COMMUNITY-BASED RECOMMENDER SYSTEMS:
ANALYZING BUSINESS MODELS FROM A SYSTEM OPERATOR’S PERSPECTIVE

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Abstract. Past research has shown that corporations benefit from using community-based recommender systems. Through them, they create digitized word-of-mouth that helps consumers make purchase decisions. While there exists much literature on the effects of recommender systems, to our knowledge, no prior studies have examined the underlying business models, nor have they considered the roles of system operators and the process for these recommender systems to achieve profitability. Based on our synthesis of relevant theory, we propose a framework for evaluating the value of recommender system business models from the viewpoint of system operators. We discuss patterns and situational characteristics that are associated with the business value of consumer-generated content and the concomitant profits of system operators.

Keywords: Business value, community-based recommender systems, recommender systems, system operators, theory development, virtual communities, word-of-mouth.

1. INTRODUCTION

Since the advent of the Internet, organizations have increasingly recognized its possibilities as a primary medium for advertising their products and services, and for supporting new and effective means of communication with consumer. Emblematic of this recognition, Amazon.com, which has mostly focused on the Internet, eliminated its entire budget for television and print advertising in 2003 [21]. The firm’s management team came to believe it is better served by digitized word-of-mouth.

Digitized word-of-mouth has become an important source of information to consumers and firms, allowing consumers to easily share their opinions and experiences about the quality of various products and sellers [7]. A community-based recommender system (or simply, a recommender systems in this research) is a system that makes use of digitized word-of-mouth to build up a community of individuals who share personal opinions and experiences related to their recommendations for products and seller reputations [15, 30]. Such systems present or aggregate user-generated opinions and ratings in an organized format. Consumers consult this information before making purchase decisions.

Recommender systems have received much attention in the information systems (IS) and marketing literature recently. IS research has emphasized intrinsic motivations and extrinsic motivations for people to provide recommendations, and the effectiveness of recommender systems on sales [16, 24]. Marketing research, on the other hand, has focused on recommender systems as complements to advertising [5, 6]. However, relatively little is known about how firms should provide and manage a recommender system and what factors are relevant in designing its strategy relevant to recommender systems. We will study the business models associated with providing a recommender system, from a system operator’s point of view, to successfully convert the potential value of recommender systems into realized value and profits [10]. Prior studies either do not specify the role of the system operator, or just address recommender systems with one specific role only in mind. Moreover, to our knowledge, no prior studies have addressed the underlying business models related to the different roles of system operators.

We provide a systematic review of the related recommender systems literature. We synthesize applicable theory to interpret what has been occurring with the different recommender systems on the market. We also build an extended framework of the related business models from the perspective of different system operators. In addition, by analyzing the business models of the current recommender systems, we discover and classify the patterns that deliver value for consumer-generated content and enhance system operators’ profits. We discuss the managerial implications of these patterns for business decision-makers.

The paper is organized as follows. §2 reviews relevant literature on recommender systems. §3 identifies different business models that map to the roles of recommender system operators, and presents a new framework for analysis. §4 shows the appropriateness of the framework relative to real-world instances of recommender systems and their sponsors in the market. We discuss system operators’ needs related to revenue structures and operating mechanisms. §5 concludes by considering contributions and limitations. The trajectory of the development of this research is shown in Figure 1.
2. LITERATURE

Several areas of the literature on recommender systems are relevant as preliminaries to the development of our extended framework on where profits arise. As a starting point, we first define recommender systems. We then present some leading results from prior research on four different dimensions: system effectiveness assessments, digitized word of mouth, intrinsic and extrinsic motivation, and the credibility of online user reviews. These four dimensions are derived from the observations of interdisciplinary literatures in IS, marketing and social psychology fields.

2.1. Recommender Systems

Dieberger et al. [15] define recommender systems as systems that collect data on ratings and comments from consumers, and then analyze the data to find patterns that suggest similar sets of interests. The simplest recommender systems produce ratings or rankings that are the same for all users, much like best-seller lists. More sophisticated systems group the data according to similarity metrics. Some systems further exploit profile information to make personal, customized recommendations. Schafer et al. [32] conclude that the term of recommender system has evolved to replace and broaden the use of the term collaborative filtering and incorporates those systems that provide best-seller lists, those that provide predictions of user preferences and those that provide community opinions. GroupLens (www.grouplens.com) is an example that has evolved beyond collaborative filtering.

