# The evolution of online reviewers

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## Abstract

Majority of the literature on online communities and online social media focuses on individual behavior and the effect of this behaviour on businesses and society. A few studies have also examined how users consume the content available on social media platforms and the effect of the content on individuals' behavior. However, we are yet to understand how the continuous participation of online community members influences and changes them. This effect can be studied in a *community of practice* in which members can frequently contribute and observe the reaction of others towards their contribution (Wenger, 1998).

The primary objective of this research was to investigate the member evolution in online Communities of practice over time. To achieve this objective, we focused on the members' behavioral changes in online community. To narrow down the research, we considered the evolution and change in online reviews in an eWOM community as a case for both *online communities* and *communities of practice*.

In a multi-publication thesis, we explored the evolution of online reviewer over time in a community of practice. We used the social theory of learning (Wenger, 1998) to explore the effect of the social learning components on the contributions of frequent product reviewers. We observed that the social learning process changed reviewers and consequently the volume and valence of their reviews. We also used the theory of e-tribulized marketing (Kozinets, 1999) to study the heterogeneity of the reviewers in the continuity of their contribution.

We showed that frequent reviewers learn by contributing to the eWOM community. Over time, they read and review less number of books but they books with higher quality. They become stricter in evaluating books in response to the social bias. They also lower the average of the *valence* of their evaluation. By an improved consumption experience (reading better books), they obtain higher standards. The higher the quality of the books, the higher the quality of reviewers' benchmarks would be. We also showed that the interaction of s*trength of social ties, the level of consumption activity*, and *reviewer's sidedness* could explain different behaviour in leaving the platform. We showed that the consumption activity has more predictive value about reviewers' on going contribution compared to the social tie and sidedness. We also showed that the mechanisms, policies, or badges that eWOM websites use to engage their frequent reviews and maintain their contribution are effective and decreases the decline in the contribution volume. We also showed that such engagement tools only affect the contribution *volume,* not the *valance.* Therefore, they do not affect the reviewer evaluations or judgments about the products.

# Dedication

This thesis is dedicated my best friend, my soul mate, and partner for life, my loving husband, **Roozbeh Yousefi** who gave me his dedicated love and support even when he was two oceans away. He sacrificed his career and followed me around the globe, which I truly appreciate. His enthusiasm toward my research and my academic career is my biggest motivation.

Dear Roozbeh, I would like to thank you today for all your sacrifices, and I wish I could do the same for you.

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I would like to acknowledge and thank Associate Professor, Dr. Arvind Tripathi, my main supervisor who always believed in me and guided and encouraged me with their wisdom and insight during the last five years. His unconditional support and patience with my complicated situation is the reason that I have reached to this point. I am proud of what I have achieved in my PhD as I have learned from Arvind, all along the way and I became a better researcher every day. He knew exactly when to push me for more work and when to give me space to rethink and redefine the research.

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I also want to acknowledge William English and Ron Tiong, who helped me as the proof-reader of the thesis as permitted by The University of Auckland policy on proof reading.

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Chapter 3: "Evolution of Online Reviewers: Social Learning Perspective"

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## List of original papers

### Paper 1

To be submitted


#### Abstract

A huge body of research on online social networks focuses on individual behavior in online communities, and the effect of this behavior on businesses and society. A few studies have also examined how users consume the content available on social media platforms or online communities and the effect of this content on individual behavior. However, we are yet to understand how sheer act of contributing or participating on social media or online communities influences/changes the participants. Are we the same people as we were when we first started contributing in online social media? This research focuses on the evolution and change in online users in an electronic Word-of-Mouth (eWOM) community to explain how *social learning* changes users/participants and how this change is reflected in their behavior.

Online customer reviews are informal communication between former and prospect consumers (Brooks, 1957). Each review provides the consumer's evaluation of the reviewed product. Moreover, reviews written by an individual about different products reveal information about the reviewer's product preferences. This inherent self-bias in online reviews (Li & Hitt, 2008; Hu, et al., 2006) reflects the reviewer's tendency toward a certain type of product.

Product reviewing is a social process (Alexandrov, et al., 2013) during which frequent reviewers gain experience and learn. The learning reflects on their reviewing behavior. Writing reviews in the online community of consumption gives reviewers the opportunity to gather social feedback, which is negatively biased (Goes, et al., 2014; Ofir & Simonson, 2001), and leads to a social bias in reviews posted by experienced reviewers.

Using longitudinal analysis, we studied historical reviewing behavior of users on a non-retailer review-hosting website. We observed that over time, frequent reviewers learn to become better reviewers while their own consumption experience improves.

We concentrated on the self-bias in reviewers and observed that it changes over time. At early stages, reviews are inflated by self-selection and the nature of the bias changes and leans towards social-bias. We also observed that engaging in the WOM community as a frequent contributor positively affects the consumption experience. Over time, frequent reviewers select and read books

with slightly higher quality. However, due to the social bias, not only do they experience better consumption based on their reviews over time, but also they become stricter in evaluating products. Moreover, we observed that although being part of an eWOM community boosts reviewers' social learning, the potential *information overload* may decelerate the learning rate and frequent reviewers are likely to decrease the *social network expansion rate* over time to respond to the learning barrier.


## Keywords:

eWOM, Self-selection bias, Social-bias, online community of consumption, Social Theory of Learning, Community of Practice (CoOP), Longitudinal Data Analysis

## Paper 2

To be submitted


### Abstract

A huge body of research on online social media focuses on the behavior of individuals in the online environment or the effect of this behavior on the business or society. Some researcher also studied the effect of social media content on individuals. What is missing is the effect that contributing in the social media has on reviewers. Are they the same people who joined the social media and started contributing? Also we do not know if the participation in online communities affects people and changes them and what drives the change in their contribution. This research focuses on the evolution and change in online users in an electronic Word-of-Mouth (eWOM) community to explain how the social process of learning affects their contribution level (review volume).

Using longitudinal analysis, we studied historical reviewing behavior of frequent reviewers on a non-retailer review-hosting website. We concentrated on the social learning components to explain the drivers and obstacles of reviewers' contribution. We observed a decrease in reviewing volume over time as reviewers gain experience. We concluded that reviewers whose motivation is to be recognized by the community or reviewers who perform community services have higher contribution volume. Also, reviewers who engage more with the features and function of the website have higher contribution volume. We also observed that where popularity (Baka, 2016), as the result of a big social network, is expected to initiate a rise in contribution volume (Goes, et al., 2014), the positive effect can be cancelled out by the interruption of cognitive learning in the social environment (Bandura, 1977). Social loafing and collective effort model (Karau & Williams, 2001) can explain this effect. We also conduct several robustness checks for potential issues to ensure the validity of our results.



### Keywords:

eWOM, Contribution Volume, Website Engagement, Online community, Social Theory of Learning, Social Loafing, Community of Practice (CoOP), Longitudinal Data Analysis

## Paper 3 (copyrighted)

Samiei, P., & Tripathi, A. (2015, December). Are Online Reviewers Leaving? Heterogeneity in Reviewing Behavior. In Workshop on E-Business (pp. 126-142). Springer International Publishing.

Available at:

http://link.springer.com/chapter/10.1007/978-3-319-45408-5_11


## Abstract

Online consumption communities evolve over time and go through different stages in their life cycle (Iriberri & Leroy, 2009). The key factor of the sustainability of the community is members' ongoing contribution. This study examines the factors affecting the ongoing contribution of online reviewers for different types of users. Drawing from theory on communities of consumption (Kozinets, 1999) and popularity effect (Goes, et al., 2014); we propose a conceptual model of drivers of ongoing contribution. We observed that social ties, sidedness, and consumption activity could explain the heterogeneity of ongoing contribution level for different users. We studied a community of book reviews. We showed that the effect of sidedness on contribution prediction is stronger for reviewers with extreme behaviour. We also concluded that consumption activity has more predictive information about the contribution compared to social ties and sidedness.



## Keywords:

eWOM, Social ties, Consumption activity, User Type, Community of Consumption, Sidedness

# CHAPTER 1. Introduction

## 1.1. Research motivation

### 1.1.1. Sustainable online communities

An online community is a computer-mediated communication platform in a social group (Rheingold, 2000). Although online communities may have some specific characteristics, in their nature "a web [online] community is simply a community that happens to exist online, rather than in the physical world" (Kim, 2000). The social and personal benefits of engaging in any community, including online communities, can be, but not limited to, *Information exchange, Social support, Social interaction, Time flexibility, Permanency and availability* (Iriberri & Leroy, 2009)

One of the important online communities that gain enourmous contribution from online users are eWOM communities. Electronic Word-Of-Mouth (eWOM) participants also engage in communication with a networks of people. These types of networks are considered to be online communities as 1) people have mutual shared interest in either products or activities, and 2) members do not know each other in real world and rely only on the online environment for their relationship (King, et al., 2014).

Online eWOM communities, same as traditional communities, evolve over time and go through different stages in their life cycle including *Inception phase, Creation, Growth*, *Maturity*, and *Termination* (Iriberri & Leroy, 2009). Different quantitative metrics can be used to measure the success of online communities; for example, size or the number of members, participation rate in form of number of visits or hits, contribution rate in the community such as the the number of posts, or relationship developments such as contact between members (Iriberri & Leroy, 2009). No matter how we measure success, maintaining the same level of success over time defines sustainability since the communities survive and thrive that can maintain their members' commitments and contributions; if the community loses its usefulness for the members, they may leave (Wenger, et al., 2002) and consequentially the community attraction will decrease for new members.

### 1.1.2. Social learning in online communities

Members of online communities have different motivations for membership and contribution. Community members participate based on their diverse motivations and have different behavioural patterns. *Belonging to the community* and *social bonding* is one important motivation for members' contribution. In addition, self-efficacy and satisfaction of cognitive needs, as well as developing a social identity, and the desire to help others by sharing one's experience are important motivations for the community's contributors (Harper, et al., 2005; Wasko & Faraj, 2005; Munzel & Kunz, 2014; Krasnova; Hildebrand; Guenther; Kovrigin; Nowobilska, 2008; Matta & Frost, 2011; Mackiewicz, 2010; Iriberri & Leroy, 2009). In addition to personal satisfaction, online communities provide *social* and *personal* support for their members; one intangible benefit of contributing in online communities is *self-satisfaction* and pride in fulfilling their altruistic goals in helping others (Iriberri & Leroy, 2009).

However, individual's motivation to contribute and socially interact with others may change over time. In a social process, even in the absence of reinforcements and just by observation, the behaviour learning can occur. The *Social Learning Theory* (Bandura, 1977) suggests that a new behaviour can be learned throughout the process of observational learning. The learning happens through the iteration of *attention, retention, reproduction, and motivation* phases (Bandura, 1977). In each iteration, individuals may revisit their motivations consciously or implicitly. This social and cognitive process results in members' social and observational learning. The learning is not limited to changes in one's motivation. Community members gain experience by observing the impact of their contribution on the community, interpret and learn from the feedback they receive from the community, and later their behaviour to respond to the feedback, hoping to satisfy their motivations.

The current literature goes as far as understanding of the underlying motivation for contributing to the community. To the best of our knowledge, there is no published research on how the motives of the members change over time or how contribution of members is distinct according to their motivations.

### 1.1.3. Communities of practice (CoOPs)

One type of online communities are *communities of practice*. A *community of practice* is "group of people who share a concern or a passion for something they do and learn how to do it better as they interact regularly" (Wenger, 2011, p. 1). Individuals in a community of practice perform the central activity that the community has shaped around. By repeating the activity, receiving and interpreting the feedback from the others, the community members learn to adjust their behaviour to fit into the community. Acting as a social being is an important element of learning in a Community of a Practice (CoOP). For active members of the community, belonging to the community and getting feedback is a learning process. Since the learning is not only a cognitive process but also includes social process (Lave, 2009; Bandura, 1977), belonging to the community facilitates the learning mechanism for members with frequent participation. In such communities, the participation and learning happen simultaneously, and the learning process does not need a separate or specific setting.

## 1.2. The contextual framework

### 1.2.1. Research objective

The majority of the literature on online communities and online social media focuses on individual behavior and the effect of this behaviour on businesses and society. A few studies have also examined how users consume the content available on social media platforms and the effect of the content on individuals' behavior. However, we are yet to understand how the continuous participation of online community members influences and changes them. This effect can be studied in a *community of practice* in which members can frequently contribute and observe the reaction of others towards their contribution (Wenger, 1998).

The primary objective of this research was *to investigate the member evolution in online Communities of practice over time*. To achieve this objective, we focused on the behavioral changes in online community members. To narrow down the research design, we considered the evolution and change in online reviews in an eWOM community as a case for both *online communities* and *communities of practice*.

Selecting an eWOM community to study the change in reviewers' behavior gave us an excellent opportunity to contribute in both literature areas. By focusing on change in reviewers' behavior over time, we have contributed to fulfilling the existing gap in the eWOM literature on the change of reviewers'' behaviour over time. As we explain in detail in the next chapter, a vast body of literature focuses on eWOM and its content and the eWOM community members. Whereas, the change in reviewers' behavior over time did not get that much of attention to the date of writing this report. Therefore, our final research objective is:

> ***Research objective****: To investigate the evolution of online reviewers in an eWOM community as a community of practice*

### 1.2.2. Research scope

This study is bounded by the overlap of *online communities* and *communities of practice.* Between all different types of online communities, we are only interested in the communities in which members contribute repeatedly and continuously and have the opportunity to observe the feedback resulted by their contribution. The conjunction of such community with the eWOM community is the focus of this research. Figure 1-1 schematically summarizes the scope of this study. The * sign is the focus of this research, which is at the intersection of *online communities*, *communities of practice,* and *eWOM.*

To achieve our objective, we have selected the following boundaries and limitations:

- The focus of the study is on the behavioural change as the result of the frequent contribution. Change in individual behavior because of any change in their personal characteristics or behavior adjustment in response to a fundamental environmental change is not within the boundary of this research.
- We only focus on community members (online reviewers) who actively participate in the community. Individuals are heterogeneous in their contribution pattern to the community (Hartmann, 2015; Munzel & Kunz, 2014). We aim to study the behavioral change of active contributors.
- We only focus on online communities of practice whose members provide product reviews. We do not claim about the generalizability of our results to any other type of community.

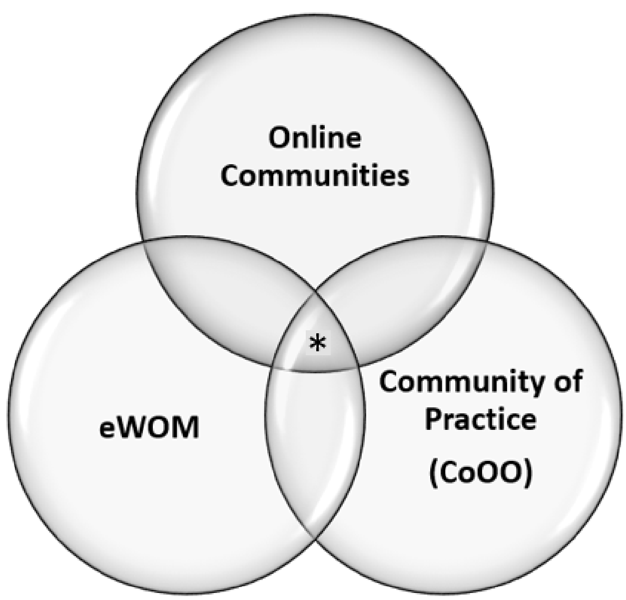



**Figure 1-1: The research scope**

### 1.2.3. Research question

To investigate the evolution of online reviewers in an eWOM community within the boundaries of this study, we limited our study to individuals who actively participate in the eWOM community. We took data samples and designed this research to answer following research question:

> ***Main research question****: what drives the change in the reviewing behaviour of frequent online reviewers?*

As we selected our sample between active members of the eWOM community, the change in their behaviour is expected to be a change in either the volume, content, or the continuity of their contribution.

Drawing on Goes et al. (2014) analysis, although the volume and valence of the reviews can be treated in model separately, their change cannot be interpreted as independent phenomena. Both volume and valence shape reviewers' behaviour and are affected by the same personal and social factors.

