chains to game the system) tend to have a higher proportion of five-star ratings on TripAdvisor relative to Expedia. Moreover, hotels that are near an independent hotel tend to have a higher proportion of one-star reviews on TripAdvisor. Overall, this suggests that businesses with the strongest incentive to leave a promotional review are doing so, and that these reviews are concentrated on platforms where it is easier. Consistent with this, Ott, Cardie, and Hancock (2012) find that Expedia, Orbitz has a lower rate of promotional content relative to TripAdvisor, using an algorithm to estimate the prevalence of promotional content.

Looking at restaurant reviews on Yelp, Luca and Zervas (2013) show that a restaurant is more likely to commit review fraud when it experiences a negative shock to its reputation. Moreover, restaurants are more likely to receive fake negative reviews after a competitor opens up. Consistent with Mayzlin et al. (2014), this paper also finds that independent businesses are more likely to commit review fraud. Overall, this research stream suggests that review fraud involves an element of cost-benefit analysis that is influenced by economic incentives.

Review platforms employ a variety of mechanisms to prevent review fraud. As discussed, Expedia's decision to verify whether the reviewer made a purchase makes it more difficult to leave a fake review. This allows Expedia to reduce the amount of fraudulent contributions to the platform but may also reduce legitimate content as well. For example, if a hotel review platform only allows verified customers to review, it would eliminate many legitimate reviews by people who have stayed at the hotel but booked through a different platform – suggesting that these types of mechanisms present an important trade-off for the platform designer.

Other mechanisms for screening fake reviews include allowing reviewers to build a reputation on the site (hence making it more difficult to leave a fake review), developing an algorithm to flag and remove fake reviews, and allowing the community to flag and investigate fake reviews. Table 3 illustrates some of the anti-fraud mechanisms used by a sampling of popular platforms.

Table 3 – Examples of Mechanisms to Prevent Fraudulent Content

Platform	**Any Verification?**	**Reviewer reputation?**	**Fraud Algorithm?**
Yelp	Yes	Yes	Yes
Rotten Tomatoes	Yes	Yes	Yes

TripAdvisor	Yes	Yes	Yes
Expedia	Yes	No	No
Amazon	Yes	Yes	Yes
Angie's List	Yes	Yes	Yes
Wikipedia	Yes	Yes	Yes

3.2. Self-Selection

The types of survey datasets that social scientists frequently use and rely on attempt to be representative at the state or national level (e.g. the Census, National Longitudinal Survey of Youth, and General Social Survey). UGC is clearly quite different. One of its central features is that contribution is voluntary, and no attempt is made to create a representative sample of the population. Thus it is difficult to assume that the UGC on a site (or in aggregate) exactly reflects the sentiment or preferences of the underlying population of readers. In the case of user reviews, there are two levels of self-selection. First, the potential reviewer selects whether to purchase a given product. Second, the potential reviewer decides whether or not to leave a review.

Because people are more likely to purchase a product if they think they will like it (e.g. Star Wars fans are most likely to see the series' final installment), people who buy a product will rate the product more highly, on average, than those who don't. This can lead to an upward bias in its review. Moreover, early buyers may be systematically different from late buyers. For example, if early buyers are the biggest fans – which Hitt and Li (2008) find to be the case for most books on amazon – the upward bias will be exacerbated.

The second source of selection bias is the decision to leave a review after purchasing. The impact of this decision on the final content depends on the factors that drive someone to review. We might assume that people are most likely to review when their opinions are extreme, but they also might want to leave a review to promote a product they consider to be relatively obscure. Clearly, the first type of motivation would lead to a different type of bias than the second.

Empirically, Hu et al. (2009) note that most Amazon products have a J-shaped (asymmetric bimodal) distribution with more positive than negative reviews, which they take as evidence of self-selection into the decision to review. According to the authors, self-selection has two major drivers: under-reporting among customers with moderate views and purchasing bias (as described above). By contrast, the distribution of ratings on Yelp is not J-shaped (Dai et al. (2013), which I return to later). In their sample, the modal review is four with fewer reviews at the extremes. Purchase selection may be leading to the high average rating. However, the single peak and lack of extremes suggests that review selection is less central on this platform. The selection function may vary with the type of product, among other factors. For example, Dellarocas et al (2010) show that very obscure movies and major blockbusters are most likely to be reviewed (as a percent of people who have seen the movie). More generally, there are many different factors causing people to contribute content, and this heterogeneity ultimately shapes the content.

