

## Effect of Social Networks on Online Reviews

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### Abstract

*The emergence and growth of free review hosting websites give customers the opportunity to share their experience about product/service with a huge audience. A majority of these review-hosting websites offer a range of social networking features. We investigate how reviewers interact on online review websites and learn from social networks. Reviewers learn and gain experience in different ways which eventually affects how they rate products. We find that social networks affect reviewers in both direct and indirect ways. Our result showed that reviewers having a large book collection begin with a larger range in their ratings, whereas reviewers connected to a larger social network begin with a smaller range in their ratings. Further, the range of ratings decreases for all the reviewers as they gain experience over time.*

### 1. Introduction

Word of Mouth (WOM) refers to an informal network between interested customers to promote new products [1] and it is a way that former customers share their experience with prospective customers. The emergence and rapid growth of the online review platforms provides the opportunity for individuals to share their knowledge about the product with an unknown and huge audience looking to buy the same product.

A vast majority of the literature on the online customer reviews, mainly in the marketing discipline, focused on the effect of the reviews on the product fate in the marketplace ([2], [3], [4], [5]). In the current literature, the quality of the reviews, reviewers' motivation ([6], [7]), reviews' content ([8], [9], [10]) and the helpfulness of the reviews ([11], [12]) were studied. Nevertheless, there is no published study about role of social networks on online reviews, though a majority of online review hosting website support a

range of social networking features on their platform. Social networks on these platforms can have direct or indirect effect on users/reviewers. Users on these platforms can follow others to learn and gain experience from others without having any formal connections. Alternatively, users can formally connect or friend other members of these website to learn and share in myriad number of ways. Even though the interaction between product, review and reviewer characteristics has been studied before, we believe that effect of social networks on how reviewers change the way they rate products has not been investigated. Aiming to fill this gap, in this paper we propose a model to answer one central question - How and why social networks affect reviewers' rating behavior over time.

Following prior literature, we believe that both direct and indirect social influences affect users in their evaluation of products [13]. Social networks can affect both quality and quantity of evaluations through two different mechanisms. One is affecting friends' assessment of the products by giving them a pre-judgment of the product prior purchase ([14], [15]). Another effect is by giving feedback to friends about their past evaluations of products. Reviewers get feedback from their social network and change their future behavior to get more positive feedbacks. We argue that these mechanisms are different for reviewers who have different motivations for contributing in the WOM environment.

Reviewers contributing to online review hosting platforms are often driven by altruistic motivation and desire to reciprocate to communities associated with review platforms. Prior literature has investigated different motivations driving people to contribute to social networks ([16], [17]). Looking through the lenses of social networks, we examine the motivations of reviewers on online review hosting websites to understand how these motivations shape the reviewers' behavior over time.

We developed a model to investigate the effect of social networks on change in reviewers' behavior over time. To test our hypotheses, we collected data from a third-party review-hosting website for book reviews. We find that reviewers learn via both formal and informal social networks and change their reviewing behavior over time as they gain experience. Our work contributes to information system and marketing literature. We conclude with the implications for online customer review platforms.

## 2. Literature review

Consumer opinions, user experiences, and product reviews are considered as exemplars of Electronic Word-Of-Mouth [18]. In another word, online customer review is an evolutionary form of WOM. WOM is a process in which former buyers share their assessment of a product or service with prospective customers. Prior research has investigated the effect of WOM on customers' purchase decision which eventually leads to the change in sales and revenue of the product and its fate in the marketplace ([2], [3], [4], [5]). According to the theory of information processing, customers go through two stages when they decide to buy a product. The first stage involves making a short list of alternatives and the second stage focuses on evaluating all the alternatives based on available information [19]. Where the eWOM can help customers in the first stage, it is also an essential element of the second stage of decision-making.