Therefore, we have three distinctive but deeply related research questions that we have investigated. We report the answer of each research question in one separate chapter in this thesis.

> ***Research question 1****: Do reviewers change over time in how they review or evaluate the product/services, and does their association with the eWOM community explain this change in reviewing behaviour?*

> ***Research question 2****: How does the contribution level of reviewers change over time, and can reviewers' association with the eWOM community this change?*

> ***Research question 3****: what drives the heterogeneity in the ongoing contribution of online reviewers?*

The result of the investigation of the research question 1 is reported in chapter 3 of this thesis and the other two questions are addressed in chapter 4 and 5 respectively.

### 1.2.4. Theoretical approach

In attempt to address our research questions we selected the *social theory of learning* (Wenger, 1998) as the theoretical foundation of this research. Wenger (1998) suggests that in a *community of practice,* individuals learn through a social process. We believe that an eWOM community is a community of practice in which people engage with reviewing. We believe that the learning in an eWOM community have different dimensions such as learning the reviewing skills. Moreover, the learning can reflect on other categories of behaviour such as purchasing decision or selecting products to review[1]. The Social Theory of Learning (Wenger, 1998) explains how learning and knowledge acquisition happen when individuals perform activities in a Community of Practice (CoOP), and observe and interpret the feedback from the environment they are working in. According to Wenger's theory (Wenger, 1998) the learning happens when individuals digest the meaning of their experience with their engagement in the society. Wenger (1998) explains that the learning process has four main components: Learning by ***practice, identity, meaning,*** and ***in the community.*** A detailed description of the theory will follow in the next chapter.

### 1.2.5. Context and research data

#### *1.2.5.1. Data collection process*

We collected the data from an eWOM community on book review website. At the time we started data collection in 2012 the website had 10 million users that increased up to 20 million in July 2013 and 50 million in December 2015 when we collected the last round of data. We used a crawling software to visit publicly available pages on the website. Visited web pages included products (books) and reviewer profiles. We started data collection with 500 randomly selected books. The crawler agent collected the reviews of the initial list and visited the profile page of the reviewers accordingly. The reviewers profile data were collected. The software agent also obtained a complete reviewing history of each reviewer whose profile page was visited. The history included all reviews that each reviewer had wrote since the first day that they have joined the website up to the date of data collection.

We ran an incremental data collection in five waves started from July 2012 until December 2015 to collect the behavioural data on reviewers in different occasions[2]. To ensure about the randomness of the sample, at the first wave of the data collection in 2012, the book and reviewer selection was performed randomly and by the crawler. After cleaning the data, we wound up with the usable data and complete reviewing history of 719 users. These 719 reviewers shaped our sample and in all next data collection waves, we visited their web page and collected incremental data on their new reviews, status, and activities.

#### *1.2.5.2. The data set*

Our dataset includes more than 81,233 books, reviewed by 719 users whose profile data including cross sections of individual-related variables were captured. We have overall 10941 individual-

[1] Different types of learning in an eWOM community are discussed in detail in chapter 3 and 4.

[2] All references, addresses, and names are deleted as we do not have the formal permission from the website. The detail can be provided upon request.

quarter records of around 36 quarters. In each publication (chapter 3-5), we have collected some supplementary data to support the research design.

To ensure that the data set is comparable to what has been used in literature, we compared its descriptive statistics with similar data sets. As an example, the average review of all books in the data set is comparable with the literature (Chevalier & Mayzlin, 2006; Hu, et al., 2006).

### 1.2.6. Research approach

The general approach in this research is as follows:

- ***Research type:*** based on validation literature in Information Systems research (Straub, 1989, p. 149), we mostly performed a confirmatory research as a quantitative empirical study with statistical techniques for theory testing. However, chapter 5 is quantitative explanatory research.
- ***Data type:*** As mentioned above we collected a panel data including a cross-section of data on reviewers over time.
- ***Data analysis:*** In two out of three papers of this research (Chapter3 and 4), we have used the longitudinal data analysis method (Singer & Willett, 2003) with a multi-level and mixed-effect models. In the last paper (Chapter 5), we have used non-parametric statistical tests.
- ***Data analysis:*** In two out of three papers of this research (Chapter3 and 4), we have used the longitudinal data analysis method (Singer & Willett, 2003) with a multi-level and mixed-effect model. In the last paper (Chapter 5), we have use non-parametric statistics tests.
- ***Validation and robustness:*** To ensure the robustness of analysis and the validity of the results, we ran procedures and reported the results on *data validity, construct validity* and, *method robustness* (Straub, 1989). Detailed report is presented in each paper (chapter)

## 1.3. A summary of findings

Frequent reviewers learn by contributing to the eWOM community. Over time, they read and review less number of books but they books with higher quality. They become stricter in evaluating books in response to the social bias. They also lower the average of the *valence* of their evaluation. By an improved consumption experience (reading better books), they obtain higher standards. The higher the quality of the books, the higher the quality of reviewers' benchmarks would be. We also showed that the interaction of s*trength of social ties, the level of consumption activity*, and *reviewer's* *sidedness* could explain different behaviour in leaving the platform. We showed that the consumption activity has more predictive value about reviewers' on going contribution compared to the social tie and sidedness.

We also showed that the mechanisms, policies, or badges that eWOM websites use to engage their frequent reviews and maintain their contribution are effective and decreases the decline in the contribution volume. We also showed that such engagement tools only affect the contribution *volume,* not the *valence.* Therefore, they do not affect the reviewer evaluations or judgments about the products.

## 1.4. Thesis structure

The rest of this thesis is organized as follows. In chapter 2 we present a summary of the literature in each area of the triplet research model (Figure 1-1), followed by the summary of the theoretical foundation of the research. In Chapter 3, we address the question about how learning explains reviewers' evaluation of products (*review valence*) changes over time. Chapter 4 focuses on how reviewers' contribution level (*volume*) changes over time. In Chapter 5, we point out the heterogeneity of reviewers in their reviewing behaviour. We focused on how this difference can explain the continuity of their contribution. Finally, Chapter 6 is a summarises the findings of all three papers, followed by answering the research question and suggestions for future research.

# CHAPTER 2. Literature review

In this chapter, my objective is to review the current literature on three main concepts that lead this research which are *electronic Word-Of-Mouth* (eWOM), *online communities,* and the *social theory of learning*. These three concepts provide a baseline for this research. However, I only provide a brief and general look to each concept as all following chapters are written as submitted or ready-to-submit manuscripts and contain the detailed and extended relevant literature. The chapter starts by presenting the general literature on *eWOM*. Then I move on to the *online community* literature. After introducing two important types of online communities, I will focus on the dynamic of heterogeneity individuals' *contribution in online communities*. At the end, I will briefly go through the *learning theories* focusing on the *social theory of learning*, which is the underpinning theory of our research. The chapter finishes with summarizing the gap in the literature that I intended to cover.

## 2.1. eWOM literature

### 2.1.1. Definition

The concept of WOM was mainly studied in the marketing research area and was defined as the *use of informal networks between people with interpersonal relations to promote new products in the marketplace* (Brooks, 1957). Brooks' research was about selling new products using WOM advertising. He noted that WOM from a peer group has an effect on purchasing decision. This argument stood for a long time and WOM is considered as one of product sales' important drivers, even before the availability of cost-efficient websites for hosting large-scale reviews (Li & Hitt, 2008).

With low-cost and general access to the internet, customer reviews and WOM can be accessible from anywhere, efficiently, and rapidly. Therefore, electronic WOM (eWOM) is the best and the most economical way for customers to gather information about products before any purchase decision is made. The effectiveness of eWOM is stronger for experience goods such as books (Nelson, 1970).

### 2.1.2. Summary of the research on eWOM

An enormous amount of research has been done on the subject of eWOM. In the early stages, most of the research was in the marketing discipline and focused on the WOM and its effect on products' sales (Shen, 2009; Liu, 2006; Zhang & Dellarocas, 2006). Later research focused on the eWOM as the online infrastructure affected the nature of WOM and how it was produced, shared, and received by people.

Some manuscripts tried to summarize and consolidate the eWOM current literature. Two of them, to the best of our knowledge are more comprehensive, which we briefly introduce:

#### *2.1.2.1. The communication model*

Cheung and Thadani (2012) differentiated between WOM and eWOM, identifying some specific characteristics of eWOM. These characteristics are *scalability and speed of diffusion, persistency and accessibility,* and *measurability*. They summarized the eWOM literature, which to the best of my knowledge is the most comprehensive summary model of the literature to the date of writing this thesis. They rightfully assumed that eWOM is a form of communication between former and prospective consumers. They used the social communication model (Hovland, 1948) in which communication is a process whereby individuals (*communicators*) transmit *stimuli* to affect other individuals (*receivers*). Figure 2-1 is a glance of their integrative framework in which the main components are *communicators, stimuli, receivers, responses,* and *contextual factor.* In the following sections, we draw on their model and summarize the literature that we used to design and perform this research.

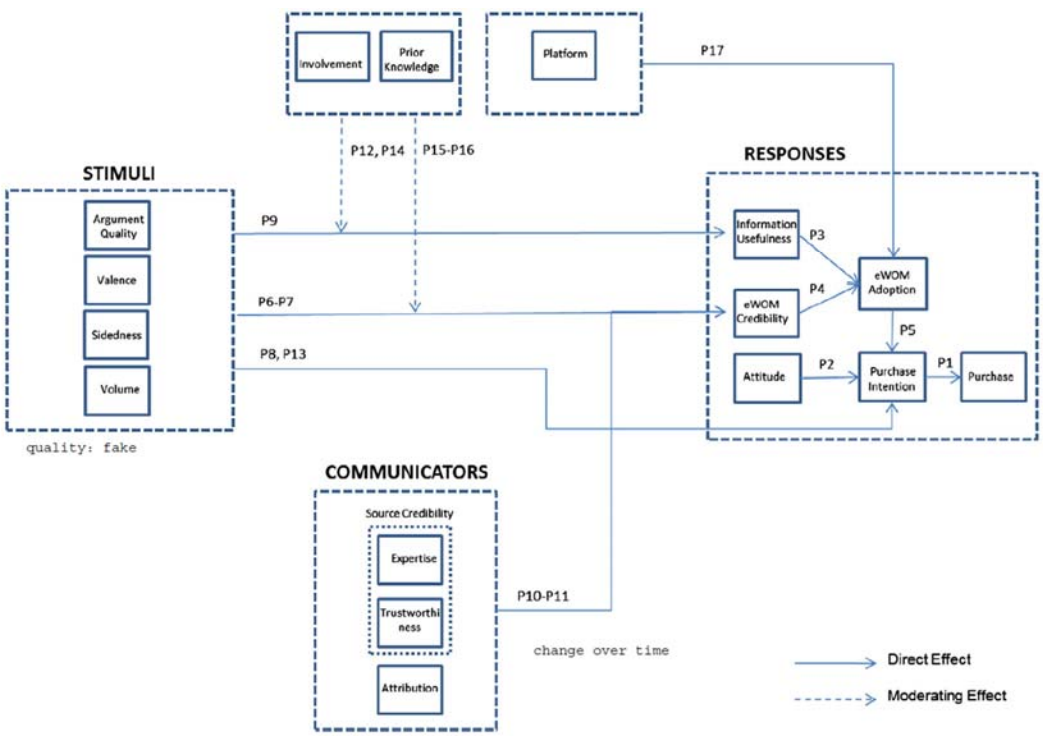



**Figure 2-1: An integrative framework for eWOM communication (Cheung & Thadani, 2012)[3]**

[3] This figure is an exact screen shot of the model in the reference paper.

### *2.1.2.2. The synthesis approach*

To consolidate the eWOM literature, King et al. (2014) suggested a two-dimensional model inspired by the current literature. One dimension includes *antecedents* and *consequences* of eWOM, which is the same categorization that Goes et al. (Goes, et al., 2014) used later. The second dimension is the unit of analysis, which only covers the *sender* and *receiver* of eWOM. These two dimensions make up four areas that each has its own characteristics and unanswered research questions. Figure 2-2 shows the overall model.

eWOM organizing framework (adapted from Nyilasy 2005).

| | | Study | |
|---|---|---|---|
| | | Antecedents of eWOM (causes) | Consequences of eWOM (effects) |
| Unit of analysis | Sender of eWOM | Q1: Antecedents of eWOM senders — why do people talk online? | Q2: Consequences to the sender — what happens to the communicator? |
| | Receiver of eWOM | Q3: Antecedents of the receiver — why do people listen online? | Q4: Consequences to the receiver — the power of eWOM |

**Figure 2-2: The eWOM organizing framework (King, et al., 2014)[4]**

Using this framework to summarize the literature, King et al. (2014) identified research gaps in each area and suggested a list of potential research questions that should be addressed by researchers to cover these gaps (Figure 2-3).

Although this model (King, et al., 2014) has an interesting overview of the literature, we adopted the model suggested by Cheung and Thadani (2012) as it is comprehensive and considers more components beyond a receiver and sender of the eWOM message.

## 2.1.3. eWOM content as the stimuli

Research on eWOM as the stimuli can be categorized in different sections. eWOM content include numerical *ratings* (known as stars) and *textual reviews. Volume* and *valence* of the rating as well as the textual reviews are different aspects of the content.

### *2.1.3.1. Volume*

Volume usually is the number of reviews posted about one product. There is a large body of literature using online reviews volume and valence especially when investigating the effect of reviews on sales, revenue (Shen, 2009), or customers' attitude (Lim & Van Der Heide, 2015). It has been established that when a product has a higher volume of reviews, the number of potential customers knowing about it will increase. This awareness has an impact on the product sales (Liu,

[4] This figure is an exact screen shot of the model in the reference paper.

2006). There could be other possible explanations of how the volume of reviews affects sales. For example, describing the observed positive effect of volume on sales, Archak et al. (2011) argued that this could be related to risk aversion. It means that when buyers are faced with two similar products with the same average rating, they prefer the one with the larger volume of reviews as they have more information on the product.

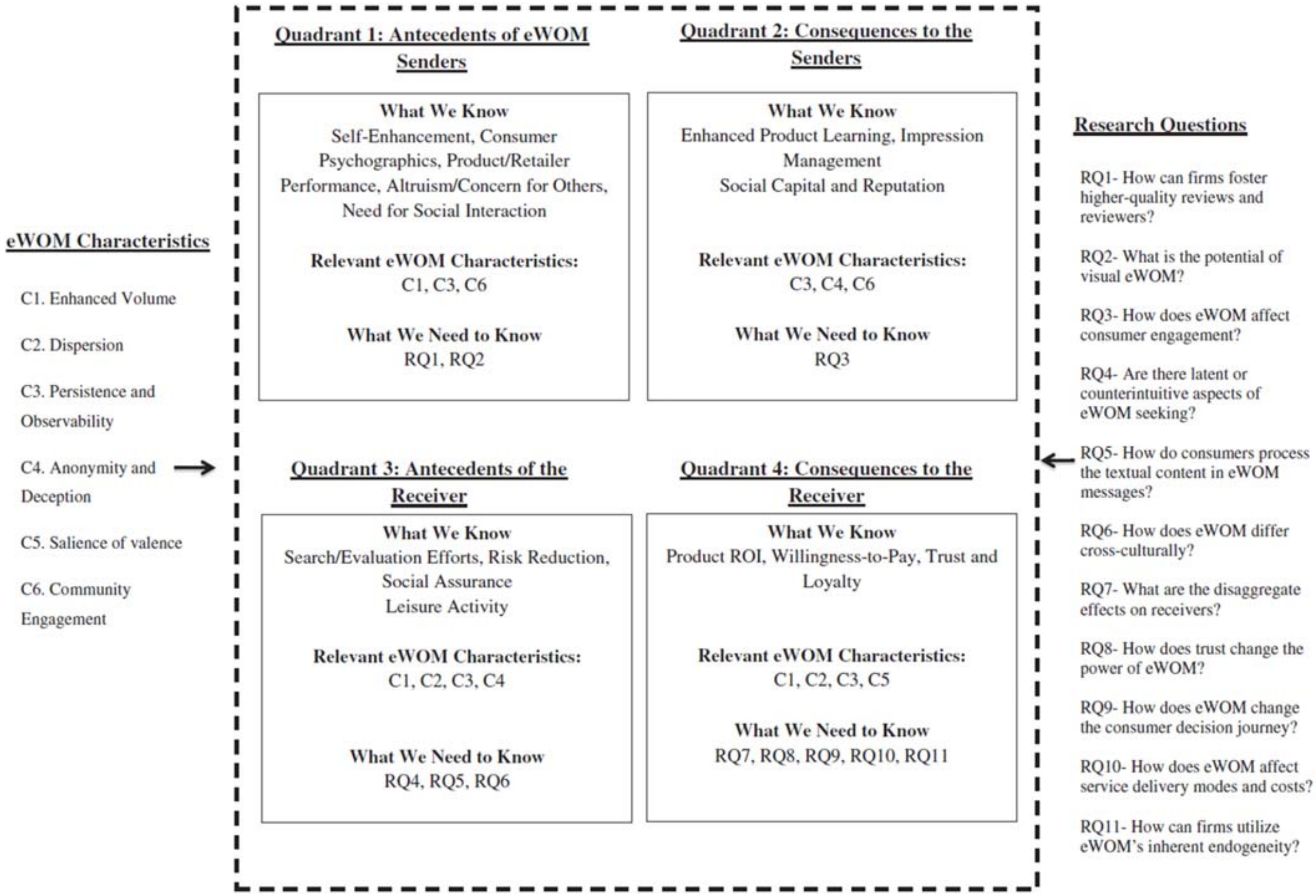



**Figure 2-3: The eWOM framework (King, et al., 2014)[5]**

The literature mostly uses the volume as the number of ratings posted about a product. However, from a different perspective, volume is sometimes used to measure the number of reviews posted by one reviewer. It worth mentioning that in chapters 3, 4, and 5 of this research, we used *volume* according to the latter definition. We have tried to always specify its type by stating it as *"contribution volume*".