Self-selection is an issue of other types of UGC as well. Readers of news blogs may gain a very incomplete picture of current events. Bloggers tend to link to other blogs with similar views (Adamic and Glance 2005; Hargittai, Gallo, and Kane 2008). Looking at the *consumption* of online news, Gentzkow and Shapiro (2011) find that ideological segregation is larger online than offline, but still relatively small in absolute terms—suggesting that reading across platforms helps to limit the extent of bias. This type of mechanism is theoretically explored in Mullainathan and Shleifer 2005.

In a parallel series of papers, Greenstein and Zhu (2012, 2014) investigate bias on Wikipedia, which tends to be more left leaning than Encyclopedia Britannica. Within an article, having more authors and edits tends to reflect less bias, suggesting that simply having more people look at and edit content can serve as a bias-reducing mechanism. Overall, their findings are consistent with a mechanism in which "opposites attract." In other words, the reduction in bias and slant over time is consistent with a mechanism in which conservative edits attract revisions and contributions that make an article more liberal or balanced, and vice versa. Most articles, however, have relatively few edits and do not deviate much from their initial slant.

Overall, the selection of contributors is a key determinant of the content offered on a platform. People who contribute may be be different from the population at large. People who contribute a lot may be different from occasional contributors. An important area for future research would be to investigate the many different motivations to contribute content and the extent and types of bias that emerges across different types of UGC. For example, to the extent to which contributors lean toward people with particular preferences (e.g. video games) or a particular demographic (e.g. male), the content of UGC platforms can become skewed toward those preferences or set of customers even if each contributor is perfectly well-intentioned.

3.3. Peer Effects and Social Influence

A third determinant of the quality of UGC is the fact that later content may be influenced by earlier content. UGC, including Yelp reviews, Wikipedia posts, tweets, Facebook posts, comments on news articles, and YouTube videos, is not created in a vacuum. Rather, each contributor decides what to contribute taking into account all other content that they see. This type of social influence can influence the final content generated.

To investigate social influence, Muchnik et al. (2013) ran an experiment on an undisclosed news aggregator that, similar to Reddit, allows users to vote articles up or down. They find that seeding an article with an up-vote increased the likelihood of receiving future up votes by 32%. Social influence is also an important component in platforms such as Twitter. Bakshy et al. (2011) find that large cascades in retweets on Twitter tend to originate with very influential users. Kwak et al. (2010) find that over 85% of retweeted topics relate to current events, highlighting the blurry lines between Twitter as a social network and as a news platform.

While social influence can distort content, it can also be a positive force. For example, in the Wikipedia editing process described in the previous section, people may try to adjust their contributions in order improve the final content taking into account previous content. Similarly, social influence may drive higher rates of contribution. Many open questions about social influence remain—such as the extent to which it exists in popular online markets, the factors that moderate it, and its welfare implications.

3.4. Other Issues

The aforementioned list of challenges to the quality of content is not exhaustive. One issue that has come up in the context of online marketplaces is that sellers often review buyers and buyers review sellers. This can lead to strategic incentives for upward biased reporting if reviewers fear retaliation. For example, even if a renter on Airbnb has a bad experience, she might be hesitant to leave a bad review if the landlord were to see the review before leaving feedback for her. There are several possible solutions to this type of reciprocal reviewing. For example, a platform can simply withhold ratings until both sides have left a review. Reciprocal has been explored in settings such as eBay (Bolton et al 2013) and Airbnb (Fradkin et al 2015).

In conclusion, understanding and improving the quality of user-generated content is an important question both for policymakers and for platform designers. From a policy perspective, each of the issues described above will influence the amount of welfare that is being created from user-generated content. From a platform's perspective, these issues should shape the design choices that the platform makes. The quality and slant of content will determine outcomes such as the number and types of users and contributions, the value of advertising to businesses, and the amount of value that the platform is creating. An important direction for future research is to explore these factors and develop mechanisms to improve the quality of content.