Most of the WOM platforms facilitate social networking features for their users. On these social networks, we believe that reviewers play different roles owing to their motivation and interests. For example, reviewers can be categorized as *Information Seekers* and *Information Leaders* [20]. *Information seekers* find their place in a social network to seek a large amount of information and advice from others before they make their product selection. Whereas *Information or opinion leaders* have a tendency and ability to provide useful and timely information to other users. They can influence other customers' purchase decisions and eventually the market dynamics of the product [21]. There are some characteristics to differentiate opinion-leaders from non-leaders such as *Product Familiarization*, *Personal involvement*, and *Public Individuation* [22].

A limited number of studies have investigated the interrelationship between social networks and eWOM. As an example, Brown and Reingen [23] have investigated the social Ties in a network between individuals and groups and its effect on the referral behavior. They showed that the strength of a tie affects the likelihood of a product referral. It means that users

refer a product to their friends more often. Other than the strength of the ties in the social network, the diffusion rate is another important factor affecting the effectiveness of WOM [24]. Looking closer to this effect, we draw attention to two different mechanisms, which can explain this interrelationship. *The first mechanism* is the effect of WOM's diffusion in the social network on the post-sale evaluation through *Social Influence* effect. Studies have confirmed that WOM recommendations are strongly associated with users' posterior evaluation ([15], [14]). Research studies have shown that prior reviews received in a social network could change the result of the product assessment for new customers. The information from the reviews stick to the receiver's mind and alter their judgment. Research showed that this effect can be moderated by reviews from socially close friends ([15], [14]). Huang et al. [14] showed that new customers tend to give good ratings to the products recommended by their friends.

*The second mechanism* which can describe the interrelationship between WOM and social networks is *social feedback*. This effect is part of the social influence too. But it mainly affects reviewers' behavior through the direct and indirect feedbacks they get on their previous reviews. Users, who write reviews or evaluations on products, monitor the reaction of their friends on the social network about their own reviews. The feedback on the reviews can affect the behavior of these reviewers through learning mechanism, and this effect can be moderated by the motivation of the reviewers. To the best of our knowledge, no research has been done to capture this influence and its effect on the behavior of reviewers over time. The change in their behavior can be captured by different measures. As an example, Zhang and Wang [25] studied the participation of reviewers and observed some individual level characteristics that drives the participation of reviewers after introducing a social network to the eWOM platform as an exogenous change.

In addition to the importance of the effect of social network on eWOM, researchers have focused on other related factors. Some of these factors fortify or weaken this effect as moderators. *The first moderator* is WOM quality. In the current literature, the quality of the WOM has been studied from different aspects such as sidedness as the balance of positive and negative points ([26], [27]), argument quality ([28], [29]), and eWOM credibility [30]. In addition, the helpfulness of a review has also been explored as one of the aspects of the WOM quality. Usefulness means how the information can affect the customer decision making and customer purchase intentions [31]. The helpfulness itself is affected by Product type [11], the reviewer and review

characteristics [32]. One important part of the WOM quality which has a two-way relationship with the helpfulness is *credibility* ([30], [12]). It consists of both *Source Credibility* and *message credibility*. Research indicated that the message in reviews has a greater impact on readers if they perceive that the communicator as a trustworthy source in their social network [28], which represents source credibility. Furthermore, the eWOM credibility shows the argument's power of the review. This factor shows how receivers consider a review as a factual, precise, and truthful piece of information. It is indicated that the eWOM credibility is derived and positively affected by source credibility and argument strength and it has a positive impact on eWOM adoption in the social network [33].

The *product type* is the second moderator of the relationship between social networks and eWOM. Zhu and Zhang [2] summarized the previous literature and showed that research results are not conclusive about the effect of reviews on purchase decisions. They concluded that *product characteristic* is one of the moderators for this effect [2]. This moderating effect is more important when the product is an experience good, because its quality cannot be evaluated before consumption [34]. It is possible for prospective consumers to evaluate the product features for Search goods before the purchase decision by using information provided by the vendor or former customers [27]. However, for Experience goods, a customer only can evaluate them after purchasing and using them [2] or by gathering information by other costly ways.