[5] This figure is an exact screen shot of the model in the reference paper.

#### *2.1.3.2. Valence*

Valence reflects the reviewers' positive or negative evaluation of the product, which is an important characteristic of stimuli. Many researchers have studied valence and whether it has any effect on a product or service's revenue. Some like Zhang and Dellarocas (2006) or Lime et al. (2015) found that valence (star ratings for movies in their case) has a positive impact on a product's sale, which was consistent with former research on the possibility of revenue forecasting based on the valence of early online reviews (Dellarocas, et al., 2004). At the same time, some other studies could not show any significant effect of valence (Liu, 2006). Considering these inconsistent results, Hao et al. (2010) tried to find moderating factors in the relationship between *valence* and *sale*. They used attribution theory and prospect theory and showed that the consideration of product type as an active factor can explain existing inconsistent results.

#### *2.1.3.3. Textual review*

Textual reviews are a large portion of eWOM content and contain information about both the reviewer and the product. Some researchers have studied textual reviews. For instance, Gebauer et al. (2008) used textual reviews and by systematic content analysis of textual reviews, they extracted the implied requirements for mobile technologies. They focused on user-perceived system requirements. The purpose of their research was seeking to identify factors related to the overall user evaluation of mobile technology devices that target business users. Other researchers used automated text mining to extract products' features from reviews too. Combining the result from this method with a theoretically motivated econometric model, they could explore the effect of textual reviews on product purchase decision (Archak, N; Ghose, A; Ipeirotis, P G, 2011). Their findings showed that the textual content in product reviews has significant predictive power for consumer behavior. It explains a large part of the variation in product demand over and above the impact of changes in numeric information such as product price, product age, trends, seasonal effects, and the valence and volume of reviews. Another research also used text analysis recently to discover product features. They analyzed textual reviews to suggest a ranking system for hotels (Ghose, et al., 2012).

#### *2.1.3.4. eWOM characteristics*

Researchers in both marketing and information systems disciplines have focused on different characteristics of eWOM content such as:

***Review helpfulness***

Review *helpfulness* or *usefulness* is a mutually correlated concept in eWOM literature. The definition of the usefulness of an e-commerce website is the level to which the website helps customers to do their shopping (Kumar & Benbasat, 2006). Review usefulness has the same meaning as research showed that the review's usefulness affects the purchase intention of customers (Li & Tang, 2010). The a*rgument quality* and *source credibility* are dimensions of the helpfulness concept (Wang, et al., 2011) and reviewer and review characteristics have significant correlation with the helpfulness of the review (Racherla & Friske, 2012). For example, reviews from popular users or high-expertise ones are considered more useful where the user expertise is context-dependent (Hee, et al., 2011). The *product type* also affects the review helpfulness (Mudambi & Schuff, 2010).

The helpfulness is one of the characteristics of the review which can be measured and explained by how review receivers respond to the review (Cheung & Thadani, 2012). Regardless of how helpfulness is categorized in the literature, the review content determines how helpful the review. Some influencing factors are: review depth (Mudambi & Schuff, 2010), semantic characteristics (Cao, et al., 2011), review length (Jurca, et al., 2010), being concrete instead of abstract (Li, et al., 2011), readability of the review (Korfiatis, et al., 2011), subjectivity, informativeness, and linguistic correctness (Ghose & Ipeirotis, 2011). On the other hand, not having enough information, being biased or being extremely emotional are some characteristics of unhelpful reviews (Connors, et al., 2011).

***Sidedness***

Reviewers are different in their reviewing sidedness. The sidedness is how positive or negative a review is. If the review only focuses on the positive or negative points of a product, it is one-sided. Some reviewers only mention the negative aspects of the product probably assuming that the vendor already communicated all the good features and positive points of the product. On the other hand, a two-sided or balanced review covers both positive and negative aspects of the product (Cheung & Thadani, 2012). Sidedness has an effect on how the receiver of the review trusts and adopts the review by affecting the perceived helpfulness of the review (Connors, et al., 2011) and the credibility of the reviewer (Cheung & Thadani, 2012). Sidedness also has an effect on the customer purchase decision making (Park & Lee, 2009) which is moderated by the product type and website reputation.

***eWOM credibility***

The credibility of the eWOM content is the receiver's judgement of how factual, precise, and truthful the review is. The literature determined that eWOM credibility is correlated and positively affected by the source credibility and argument strength, and it has a positive impact on eWOM adoption (Cheung, et al., 2009). The argument quality increases the credibility of the review (Cheung, et al., 2012) and then affects adoption. However, there is a difference between the *eWOM credibility* and the *reviewer's credibility*. The reviewer's credibility reflects the reviewer's trustfulness and can be measured as the aggregated measure of the the credibility of the review on all her/his contributions (Zhang, et al., 2012).

### 2.1.4. Reviewers as communicators

Reviewers who generate the review content are considered as *communicators* in the eWOM literature summary (Cheung & Thadani, 2012). They have different characteristics and motivations, which can explain different behavioral patterns to some extent. Researchers have studied their *characteristics* and *motivations* to understand the heterogeneity in their behavior.

#### *2.1.4.1. Reviewer characteristics*

Reviewers divide their time, as a limited resource, between using and generating online reviews (Ghose & Han, 2011). How they assign their time makes their behavior different. Reviewers' behavior is different in both choosing the product to review and how they write their review (Shen, 2009). Despite more than a decade of investigation of this phenomenon, current literature is not comprehensive in explaining reviewers' behavior and its change over time.

***Source credibility***

The *source credibility* in an important and well-investigated communicator characterstic. The literature suggested a way to define and measure a reviewer's credibility. In this measuring algorithm, the customer's credibility decreases if they give a good rating to a bad product and vice versa (Zhang, et al., 2012). The source credibility also affects the attribution of the reviewer. The *attribution* shows how the receiver of the review perceives the person who wrote the review (Cheung & Thadani, 2012). If the review only contains arguments and points about the product and the reviewer seems to be un-biased, the receiver is more likely to consider the review helpful, and it affects the purchase decision. On the other hand, if the relevance of the review content to the product is not clear or there are signs of a biased reviewer, the probability of considering the review in the decision making process decreases. This was one of the reasons that Amazon.com has changed its policy about the reviews. Many of the reviews written by relatives, employees, or colleagues of the writer or publisher of a product were considered biased and therefore removed in 2012 (Streitfeld, 2012). Also, source credibility has two dimensions: *expertise* and *trustworthiness* of the reviewer (Cheung & Thadani, 2012).

***Expertise***

Research showed that people who read online reviews not only pay attention to the review content, but also consider the reviewer's data such as her/his reputation and exposed experience (Hu, et al., 2008). The expertise "implies an in-depth mastery of a field of knowledge" and product expertise can be implied by the assertion of product-specific experience or the assertion of familiarity with the related products (Mackiewicz, 2010). Therefore, a reviewer's expertise enhances the credibility of the reviewer. Connors et al. (2011) showed that a reviewer's self-stated expertise has a positive impact on the review's helpfulness. Furthermore, research showed that reviews from high-expertise people are considered more useful (Racherla & Friske, 2012).

***Trustworthiness***

Where the reviewer's *credibility* concentrates on the possibility of the biasness of the review, the reviewer's *trustworthiness* addresses the possibility of the review being fake or untruthful. For example in 2012, an entrepreneur in the United States started to sell positive book reviews to self-published authors. He has a contract with authors who have books in Amazon.com to boost the rating for their book (Tenner, 2012). Li and Hitt (2008) called this *forum manipulation*. By their definition, it happens when firms use professional reviewers to change the actual rates on their products. Since review communities let these kind of arrangements happen, trusting the communicator who writes the review is even more important.

They are ways to identify untruthful reviews and reviewers. Research showed that misleading or fake reviews are different in their language structure. The result of Yoo Cheung and Gretzel (2009) showed that fake reviews were much alike true reviews and marketers are good liars. However, trustful and deceptive reviews were different in language complexity and use of self-pronouns (Yoo & Gretzel, 2009). Brand and product names (hotel name in their case) were mentioned repeatedly in them. None of these differences can determine fake or misleading reviews with certainty but as this research suggests, they can raise a red flag, and numerous flags can raise the question of untrustworthiness of a specific review (Yoo & Gretzel, 2009). In addition, based on computational rules from psychology and linguistics, research showed that in addition to the review text, the context and possible motivation of fake reviewers should be considered to detect deceptive reviews (Ott, et al., 2011). The possibility of reviewers writing deceptive reviews also depended on the community. If the reviewing cost is low, the deception rate is higher where the cost is the requirement for posting a review. They also showed that by changing the policies to increase the cost, for example, by deleting the reviews by first or second time reviewers the prevalence of deception decreases in the community (Ott, et al., 2012).

#### *2.1.4.2. Reviewer Motivations*

Members of online communities may receive social and emotional support from other members. Moreover, the third benefit they might obtain from their participation is the self-satisfaction and pride for fulfilling their altruistic goals in helping others (Iriberri & Leroy, 2009). The expected benefit can act as their motive and based on their motivation, online reviewers, as community members, may have different behavioral patterns. Not all the potential motivations are altruistic. Some reviewers may have *egoistic* motivations. For example, Jurca et al. (2010) showed that reviewers write more when they expect greater risk for the purchaser.

| **Motivation** | **(Nobarany, et al., 2012)** | **(Chen & Huang, 2013)** | **(Wasko & Faraj, 2005)** | **(Zhang & Dellarocas, 2006)** | **(Munzel & Kunz, 2014)** | **(Matta & Frost, 2011)** | **(Mackiewicz, 2010)** |
|---|---|---|---|---|---|---|---|
| *Pleasure or fun* | ✔ | ✔ | | | | | |
| *Increasing professional reputations and esteem* | | | ✔ | ✔ | | | |
| *Help system to improve* | ✔ | ✔ | | | | | ✔ |
| *Feel responsible to share the experience* | ✔ | | ✔ | | | | |
| *A desire to influence, make an impact or help others* | ✔ | ✔ | | | ✔ | | ✔ |
| *Keep self-record* | ✔ | | ✔ | | | | |
| *Belonging to the social network and social bonding* | | | ✔ | ✔ | | | ✔ |
| *Altruism, self-efficacy, and satisfaction of the cognitive needs* | ✔ | | | ✔ | | | ✔ |
| *Peer pressure* | | | | ✔ | | | |

**Table 2-1: Reviewers' motivations; summary of the literature**

Many of eWOM hosting websites supports some aspect of social networks. So, existing literature about the motivation of user participation in social networks can be adopted in online review research. Wasko and Faraj (2005) investigated the relation between social capital, individual motivation, and using social networks and showed that Increasing *professional reputation, sharing one's experience, sharing because one is structurally embedded in the network* are the main motivations for online contributors. Krasnova et al. (2006) also concluded that the *satisfaction of the needs for belongingness, esteem needs through self-presentation, satisfaction of the cognitive needs*, and *peer pressure* are some of the users' motivations for being involved in social networking websites.

Table 2-1 includes a brief summary of motivations that reviewers or participants in online communities might have. Some other researchers studied reviewers' motivation in more detail. For example, Matta and Frost (2011) summarized the literature of motivation including *self-involvement/social benefit, others-involvement, exerting power, helping the company, product involvement, self-enhancement, economic rewards, vengeance, restoring balance, advice seeking, platform support, crowding out effect, opportunity cost, message involvement, and dissonance reduction.* Considering the motives recognized by literature, it is obvious that these incentives are not the same for individuals as the underlying reason of them is different. Some are altruistic and some are egoistic. Far too little attention has been paid to the question regarding how it could affect review patterns of reviewers over time.

### 2.1.5. Potential customers as receivers

Before the eWOM era, the only information that potential customers had for their purchasing decision was the vendor-provided information, the WOM from their friends and family and reviews by expert which were published in magazines, newspapers, on radio and TV. Nowadays, eWOM provides information with a very low search cost and can change the attitude of potential buyers towards products or brands (Cheung & Thadani, 2012). If the review receiver adopts the review, she/he will trust the review and its source and will absorb the information in their purchase decision (Cheung & Thadani, 2012).

There are tons of studies focusing on review receivers and how they react, or adopt a review. However, I do not include more literature on the receiver as the receiver is not within the scope of this research.

### 2.1.6. Effects of eWOM as responses

The response is the act that the receiver will do when they see a message in a communication. In an eWOM platform, the response usually aimed at the communicator. The main response that a reviewer can hope for is her/his idea being considered in the receiver's purchase decision. The response people give to an online review is not a self-definitive concept. The communicator and the stimulus affect it. It has been demonstrated that reviews written by highly exposed or popular reviewers receive more favorable responses (Hu, et al., 2008).

Many eWOM platforms provide an environment for user interaction. In such environments, reviewers may observe or earn some responses from receivers to their reviews. Early responses will affect the *purchase intention* (Cheung & Thadani, 2012) and consequently the *sale* of the product (Zhu & Zhang, 2010; Chevalier & Mayzlin, 2006); whereas the later responses will be comprehended as *social feedback* and *social bias* for reviewers (Goes, et al., 2014).

#### *2.1.6.1. Effect of eWOM on purchase intention and sale*

Adopting or receiving the eWOM content can affect the purchase intention of potential customers and consequently boost sale volumes. It also can affect customers' product evaluation or post-purchase behavior *(King, et al., 2014)*.

##### *Purchase intention and sale*

Many researchers have addressed the effect of valence of the reviews on sale, demand, or revenue (Zhu & Zhang, 2010; Chevalier & Mayzlin, 2006). It can change the fate of the product. Researchers have studied books sold in two separate retailer websites. With different review sets, the same book ended up earning different revenues on each website (Chevalier & Mayzlin, 2006). The same effect is expected for other experience products such as TV shows (Godes & Mayzlin, 2004; Zhang & Dellarocas, 2006). As Godes and Mayzlin (2004) showed, the WOM in online communities positively affects the popularity of TV shows. The review valence was found to be influential on the revenue of the product (Zhang & Dellarocas, 2006; Dellarocas, et al., 2004).