4. Incentive Design and Behavioral Foundations

Consider the hotel review platform TripAdvisor.com. The website is the largest provider of information about hotels in the world, hosting more than 170 million reviews related to travel services (hotels, destinations, tours, etc.)—all of them provided for free. If the company offered, say, a penny per review, many users would probably be so offended that they would not review at all. Any reasonable level of payment for reviews (for example, \$15 for a thoughtful review) would be financially unsustainable. In this sense, perhaps the most surprising aspect of platforms such as TripAdvisor is the simple fact that they exist and are viable.

In a world where contributors do not typically receive financial compensation, why do people contribute at all? This is a fundamental question about the existence of UGC. After all, it takes time and effort to contribute meaningful content. In practice, there are many factors that cause people to contribute. One important factor is that although *financial* incentives are rare, *nonpecuniary* incentive design is a core function of a platform designer. For example, Yelp and AngiesList provide incentives to elicit reviews for services, with an emphasis on both the quantity and quality of content. YouTube provides incentives to encourage users to generate videos that viewers will find interesting. Facebook and Twitter encourage users to post information that others will read. In this section, I discuss the main nonpecuniary incentives driving production of content—incentives largely grounded in ideas from behavioral economics–and the choices that designers make to create these incentives.

There is significant heterogeneity in the way that different platforms design incentives for contributors. For example, some platforms – such as Yelp and Wikia – have personnel who manage the contributing communities and engage directly with prolific contributors. Other platforms are more passive. Still others send heavy handed messages reminding people to contribute content. Across all platforms, the design of the platform creates incentives that determine whether there will be more or less, and better or worse content.

One popular incentive used by platforms is to allow users to develop a reputation. User reputation systems come in two flavors. The first is a top-down system, typically in the form of badges or other outward-facing rewards from the platform. For example, Yelp provides "elite" status to reviewers who have written many high-quality reviews (as identified by Yelp); TripAdvisor, Amazon, and many other platforms have similar systems. The second type of social status is peer provided. UGC platforms often offer ways for other users to evaluate contributions, such as Yelp's "cool," "funny," and "useful" ratings, Amazon's "useful" rating, and Stack Exchange's "upvotes." Designers often enhance peer reputation by making it salient through titles and badges.

Easley and Ghosh (2013) analyze the role of badges as incentives for content creation. For example, Amazon and Yahoo! Answers award top-contributor titles to the users who produce the highest amounts of useful content. StackOverflow gives users badges for completing certain actions, such as voting on answers 300 or more times. Badges are clearly effective sources of motivation: there are entire discussion communities dedicated to becoming and staying top Amazon and Yahoo! Answer contributors. Empirically, Anderson et al. (2013) find that StackOverflow users participate more actively as they get closer to attaining certain badges. A growing literature is now beginning to investigate the effects and optimal design of these types of incentives. Once a platform has chosen an incentive system such as a badge or leaderboard, it must decide what someone should have to do to receive a reward. For example, Miller, Resnick, and Zeckhauser (2005) propose a scoring rule based on a comparison of the posterior beliefs implied by a user's rating and the rating of a reference user.

Looking at the entire review ecosystem, rather than the behavior of individual reviewers, Wang (2010) analyzes differences between the reviews and reviewers of three popular websites: Citysearch, Yahoo Local, and Yelp. Although Yelp entered into an already existing online review market in which Citysearch was popular, Wang observes that Yelp has received a higher number of prolific reviewers than either Citysearch or Yahoo Local. He argues that the primary distinction between Yelp and the two incumbents is that Yelp provides social image incentives, suggesting that the reputational motivation must be a stronger driver of review provision than the intrinsic motivation. If reviewers were primarily motivated by altruism, the difference between the number of reviews on Yelp and the number of reviews on other websites might be smaller, since review readers benefit from reviews regardless of where they read them. While the study does not isolate the causal effect of social image, it suggests a potentially important role of social image in UGC.