The last but very important moderator of the relationship between social network and eWOM is *reviewer's motivation*, which is a well-studied research theme about reviewers who contribute in online communities. Different motives have been recognized that influence individuals writing online reviews. *Perceived risk level* of buying the product is one of them. Jurca et al. [35] showed that reviewers write more when they expect greater risk towards the purchaser. On this subject, researchers have borrowed from *knowledge sharing* and *Social Network* literature. Wasko and Faraj [6] investigated the relation between *social capital*, *individual motivation*, and *using social networks*. They have shown that *increasing professional reputation* is one of the motivations for people to contribute to social networks. It is consistent with the *reputation* and *peer pressure* argument in the WOM's motivation literature [7]. Other recognized motivations include *pleasure* or fun, *desire to influence*, *belonging* to the network, feeling responsible to *share the experience*, keep *self-record*,

satisfaction of the *cognitive needs*, and having a *strong opinion* (summarized form [6], [7], [36]).

On the other hand, the behavior of users on social network differs based on their motivations. It can be described in two categories. *Opinion seeking* and *opinion giving* behavior were identified as two main behaviors in social networks [16]. Opinion givers tend to be *Opinion leaders*. They were considered as an important part of market dynamics in marketing researches before [16], but the construct had never been measured. Flynn et al. [16] have adopted from the previous literature and defined *opinion leaders* as individuals whose opinion have a big influence on others' decision making. People, who have the intention or will to affect others' decisions, tend to communicate with others. They usually find WOM-related social networks are suitable bases to find their audience.

One important factor missing in the current literature is the change in reviewer behavior over time. Reviewers are influenced by above-mentioned mechanisms in social networks on the review-hosting websites. We do not understand if and why reviewers and the way they assess products changes over time and how this change is influenced by social networks on eWOM. Although some recent studies have treated reviews as a changing phenomenon over time ([37], [35], [38], [39]), no study has examined if and why reviewers change and how being part of a social network can affect this change. This research aims to fill this gap. We intend to examine how reviewers gain experience and if this experience affects the way they review products.

### 3. Conceptual model and Hypothesis development

An eWOM environment consists of *products*, *reviews* and *reviewers* as interrelated components which have a multilateral relationship in a context of the hosting platform. The platform itself has a well-established effect on both reviews and reviewers ([40], [27], [41]). Investigation of the interaction between all the components is challenging, if not impossible, to study them in a single research setting. Therefore, many studies have controlled for one or two components while studying others. Extant literature has focused on the interaction between these components ([2], [14], [14], [42], [11]).

Considering all these multilateral relationships, reviews that each reviewer writes over time is a dynamic phenomenon. We argue that as reviewers learn and mature, they change in the way they evaluate or review products. For example, controlling for the

product category and the reviewer, we posit that a reviewer gains knowledge from his/her own experience and learns from others associated with the review-hosting platform. In other words, a reviewer reviewing different products within the same category may change his/her reviewing behavior owing to his/her experiences, interaction with the platform and others associated with the platform.

We believe there are two main factors driving the change in reviewers' behavior. First, customer's satisfaction of the same product is a dynamic concept. In other words, people change over time in how they evaluate products. Their perceptions and expectations of the product increase and it gets harder to satisfy them. Research in marketing showed that the customer satisfaction judgment develops over time and *affect* and *Cognition* influence this process [43]. As mentioned before, both *affect* and *cognition* elements of the satisfaction decrease over time, which changes the customer's satisfaction of a specific product. Reviewers often join review-hosting websites with a low experience on evaluating products. Over the time, reading other reviews and writing their own, they gather some experience and develop some expertise and change in how they evaluate the products.