On the other hand, there are some studies arguing against the current findings. For example, to investigate the effect of reviews on product sale, Duan et al. (2008) studied both persuasive and awareness effects of eWOM. By analyzing a panel data set of daily movie box office sales and related reviews, and considering the assumption of reviews being endogenous, they observed that valence does not significantly change the revenue. However, they found the *volume* of online reviews significantly important. They justified this result with the awareness effect. This result was consistent with previous research where Liu (2006) established that WOM volume has an impact on the product sale: when a product has a higher volume of reviews, more potential customers are likely to hear about it. He observed that even when there were different types of products involved, the result was the same. Liu used online movie reviews on a Yahoo Movie website in his research. Comparing WOM before and after the release date of the product, he concluded that the early reviews are more influential. Furthermore, research showed that besides valence and volume, the variance of the rating scores significantly affects the sale or the product position in the market (Clemons, et al., 2006).

### *Post-purchase effect*

Although reviews are aimed to affect the purchase decision, they also affect the post-purchase attitude of consumers towards the product. After purchasing the product, a potential customer, the eWOM receiver, becomes the former customer and a potential reviewer. Former studies showed that receivers are still influenced by the effect of adopted reviews (Lee, et al., 2010) due to the *herding effect.* Herding behavior is following others without having a self-thought opinion about the subject. Lee et al. (2010) showed that people follow previous reviews when writing about their own consumption experience. This effect is expected to be moderated if the reviewer is a socially close person, friend, or family. Prior reviewers can moderate this effect. Their result showed that ratings submitted by friends could reduce the herding behavior (Lee, et al., 2010).

Herding behavior could affect the posterior evaluation of the product, to the extent of the social influence of the early reviewers. Using book and movie reviews, Huang et al. (2012) verified that WOM recommendations are strongly associated with users' posterior evaluations, especially if the recommendations came from their friends. Methods to identify reviewers with higher social influence have been developed and some researchers reported to be able to identify up to 78% of influential friends in a network (Huang, et al., 2012).

## 2.1.7. Contextual factors

Online reviews are more effective than information provided on corporate websites (Bickart & Schindler, 2001; Jonas, 2010). It implies that people trust reviews on third party websites more than the vendor-provided information. The environment and the context that host the review exchange affects both the eWOM generation and adoption. The quality of the communication between reviewers and receivers depends on the characteristics of the review-hosting website (platform). The website’s reputation plays a role and product reviews on established and well-known websites are more influential (Park & Lee, 2009). In addition to the reputation of the website, rules, policies, and regulations of a website affect the review exchange. One important effect of such policies is on the likelihood of posting fake or paid reviews. Cost and benefit of writing a deceptive review are defined by a website’s policies and can affect the probability of writing or sharing a non-factual review (Ott, et al., 2012).

To sum up, there are different types of the eWOM environments or websites, and each have their own specific characteristics. Vendor-owned review platforms, retailer-based review websites (e.g. Amazon), review platforms for one product type (e.g. CNET for technology, Goodreads for books, IMDB for movies, TripAdvisor for travel, etc.), and general purpose fan pages (on Facebook, or Twitter) are some of those types.

### 2.1.8. eWOM over time

Time is an important, yet overlooked, factor in the eWOM literature. We know very little about the change of reviews and reviewers over time. For a long time, nobody considered reviews or reviewers' contributions as a time variant concept. In recent years, some researchers have treated reviews and reviewers over time (Li & Hitt, 2008; Duan, et al., 2008; Jurca, et al., 2010; Otterbacher, 2009). However, they mostly studied the reviews over time, and not the reviewers. As one example, Li and Hitt (2008) investigated the self-selection bias using time series analysis. They examined the assumption that early buyers' preferences change the behavior of upcoming customers. Their result showed that early reviewers are biased and the underlying reason comes from the reviewer, not the product. In one other research, Jurca et al. (2010) investigated the effect of early reviews on the latest ones. Using time series, they focused on underlying factors influencing reviewers. They confirmed that considering the time sequence of reviews, previous reviews could affect the ones that come later.

An interesting result in this area is how the effectiveness of a review changes over time. Hu, Liu et al. (2008) showed that the effect of online reviews on sale fades over time. Later, Otterbacher (2009) recognized a solid relation between the time order of the reviews and their helpfulness. There are very few studies in this area of treating reviewer's opinions as a dynamic changing phenomenon over time. To the best of our knowledge, Goes et al. (2006) has done the most comprehensive research tracking the change in reviewers' behavior to study the effect of popularity on reviewing behavior. I strongly relied on their arguments and results in the design and implementation of this research.

## 2.2. Online community literature

### 2.2.1. What is an online community?

Some eWOM hosting platforms have a social network embedded in them (e.g. Yelp, Foursquare, and Goodreads). By facilitating the communication between customers (reviewers and readers), an online *community* may take form between users who are interested in common products and share consumption-related information.

An online community (same as a virtual community in our context) is a platform for a computer-mediated communication in a social group (Rheingold, 2000). The definition is broad and covers different technologies from the older mailing lists to social media with user-generated content. Although online communities may have some specific characteristics, in its nature “a Web [online] community is simply a community that happens to exist online, rather than in the physical world” (Kim, 2000).

eWOM participants also engage in communication with a network of people and these types of networks can be considered an online community as 1) people have mutual shared interest in either products or activities, and 2) members do not know each other in the real world and only rely on the online environment for their relationship (King, et al., 2014).

Members of online communities have different motivations for being a member and contributing to the community. Many of the motivations mentioned for online reviewers (section 2.1.4.2) are applicable in any type of online community. The social and personal benefits of engaging in online communities can be, but are not limited to, *information exchange, social support, social interaction, time flexibility, permanency and availability* (Iriberri & Leroy, 2009). The first three of these benefits exist in conventional and physical communities too. Whereas the last two are specifically possible in online communities. Iriberri and Leroy (2009) suggested that one intangible benefit of contributing in online communities is *self-satisfaction* and pride in fulfilling their altruistic goals in helping others.

### 2.2.2. Contribution in an online community

Online communities of consumption thrive on the voluntary contribution of reviewers. Therefore, the continuous contribution of reviewers is vital for a community’s long-term success (Wei, et al., 2015). The contribution takes different shapes and forms depending on the type of community. In an eWOM community, members share their experience of the product or service consumed and their contribution is measured by *volume*, *valence*, and *textual reviews*. Contribution levels can be explored using different perspectives such as *volume*, *frequency*, and *continuity* (Samiei & Tripathi, 2014).

The desire and commitment of community members to maintain their level of contribution over time (Wang, et al., 2012) is critical to sustain these communities. However, in reality, many reviewers gradually lower their level of contribution and become inactive. Explicit recognition, visibility of contributions, and granting rewards for the expertise, loyalty and commitment are some successful policies through which communities maintain their active members (Iriberri & Leroy, 2009).

In an eWOM community, reviewers share their opinions with other people in the community and receive feedback. We expect reviewers as rational agents to modify their behavior in hopes of receiving more attention. Even if reviewers have altruistic motivations, receiving feedback and attention could ensure them about the effectiveness of their reviews. Recent studies have found that over time, reviewers gain experience, learn, and change their reviewing behavior and their level of contribution (Li & Hitt, 2008). This is also in line with the well-established Hawthorne effect (Adair, 1984), which shows that the presence of an observant affects the behavior of people. Current literature suggested that the presence of an audience and their actions, such as friend requests and helpful votes[6], affect the volume of a reviewer's reviews and also the type of review content they write (Goes, et al., 2014). However, existing research is not conclusive about the direction of this change.

### 2.2.3. Online community life cycle

Online eWOM communities, like traditional communities, evolve over time and go through different stages in their life cycle (Iriberri & Leroy, 2009). After running a comprehensive and systematic literature review on online communities, Iriberri and Leroy (2009) suggested a life cycle model for online communities (Figure 1-1). The phases for the life cycle are: *Inception phase, Creation, Growth*, *Maturity*, and *Termination* (Iriberri & Leroy, 2009). Another model has been introduced showing the online community life cycle. The Figure 2-5 shows their suggested model.

The only difference with the Iriberri and Leroy (2009) model is the Mitosis phase. In this phase, larger communities may split in smaller sub-communities. Each sub-community may re-start the whole life cycle and return to the creation phase. This phase can be interpreted as the maturity stage in which communities may encourage creating decentralized subgroups managed by volunteer members and reward systems for members' contributions (Iriberri & Leroy, 2009).

[6] In some eWOM communities, users who read any reviews can leave their evaluation of the review's quality or helpfulness with a *like* or *helpfulness* vote.

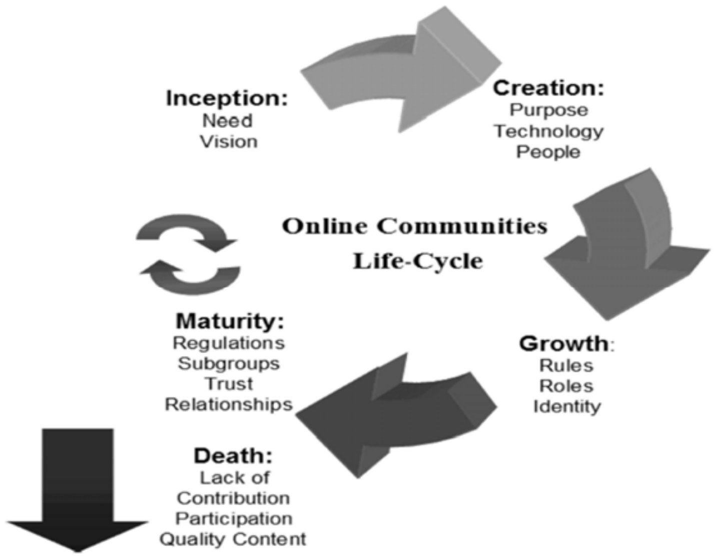



**Figure 2-4: The online communities' life cycle (Iriberri & Leroy, 2009)[7]**

### 2.2.4. Online community sustainability

To understand the sustainability of an online community, it is important to define its success. Researchers have used different quantitative metrics for online communities such as size (i.e. number of members), participation (i.e. number of visits, or hits), contributions (i.e. number of posts), or relationship developments (i.e. contact between users) (Iriberri & Leroy, 2009). All of these factors could be dependent of many contextual, managerial, design-related and environmental factors. No matter which factor we choose to measure the success, maintaining the same level of success over time could be the definition of sustainability as only those communities that survive and thrive can maintain their members' commitments and contributions.

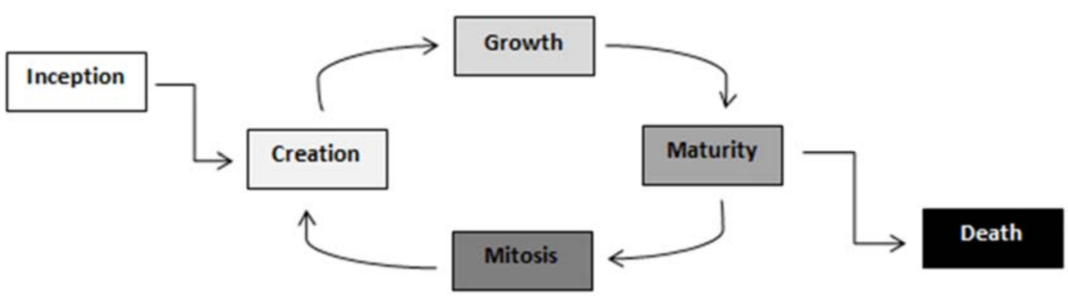



**Figure 2-5: The online community life cycle (Edgell, 2016)[8]**

[7] This figure is an exact screen shot of the model in the reference paper.
[8] This figure is an exact screen shot of the model in the reference paper.

While it is important to attract new members in the early stages for creation and growth, retaining members during the maturity stage is no less critical to the long-term success and sustainability of these communities. Members might leave the community if it loses its usefulness for them (Wenger, et al., 2002).

At the maturity stage, the *recognition* of contributions of members is a success factor of sustainable online communities and can help to increase the chance of sustainability of a community. Active participation from volunteers should be acknowledged and rewarded with tangible or intangible but rewarding and positive feedback (Iriberri & Leroy, 2009). Communities can develop mechanisms to encourage participants to maintain their contribution level. Therefore, understanding the drivers of their members' ongoing contribution is vital for their sustainability. The recognition could be in the form of appreciation for the contribution, recognizing volunteers who contribute and including them in the reward system, and providing any positive feedback such as assigning an identity (Taylor, 2010) to contributors. Previous work (Iriberri & Leroy, 2009) suggested that recognizing the uniqueness, helpfulness, and social benefits of the contribution can help communities to keep their members and contributors motivated and active. Physical or monetary gifts or any extrinsic reward as well as the visibility of the contributors can have the same effect.

## 2.3. Theoretical background

In attempt to address our research questions, we focused on the behavioural change in frequent online reviewers. In this research, we believe that the *social theory of learning* (Wenger, 1998) could be the theoretical foundation of this research.

In this section, first I draw a brief and summative view of the learning theories. Then I go through the main *social learning theories* and justify my decision to adopt the *social theory of learning* by Wenger (Wenger, 1999).

### 2.3.1. Learning theories

Learning is such a vast and general phenomenon that we have various theories of learning in many disciplines just to understand it. Different theories of learning resulted from researchers in different areas approaching the concept of learning from different perspectives and with different primary assumptions (Phillips & Soltis, 2004). These different definitions and lenses to the learning phenomenon have caused disagreements and debates on the subject. Smith (1999) suggested the main debatable areas are how theories focus on questions of *what it means to learn* and *what form of learning* is used. The communal part of all theories is the agreement on the fact that learning is a process, which results in the learners achieving her/his personal potential.

Learning has four orientations: *behavioral*, *cognitive, humanist, and social and situational*. At first, the learning literature was only focusing on the first three orientations (Merriam & Caffarella, 1991, 1998). Later on, researchers noticed the importance of *social and situational* learning and developed new theories to address learning as a social process. To summarize the existing and different, but overlapping learning theories, Smith (Smith, 1999) suggested a matrix model, which has different aspects of the theory as the second axis (in addition to the learning orientation). The Figure 2-6 shows these characteristics and a summary of learning theories.

Although, *behaviorist, cognitive,* and *humanist* learning theories can explain some aspects of learning, a*s* the focus of this research, I only focused on social learning theories. This reflects the fact that reviewers on an online eWOM community are social agent acting in a social context.

| Aspect | Behaviourist | Cognitivist | Humanist | Social and situational |
|---|---|---|---|---|
| View of the learning process | Changes behaviour | Process entirely in the head of the learner (including insight, information processing, memory, perception) | A development of personal potential | Interaction/ observation in a group context, akin to an apprenticeship |
| Site of learning | External resources and tasks are what matters | Making connections in learner's head is what really matters | Emotion, attitude and thinking are important | Learning needs a relationship between people and environment |
| Purpose in education | Produce behavioural change in desired direction | Develop capacity and skills to learn better | Become self-reliant, autonomous | Full participation in communities of practice, ie you graduate from apprentice to craftsman |

**Figure 2-6: A summary of *learning theories* adopted form (Kirriemuir & McFarlane, 2004)[9]**

### 2.3.2. Social learning theories

Interactions between people and environments in a social contexts result in social learning (Kirriemuir & McFarlane, 2004). Focusing on people as social beings, social-oriented theories of

[9] This figure is an exact screen shot of the model in the reference paper.

learning (Bandura, 1977; Wenger, 1998; Lave, 2009) suggest that learning is a social process, as well as a cognitive one.

### 2.3.2.1. *Theory of social learning*

The first dominant theory with social orientation was the *social learning theory* (Bandura, 1977). According to this theory learning is a cognitive process, which happens in social or interpersonal contexts (Bandura, 1977). This cognitive process happens through observations and sensory conditioning and regulates behavior based on observations. Observations can be any verbal or imaginal system. By emphasizing the social context, Bandura (1977) suggested that even in the absence of reinforcements and just by observing, learning can occur. The theory also explains that learning happens through the iteration of *attention, retention, reproduction, and motivation* phases (Bandura, 1977). Later Wenger and Lave introduced the concept of Community of Practice, using some anthropologist studies in different contexts (Wenger, 1999, pp. 11-12). The next section includes a brief introduction to both theories (Bandura, 1977; Wenger, 1999).