Another important behavioral component of UGC is users' beliefs about the impact and quality of their contributions. Looking at Chinese government blocks of Wikipedia as exogenous shocks to the size of content readership, Zhang and Zhu (2011) show that the size of readership has a causal effect on contributions. The incentive to contribute increases with the size of the readership, suggesting that prosocial motivations underlie contribution decisions. A related factor pertains to a contributor's beliefs about the quality of her contribution. Zhang and Zhu (2006) show that Wikipedia contributors are less likely to contribute content after their earlier content has been edited or corrected, perhaps because this feedback suggests to them that their contributions are inferior. In a field experiment on MovieLens, Chen et al. (2010) show that providing information about how many ratings a median user has contributed leads to a large increase in contribution rates for low frequency users and a drop in contribution rates for high frequency users – suggesting that social norms guide the rates of contribution.

There are two main directions for future research in this area. First, UGC platforms create rich empirical contexts for testing behavioral theories. Second, the optimal design of incentives at the platform level, given the preferences of platforms users, remains a largely open question.

5. Other Issues

This section broaches several other important issues related to UGC. These issues serve as potentially fruitful areas of future research concerning UGC.

5.1. Business Models

Looking across UGC platforms, there are three main ways that UGC platforms generate revenue.

The first—and most common—way to generate revenue is to sell advertising, which is the approach taken by Facebook, Twitter, Yelp, and many others. One benefit of this approach is that UGC platforms often know a lot about contributors and users, including what they are interested in (for example, Yelp knows when users are searching for Thai food). However, advertising sales can also lead to policy and legal issues ranging from privacy (what data Facebook should be allowed to use to target ads) to fairness (how many advertisements should be shown in a newsfeed, relative to organic content). Advertising can also create incentives for contributors to alter their content. For example, Sun and Zhu (2013) find that after the introduction of an advertising revenue sharing program on a Chinese portal, bloggers altered their content in order to receive more viewers.

Another related research question pertains to the optimal way to sell ads. One option is to use an auction, as Google and other platforms commonly do. By contrast, Yelp (like several other major platforms), has a large sales team that interacts with businesses to sell advertisements at a fixed price. Platforms that sell advertisements are then often able to offer content to users without a separate charge.

The second approach to revenue generation is to sell subscriptions to users who want to access the content. For example, AngiesList charges an annual membership fee to users. While this approach can eliminate some of the challenges of relying mainly on advertisements, it can also restrict the number of contributions (since fewer people will view the content) and ultimately the reach of the platform.

The third main approach to revenue generation is to sell analytics and data. For example, Facebook can presumably predict fashion trends across the country better than most other organizations can, by studying changes in user behavior and network data. Similarly, Yelp can presumably predict food trends better than other organizations. Such analyses could potentially change the way that businesses optimize their operations.

A fourth alternative is not to pursue profit at all. Some UGC platforms—such as Wikipedia—have opted to pursue a non-profit approach, relying on donations and fundraising drives to stay afloat.

There are many open questions in this area. For example, do Facebook advertisements work? Do they create a conflict of interest with the business's dedication to protecting privacy? To what extent does a paywall (such as AngiesList's) reduce content? Does a paywall reduce usage by making the profit motive salient to customers? Does an advertising-based model lead platforms to obscure the difference between paid and unpaid content, as suggested by Edelman and Gilchrist (2012)?

More generally, there are several main research topics related to business models and UGC: (1) the optimal pricing of these services, (2) the measurement of their efficacy, (3) identification and quantification of the unintended consequences, and (4) the conditions under which each business model is optimal.

5.2. Competition and Network Effects

The value of social media sites such as Facebook, Yelp, Twitter, LinkedIn, and Youtube to a given user depends on who else is using it. As mentioned earlier, this network effect is a feature of all UGC, such that the value of a UGC platform increases with the number of users. This helps to explain why investors often consider the number of users a site has in addition to its revenue. Network effects are also a natural source of market power. When Facebook has a large network, the value to each user goes up, making it harder for a competitor to capture users.

Despite the importance of network effects, there have been important examples of large UGC platforms that have been overtaken by competitors. Facebook was not the first popular online social network; Myspace preceded it. Similarly, Citysearch predated Yelp as a popular online review platform. In these cases, strong entrants with improved technology overcame the network-effects barrier. While considerable work documents social media networks and investigates influence within a network (see section 2 and 3.3 above, or Jackson and Yariv 2011), many open questions remain about the role of network structure in online social networks. Important directions for future research include quantifying the value of network effects in these platforms, estimating the extent to which they provide market power, and exploring the factors that allow a competitor to overcome the network-effects barrier. For example, it could be that there is a tipping point at which users move en masse from one platform to another.