2.2. Leading Results in Prior Research

Researchers have examined whether recommender systems affect overall sales, customer attention and retention, and strategy effectiveness. Others have asked what makes people willing to contribute opinions. Still others are interested in the sources that make recommender systems so powerful. Digitized word-of-mouth, trust and reputation are central to this power. Another issue is the credibility of online user reviews, where identity is anonymous and virtual. Firms can manipulate messages to favor their products or to attack those of competitors.

Effectiveness. A convincing quantitative indicator of recommender system effectiveness is the corresponding sales of the recommended products. The premise is that by acquiring additional information from other consumers, the uncertainty discount associated with a sale item can be reduced [9]. This impacts consumer decisions, increasing the likelihood of making a sale. For example, improving book review scores on Amazon.com and BarnesandNoble.com tend to increase its sales. Empirical studies show that a large number of reviews – not just the review ratings – are important [4].

Recommender systems are important in strategic marketing Chen and Xie [5]. They modeled how firms should take advantage of community-based recommender systems by combining them with pricing and conventional advertising strategies [6]. Recommender systems are also beneficial to attract and retain users. Kumar and Benbasat [23] examined the relationship between user loyalty and recommender systems in an empirical study of data from Amazon.com. They found that providing consumer reviews increases perceived usefulness and the quality of a user’s psychological connection with a web site. This, in turn, influences consumer attraction and customer retention.

Digitized word-of-mouth. Duan et al. [16] modeled video sales and movie recommender systems, and found that word-of-mouth is central to their efficacy. This result is consistent with the ideas of social validation in social psychology [8], social interaction in marketing [18] and digitized word-of-mouth in IS studies [12].
Via community-based recommender systems, consumers with interests in similar products can interact. The results of their interactions become trusted information which reduces information asymmetries, which induces more trust and fosters confidence in their purchasing decisions [2, 33]. Digitized word-of-mouth is the main driver of sales, although online review sites also have a secondary influence [16]. Godes et al. [18] propose four strategies that the firm might implement to leverage digitized word-of-mouth.

**Intrinsic and extrinsic motivations.** Although the Internet provides an unprecedented for spreading information by word-of-mouth, without consumers’ participation, recommender systems will not succeed. As a result, the willingness of users to contribute their opinions becomes interesting to the system providers. They exhibit intrinsic motivations and extrinsic motivations. One intrinsic motivation is social comparison, which Harper et al. [20] define as making comparisons with peers, who supply information about their contributions above, below, or at the average. Other possible intrinsic reasons involve the desire to share opinions for fun and to engage in an exchange relationship with others who share theirs [24, 30]. Shapira et al. [35] assert that there are inexpensive extrinsic motivations (like pizza in meetings) that produce modest increases in cooperation.

**Online user review credibility.** Suggestions from community-based recommender systems involve people who may not disclose their identities. So it is possible for firms to strategically manipulate the reviews so their own products are viewed more favorably. An example is Amazon.com’s Canadian site in 2004. It mistakenly revealed the true identities of some of its book reviewers. Unfortunately, the books’ authors and publishers wrote many of the reviews, as did their competitors [19].

Dellarocas [13] offered a theoretical analysis of the impact of strategic manipulation on firm profits and consumer surplus. He notes that firms have an incentive to inflate the ratings of their products. With community-based recommender systems, the better a firm is perceived to be – even with manipulation – the more it stands to gain. The findings of an empirical study by Chen and Wu [4] on Amazon.com support Dellarocas’ theory. Though rating manipulation is possible, its effects on sales will be limited because high ratings only are meaningful when they are provided by a large number of reviewers. Many recommender systems currently ask users to rate the usefulness of posted reviews and some researchers focus on statistical and cryptographic mechanisms to discourage manipulation. [11, 17]. An empirical study by Chen et al. [3] based on data from Amazon.com has shown that reviews that have received a high number of usefulness votes have stronger impact on sales. This result suggests that simple manipulation of reviews and ratings may not work under the “rate the review” system.