### 2.3.2.2. *The social theory of learning*

The world as we know it is a community of practice itself as an informal setting in which people engage with performing repetitive actions (Wenger, 1998). Many learning theories explain some parts of the social process of learning. The affordable access to the internet makes the online environment a big part of our everyday life, and we learn and change every day by contributing to online communities. Even though the *Social Theory of Learning* was initially developed to explain learning in real-life, face to face communities, after emerging excessive use of virtual communities, it was applied to online communities as well (Gray, 2004; Johnson, 2001).


**Figure 2-7: Components of learning in a social participation (Couros, 2006)[10]**

[10] This figure is an exact screen shot of the model in the reference paper.

The Social Theory of Learning (Wenger, 1998) explains how learning and knowledge acquisition happens when individuals perform activities in a Community of Practice (CoOP), observe, and interpret the feedback from the environment they are working in.

According to Wenger (1998), learning happens when individuals digest the meaning of their experience with their engagement in society. Wenger (1998) explains that the learning process has four main components: Learning by ***practice,*** ***identity,*** ***meaning,*** and in the ***community***. Comprehension happens during and after the *practice*, when people extort the collective *meaning* out of their experience and the feedback they get from others. They also observe and understand their *identity* in the *community* they are practicing in.

The main characteristics of Wenger's theory (Wenger, 1998) is the centrality of practice in the learning process.

Wenger introduced *practice* as the first component of the social theory of learning (Wenger, 1998). He later defined *practice as* "a way of talking about the shared historical and social resources, frameworks, and perspectives that can sustain mutual engagement in action" (Wenger, 2009). Johnson (2001) in a survey of research on online community of practice suggested that having a "completely authentic task" to build the community around is an inseparable component of a task-oriented community of practice. Members of the community are learning partners who do not necessarily support each other's practice (Wenger, 2010). They may criticize or comment on other members' practice, and this builds up a big opportunity to learn for all members. For members, practice may not be aligned with the community. Therefore, learning reflects in the behavior change in members towards the realignment with others, and with the task agenda of the community (Wenger, 2010).

The direct and indirect feedback community members receive during and after their practice is new data for them to process and contemplate to understand their position in the community and evaluate their performance as the member of the community. A member is supposed to contribute in the core task of the community (Johnson, 2001). If they believe they cannot perform the core activity of the community correctly or good enough, they are more likely to leave the community or stop their contribution. Therefore, drawing from Wenger's theory (1998), we believe that the learning process is in place to help members to observe, interpret, and enjoy their learning as an extra motivation to continue their contribution over time. They learn through the social learning process how to keep performing activities (practice) and focus on gaining progress. In an eWOM community learning reflects on both their reviewing behavior and their purchase decision on which product to consume and review[11].

We selected **the *social theory of learning*** (Wenger, 1998) as our underpinning theory because it includes many theories that are applicable to our context. It is aligned with the general theories of learning such as the *theory of social learning* (Bandura, 1977). At the same time, the theory is situated at the intersection of two axes of theories, in the middle of *identity theories* and *social practice theories* on one hand, and *social structure theories* and *situated experience theories* (Wenger, 1999, p. 12) on the other. Figure 2-8 shows a schematic view of the situation of Wenger's theory between other related theories.

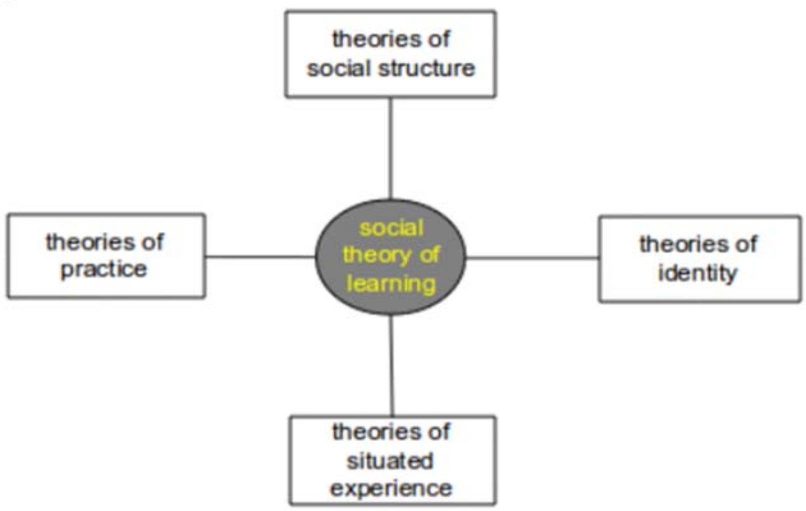



**Figure 2-8: The relation of the *social theory of learning* with other theories (Wenger, 1999)[12]**

### 2.3.3. eWOM and community of practice

We draw on Johnson's work (2001) to argue that the eWOM community is a community of practice (CoOP). To do so, we have to show that the basic requirements of a Community of Practice are satisfied. We used Johnson's components (2001) which he claimed make the distinction between a community of practice (CoOP) and any other community or a learning environment. **First**, the community initially starts as a designed platform, but it will evolve by later members' contributions in the form of the main task around which the community was designed for in the first place. **Second**, there is a legitimate task-oriented reason which community members are motivated to

[11] This will be discussed in detail in chapter 3 and 4.
[12] This figure is an exact screen shot of the model in the reference paper.

engage with. Last, is the structure of the community, which consists of people with different levels of expertise who work together (Johnson, 2001, p. p. 53).

An eWOM community around product reviews and recommendations is a *community of practice* in which reviewers repeatedly practice their activity (rating products and writing textual reviews). At the same time, they have the opportunity to observe their peers' behavior, the reaction to their reviews, and receive social feedback.

It is consistent with the situation in which frequent reviewers constantly revisit their motivation to continue through a social learning process through the process of retention, reproduction, and motivation (Bandura, 1977). However, we believe that the social theory of learning (Wenger, 1998) can explain the dynamics of an eWOM community more precisely. In an eWOM community, reviewers are members of the community (situated experience). They also have to follow rules and regulations of the platform (social structure) (Wenger, 1999). By repeatedly reviewing products they try social practice and develop an identity for themselves.

Overall, we safely assume that an eWOM community with members with repetitive contribution is a Community of Practice and we draw on the social theory of learning for this research.

In our context, reviewing books is the main activity or *practice* that the eWOM community is shaped around. Different individuals gain different reviewing experience overtime; their own special practice experience, which reflects in their practice. However, what all have in common is that reviewers expose themselves and their evaluation of books by writing frequent reviews. Later, by observing and gathering data about the reaction of other members towards their practice, reviewers learn to adjust their behavior. Their contribution level and product evaluation and consequently the volume and valance of reviews changes over time.

## 2.4. Conclusion

A summary of the literature presented in this chapter is that *time* and *experience* are overlooked areas in the literature. The majority (almost all) of the research on online communities focus on the *user behavior* in an online environment. Whereas we believe that the experience users gather during their repetitive contributions evolve over time, affecting members of online communities. They are not the same people after a long period of repetitive practice in an online social context. We focused on one important change that happens to them: *learning in a social context when doing the practice of generating eWOM content.*

An eWOM community with members who repeatedly write reviews can be considered as a *Community* of *Practice.* To answer our research questions, I focused on an eWOM community and studied the reviewers' behaviors over time to explain the change in their behavior by considering learning by practicing in a community of practice.

# CHAPTER 3. Evolution of Online Reviewers: Social Learning Perspective (Paper 1)

## 3.1. Abstract

A huge body of research on online social networks focuses on individual behavior in online communities, and the effect of this behavior on businesses and society. A few studies have also examined how users consume the content available on social media platforms or online communities and the effect of this content on individual behavior. However, we are yet to understand how sheer act of contributing or participating on social media or online communities influences/changes the participants. Are we the same people as we were when we first started contributing in online social media? This research focuses on the evolution and change in online users in an electronic Word-of-Mouth (eWOM) community to explain how *social learning* changes users/participants and how this change is reflected in their behavior.

Online customer reviews are informal communication between former and prospect consumers (Brooks, 1957). Each review provides the consumer's evaluation of the reviewed product. Moreover, reviews written by an individual about different products reveal information about the reviewer's product preferences. This inherent self-bias in online reviews (Li & Hitt, 2008; Hu, et al., 2006) reflects the reviewer's tendency toward a certain type of product.

Product reviewing is a social process (Alexandrov, et al., 2013) during which frequent reviewers gain experience and learn. The learning reflects on their reviewing behavior. Writing reviews in the online community of consumption gives reviewers the opportunity to gather social feedback, which is negatively biased (Goes, et al., 2014; Ofir & Simonson, 2001), and leads to a social bias in reviews posted by experienced reviewers.

Using longitudinal analysis, we studied historical reviewing behavior of users on a non-retailer review-hosting website. We observed that over time, frequent reviewers learn to become better reviewers while their own consumption experience improves.

We concentrated on the self-bias in reviewers and observed that it changes over time. At early stages, reviews are inflated by self-selection and the nature of the bias changes and leans towards social-bias. We also observed that engaging in the WOM community as a frequent contributor positively affects the consumption experience. Over time, frequent reviewers select and read books with slightly higher quality. However, due to the social bias, not only do they experience better

consumption based on their reviews over time, but also they become stricter in evaluating products. Moreover, we observed that although being part of an eWOM community boosts reviewers' social learning, the potential *information overload* may decelerate the learning rate and frequent reviewers are likely to decrease the *social network expansion rate* over time to respond to the learning barrier.

**Keywords:** eWOM, Self-selection bias, Social-bias, online community of consumption, Social Theory of Learning, Community of Practice (CoOP), Longitudinal Data Analysis

## 3.2. Introduction

In this research, we focused on the online reviewers' evolution and analysed it with the Social Theory of Learning (Wenger, 1998) to study how the experience as frequent reviewer affects them. A huge body of literature on eWOM focuses on reviews and their effect on products' fate in the marketplace. The online customer review has been considered as a type of Word-Of-Mouth (WOM), which spreads over the internet. Researchers have studied this phenomenon for more than a decade now (Archak, N; Ghose, A; Ipeirotis, P G, 2011; Cheung & Thadani, 2012; Dellarocas, et al., 2004; Zhu & Zhang, 2010; Goes, et al., 2014; Li & Hitt, 2008; Mudambi & Schuff, 2010). Nevertheless, the literature still cannot comprehensively explain reviewer's behavior, and what steers and drives this behavioural change is yet beyond our understanding. Reviewers are different in characteristics and motivation, which in some extent can explain some of their heterogeneous behavioural patterns. Effect of experience, user characteristics such as specialized skills (Connors, et al., 2011), expertise (Mudambi & Schuff, 2010) , and motivation toward social networks (Wasko & Faraj, 2005) are some of those personal constructs. Their personal characteristics and the motivations of their volunteer contribution lead reviewers to contribute to different communities. They select various social media platforms or communities to join and satisfy their heterogeneous needs and requirements (Alexandrov, et al., 2013). This is not the whole story. Reviewers are heterogeneous in person and they also change over time. This change in their behavior is not explored much in the current literature (Goes, et al., 2014), and there are only a few published works concentrating on the dynamic nature of online reviewers. Also, most of the research until recently did not consider WOM as a social process (Alexandrov, et al., 2013).

In recent years, researchers started to consider reviewers, as active and dynamic agents who contribute to the community to satisfy their motivations and needs (Wasko & Faraj, 2005; Alexandrov, et al., 2013). For a long time, even when reviewers were the subject of studies, the change in their personality, knowledge, and behaviour was overlooked. Recently some scholars have examined reviewers' behavior over time (Goes, et al., 2014). However, still many of these published works mainly focus on how reviewers with different motivations affect an eWOM community and products' fate in the marketplace. The counter effect that the community has on reviewers is then mainly unexplored. To address this gap, we focused on this research question:

> *Do reviewers change over time in how they review or evaluate product/services, and does their association with an eWOM community explain this change in reviewing behaviour?*

To answer this question, we studied frequent reviewers using the Social Theory of Learning (Wenger, 1998) as our theoretical lens, as we believed that reviewers practice reviewing products, gain experience, observe feedback from their peers, and alter their behaviour in response. They become better reviewers while their contributions improve their consumption experience and buy product with higher quality. Building upon the Social Theory of Learning (Wenger, 1998), we believe that an eWOM environment is a Community of Practice (CoOP). Communities of Practice are "groups of people who share a concern or a passion for something they do and learn how to do it better as they interact regularly" (Wenger, 2011).

Frequent reviewers perform the central activity of the community-reviewing products, and by keep doing the activity, receiving and interpreting the feedback from the community, reviewers learn to adjust their behaviour to fulfil their cause. This is the fundamental change mechanism in reviewers' behavior over time. Acting as a social being is an important element of learning in a Community of Practice (CoOP). For frequent reviewers, membership in the eWOM community and getting feedback is a learning process. Being part of the embedded social network in some eWOM community facilitates the learning mechanism for frequent reviewers.

We have selected a website that hosts online reviews of books, as we wanted to control for the product type in our research .Moreover, we did this as books are considered as experience goods. Experience goods unlike search goods (Nelson, 1970) are products that a customer only can evaluate them after purchasing and using them (Zhu & Zhang, 2010) or by gathering information using other costly ways. Online reviews can immensely decrease the information-seeking cost for prospective readers (customers) and could have a huge effect on their purchase decision. However, the taste has a significant role in customer evaluation of a book, as "Good reading is a highly personal experience whose quality depends upon the taste, the intellect, the imagination, and the sensitivity of the individual reader" (Radway, 1997, p. 266).

Analyzing the data using a mullti-level longitudinal data analysis method, we conclude that frequent reviewers do change over time and by gathering experience in the eWOM community as a

Community of Practice, reviewers learn to become *better readers and reviewers*. We also observed that at the beginning, their reviews are boosted with the *self-selection bias*, which is due to the reviewing books from previous positive and memorable experience. Later, in response to the social bias towards negative reviews, they review books with lower valence, even though on average they read books with a higher quality score. Association with the community and developing a social identity facilitate the learning. However, association with the community by belonging to a huge social network encounters them to information overload and decelerates their learning process. On average, frequent reviewers notice this issue and lower the expansion rate of their social network. At the same time, we observed that frequent reviewers lower their contribution, in the sense of volume and textual reviews over time, while they become stricter and their reviews become more negative.

The rest of this chapter is structured as follows. Theoretical background and conceptual modelling (section 3.4) follows a quick overview of related background literature (section 3.3). The related literature will be discussed deeply and the research model is designed based on these discussions. Related hypotheses are formulated using arguments built on the theoretical background and the current literature. In section 3.5, data, modelling and analysis of the results are discussed followed by discussions on the results (section 3.6). Finally, after checking the robustness of the results (section 3.7), we will have our closing remarks (section 3.8) including our current findings and outcomes along with their theoretical and practical implications at the end of the chapter.

## 3.3. Previous work and literature review

To summarise extant research and highlight relevant research questions, we draw from literature on *online customer Review or eWOM, user contribution in online communities,* and *self-selection and social biases.*

### 3.3.1. Current eWOM literature

Word-of-Mouth (WOM) is a process, which facilitates the information flow between customers, whose purchase has a time lag with one another. The information flow caused by WOM can affect the information asymmetry in the marketplace in the first place (Mackiewicz, 2010). The information asymmetry exists in the marketplace as the vendors usually share information about the quality, functions, flaws, and possible problems with respect to prospective customers. In addition, the customers who had purchased the product before and already had their consumption experience are more aware of such data. Online customer review platforms have a key role in filling this gap. Having this in mind, WOM, as Brooks (1957) defined, refers to an informal network between interested customers to promote new products, and it is a way that former customers share their experience with prospective customers (Brooks, 1957). eWOM is a form of WOM which is distributed on an online or electronic platform, rather than face-to-face interactions.