Second factor driving the change in reviewing behavior over time, is the effect of social network, associated with the review-hosting platform. Most of the online review-hosting platforms offer a range of social networking features. We posit that belonging to a reviewing social network, reviewers learn formally and informally from the social network around them on these review-hosting platforms. Learning mechanisms that affect reviewers through their social network affects their experiences and knowledge they gain on these platforms. This change is reflected in their reviews over time later.

### 3.1. Effect of Experience

Reviewers contributing to online review-hosting website are volunteers who spend their time and effort to share their experience about the products/services, with other prospective buyers. A majority of these reviewers are users who benefit from others' reviews and like to reciprocate to the online community. However, writing good reviews is no trivial task, which explains why only a few reviews are truly helpful [12]. In fact, users join review-hosting sites as beginners and learn to write good reviews over time. After gaining some experience, these users play both the roles- users as well as reviewers.

Literature on consumer behavior has shown that the customer satisfaction develops over time and *affect* and *Cognition* influence this process [43]. The customer

satisfaction with the same product type is a function of the comparison between expectation and the actual product. As the expectation grows over time, we expect the satisfaction to decline. We argue a similar phenomenon unfolds in online review environment. As users become experienced reviewers, their expectation of a product (book) is higher and they are likely to give a lower rating if the product/service fails to meet their expectations. We argue that as reviewers gain experience of a wide range of products, they develop their own benchmarks for high quality products and compare new products with their benchmarks. As a result, these experienced reviewers become tough evaluators and find a very few products worthy of highest ratings.

Writing reviews for books is different from writing reviews for other consumer products. Books are categorized as experience goods. Experience goods are products whose quality cannot be evaluated before consumption [34]. Hence, reviewers who wish to review a book need to read it before writing a review. Since books are an experience good, readers select books in a way to get a good experience. In other words, readers or reviewers gradually develop their taste for types of books they prefer or want to experience. Some users even list their favorite authors, genre, etc. on the web page. As reviewers gain experience over time, they use others' reviews and their own experience in selecting new books that they intend to review. Hence, these reviewers are more likely to choose top rated books in narrow bands of their taste to get a good experience. These top rated good quality books are less likely to get a lower rating from these reviewers. We argue that over time, these experienced reviewers are less likely to read and rate very low quality books.

The cumulative effect of these factors results in a lower spread in ratings given by these experienced reviewers. In other words, the ratings given by these reviewers are likely to converge to a narrow band of low and high ratings over time. Formally we hypothesize that:

*H1: The range of ratings given by a reviewer is likely to decrease over time.*

### 3.2. Effect of Specialized Skills

Expertise/skills of the reviewers affect how readers receive reviews. Connors, et al. [12] showed that self-described expertise of a reviewer affects his/her credibility and helpfulness of his reviews. A few empirical studies have also confirmed the positive correlation between reviewer expertise and helpfulness of their reviews [32].

One of the reviewer categories on this review-hosting site is *librarian*. Individuals, who have been contributing long enough on the website and claim to be a specialist about books, are designated as librarian by the review hosting community on this platform. As it is stated on the website's help, "*Librarians are volunteers who are dedicated to improving this sites' data. Librarians can edit book and author information, as well as combine separate editions of books to help aggregate reviews and ratings. Librarians are book experts who are familiar with a wide range of books from different authors and genres. These experts organize and manage books as well as reviews contributed by the reviewers. Being recognized as librarian signals reviewers commitment and contribution to the review hosting website.*"

Since the status of these experts is conditional on their knowledge and familiarity with a wide range of books, they are less likely to limit themselves to a narrow band of books of their taste. We argue that these book experts read and review a large variety of books of different quality to maintain their status as book experts. While covering a large variety of books, they encounter and rate books of varied quality and therefore tend to have a larger spread in their ratings compared to other reviewers. Hence, we argue that the range of ratings given by these reviewers is likely to be larger compared to other reviewers. Formally, we hypothesize that:

*H2: For book experts, the range of ratings is likely to be larger compared to other reviewers.*

### **3.3. Effect of Social Network**

On review hosting websites where users contribute to social good, altruism and reciprocity trumps personal gains. These website galvanize users to form communities where new comers learn from experienced and senior members of the community. In fact, a majority of online customer review websites supports some aspects of Social Networks. Users can follow celebrity reviewers and can be friends with others with similar interests.