3. A FRAMEWORK FOR STUDYING RECOMMENDER SYSTEMS

As with any type of investment, a rational firm should be able to justify its investments in a recommender system. But how should managers adjust their business models to leverage recommender systems? How do different types of firms extract business value the virtual communities create with recommender systems?

However, few researchers have focused on this theme. In the following subsections, we will use the initial model of Resnick and Varian [31] to point out how our understanding of recommender systems business models should be understood, as a basis for building the skeleton of our extended framework. The relevant constructs for defining a business model in this area include firm type, business operating mechanism, revenue structure and customer base.

3.1. Base Framework

Resnick and Varian [31] summarize the revenue sources for recommender systems with three business models. The first is a subscription-based per-use fee model for those who want to purchase decision support. The second is a vendor ratings-purchase model, in which filmmakers, for example, pay consumers (or via an intermediary) for their opinions on the movies they release. The third is an advertiser support and subsidy model. When consumers click-navigate through recommender systems, they also create signals for system operators about their product interests. Operators sell this information to promote targeted ads.

Attribution theory suggests that a sender will be perceived as biased if the recipient infers that the message creates the possibility of personal gain [22, 27]. If consumers perceive the recommendations to be biased by non-product-related motivations, such as advertisers support, the perceived fairness of the recommendations will be discounted. In the three business models, the latter two have the corruption concern. Because the income streams are either from the product holders or advertiser, system operators have an incentive to favor the companies that pay more. To eliminate the negative effect on product reviews and ratings brought by possible non-product incentives, Resnick and Varian further propose a business model that the recommender systems is held by an independent third-party and the independent operator then subcontracts with sellers of products. For example, a book rating and review
service might operate autonomously and sell its recommendation services to a number of independent online bookstores.

3.2. The Extended Framework

In Resnick and Varian’s framework, they mainly focus on revenue structures. Nevertheless, to realize value of recommender systems, system operators need to know what operation mechanisms help them attract and retain customers. In addition, different types of system operators may require distinct combinations of revenue structures and operating mechanisms. But the mapping between expected revenue sources and the role of systems operators is not clearly specified. Revenue structures have evolved in these years and are different from those of systems in the 1990s. Our framework considers these issues.

Evolving revenue structures. Current recommender systems have revenue streams that are evolving beyond the patterns suggested in the original framework. To assess the multiple sources of revenue streams, we apply Novak and Hoffman’s [28] ideas regarding revenue structures for the Web channel to classify the different kinds of revenue streams for recommender systems. This model offers some clear definitions for various revenue sources, such as pay-per-use and referral fees. Based on this, we are able to go beyond Web-based revenue structures to categorize revenue structures for recommender systems.

The role of system operators. Firms are burdened with the costs of establishing and maintaining recommender systems, and monitoring the digitized word-of-mouth and profit from the systems. Different types of system operators have distinct strategies for investing in recommender systems, which leads to different business operating mechanisms and revenue structures. For example, product manufactures build recommender systems to understand their customers’ reactions and improve their product designs [12]. Retailers adopt recommender systems because the systems act as a lever for improving sales. Such differences contribute to the disparate supporting revenue structures that we see with different system operators.

Senecal and Nantel [34] suggest that recommendation sources can be used and promoted by three different types of websites: retailer or manufacturer, commercially-linked third parties (e.g., comparison shopping web site), and non-commercially-linked third parties (e.g., product or merchant assessment Web sites such as CNet.com). Peterson and Yang [29] classify recommender systems according to the role of system operators, as outside, independent parties apart from goods and service providers, and distributors or sales agents. These studies suggest that the three roles of system operators are product manufacturers, distributors and sales agents, and independent third parties.