According to the literature, WOM content, which is the result of the reviewers' contribution, includes Valence, Volume, and Textual comment. Many scholars have concentrated on "the influence of these content elements on the wide range of outcomes such as consumer choice, product sale and even investor decisions" (Goes, et al., 2014). It is well established that all these factors influence the product sale, directly or indirectly. There is a large body of literature investigating the effect of review's volume (Shen, 2009; Liu, 2006) and valence (Zhang & Dellarocas, 2006; Liu, 2006) on sale or product fate in the marketplace. Mostly in the marketing discipline, many researchers focused on the effect of WOM and eWOM on the product sale and revenue (Chevalier & Mayzlin, 2006; Godes & Mayzlin, 2004; Liu, 2006; Zhu & Zhang, 2010).

In spite of the extensive research history in this area, the effect of time on reviewers' characteristics, preferences, and behaviour was overlooked for a long time. We did not understand why and how reviewers and reviews change over time, until recently, that researchers started to consider the dynamic nature of the reviews over time. For example, some have used time series data and modelled this change; (e.g. (Li & Hitt, 2008; Hu, et al., 2008)). Although these researchers treated reviews as a changing phenomenon over time, we still do not understand what drives the change in reviewers' participation and contributions over time.

Even with these gaps, researchers tried to summarise the large body of literature on eWOM systematically using different approaches. For example, Goes et al. (2014) categorised the literature based on the focus of the research on the *antecedent* (generation) of eWOM, its content or *consequences*. In another study, Montazemi and Saremi (2014) proposed a conceptual model in which they have categorised eWOM into five dimensions of *receiver, source, eWOM content, response, and focal product/service.* They have categorised the effect of these five dimensions on the three stages of *product/service adoption*. Before them, the same five eWOM dimensions were used (Cheung & Thadani, 2012) in another literature review of eWOM. Cheung and Thadani (2012) have considered eWOM as a communication process, which includes a *sender, receiver, message,* and *response.* Later, King et al. (2014) consolidated the eWOM literature using the interaction of *unit of analysis* and *cause-effect.* As the unit of analysis, they suggest that the researchers focused on either the *sender* or *receiver* or the message. For addressing the cause and effect dimension, same as Goes et al. (2014), they focused on the antecedence (as the cause) and consequence (as the effect) of eWOM.

### 3.3.2. Motivation and Contribution in online community

Where the concept of contributing to an WOM community is simple and straightforward, measuring the contribution level is challenging. Chen and Huang ( 2014) explored the characteristics of reviews and reviewers. To take a deeper look into the reviewers' contribution, they used review frequency and reviewing continuity as proxies for the contribution concept.

Researchers also studied what drives the contribution of online reviewers. There are many published works about the motivations and incentives drive reviewers' contribution (Mackiewicz, 2010; Cheung & Lee, 2012; Munzel & Kunz, 2014). To answer this question, scholars have drawn from research on volunteer activities (Clary, et al., 1998) and suggested main functions that would drive volunteers to perform their unpaid work. *Value*, *Social*, *Career development*, *Protective*, and *Enhancement* are those factors, which have been used in in development of a tool to measure these functions. This is aligned with prior research, which confirmed that reviewers decide based on the trade-off between perceived required *effort, cost* of the contribution, and their motivations (Tong, et al., 2013). Expected satisfying benefits that reviewers can get from writing reviews, as Tong et al. (2013) suggested, come from the satisfaction of *helping others*, *influencing the merchant*, and *enhancing self-image* in contrast with *executional cost*. Many of these studies are based on the findings of Hennig-Thurau et al. (2004). Inspired by research on virtual community and traditional WOM literature, they have observed eight factors explaining reviewers' incentive of contribution. *Platform assistance, venting negative feeling, concern of other consumers, extraversion/positive self-enhancement, social benefits, economic incentives, helping the company, and advice seeking* are those factors (Hennig-Thurau, et al., 2004). They summarised all motives in five main utilities each focusing on one main issue: *Focus-related utility* (i.e. concern of others), *consumption utility* (advice seeking), *approval utility* (social approval), *moderator-related utility* (convenience, problem solving), and *"Homeostase utility"* (expression gratitude, venting anger).

One more reason for reviewers to share their consumption story with others could be the need to balance and resolve their unpleasant feelings from a bad consumption experience. If customers have a negative experience, they might get back to the vendor, supplier, or the recommender of the product by writing negative reviews. By sharing a negative WOM they take action for their unpleasant feeling and become emotionally satisfied or at least stable (Hennig-Thurau, et al., 2004). Even though, many of the mentioned motivations, such as making balance in one's consumption journey could explain reviewers' continuous contribution, Moe and Schweidel (2012) believe that reviewers primarily find the answer to two questions before contributing to the online communities; the questions are "*whether to contribute"* and "*what to share"* (Moe & Schweidel, 2012).

One important incentive for reviewers is the embedded social network in the platform. By expanding their audience of WOM to online users, reviewers show their interest to share their opinion with a larger number of audiences. That is the reason why the majority of reviews-hosting websites offer a range of social networking features. Reviewers interact on online review websites and learn from the social feedback they get from them. As Goes et al. (2014) suggested, by writing reviews, reviewers have a better opportunity to observe the feedback from their audience in the social network and to change their behaviour accordingly hoping to get more popular (Goes, et al., 2014). This is aligned with the possibility of users being motivated to engage in content development activities, and to build a social presence and social capital for themselves (Munzel & Kunz, 2014). Taking the established results about the effect of motivation on reviewers' contribution behaviour (Shen, 2009), social network motives are important for understanding the reviewing behaviour. Previous studies showed that the embedded social network in a WOM-platform affects the reviewing behaviour in direct and indirect ways (Samiei & Tripathi, 2013; Brown & Reingen, 1987).

## 3.4. Research model and hypotheses development

In this section, we leverage on the *Social Theory of Learning* (1998) as the underpinning theory to argue our hypotheses based on which, we have developed our research model ( Figure 3-1). Using this theory, we empirically investigated the evolution of repeating reviewers on an eWOM community. We believe that this evolution reflects on the reviewers' behaviour on WOM platforms over time and on their *contribution, which* is the main concept we should focus on to capture the reviewing behaviour. After establishing our definition of *learning in frequent reviewers,* we focus on four main *components* of the theory, discussing learning process, which explains the learning and behaviour change in frequent reviewers.

### 3.4.1. The social theory of learning

To answer the research question, we build our model on the Social Theory of Learning (Wenger, 1998). Many researchers believe that learning is not just a cognitive process in an isolated environment (Bandura, 1977; Wenger, 1998; Lave, 2009). Focusing on people as social beings, social-oriented theories of learning (Bandura, 1977; Wenger, 1998) suggest that learning is a social process, as well as a cognitive one. Learning happens in real life situations where people actively engage in the world among their friends, family, neighbours, classmates, work colleagues, or strangers.

The World, as we know, is a community of practice itself. It is an informal setting in which people engage with performing repetitive actions. Many learning theories explain some parts of the social process of learning. One of the well-cited ones is the *Social Learning Theory* (Bandura, 1977) in which Bandura explains that the learning happens through a repetition of *attention, retention, reproduction, and motivation* (Bandura, 1977). Later, Wenger and Lave have introduced the concept of Community of Practice, using some anthropologist studies in different contexts (Wenger, 1999, pp. 11-12).

The Social Theory of Learning (Wenger, 1998) explains how learning and knowledge acquisition happen when individuals perform activities, observe, and interpret the feedback from the environment in a Community of Practice (CoOP), . According to the Wenger's theory (Wenger, 1998), the learning happens when individuals digest the meaning of their experience with their engagement in the society. Wenger (1998) explains that the learning process has four main components: Learning by ***practice, identity, meaning,*** and in the ***community.*** People ***practice*** some behaviour or task when they are situated in the ***community***. The comprehension happens when during and after the *practice*, people extract the collective ***meaning*** out of their experience and the feedback they get from the others. They also observe and understand their ***identity*** in the *community* they are practicing in. On the other hand, the affordable access to the internet makes the online environment a big part of our everyday life, and we learn and change every day by contributing to online communities. Even though the *Social Theory of Learning* was initially developed to explain learning in real-life or face to face communities, after the emergence of pervasive use of virtual communities, the theory was applied to online communities as well (Gray, 2004; Johnson, 2001).

We selected the *Social Theory of Learning* (Wenger, 1998) as our underpinning theory because it includes many theories that are applicable to our context. It is aligned with general theories of learnings such as the *theory of social learning* (Bandura, 1977). As mentioned in chapter 2, at the same time, the theory is situated at the intersection of two axis or theories (Figure 2-8); right in the middle of *identity theories and social practice theories* on one hand, and *social structure* and *situated experience theories* (Wenger, 1999, p. 12). Our context is an eWOM community, in which reviewers are community members (situated experience) and they have to follow rules and regulations of the platform (social structure). By repeatedly reviewing books, they try social practice and develop an identity for themselves. Their reviewing practice provide data on the reviewed products which is intended to help other members of the community in their purchase decision (Archak, N; Ghose, A; Ipeirotis, P G, 2011).

However, to apply the theory in any community, the basic requirements of a Community of Practice should be satisfied. To do so, we draw on the literature where Johnson summarized (2001) components that make the distinction between a community of practice (CoOP) and any other community or learning environment. **First**, the community initially starts as a designed platform, but it will evolve by later members' contribution in the form of the main task around which the community was designed for in the first place. **Second**, there is a legitimate task-oriented reason, with which community members are motivated to engage. And the **last**, but not the least characteristic of a CoOP is the structure of the community, which consists of people with different levels of expertise who work together (Johnson, 2001, p. p. 53).

An eWOM community around book reviews and recommendations is a *Community Of Practice* in which reviewers repeatedly practice their activity (rating products and writing textual reviews). At the same time, they have the opportunity to observe their peers' behavior and reaction to their reviews, and to receive social feedback. By interpreting their observations, they gather experience and adjust their future behavior accordingly hoping to attract more attention. We believe that this behavioral change happens through a social learning process, and frequent reviewers go through them because they crave for others' attention (Mackiewicz, 2010).

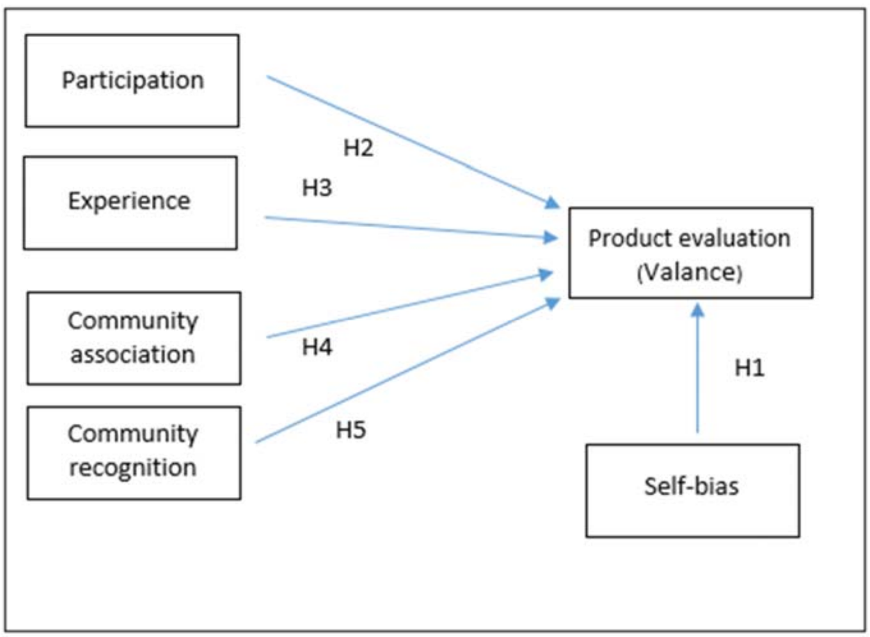



**Figure 3-1: The Research Model**

In our selected platform, the community consists of consumers (book readers) who share their reviews and recommendations with other members hoping to improve their reading experience. There are many reviewing platforms hosting book reviews. Many of formal newsletters, channels and publishers host professional book reviewers. The Amazon website (Streitfeld, 2012), as a retailor who sells books, hosts book reviews too. However, our platform started as a designed community to host and share book reviews and succeeded to attract and maintain more than 20 million book readers, which satisfy the first requirement of a CoOP. The community evolved around *reviewing* *books* as *THE TASK* that connects members. Moreover, in the very same community, many of the active participants have different levels of expertise. Some are book experts such as authors, or publishers. Some are volunteer experts in using and organizing the website (librarians). Also, a huge number of users manage to prove their expertise in reviewing books. The website uses tags, badges, special profiles, or official status to distinguish experts from regular reviewers and share this information with all members. Therefore, we believe that the second and third characteristics of a CoOP are satisfied.

To sum up, we consider an active and successful eWOM community as a community of Practice (CoOP) on which the *Social Theory of Learning* is applicable as our theoretical lens to study the reviewers' evolution.

Using this lens, we can use the current literature of WOM and eWOM to understand how repeating reviewers learn in a social environment and investigate reviewers' informal situated learning.

### 3.4.2. Learning in Online Review Communities

By a continuous contribution, frequent reviewers learn about their consumption as well as their contribution to the eWOM community. Lave defined learning as a "situated activity that involves changes in knowledge and action" (Lave, 2009). We believe that both knowledge and action of frequent reviewers get affected by their learning in the eWOM community as a Community of Practice (CoOP). The question is: what does reflect this learning in their behaviour?

Frequent reviewers learn to become both *better readers* and *better reviewers* over time. They become better readers as the quality of their read list increases. They also become better reviewers as, over time, they learn and overcome their self-selection bias. Simultanously, they lean towards reviewing behaviours that respond to the social bias in the community, which give them opportunity to adopt strategies to attract more attention in the community (Shen, 2009). While posting reviews, they are aware of the community they are participating in, and by interacting with other members along with observing the feedback on written reviews, reviewers alter their future behaviour.

By practicing the continuous reviewing activity, reviewers become better readers. Books are experience goods for which that a customer can only evaluate after purchasing and using them (Zhu & Zhang, 2010) or by gathering information in another costly way. when practicing the continuous reviewing activity, reviewers are situated in a consumption community among people who are interested in reading books. They have the opportunity to observe other reviewers' reading lists and their evaluations of books. Being a member of the eWOM platform, reviewers also have access to the recommendations of an automated algorithm which suggests books to members based on one's previous reviews and their homogeneity with their friends.

Accessing recommendations and reviews is a low cost way to obtain information on new potential books to read and could be the most beneficial effect that reviewers get from participating in the eWOM community. This may minimize the risk they take in selecting their next read and help them to read books with higher quality over time.

Frequent reviewers also learn to become better reviewers by continuously participating in an eWOM community. In the beginning, their reviews are very likely to be inflated by self-bias. Over time and by practicing the reviewing activity and observing the consequences, and also reading other members' reviews they learn to control their self-bias and become more critical in reviewing books to be more helpful and get more attention from others (Mackiewicz, 2010). This will be discussed in more detail in following two sections.

### 3.4.3. Self-selection bias

Typical book reviewers do not write a review on everything they read. The subgroup of the books they review is not only selected randomly (Hu & Li, 2011), but also reflects their preferences in both reading and expressing their opinion.

At early stages of joining an eWOM community, the majority of reviewers start with reviewing books that they have read before joining the website. They might review books they have enjoyed a lot with a high score. It can inflate the valence of ratings in early stages and is one of the underlying reason for *self-election bias.*

When people do not have the intention to write a review on a product, they only store their overall feeling of the product. When recallinging their consumption experience later, they only rely on their fuzzy memory, which is highly likely to be affected by all kind of personal biases (Ofir & Simonson, 2001). According to Hu et al. (2009), due to the *purchase bias* and *underreporting bias*, it is more likely for people to write reviews on their recalled extreme experiences, which result in a bimodal distribution of reviews (Hu, et al., 2009). This is consistent with Hu et al. (2009) who showed that numerical ratings of online reviews are drawn from a U-shaped distribution in which the number of reviews with high and low ratings is higher than the average ratings. However, it is more likely for reviewers to recall their extreme positive experiences comparing to negative ones. As reading books is a hobby for most of the people, they do not continue reading the ones they do not like and leave the bad books unread and therefore not reviewed. Research shows that even on the retailers' website on which reviewers are more motivated to warn others about the bad quality of products, the average score of books is mostly positive, with an average bigger than 4 out of 5 stars (Chevalier & Mayzlin, 2006). This results in the distribution of book reviews with a J-shape distribution. As time passes, frequent reviewers start writing reviews on books that they are currently reading, and as they have the intention to review them, the bias Ofir and Simonson mentioned (2001) will be less and less.