A related element of competition occurs between social media and more traditional media outlets. Wikipedia competes with traditional encyclopedias, blogs with newspapers, Yelp with the Michelin Guide, etc. A fruitful area for future research is to explore the extent and implications of this type of competition.

5.3. Digital Exhaust, Property Rights, and Privacy

Every Facebook post, every "like," every tweet, every Yelp review, every Instagram picture, and every Foursquare check-in leaves a trace on the web, a trail of what is sometimes referred to as *digital exhaust.*

Digital exhaust provides valuable new data. Bollen et al. (2011) show that the public mood, as assessed from Tweets, predicts stock market outcomes. Kang et al. (2013) find that text from Yelp reviews predicts restaurant hygiene violations, thus suggesting that reviewers can help health inspectors decide which restaurants to inspect. Digital exhaust can be used for social good – for example, a city government might use Facebook networks to predict college dropout decisions or Tweets to predict crime.

However, digital exhaust leads to issues of property rights. In particular, who owns the massive amounts of data that you are providing to these platforms? UGC platforms frequently sell data about users to enhance advertisers' ability to identify potential customers. Reducing the amount of user data platforms can sell may reduce the ability of advertisers to target consumers. Examining the effects of EU regulation on the amount of data online advertisers can collect, Goldfarb and Tucker (2011) find that advertising effectiveness, measured by participant on a five-point "likelihood of purchase" scale, fell by 65% in Europe relative to the rest of the world after this restriction was introduced. However, Tucker (2014) finds that social media users are more likely to click on personalized advertisements when they believe they have control over their personally identifiable information.

Digital exhaust also raises issues related to privacy and anonymity. What are the welfare effects of contributor anonymity? Facebook, for example, has many different privacy levels for profiles, pictures, and posts, based on user preference. A contributor to Yelp, Wikipedia, YouTube, TripAdvisor, or most other platforms has the ability to post material fairly anonymously (or to choose to make him- or herself public). Allowing anonymous contributions may improve content—especially in sensitive areas—but may also increase self-dealing (or, as discussed in section 3.1, promotional content). In ways that may be good or bad, depending on the situation, anonymous users may also feel more comfortable violating social norms.

Public contributions give contributors social capital that provides incentives to generate high-quality content and also deters fraudulent content. In settings where a designer may want to deter certain types of conversations – such as limiting hate speech or bullying on a discussion board, requiring contributions to be public may be an important tool.

However, there is a tradeoff because public contributions may restrain users from contributing important content for fear of stigma or retribution. In some situations, forbidding anonymous complaints can backfire; for example, the fear that the police could identify contributors to a site could suppress complaints or tips to the police. For further discussion on the economic of privacy in media outlets, see "Chapter [Tucker]".

To empirically investigate the role of anonymity on Wikipedia, Anthony, Smith, and Williamson (2009) distinguish between registered editors and anonymous editors. While registered users provide more content, content by unregistered users is more likely to be retained over time, and hence may be more reliable.

In sum, understanding the growing tradeoffs surrounding privacy and anonymity in UGC is an important area for future research.

5.4. Information Aggregation

Consider a town with two hypothetical hotels: the Hotel California and the Hotel Yorba. Both hotels are quite popular on TripAdvisor, obtaining an average of 3.5 stars from hundreds of reviewers. On the surface, the two hotels seem similar. Yet as you look closer, you see that most of the favorable reviews for the Hotel California were from a long time ago and that the reputation has gone downhill from there. By contrast, Hotel Yorba has received a lot of favorable ratings over the last couple of years. Which hotel would you pick? Most likely, you would choose the Hotel Yorba.

Taking this hypothetical a step further, what overall rating should TripAdvisor display for the two hotels to its users to provide an estimate for the true quality of the hotel, and what order should they be listed in? As noted above, the arithmetic average rating for each hotel is 3.5 stars. Yet, it is only under very restrictive assumptions that an arithmetic average is the optimal way to aggregate this information. For example, an average might be optimal if each review were an independent and identically distributed draw of quality with no peer effects, quality changes, or heterogeneity in quality of reviews.