Based on observations of real-world community-based recommender systems, we further classify them based on the recommended targets: systems supporting product review; systems for product providers, and systems for product sellers. Often, product providers are product sellers. Manufacturers typically only provide recommendations for their own branded products, not those more broadly available in the market. The other two roles provide reviews for different brands and targets. For example, a sales agent like eBay, provides reviews for product providers based on their transaction histories. Likewise, a sales agent like Amazon.com supplies recommendations for different brands of products. By the same token, a third-party operator, such as Shopping.com, provides suggestions both for products and product sellers.

The role of the product manufacturer is the least complex. We make no claims that systems operated by manufacturers are not worthy to explore; there has been research regarding the role of manufacturers [5]. Nevertheless, we focus more on the other two roles to understand the complex dynamics of community-based recommender systems.

Recommender systems operated by independent third parties typically are viewed in a more favorable light than those operated by sales agents and distributors. More independent web sites facilitate consumer search effort, where it is desirable to achieve low search costs [25]. Consumers often believe that recommendations suggested by sales agents are based on their interest to make a sale, and not to help the consumer to maximize her own utility. When recommendations are generated by other consumers, not the system operators themselves, the credibility concerns are lessened [32]. Recommender systems also allow distributors to tap into communities and build relationships with customers to support retaining them. This is valuable since the cost of acquiring a new customer is higher than retaining an existing one [23].

Business operating mechanisms. Operating mechanisms and revenues are key elements in a business model. Based on studies that investigate the facets of business operating mechanisms for recommender systems [32], we propose dimensions that a system operator needs to consider when it designs its operating mechanisms: the contributor, the recommended target and the mediation environment. Each construct includes key factors. For example, we address the mediation environment by exploring types of recommended targets, ways that community opinions are collected, mechanisms that prevent manipulation, and whether
expert reviews are included, among other distinguishing features.

Ba [1] asserts that the quality of online services has a significant effect on online retailers’ sales and customer satisfaction. The same goes for recommender systems, and the potential interactions that arise when their operating mechanisms and services are considered. See Table 1. These features will have an impact on the number of consumer members who are willing to join the recommender. We also expect there to be direct and indirect revenue effects. As a result, we investigate the business operating mechanisms for each of the types of recommender systems.

Table 1. Interactions among Business Operating Mechanism, User Base and Revenue Structure

<table>
<thead>
<tr>
<th>BUSINESS OPERATING MECHANISMS</th>
<th>USER BASE</th>
<th>REVENUE STRUCTURES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimension</td>
<td>Key Factors</td>
<td>Sources</td>
</tr>
<tr>
<td>Contributors</td>
<td>What operating mechanism increases contributors’ motivations</td>
<td>Improve in product sales</td>
</tr>
<tr>
<td>Recommended target</td>
<td>Type of recommended target</td>
<td>Improve in number of transactions done</td>
</tr>
<tr>
<td>Mediation environment</td>
<td>How community opinions are collected</td>
<td>Improve in number of subscription base</td>
</tr>
<tr>
<td></td>
<td>How community opinions are presented</td>
<td>Improve in number of advertised item</td>
</tr>
<tr>
<td></td>
<td>How manipulation is prevented</td>
<td>Referral fees</td>
</tr>
<tr>
<td></td>
<td>How expert reviews are put in place</td>
<td>Subscription fees</td>
</tr>
<tr>
<td></td>
<td>What special features are provided</td>
<td>Content license fees</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Software license fees</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pay-per-performance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Advertising</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sponsorships</td>
</tr>
</tbody>
</table>

Note: The classification of revenue sources is based on Novak and Hoffman’s web-based revenue framework.

4. BUSINESS MODEL ANALYSIS

We next apply this framework to recommender systems that are discussed in prior empirical studies. We expect some specific patterns, composed of common features and unique characteristics, across the different roles of system operators.

4.1. Revenue Structure Analysis

Since revenue models specify how a system operator translates customer value into a revenue stream, operators should be especially careful to develop an effective revenue model. The role that system operators play impacts the potential value of a recommender system to its stakeholders. For sales agents and distributors, user-generated recommender systems serve as value-added service to retain customers and thus stimulate sales. The main source of their revenue does not rely on recommender systems but on selling products and services. See Table 2.