If reviewers are fair and un-biased, they will write reviews with a score based on the true quality of the book. However, their review is not only about the observed quality of the book (Hu, et al., 2006), but also encompasses their biases. One of the most important potential biases is *self*-selection bias, which inflates the early reviews of frequent reviewers. We hypothesise that:

> ***Hypothesis 1 (H3-1)****: Due to the self-bias, frequent reviewers post positively inflated evaluations for books at the beginning of their contribution*

### 3.4.4. Learning as experience

Frequent reviewers learn through their participation and cumulative experience. They implicitly extract meaning out of the direct and indirect feedback they observe in the community. Their interpretation of their experience reflects their ongoing reviewing behaviour. The social learning results not only in the quality of books they review but also changes their product evaluation. The effect alters the way they evaluate products and the score they assign to books. It also affects how they choose books to read.

As mentioned before, we believe that the reviews shared by frequent reviewers in early stages of joining the WOM community are highly affected by self-selection bias (Hu, et al., 2009). We argue that the self-selection bias will diminish over time. Moreover, by learning from their continuous experience, the *effect of* time and the inherent *social bias* in the community affect reviewers' behaviour, and lead to the valence of their ratings decline over time. This decrease can be explained by the effect of *time*, and lagging *social bias*.

The valence of reviews of reviewers decreases as the consequence of the dynamic behind the consumer satisfaction. Consumer satisfaction has two main elements: *Cognition* and *affection* (Homburg, et al., 2006). We argue that by using more products over time, reading more books in our case, the *affection* lessens and it gets harder to satisfy individuals. On the other hand, the cognition effect of satisfaction also decreases. The cognition element refers to the comparison between the actual product and the customer's expectation. By gathering more experience in reading and reviewing books over time, frequent reviewers are more likely to come across books with high quality. The sample of read books shape a better benchmark portfolio and result in a higher standard of quality for them, which increases their expectation from their next read. Reviews are consumers' evaluation of the product. When they evaluate the product, they compare the utility they received with their expectation. Due to the disconfirmation effect, higher expectation result in reviews that are more negative (Hu & Li, 2011). Therefore, with higher expectations, it is more likely to have less cognition satisfaction with new books. Overall, with decreasing affection and cognition, the satisfaction of frequent reviewers with the books they read is *likely to decrease over time*.

To sum up, by reading other reviews and writing their own, frequent reviewers gather some experience, develop some expertise, and modify how they evaluate products. Time affects them and makes it harder for them to be satisfied with books they read and review. Moreover, the self-selection bias, which makes it more likely for reviewers to give books higher score at the beginning, declines gradually. All these factors will lead to a significant systematic decrease in review valence. Therefore, we hypothesise:

> ***Hypothesis 2 (H3-2)****: The average valence score, at which users review books, is likely to decrease over time.*

### 3.4.5. Learning by participation

In a community of practice (Wenger, 2009), *practice* component of the theory is defined as "a way of talking about the shared historical and social resources, frameworks, and perspectives that can sustain mutual engagement in action". Johnson (2001), in a survey of research on online community of practice, suggested that having a "completely authentic task" to build the community around is an inseparable component of a task-oriented Community Of Practice. Members of the community are learning partners who do not necessarily support each other's practice (Wenger, 2010). They may criticize or comment on other members' practice, and this builds up a big opportunity to learn for all members. For members, practice may not be aligned with the community. Therefore, learning reflects in the behaviour change in members towards the realignment with others and with the task agenda of the community (Wenger, 2010). In our context, participation in reviewing books is the main activity or *Practice* that the eWOM community shapes around. Different individuals have their own practice experience, which reflects on their practice.

#### *3.4.5.1. Social bias*

By writing book reviews, reviewers expose their opinion and preferences by sharing their evaluation of books. Later by observing and gathering the reaction of other members towards their practice, they learn to adjust their behaviour. Frequent reviewers are likely to get affected by social-bias, the direct or indirect observational feedback in an eWOM community.

Reviewers are known to use strategies for attracting social attention (Shen, 2009). To increase the chance of getting positive attention, they might alter their behaviour after receiving and interpreting the social feedback in the community. This shapes the social-bias mechanism in eWOM communities. Socially biased reviews are not solely about the product and consumption evaluation, but also include reviewers' strategies in response to their social experience.

When choosing a new product to purchase, prospect customers, as logical risk-averse agents, are more likely to be interested in online reviews that emphasise on potential negative aspects of the product. Important positive points about the product are usually communicated by the vendor and all could have been considered when the prospect customer starts reading online reviews. This can lead to a negative preference towards online reviews. Therefore, the feedback mostly reflects the community's social bias towards negative reviews (Goes, et al., 2014), which leads frequent reviewers to post reviews that are more likely to be negative.

Reviewers may not be aware of this implicit preference at the beginning and only notice it when getting experienced (Goes, et al., 2014). When their motive of getting the attention of the crowd in social media (Mackiewicz, 2010) is strong enough to keep them reviewing books frequently, it is more likely that they lower the valence score they give to books. Because the more they are exposed, the more their chance of receiving and noticing the social bias is. Moreover, frequent reviewers are likely to have motivations to share their reviews with the community. Research shows that when users are expected to share their reviews in the community, they behave with a negative enhancement (Ofir & Simonson, 2001). With both these mechanisms, we believe that they will consequently lower their evaluation of books to address this bias. We investigate this argument by hypothesising:

> ***Hypothesis 3 (H3-3)**: The more frequent reviewers review books, the more likely is for them to notice the social bias and have lower average valence.*

### 3.4.6. Learning by seeking community recognition

In a social group, individuals define themselves with their relationships and bond with others (Brewer & Gardner, 1996), which is consistent with the social theory of learning. According to this theory, *belonging* and *social identity* are mutually defined and very closely related (Wenger, 2009). Wenger also suggested that developing an *identity* leads to *learning by becoming* as an important element of learning in a Community of Practice (CoOP).

Individuals may belong to a community and use social feedback to change their behaviour in order to achieve their desired social identity (Qu & Lee, 2011). Some individuals, though, first select the identity they want and then decide to join a community or a group to develop that specific identity

(Tajfel & Turner, 1979). No matter how they build their identity, the desire of being recognized in a social environment and the consequent collective identity (Brewer & Gardner, 1996) are always motivations for the members of the community.

To address this desire, a majority of review hosting websites, offer a range of social networking features, which makes them a functional eWOM community. In such a community, frequent reviewers build a social network to fulfil their need of belonging and to find an audience. Then, the best way to build an identity is by participation (Yoo, et al., 2013; Tajfel & Turner, 1979), and the ongoing participation, positively affects the *becomin*g process and strengthens their identity (Qu & Lee, 2011). The repetitive participation in the eWOM community helps frequent reviewers build a personal history in the community with their participation, which shapes their identity (Wenger, 1998). When the community recognizes their contribution and developed identity, they find the opportunity to contemplate and resonate the social learning process.

There are many ways to build an identity for frequent reviewers. The easiest way is to make regular contributions and build a collective identity as a contributor, which results in the learning alongside the practice. Some eWOM platforms distinguish users with such contribution to motivate frequent reviewers. Moreover, taking an extra role in the community is another way to build special identity (Yoo, et al., 2013). Inspired from the current literature, Yoo et al. (2013) suggested that contributing with taking up an extra role can affect building the identity in the community.

Some eWOM platforms encourage volunteer contributions of members for running the community that can help in identity development for frequent reviewers. In our selected platform, one important extra role that each frequent reviewer can take is becoming a *Librarian*. After reviewing at least 50 books reviewers can apply for the badge and engage in extra activities such as creating, and editing book profile pages, and so on. *Librarians* act as community experts on books. If a reviewer gets accepted as a *Librarian* the status will show in her profile. To maintain the status and the identity they most probably intend to build, they may feel obliged to keep up with the image of a knowledgeable person about books. They will deal with different books and related reviews, even with the books that they do not intend to read. We argue that developing and maintaining an identity facilitates the social learning for frequent reviewers. It will give them a very special opportunity for researching a broad range of books and making more well-informed decisions when selecting their next read, which can result in having a better reading experience and consequently reviewing books with higher score. The related hypothesis is:

> ***Hypothesis 4 (H3-4)****: Frequent reviewers who take extra role as the community expert (Librarian) will have a higher valence in reviewing books.*

### 3.4.7. Learning by association to the community

As mentioned before, online reviewers learn by developing an identity in the eWOM community. Moreover, by building a social network as the audience, frequent reviewers can accelerate the identity building process. Therefore, as the social theory of learning (1998) suggests, an established association with the community facilitate the learning process.

The social network also can strengthen and satisfy the need to belong (Baumeister & Leary, 1995) for individuals, which is an essential component for the social learning (Wenger, 1998). People need to belong and bond with others, and they usually satisfy it with a pleasant association with others (Alexandrov, et al., 2013). A hobby oriented eWOM community is a unique opportunity for such association assuming that all people on the platform are highly interested in a certain hobby, i.e. book reading in our case. This can bring social benefit for members (Hennig-Thurau, et al., 2004). Participants also feel belonging to the community when they contribute repeatedly. However, participation is not enough and frequent reviewers want their participation to be recognized as competent and helpful (Iriberri & Leroy, 2009). Therefore, the feedback others give them and their interpretation of it is very important in their learning. Being a member in an expert community, not only infuses the feeling of belonging, but also implies that the member is qualified and competent.

Dependent on the primary motivation for joining the community, individuals who are associated with the community may behave heterogeneously. Flynn et al. (1996) suggested that different participation patterns of people could be described in two categories: *opinion givers* and *information seekers.* Opinion givers tend to be opinion leaders and have the desire to be recognized for their contribution. On the other hand, information seekers want to be connected to people who share information as they find the information provided by friends more credible (Flynn, et al., 1996, p. 138). In our context, we believe that frequent reviewers, who are connected to a large number of friends, are either opinion leaders or information seekers.

For learning through association with the community, our argument has two sides. **First,** the reflection on their contribution is vital, especially for frequent reviewers with the tendency to become opinion leaders. Therefore, they are expected to be more sensitive to the feedback on their posted reviews. In summary, people with bigger social network and such motivation have bigger potential audience and have more opportunities to get feedback on their behaviour.

Drawing on the previous literature (Moe & Trusov, 2011), Goes et al. (2014) suggested that posting negative reviews makes the reviewer look smart and competent. Therefore, the eWOM community has a tendency to encourage negative reviews and rating (Goes, et al., 2014). We summarise our argument by suggesting that *opinion leaders, who have a big social network, are motivated to share more negative reviews*. Therefore, the valence of their reviews is expected to be less than others. In other words, they are more likely to recognise and respond to the bias in the eWOM community through negative reviews.

**Secondly**, information seeker reviewers are connected to a large number of friends and build a big social network just to have access to more information from credible friends (Flynn, et al., 1996). However, that does not necessarily result in a better reading experience. Within a larger social network, it is more likely for reviewers to have friends with less homogeneity in term of interest and taste in books. Therefore, they are more likely to observe recommendations and reviews from friends, which does not help them become better readers. This could significantly reduce the effectiveness of an eWOM community in learning of frequent reviewers and lower their overall valence. Overall, we conclude that:

> ***Hypothesis 5 (H3-5)****: frequent reviewer with a larger social network will have a lower valence in reviewing books*

## 3.5. Data, measures, and analysis

### 3.5.1. Data Collection

We collected the data for this research from an eWOM community on a book review website. The primary focus of this research is to reviewers who share their opinion about products repeatedly. We intended to investigate how their behaviour is affected by their experience in an eWOM community. Moreover, literature has determined that the product type affects reviews' quality and perceived helpfulness (Mudambi, et al., 2014). How one's peers evaluate the helpfulness of one review, directly or indirectly affects the frequent reviewers' behaviour. As mentioned before, the indirect effect is through the social feedback mechanism and observational learning. Therefore, we decided to control the effect of product type by collecting our data on an eWOM community that only includes reviews for one particular product type.

To obtain the data we need, we used a crawling software to visit publicly available pages on the selected review platform. Visited webpages included products (books) and reviewers' profile. We started with 500 random books. The crawler agent collected reviews of the initial list and visited the profile page of reviewers who wrote those reviews. The profile data of reviewers were collected. The software agent also collected a complete review history of each reviewer whose profile page was visited. The history includes all reviews that each reviewer has done from the first day that they joined the website up to the date of data collection.

As we wanted to investigate reviewers' evolution over time, we needed to capture behavioural data of reviewers in different occasions. Therefore, we collected data on online reviewers in five waves started from July 2012 until December 2015. At the time we started our data collection in 2012 the website had 10 million users, which increased up to 20 million in July 2013 (Chandler, 2013) and 50 million in December 2015 when we collected the last round of data (Chandler, 2016).

As a result, our dataset includes more than 81,233 books reviewed by 719 frequent reviewers. At reviewer level, we have a dataset consisted of 719 user profiles, including cross sections of individual-related variables across over a nine-year period (complete history for each reviewer). The number of total contributions of reviewers is between 1 and 36 quarters. We have overall 10941 individual-quarter records of data.

At the book level, we have a cumulative crowds-given score for each data collection wave. We also used a separate crawling agent to collect complementary data on books from the Amazon.com website. The complementary dataset includes basic data on all books such as author and publisher name, time of release, and number of pages.

### 3.5.2. Constructs and Measurements

To investigate our research question, we focused on the change in reviewing behaviour over time. Reviewers review books they have read while they may have different pace in reading. They also joined the website at different times. Therefore, we needed to define a sensible time clock with which the reviewers' behaviour can be compared.

The time clock for each reviewer, started when one reviewed the first book on the platform, which probably was on different dates. We also chose 90 days or a quarter as a unit of time and collected reviewing activities of the reviewers for each quarter. We aggregated daily data records for each reviewer and re-calculated all behaviour based on this time clock.

We calculated all variables to measure related constructs. Based on our research design, we have both *time-invariant* and *time-variant* variables. *Time-variant* variables usually reflect reviewers' behaviour or performance and have one value for each quarter. Whereas *time-invariant* variables mostly reflect the reviewers' characteristics extracted from their accumulated behaviour and have a constant value for each individual during the data collection period.

Both book and reviewer level constructs have observed and unobserved measures to consider. At *the reviewer level*, we use a mixed effect analysis method to deal with the issue. The random part of the model accounts for the unobserved characteristics of different individuals. We tried to capture the heterogeneity and we used a mixed effect analysis model, which considers the between individual different with suitable error structure.

At *the book level,* we have unobserved measures such as *Book Quality,* which cannot be measured subjectively. Although measuring the quality of a book is challenging, Preece and Shneiderman (2009) believed that the *"user ratings can indicate rising or falling quality."* Therefore, we estimated the unobserved measure of *book quality* with the crowd-given score (valence) for each book as the proxy of the book's quality. We discuss this estimation in more detail in section 3.6.1.3 .

### *3.5.2.1. Outcome variables*

The core of this research focuses on the change in the behavior of frequent online reviewers, which is the result of learning from contributing in a social setting. If the learning happens, we expect it to affect the quality of book reviewers read. However, we argue that the increase in the quality does not reflect on the review valence. As reviewers contribute in the eWOM community and get experienced, they have more chance to observe and learn about the social negative bias towards reviews (Goes, et al., 2014; Ofir & Simonson, 2001). Therefore, they may respond to evaluating books with lower valence to have a chance to be recognized by their audience. Therefore, review valence is the *outcome* variable in our research.