A question faced by UGC platforms is then how to aggregate this information. Looking at Yelp reviews, Dai et al. (2013) provide one structural approach to aggregation of UGC. Their model allows for peer effects in content, changes in restaurant quality, and reviewer heterogeneity, among other factors. Their results derive an optimal aggregation of Yelp ratings, which endogenously provides more weight to later reviews, and to elite reviewers, among other factors.

At the opposite extreme of arithmetic averages is the approach of finding "bad" content and removing it all together. Platforms that use algorithms to identify and remove content thought to be fake use this approach, as do spam detection algorithms (for example, in Ott et al. 2011). As with the case of arithmetic averaging, the approach of removing content altogether is only optimal under very restrictive assumptions, as it assumes that the removed content contains no useful information. Taking a step back from this specific application, it seems that given some model of reviewer behavior, it should be possible to derive the optimal way to aggregate information to provide to users. To the extent that users have different preferences, it is then possible to customize content based on preferences of customers. In practice, information may literally be reweighted and displayed to customers. An alternative is that platforms can use these insights when deciding the order in which to display results.

5.5. Welfare Effects

TripAdvisor creates value for society by increasing the amount of information available to people who are choosing a hotel. Quantifying this welfare gain is complicated, as it requires data and assumptions about where people would go in the absence of TripAdvisor as well as the value people receive from going to different hotels. This is complicated further because new information can influence the diversity and quality of hotels in the market.

LinkedIn creates value by allowing people to connect with each other in an employment-focused setting, which could potentially reduce unemployment and lead to better job matches. Yet, computing this value is complicated because of the endogenous nature of connections, including the simple decision of whether to join LinkedIn as well as the difficulty in estimating the value of a connection.

Similar challenges arise when quantifying the welfare gains for virtually any type of UGC. This quantification remains an open direction for future research. Beyond the overall gain from new information, there are likely quite heterogeneous effects for consumers. For example, while AngiesList is tailored to customers who are willing to pay for it, Yelp is tailored to a broader audience. Similarly, online news conveyed through blogs and Tweets may be very different from coverage on the *New York Times*. Future research can help to understand more about the winners and losers among customers, workers, and businesses.

6. Discussion

Virtually every industry is touched by user-generated content. Every online interaction has a social element to it, and every type of media is incorporating, competing with, or being replaced by user-generated content. Describing much of the current research being done in this area, this chapter has focused on the impact of UGC on behavior, the unique biases and challenges to the quality of content that these platforms face, and the design of incentives to generate sufficient high-quality content, among other issues.

Several themes have arisen throughout the chapter. One is methodological. Much of the frontier of this field involves finding the correct method to study a given problem. In many cases, this means identifying strategies to pinpoint causal effects that go beyond descriptive work and associations. There is also scope for pure prediction problems in cases where user-generated content may help to predict and target a variable of interest. But it is important to be clear about whether a paper is moving toward a causal claim, or trying to predict an outcome. Much of the current empirical work in this area lacks emphasis on causality, and often focuses on associations, with several notable exceptions. With an abundance of data and the growing feasibility of running experiments with companies, moving more toward causal estimates is a productive area for future research.

A second theme concerns the role of the economist. One important practical advance within economics has been the development of the idea of the economist as engineer (Roth 2002). In this context economists not only study UGC but also help to design UGC platforms. As described by Roth, this shift in the economist's role has necessitated a deeper understanding of the contexts we study and greater attention to assumptions and institutional details. This is reflected both in the work on incentive design (where practical new mechanisms are developed to encourage high-quality content) and information design (where new approaches are taken to aggregating and presenting material to users).

A third related theme has been a focus on the phenomenon. The field of economics often prides itself on abstraction and removing itself from the confines of a particular context. By contrast, research on UGC has focused considerably more on phenomena, potentially in part because of closer ties between organizations and researchers. Although this difference is appealing in many ways, the emerging literature on UGC might benefit from a heavier reliance on theory. For example, the theoretical literature on networks could be brought more directly into empirical studies of influence in social networks.

Ultimately, UGC platforms are a rapidly growing field, both in practice and in research, creating a unique feedback loop. There are ample opportunities for future research to develop new theories and analyses of how UGC is shaping the world around us, how UGC platforms currently work, and how they should work.

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