Acquiring a new customer costs five to ten times more than retaining one and, repeat customers tend to spend 67% more than new ones, on average [37]. So building customer loyalty is critical. Kumar and Benbasat [23] found that web sites that offer consumer reviews increase customers’ social presence and perceptions of usefulness, thus enhancing customer loyalty. For sales agents and distributors, providing community-based recommender systems buttresses customer loyalty and leads to more revenues.

Sales agents and distributors build recommender systems in-house or subcontract with third parties for external development. Resnick and Varian foresaw outsourced development to a greater extend. Sales agents and distributors, among the three operator roles, are most likely to build recommender systems in-house. Schafer et al. [32] suggest that distributors can improve their credibility by building own systems. Customers can rely on recommendations from the web site without concern for the distributor’s motivation. If sales agents build the systems, customers will project a sense of community generated from the recommender systems to the distributor’s web site. But if a distributor buys a recommender system service from a third-party operator, the customer’s sense of community will be with the recommender systems provider, not the distributor. This is disadvantageous for the distributor.

Third-party operators, for this reason, typically do not follow Resnick and Varian’s model of providing content as a value-added service. Instead, they charge subscription and referral fees. These are called offline third-party charges when the systems are based on offline publications. Others charge referral fees, or online third-party charges. They focus on the online channel only. The former has been implemented by
Zagat’s (www.zagat.com) and Consumer Reports (www.consumerreports.org), which operate successful traditional recommendation magazines. These and other successful offline recommender firms provide recommendations online to increase their accessibility and flexibility for their subscribers. Their use of the bricks-and-clicks approach provides these firms with more opportunities to interact with their customers and build higher revenues.

Table 2. Analysis of Recommender System Revenue Structures

<table>
<thead>
<tr>
<th>SYSTEM OPERATOR</th>
<th>SYSTEM</th>
<th>REVENUE STRUCTURE</th>
<th>PAYER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales agent / distributor</td>
<td>Amazon customer</td>
<td>Improve product sales</td>
<td>Product buyers</td>
</tr>
<tr>
<td></td>
<td>comments</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Circuit City customer review</td>
<td>Circuit City customer</td>
<td>Improve product sales</td>
<td>Product buyers</td>
</tr>
<tr>
<td></td>
<td>review review</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elance customer review</td>
<td>Elance customer</td>
<td>Improve transactions done</td>
<td>Product and service providers</td>
</tr>
<tr>
<td></td>
<td>review review</td>
<td>Improve subscription base</td>
<td>Service providers</td>
</tr>
<tr>
<td>eBay feedback profile</td>
<td>eBay feedback profile</td>
<td>Improve transactions done</td>
<td>Product and service providers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improve advertised items</td>
<td>Product providers</td>
</tr>
<tr>
<td>Third-party with offline publications</td>
<td>Zagat.com</td>
<td>Subscription fees</td>
<td>Subscribers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Advertising fees</td>
<td>Advertisers (not product providers)</td>
</tr>
<tr>
<td>ConsumerReports.org consumer survey</td>
<td>ConsumerReports.org</td>
<td>Subscription fees</td>
<td>Subscribers</td>
</tr>
<tr>
<td>Operators that use the online channel only</td>
<td>CitySearch.com</td>
<td>Referral fees</td>
<td>Product sellers</td>
</tr>
<tr>
<td></td>
<td>Epinions.com</td>
<td>Ad, pay-per-use, referral fees</td>
<td>Product sellers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sponsorship fees</td>
<td>Sponsors</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Content, software licensing</td>
<td>Aligned partners</td>
</tr>
<tr>
<td>ConsumerReview.com</td>
<td>ConsumerReview.com</td>
<td>Ad referral, pay-per-use fees</td>
<td>Product sellers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sponsorship fees</td>
<td>Sponsors</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Content license fees</td>
<td>Aligned partners</td>
</tr>
<tr>
<td>Shopzilla.com + BizRate.com</td>
<td>Shopzilla.com + BizRate.com</td>
<td>Referral fees</td>
<td>Product sellers</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Software, content licensing</td>
<td>Aligned partners</td>
</tr>
</tbody>
</table>

The other revenue model, found in Citysearch.com, ConsumerReview.com, Shopping.com and Shopzilla.com is mainly supported by referral fees. These recommender systems advertise products by user-created, not seller-provided product information and charge product sellers for information on consumers who read the reviews, express an interest in the products, and click the links that direct them to product sellers’ e-commerce web sites.