Reviewers' motivation to contribute is critical for long-term sustainability of online review platforms. Motivated reviewers create the valuable content (online reviews) which attracts other users to these review-hosting websites. Following the literature on social networks and knowledge sharing, we believe that *Social Capital* is a critical motivation for contributors on the online review hosting websites ([6], [7]). Looking through the lens of online social networks, we find that reviewers on online review hosting websites play different roles owing to their

motivation and interests. For example, reviewers can be categorized as *Information Seekers and Information Givers* [17], [16].

A large social network can provide hoards of followers and supporters to information givers and at the same time, can be a treasure tove of information for information seekers, looking for the wisdom of the crowds. However, these review platforms may also cause an information overload to individuals connected to a large social network comprising of extremely active members.

**3.3.1. Information Givers (Leaders):** On the review-hosting websites, the social capital accrued by reviewing activities, is important for contributors [42], especially for *information givers* (leaders). The information leaders earn respect and leadership status in the community through their commitment to the community. These reviewers like to maintain their leadership status by providing high quality reviews ([6], [7]). We argue that, in order to maintain leadership and attract a broad range of followers/users, these information leaders have to review books outside of their personal interest to cover the taste of their friends and followers. In the process, these information leaders build a large collection of books that they have reviewed. A larger book collection is likely to include books with different quality and eventually affects the range of ratings given by these information leaders. We argue that the spread of ratings from these information givers is likely to be larger than other reviewers.. We hypothesize:

*H3: For the reviewers with a big book collection, the range of ratings is likely to be larger compared to other reviewers.*

**3.3.2. Information Seekers:** Individuals wishing to learn from the wisdom of crowds, flock to online review hosting websites. These information seekers make effort to gain information freely available in the community. Information on these review-hosting sites are available in various forms and at different levels. For example, to select a good book, one can go through a large number of reviews available for different books, or look through the books suggested by their social network, which requires less effort.

Prior literature has found that in social networks, users tend to connect with others with similar interests or same perceptual characteristics [44]. On these review hosting websites, users are also likely to connect with other users/reviewers with similar reading tastes. We contend that in order to learn from their social network, information seekers prefer to connect with a large number of friends with similar taste. These

individuals will be influenced by the information provided by their friends and will find their taste in books sooner. In their desire to seek information and draw from the wisdom of crowds, information seekers are likely to pick popular books recommended by most members in their social networks. The size of their social network allows them to narrow down on popular books of their taste, sooner and without much effort. In other words, we argue that they are less likely to read and review books too far outside of their taste and liking and hence, are less likely to have a larger spread in their book ratings. Formally, we hypothesize that:

*H4: For users with bigger social network, the range of ratings is likely to be smaller compared to other reviewers.*

**3.3.3. Information Overload:** In general, the Information seekers on social networks tend to connect to big networks and they work as conduit to pass on information from one large network to other or to individuals connected to them.

Information seekers by definition seek large amount of information. Having access to a large social network allows them access reviews and recommended book lists of their friends. However, the downside of this strategy is that these information seekers often end up with a very large friend list who had reviewed many books. Overall, the book collection from a users’ social network becomes very large. Information seekers have access to reviews and comments from their friends on this large book collection.

Being part of a large social network with a big related book collection coming from their friends, may result in an information overload even for these information seekers as they try to select their next book to read and review. It can delay the process of finding their own taste in reading. Worst-case scenario is that the user in this situation could end up reading books far outside their tastes which results in a larger spread in their review ratings. Formally, we hypothesize that:

*H5: Users with a bigger book collection from their social network, are likely to have a larger range of ratings compared to other reviewers.*

## 4. Method

### 4.1. Data Collection

To test our hypotheses and investigate the effect of social network on reviewers over time, we collected data from a third party review-hosting website. This site facilitates a platform to review books and is by far

the leading platform for online book reviews. As a social cataloging infrastructure, this website requires users to sign up to review books, and allows them to create their library catalogs and reading lists. Users also have the opportunity to communicate with their friends and other members of the site to discuss about books and reviews on this platform. At the time of data collection, the site reported 10 million members and 20 million monthly visits. By collecting data from this online book review platform, we have controlled the effect of product type in our data set.

For reviewing books, like all other review hosting platforms, users need to rate the product between one and five (Star ratings). They also can write a text review or comment on the book. Each book (as a product) has its own web page with the general information and reviews, the book lists it belongs to, and all community reviews. Users can connect to other members on the review-hosting site as friends, along with their own friends on the Facebook.

We have used a software agent to collect data and started with a randomly selected 500 books from the list “best books ever”. This list has over 20,000 books. Each user can vote for a book to be added in a list and a book can belong to many lists.

First, we collected all the reviews for these 500 books and then collected all the data about reviewers who wrote reviews for these books. For each reviewer we collected reviews and ratings with time tag. In summary, we have collected data on review/rating history of books and review and rating activities of reviewers. Table 1 shows a summary of the data set.

The users have joined this platform and started rating books at different times. For each user in our dataset, we have recorded their reviewing activity since they joined the platform. We have collected data about Volume, Valance, and textual reviews of the books.

**Table 1: Summary Statistics of the data**

Fixed effects	Value
Number of unique reviewers	719
Number of books	11,425
Number of unique book ratings	133,800

We are aware that fake reviews and *Forum manipulation* plague most of the review hosting platforms. However, we believe that this issue is mitigated in our dataset for two reasons. First, this website does not sell books and forum manipulation happens mostly on retailer websites, where customers make purchase decisions. Second, the dataset was randomly collected from the website therefore, fake reviews, if any, would be randomly distributed and less likely to affect our analysis.

We have collected data about reviewers since they joined the review platform. We have measured time in quarter, and computed a variable  $Score\ Domain_{ij}$  to capture the range of ratings given by a user.  $Score\ Domain_{ij}$  is the difference between the lowest and highest rating given by user  $i$  ( $i \in I$ ) in quarter  $j$  ( $j \in J$ ). The  $Time$  variable in our model for a user represents the number of quarters since they joined the platform.

This dataset captures characteristics of the reviewers and measures to gauge changes in their reviewing activities over time. For example, for each user we record the total number of books rated/reviewed since joining the platform ( $UserCollectionSize_i$ ), status on the website as a

Librarian ( $Expertise_i$ ), and total number of friends on this platform representing the size of their social network ( $ImmidiateSN_i$ ). This review-hosting website facilitates a platform where users communicate with other members with common interests. Users' desire to follow and connect with other members grows their social network. A user can access the book collection of any member in their social network. The total book collection from a user's entire social network become very large and is measured as and  $RelatedBookColl_i$ .  $RelatedBookColl_i$  is the number of books rated by all the friends (Social Network) of a user  $i$ . Some users use this list as a suggestion list for selecting their next book. Table 2 lists all the variables used in the model.

**Table 2: Variable list**

Variable	Meaning
$Score\ Domain_{ij}$	The interval between the lowest and highest score given by each user in each quarter
$Intercept$	The average of Score Domain for the population without considering the change over time
$Time$	One time period is a quarter of a year (90 days)
$UserCollectionSize_i$	Total number of books rated by a user
$RelatedBookColl_i$	Number of books rated by friends connected via social network
$ImmidiateSN_i$	The number of friends connected via social network for each user
$Expertise_i$	The status of user $i$ on the website as Goodreads Librarian, which is equivalent of active users, who has more access rights to change the profile page of books.