Some question how advertising affects the quality of recommendations from these kinds of systems. The main worry is that sellers and product evaluators only write positive and favorable reviews for other firms that are heavy advertisers, not wishing to offend them. Their most important asset is their installed base of users, who permit them to negotiate with product sellers to limit referral fees. When the system has offers a higher level of credibility, a larger installed base of users is likely to come together. If system operators try to favor any product seller by only posting positive reviews, customers can easily sense it and the credibility of the system will diminish quickly through word-of-mouth. So will the user base. The consumer whose review is removed because of possible advertising corruption would notice this and spread the news. Others may question whether there is strategic manipulation by product sellers or owners who create false word-of-mouth news. Prior studies have shown that online product review sites retain their informativeness even when manipulation occurs [3, 4, 13]. The firm with higher quality products benefits from more favorable and honest opinions, and may have an incentive to manipulate. Consumers still will be able to adjust their beliefs and make their own decisions about the true quality of the products they are reviewing.

4.2. Operating Mechanisms: Performance

Business operating mechanisms determine customer satisfaction and will directly or indirectly impact system operators’ revenues. We next analyze some of the well known community-based recommender systems using factors to describe the operating mechanisms in our proposed framework.

Recommended targets. Based on the products or services that they recommend, recommender systems can be divided into three types: reviews of products, reviews of product providers and reviews of product sellers, as we noted earlier. Within this classification, sales agents are classified as retailers and exchange operators.

Retailers who provide recommender systems hope to leverage the sales of the goods and services they offer. Product recommendations from other consumers work like a selling assistant or a mapping agent who helps consumers efficiently locate the products they like. This increases sales and consumer satisfaction with the retailers. On the other hand, for exchange
operators, their recommender systems focus on reviews on product providers and product sellers. They earn money by providing places for buyers and sellers to conduct transactions and charge some associated transaction fees. The problem of distrust among people in the virtual world creates barriers to transactional exchange. So to guarantee trust at some basic level, the system operators provide reviews of the sellers’ transaction histories, instead of products they sell.

For an independent third party, recommended targets include leisure activities, such as night-life and attractions, common merchandise and product sellers’ transaction histories. Among all the targets, leisure activities are hard to digitize and thus it is difficult to conduct meaningful price and value comparisons. Take restaurant suggestions, for example. It is not very meaningful to compare the prices of two restaurants, since they may have different dishes, different ambiances, and different service quality levels. Also, even though they may serve the same dish, the taste of the food may be different, since the dishes are made by different chefs and may use different quality ingredients. With this background in mind and the online and offline channel differences we mentioned earlier, we define third-party systems as offline operators with offline publications aiming at leisure activities and merchandise sales. In addition, there are online operators, including generic operators that provide reviews for leisure activities, and advanced operators that focus on merchandise quality and seller reputations.

Contributor motivation. Amazon.com (www.amazon.com/gp/customer-reviews/top-reviewers.html) has established a mechanism that motivates reviewers to be frequent contributors. It has adopted the practice of identifying “Top Reviewers.” People who post the most high-quality reviews are selected as top reviewers and their reviews are placed at the beginning of product review pages. Epinions.com (www.epinions.com/help/faq/?show=faq_earnings) uses an e-royalties program to encourage review. Reviewers can earn a referral fees based on how much their opinions help other users decide what products to purchase.

These motivations are intrinsic and extrinsic. The top reviewer mechanism is built on intrinsic incentives: social comparison [20]. The income-sharing mechanism is based on the most common extrinsic incentive: money [35].

Social psychology theories are useful in understanding the extent to which people contribute in online communities, but they are insufficient in providing concrete guidance for system operators. Different psychological states and processes may lead to inconsistent outcomes. This may explain why few system operators have adopted mechanisms to motivate consumer review contributions. It also may signal to other users that their behavior is being manipulated [24].

Community input and presentation. The recommendations given by contributors may be explicit, implicit or both. Since we are focusing on recommender systems that operate in a community context, we expect to see opinions that are rather similar, rather than expressed in dramatically different terms. For example, the use of 1-5 rating scales, text reviews, separate pros and cons, and overall comments are common. Aggregate overall ratings, either reported as means or weighted averages, are typical. Some operators also ask customer-reviewers to evaluate products based on more specific product dimensions, such as cost-benefit and easy-of-use. Some systems also reveal the background of their review contributors, such as their age and sex. Some also ask about the condition of the products the reviewers have purchased. These considerations are natural because people of different ages and genders may have different views on certain kinds of products, based on their interests (e.g., used cars, furniture, DVD players, computers, and so on).

Expert reviews. Some system operators provide experts’ opinions as a supplement to consumer-generated reviews. For example, CircuitCity.com (www.circuitcity.com), Shopping.com (www.shopping.com), and Shopzilla.com (www.shopzilla.com) supply experts’ opinions and buying guides from outside trusted organizations as second opinions on consumer electronics. ConsumerReview.com (www.consumer-review.com) provides discussion forums hosted by professional enthusiasts in outdoor sports (www.outdoorreview.com) and digital photography (www.photographreview.com). Citysearch.com (www.citysearch.com) hires professional editors from different cities to write professional reviews with entertainment suggestions, such as restaurants, beauty salons and health spas. Generally speaking, system operators seem to provide professional reviews as supplements to user reviews when the products are complex, such as consumer electronics, and professional expertise helps in making decisions.

The underlying questions that this operating mechanism prompts are: Why do some operators provide professional reviews, while others do not? How do system operators who purchase professional opinions justify their strategy? What is the correlation between professional reviews and consumer-generated reviews? Which has greater impacts on consumer purchases and operators’ profits? Although people tend to value expertise highly, Dellarocas et al. [14] find that user ratings are more influential in predicting future revenues of movies than average professional critic reviews. Further empirical analysis is necessary to answer some
of these questions.

**Preventing Manipulation.** One of the main concerns of recommender systems is manipulation by product firms that wish to boost their sales. Product firms try to disguise promotional activities as customer reviews, and prior work has examined the impacts of doing this [18, 26]. Dellarocas [13] suggests system reviews, and prior work has examined the impacts of firms try to disguise promotional activities as customer product firms that wish to boost their sales. Product concerns of recommender systems is manipulation by strategic manipulation. Currently, most system operators only have the most rudimentary means in place to prevent manipulation (e.g., “rate-the-rater”).

eBay’s product feedback profiles and Elance’s (www.elance.com) reviews of application developers and web design professionals do not have this problem. These systems only allow people to provide reviews if they have bought a given product or obtained their services. This way, they will know the quality of the products and services that have purchased. We further note that eBay allows both buyers and sellers to comment on one other, so there may be some “war games” that occur. Buyers and sellers retaliate in response to the other when they do not like the review comments.

**Welfare efficiency.** A final dimension of interest involves consumer welfare benefits and efficiency.

Almost all recommender systems are equipped with some kind of functionality that enhances convenience in consumer search. Some examples include sorting recommended targets by prices, brands and sellers. A good example is RateBeer (www.ratebeer.com), which offers information about the raters too—the so-called “ratebeerians”—by beer style, brewer, beer type (e.g., stout, Belgian beer, etc.). Recommended targets lead to different degrees of search efficiency. See Table 3.

- With recommender systems operated by retailers, customers save on effort via reviews of products to find high-quality products or to find a product that provide a better fit for them (e.g., movies) through online suggestions. We call this Welfare Type 1. This is especially relevant for products that are experience goods in nature.
- Consumers use exchange operators’ recommender systems and infer product quality from the reviews of product providers. In this case, welfare efficiency comes from reducing search costs for high-quality products via guaranteed transaction histories. We call this Welfare Type 2. This is most relevant for transactions that involve information asymmetry.
- Other than search efficiency derived from reducing quality, fit uncertainty and information asymmetry, advanced recommender systems also deliver benefits by exploring the extent to which price dispersion occurs in posted prices from reliable online stores and providing a value-price comparison that target customers with different risk preference. We call this Welfare Type 3.