## 4.2. Model Specification

We have developed a mixed-effect model to test our hypotheses. We have treated each reviewer as a unique individual and tracked his/her reviewing behavior and its predictors over time. The model we have developed has two levels. The first level is capturing within-person changes for each reviewer. In particular, we investigate the change in the range of ratings given by a reviewer over time. This level covers the individuals' growth model (over time) to address the change of  $Score\ Domain_{ij}$  over time. The main independent variable in this level is  $Time$ . The  $\pi_{0i}$  and  $\pi_{1i}$  represent change parameters that shape the change of  $Score\ Domain_{ij}$  over time. The **level-1** model is as follows:

$$ScoreDomain_{ij} = \pi_{0i} + \pi_{1i}Time + (\varepsilon_{ij})$$

We extended our model using level one predictors including  $UserCollectionSize_i$ ,  $ImmidiateSN_i$ ,  $RelatedBookColl_i$ , and  $Expertise_i$  in the second level of our model which examines how reviewers are

different from each other in their behavior over time. This level's model is as follows:

$$\begin{aligned} \pi_{0i} = & \gamma_{00} + \gamma_{01}UserCollectionSize_i \\ & + \gamma_{02}ImmidiateSN_i + \gamma_{03}Expertise_i \\ & + \gamma_{04}RelatedBookColl_i + \zeta_{0i} \end{aligned}$$

$$\pi_{1i} = \gamma_{10} + \gamma_{11}UserCollectionSize_i + \zeta_{1i}$$

And the final model is:

$$\begin{aligned} ScoreDomain_{ij} = & \gamma_{00} + \gamma_{01}UserCollectionSize_i \\ & + \gamma_{02}ImmidiateSN_i \\ & + \gamma_{03}IsLibrarian_i \\ & + \gamma_{04}RelatedBookColl_i \\ & + \gamma_{10}Time \\ & + \gamma_{11}UserCollectionSize_i * Time \\ & + (\varepsilon_{ij} + \zeta_{1i} * Time) \end{aligned}$$

For predicting above-mentioned coefficients, we have used Xtmixed function from Stata package (11.2). Table 4 shows the estimated coefficients.

**Table 3: Descriptive Statistics**

	Min	Max	Mean	SD <sup>1</sup>
Score domain (%)	0	80	38.16	26.91
Time (Quarters)	1	20	7.102	4.82
UserColSize	.416	321.3	28.70	25.85
UserColSize*Tim	.416	2506.	195.1	224.7
ImmidiataSN	.045	504.7	10.4	34.40
Expertise	0	1	.11	.32
RelatedBookCol	0	100	12.53	12.14
<b>Book Experts</b>				
Score domain (%)	0	80	41.7	26.88
UserColSize	5.6	321.3	44.68	37.24
ImmidiataSN	0.66	301	23.06	46.6

**5. Analysis and Discussion**

First, we report the descriptive statistics of the data set in Table 3. We have reported the descriptive measures for Book experts and the whole data set.

Then we have estimated the time relevant coefficient. In the next step, we have added independent variables one by one and estimated the related coefficients. Model A in table 4, shows the estimated coefficients for variables. Then we deleted the insignificant measures and estimated the model again (Model B). As Singer and Willett [45] suggested, we have used measures of the deviance (AIC<sup>2</sup> and BIC<sup>3</sup>) as the goodness of the fit and selected the Model B as the better fit for the model. We observed that the Score domain (as the interval between the maximum and minimum of the star ratings in each quarter) is decreasing over time for individuals. This result supports our first hypothesis (H1).

Table 5 shows a summary of hypotheses and results. We find that except one, all of our hypotheses are supported. Our results confirm that range of ratings given by reviewers decrease over time. Our results also confirm the effect of social networks on how reviewers change the way they rate books over time. We have observed that the score domain (range of ratings) of a reviewer decreases by 2.16 percent in each quarter (H1). This convergence represents how users narrow down their taste in selecting books.

Studying the effect of specialized skills, we argued that book experts would review a large variety of books, which will result in a larger range in their ratings. Our data did not support this hypothesis (H2). One possible explanation is the nature of the product they are reviewing. Books are experience

goods and cannot be evaluated without being used (or read in this case). Users with specialized skills should spend time reading books to review them, which take lots of time and effort. So the cost of reviewing runs counter to desire of being book experts. However, this needs further investigation.

**Table 4: Models**

			Model A	Model B
Fixed effect	Intercept	$\gamma_{00}$	45.73 ***	46.22 ***
	Time	$\gamma_{10}$	-2.05***	-2.16 ***
	UserColSize	$\gamma_{01}$	0.176***	0.161***
	UserColSize*Time	$\gamma_{11}$	-.004	
	ImmidiataSN	$\gamma_{02}$	-.053***	-.053***
	Expertise	$\gamma_{03}$	1.78	
	RelatedBookCol	$\gamma_{04}$	0.099 *	0.104 *
	Variance	Within-person	$\sigma_e^2$	502.47 **
Initial Status (Constant)		$\sigma_0^2$	89.18 **	89.18**
Rate of change		$\sigma_1^2$	0.57 **	0.57 **
Covariance		$\sigma_{01}^2$	0.65 **	0.65 **
	AIC		57075.66	57074.33
	BIC		57149.73	57134.93

P<0.001\*\*\* - P<0.01 \*\* -P<0.05 \* -P<0.1 ~

People with the motivation of being information leader are likely to have bigger book collections. We argue that these users probably have written reviews on books outside their personal interests to provide a wide range of information for their followers to maintain their leadership in the community. The results have supported this interpretation and showed that the starting range of ratings has a positive relation with the book collection size (H3).

We also hypothesized that information seekers associated with a larger social network are likely to narrow down their taste quickly. In another word, the effect of time in decreasing the range of ratings will be accelerated for users with a larger network of friends and they are more likely to have a lower range of ratings. Our data support the relationship between the size of social network information seeking behavior of reviewers. The analysis showed that having a bigger immediate social network (number of friends) lead to a smaller range of ratings (H4).

Finally, we investigated the negative effect of social network on reviewing behavior. Users have access to the book collections of all members of their social network. The downside of this access could be the possibility of users ending up accessing or looking at a very large book collection. In other words, we argue that users who have a bigger list of book reviews done by their immediate social network, has a larger range in their ratings (H5). It

<sup>1</sup> Standard Deviation

<sup>2</sup> Akaike information criterion

<sup>3</sup> Bayesian information criterion

shows the delay in the process of finding their own taste in reading. This hypothesis was supported by our model.

**Table 5: Hypotheses**

	Hypotheses	Result
H1	The range of ratings given by a reviewer is likely to decrease over time.	Supported
H2	For book experts, the range of ratings are likely to be larger compared to other reviewers.	Not supported
H3	For the reviewers with a big book collection, the range of ratings is likely to be larger compared to other reviewers.	Supported
H4	For users with bigger social network, the range of ratings is likely to be smaller compared to other reviewers.	Supported
H5	Users with a bigger book collection from their social network, are likely to have a larger range of ratings compared to other reviewers.	Supported

## 6. Conclusions and Future Research

This research has explored the role of social network on reviewers on online review platforms. Reviewers use social networks in different ways to learn and gain experience, which eventually affects their reviewing behavior. We have shown the social network affect reviewers in direct or indirect manner. This is a preliminary work in this area and it has many limitations, future work is needed to explore this further. Future research will investigate how reviewers choose and form their social network based on their motivations. Another way of expanding this research is to investigate the quality of the reviews comparing to the real quality of the products, which are being reviewed.

We also believe that this research could have several implications on review-hosting platform. They have some mechanisms to identify and distinguish valuable reviewers by offering them some badges such as best users or top reviewers. Using the results of this research could be help eWOM hosting websites to develop methods to acknowledge users who create more values to their platform.

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