Table 3. Classification of Current Recommender System Business Models

<table>
<thead>
<tr>
<th>SYSTEM OPERATORS</th>
<th>BUSINESS OPERATING MECHANISMS</th>
<th>USER BASE</th>
<th>REVENUE STRUCTURES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Role</td>
<td>Recommend Target</td>
<td>Manipulation Prevention</td>
<td>Welfare Type</td>
</tr>
<tr>
<td>Sales Agent</td>
<td>Retailer</td>
<td>Rate the rater</td>
<td>Type 1</td>
</tr>
<tr>
<td>Exchange</td>
<td>Product and service providers’ transaction history</td>
<td>Immune from</td>
<td>Type 2</td>
</tr>
<tr>
<td>Third Party</td>
<td>Operators with offline publications</td>
<td>Merchandise and leisure activities</td>
<td>Rate the rater</td>
</tr>
<tr>
<td>Generic operators</td>
<td>Leisure activities</td>
<td>Rate the rater</td>
<td>Type 1</td>
</tr>
<tr>
<td>Advanced operators</td>
<td>Merchandise and product sellers’ transaction history</td>
<td>Rate the rater</td>
<td>Types 1 and 3</td>
</tr>
</tbody>
</table>

Note: There are three types of recommender system welfare efficiency. Type 1 involves lower search costs for high quality and idiosyncratic products because of product recommendations. Type 2 is lower search costs for high quality products because of product and service provider recommendations. Type 3 is lower search costs for cheaper prices and lower transaction costs due to best-price comparisons for recommended product sellers.

An example of Type 3 is MySimon (www.mysimon.com). Its use results in lower search costs for cheaper prices, so it can lower transaction costs for consumers. This additional efficiency is based on the premise that people will pick the recommended product with cheaper price from the best-price comparison list regardless of fame of product sellers.

However, Smith and Brynjolfsson [36] find that consumers who are price-sensitive prefer offers from well-known retailers even though product prices and characteristics from other competing retailers are visible. Consumers use brand as a proxy for retailer credibility relative to non-contractible aspects of the product and service bundle, such as shipping reliability.
That is the underlying rationale that advanced recommender systems adopt with merchant reputation profiles built from consumer reviews and ratings. These profiles will assure the credibility of the online stores listed in the best-price comparison list. By providing merchant reputation profiles along with the prices offered by different sellers, consumers can make purchase decisions on the basis of prices, store service quality and brand. This allows consumers with different risk preferences, that is, with different tradeoffs between price, service quality and brand, to make a choice that optimizes their utility.

Overall, some operating mechanisms seem to be common across system operators, while others are unique to sub-group of operators. We focused on characteristics specific to each system operator role.

5. CONCLUSION

This paper analyzes and classifies the business models of community-based recommender systems to demonstrate how system operators leverage user-generated reviews for profitability.

We address the needs of system operators related to business operating mechanisms and revenue structures by extending Resnick and Varian’s framework. We derived five different roles for system operators, and associated these with distinct business models. We emphasized the main revenue sources and welfare efficiency generated by different operating mechanisms. The final classification functions as the underpinning for future practitioners, especially as investors and managers try to understand and evaluate the value proposition of community-based recommender systems.

We make no claims that this exploratory research is exhaustive. Instead, we view it as a starting point to stimulate further research on the business models of recommender system providers. One limitation is that we do not provide a definitive empirical test of the business model analysis framework that we have proposed, even though our assessment suggests that it has meaningful face validity. In addition, we have not validated all of the constructs that we use in the framework beyond referencing the published research that supports them. Although some readers may believe that this is sufficient, a stronger approach is to validate all of the elements included in the model, a better way to do this also lies in conducting empirical research. Finally, we have not considered the relationship between the operating mechanisms for recommender systems and the system operators’ profits. We also have not explored the efficacy of the different strategies that different kinds of system operators can use. Nor have we attempted to make comparisons for systems operated by different kinds of operators. All of these will make for interesting future research.

REFERENCES


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