The *review valence* was measured at the reviewer-quarter level by taking the average of rating score each reviewer assigned to different books in each quarter ( $AvgScore_{ij}$). We accumulated this measure for all books in each quarter as we followed the previous research (Li & Hitt, 2008) on the existence of self-selection bias in selecting, reading, and reviewing books. By taking an average, not only we can measure the change of *review valence* over time, we also can account for the hidden selection bias in frequent reviewers' behaviour.

We included three control variable to deal with the potential aggregation issue with the average function in calculating $AvgScore_{ij}$, which may weaken our inference by concealing the range of scores one may assign to different books. To include the range of scores, we included a reviewer-quarter level variable, $ScoreSpread_{ij}$ in our analysis. This measure, accounts for the interval between the lowest and the highest score given by each reviewer in each quarter. Introducing $ScoreSpread_{ij}$ to our model, we followed the prior work, which observed that $ScoreSpread_{ij}$ gets affected by the existence and product collection of one's social network (Chen & Huang, 2013).

However, $ScoreSpread_{ij}$ alone cannot capture the range of scores accurately. As it has the same value for a hypothetical reviewer who evaluated books with the same $ScoreSpread_{ij}$ of 2. This could be a measure for someone who reviewed books with scores between 1 and 3 stars or 3 and 5. To differentiate, we included another control variable, $FiveStars_{\mathrm{ij}}$, which captures the number of books scored with five stars in a quarter. When there are more reviews with five stars posted in a quarter, it is more likely that the score spread of 2 is coming from scores between 3 and 5. Finally we included $BestBook_{ij}$, a variable to deal with the potential aggregating issue for $\mathrm{BookQuality}_{ij}$, which marks the higher bond of the quality measure for the set of books each reviewer reviews on each quarter.

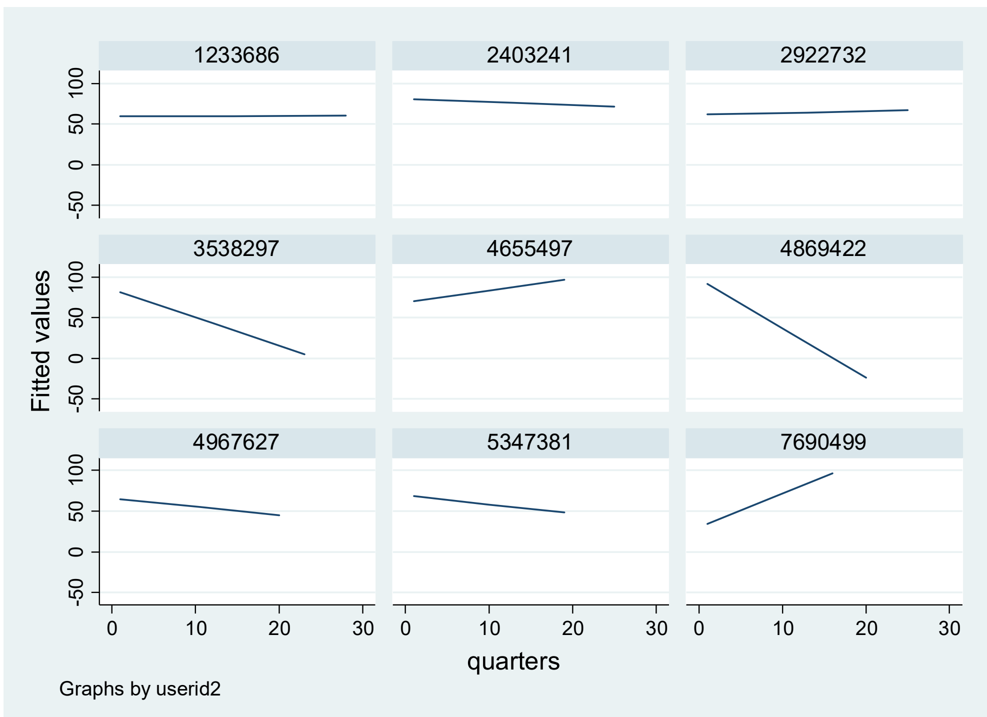



**Figure 3-2: Different Valence Patterns**

### *3.5.2.2. Key independent variables*

The focus of this study is on explaining the evolution of online reviewers from the Social Learning perspective. Our hypotheses are based on social learning mechanisms of *practice, experience, belonging, and identity*. We measured the *experience* component with *time* ($Quarters$), which represents the length of contribution of each reviewer on the platform. Frequent reviewers also learn by practicing in an eWOM community. The number of reviews per quarter represents the *practice* for each individual-quarter and is measured by *review volume* (as $VolumeQ_{ij}$). In addition to assigning numerical scores to books ( $AvgScore_{ij}$), reviewers may write textual reviews on books. To include this practice in our analysis, we used the measure of $ReviewRatio_{ij}$. In each quarter, the measure shows the percentage of the total reviews written by each reviewer that include a textual comment.

Building an *identity* is a mechanism of social learning (Wenger, 1998) and for reviewers in an eWOM community, maintaining a collective identity as a credible reviewer, demands continuous participation (Qu & Lee, 2011). Being compared to others could result in building a desired identity (Tajfel & Turner, 1979). Writing book reviews frequently and being an active member of the eWOM community is a manifest of expertness in books itself, which we consider as a collective identity (Mackiewicz, 2010). However, one can strengthen this identity by taking extra volunteer roles in the community (Yoo, et al., 2013) which demonstrates the in-depth proficiency and expertness compared to other members of the community (Mackiewicz, 2010). In our community of interest, reviewers who already contributed to a certain level in the community could apply for an honourable and volunteer position of being a *Librarian.* People may apply or attain the job anytime in their life cycle of contribution to the community and it is a time-variant status. Therefore, we used a binary measure as $IdentityQ_{ij}$ to capture the identity component. The measure is 1 if the reviewer is a *librarian* at the time. But we only had the data about this status at the time of data collections. Therefore, we estimated the $IdentityQ_{ij}$measure with a step-wise function assuming that it stays constant for quarters between two data collection points.

The last, but the most important components of social learning in an eWoM community is *belonging.* As mentioned in section 3.4.7, the size of the connected social network that reviewers should handle has an effect on their behaviour and learning in the next steps. Reviewers can build their own social network by connecting to other reviewers on the platform. The friendship is a two-way symmetric relationship, which shapes after one requests and the invitee accepts. At first, the platform recommends people to connect with their friends from other social networks such as Facebook. Despite that, in a focused eWOM community one's review will be shown to their friends before reviews from other members of the community. Therefore, one's friends are her immediate audience and many reviewers might prefer to keep their relationships professional and mainly connect to other reviewers with similar interests in books, authors, or genres.

Therefore, we decided to capture the *association with the community* with the lagged measure of Social Network Size (captured by $Friends_{i(j-1)}$), which is reviewers' number of friend in the previous quarter. On the other hand, using the connected social network size (as $Friends_{ij}$), does not capture all information on how reviewers satisfy their need to belong. It shows how big the community that reviewers belong to is, but does not capture the rate at which reviewers connect to others. People may have different strategies in expanding their ties to the eWOM community. Some may expand their social network very fast during first quarters after joining the community; whereas, others may develop their relationships gradually. The latter group may focus on reviewing products first and later form social ties. These strategies represent the heterogeneity in reviewers (Samiei & Tripathi, 2015). To capture data on such strategies, we calculated the rate of social network expansion for each individual by dividing $Friends_{ij}$to *Quarters* on three data points of our data collection. The results are stored in $SNExRate_{i(t1)}$, $SNExRate_{i(t3)}$, and $SNExRate_{i(t5)}$ variables. For the *Quarters* on each of those data points ($t_1$, $t_3$, and $t_5$), and for each individual, we used the number of days between joining the platform and the data collection time for three rounds of crawling data.

### 3.5.2.3. Literature recommended control variables

To maintain the internal validity of the data analysis model, we used two sets of control variables. In the previous sections, we mentioned control variables, which we used to ensure an accurate measurement of dependent and independent variables. We also included factors that prior research proved to be determinants affecting outcome variables of our analysis as follows:

***Product characteristics***

Based on the social identity structure, researchers suggest that reviewers' behaviour on eWOM communities are either community related or product related (Qu & Lee, 2011). We have considered community-related behaviour as the social bias effect for frequent reviewers, but not the product related behavior. Despite the social bias mechanisms and by common sense reviewers are expected to assign higher average valence to books with high quality. Therefore, we used the crowds-given quality measure of books ($BookQuality_{ij}$) in modeling the learning to control for the product quality. We calculated the measure as the average quality score of all books that reviewer *i* selects to read and review in quarter *j.* To mitigate the possible aggregation issue when using the average function, we included another control variable ($BestBook_{ij}$), which specifies the quality score range. The $BestBook_{ij}$ measure is the quality score of the book with the highest quality score read by each reviewer ($i$) on each quarter (*j*). In section 5.3 we explain, in detail, how we estimated the unobserved measure of book quality with a crowd-given score in our platform.

***Pleasant experience***

It is obvious that having a pleasant experience in reading books could affect the social learning process. We introduced a binary variable to account for the possible *pleasant* experience on reviewer-quarter level. As people are different in their interests, expectations, and tastes in reading books, we normalized this measure for reviewers based on their own experience. The measure is 1 if their good experience in one quarter is higher than their overall experience. In this definition, we consider reading a book a good experience if the reviewer evaluates the book with a five star score.

***Reviewer heterogeneity and sidedness***

Reviewers had different motivations for their contribution, which could lead them to demonstrate different behavior patterns (Munzel & Kunz, 2014). Based on these motivations, they might observe and interpret the social feedback differently and be heterogeneous with their social learning. Therefore, we needed to control this heterogeneity in our analysis.

| Construct | Variable | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Reviewing valence (outcome)** | $AvgScore_{ij}$ | 71.43 | 16.11 | 0 | 100 |
| **Experience** | $Quarters$ | 12.53 | 8.05 | 1 | 36 |
| **Association with the community** | $Friends_{i(j-1)}$ | 138.73 | 462.89 | 0 | 5668 |
| | $SNExRate_{i(t1)}$ | 13.69 | 45.51 | 0.05 | 673 |
| | $SNExRate_{i(t3)}$ | 9.32 | 34.6 | -11.6 | 530.8 |
| | $SNExRate_{i(t5)}$ | 3.32 | 12.74 | -47.57 | 174.85 |
| **Practice** | $VolumeQ_{ij}$ | 27.92 | 67.5 | 1 | 2789 |
| **Identity** | $LibrarianQ_{ij}$ | 0.1 | 0.3 | 0 | 1 |
| **Control Variables** | $BookQuality_{ij}$ | 78.29 | 3.49 | 40.1 | 100 |
| | $BestBook_{ij}$ | 886.12 | 5.22 | 54.6 | 100 |
| | $ReviewRatio_{ij}$ | 0.55 | 3.2 | 0 | 100 |
| | $PlsntExp_{ij}$ | 0.22 | 0.41 | 0 | 0 |
| | $FiveStars_{ij}$ | 7.03 | 21.45 | 0 | 761 |
| | $ScoreSpread_{ij}$ | 55.09 | 32.55 | 0 | 100 |
| | $Sidedness_{\mathrm{i}}$ | 0.45 | 0.49 | 0 | 1 |
| | $AvgDeviation_{ij}$ | -0.34 | 0.78 | -4.69 | 2.2 |
| | $AvgABSDeviation_{ij}$ | 0.9 | 0.57 | 0 | 4.69 |

**Table 3-1: Descriptive Statistics**

As we focus on the *review valence* as one of the outcome variables, reviewer *sidedness* is one factor we should control. Individuals are different in their reviewing sidedness. Some just mention the negative aspects of the product, books in our case, probably assuming that the vendor has already communicated all the good features and positive points. On the other hand, some have more balanced sidedness and consider both positive and negative aspects of the product (Cheung & Thadani, 2012). Sidedness has an effect on how the receiver of the review trusts and adopts it by affecting the perceived helpfulness of the review (Connors, et al., 2011) and the credibility of the reviewer (Cheung & Thadani, 2012). To capture the sidedness of frequent reviewers, we first calculated the overall reviewing score given by each reviewer in the whole data set. Then we compared it to the average score of the population in our data set. We used a binary measure, $\mathrm{Sidedness}_i$, which is 1 for reviewers whose overall valence is more than the same measure for the population. We summarized all constructs, their measuring variables along with the description statics of our data in Table 3-1.

Table **3-2** presents the pairwise correlation between our dependent, independent, and control variables.

| **Variable** | $\mathrm{AvgScore}_{ij}$ | $\mathrm{Friends}_{i(j-1)}$ | $\mathrm{VolumeQ}_{ij}$ | $\mathrm{LibrarianQ}_{ij}$ | $\mathrm{ScoreSpread}_{ij}$ | $\mathrm{BookQuality}_{ij}$ | $\mathrm{BestBook}_{ij}$ | $\mathrm{ReviewRatio}_{ij}$ | $\mathrm{FiveStars}_{ij}$ | $\mathrm{PlsntExp}_{ij}$ | Sidedness | Quarters |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\mathrm{AvgScore}_{ij}$ | 1.000 | | | | | | | | | | | |
| $\mathrm{Friends}_{i(j-1)}$ | 0.0318 | 1 | | | | | | | | | | |
| $\mathrm{VolumeQ}_{ij}$ | -0.0131 | 0.0931 | 1 | | | | | | | | | |
| $\mathrm{LibrarianQ}_{ij}$ | -0.0115 | 0.1229 | 0.1214 | 1 | | | | | | | | |
| $\mathrm{ScoreSpread}_{ij}$ | -0.2607 | 0.0659 | 0.3412 | 0.0777 | 1 | | | | | | | |
| $\mathrm{BookQuality}_{ij}$ | 0.2065 | 0.0668 | -0.0195 | -0.0323 | -0.0715 | 1 | | | | | | |
| $\mathrm{BestBook}_{ij}$ | 0.1103 | 0.1512 | 0.3475 | 0.0712 | 0.393 | 0.501 | 1 | | | | | |
| $\mathrm{ReviewRatio}_{ij}$ | 0.0343 | -0.0358 | -0.0266 | -0.0202 | -0.0109 | 0.0204 | -0.0118 | 1 | | | | |
| $\mathrm{FiveStars}_{ij}$ | 0.2399 | 0.1203 | 0.7649 | 0.0543 | 0.2377 | 0.0522 | 0.3348 | -0.0164 | 1 | | | |
| $\mathrm{PlsntExp}_{ij}$ | 0.1565 | -0.0329 | 0.3173 | 0.0137 | 0.2261 | 0.0686 | 0.2529 | 0.027 | 0.4097 | 1 | | |
| $\mathrm{Sidedness}_i$ | 0.3192 | 0.1121 | 0.0061 | -0.0891 | -0.0601 | 0.0924 | 0.0653 | 0.0017 | 0.2302 | 0.0126 | 1 | |
| Quarters | -0.0401 | 0.1321 | -0.1199 | 0.0613 | -0.1094 | 0.031 | -0.0221 | -0.1135 | -0.1309 | -0.1496 | -0.1131 | 1 |

**Table 3-2: Correlation Matrix**

It worth mentioning that we have two measures to capture the situation in which a reviewer read a book in her taste and review it with high score. The two variables are $PlsntExp_{ij}$ and $FiveStars_{ij}$. Although both variables are about pleasant reading experience, they are not highly correlated (0.3890) confirming that they measure two different sides of the same experience and can be used in the same model.

### 3.5.3. Analysis Model

For the analysis, we have used a mixed effect longitudinal data analysis method. The nature of our data set is a panel data, as we have reviewing activity of individuals over time. We intended to study the evolution of frequent reviewers over time. Thus, *time* (measured by Quarters) is the main independent variable in our data set. With a closer look to our hypotheses, we need a model with two levels; population and individual level. We also have to account for the within and between individual differences. Therefore, we need a multi-level model with random effects. We adopted the longitudinal data analysis method suggested by Singer and Willett (2003) for *Review Valence*.

We used the multi-level, mixed effect longitudinal analysis method (Singer & Willett, 2003). To investigate our hypotheses (H3-1 to H3-5), we developed a longitudinal model with the $AvgScore_{ij}$ as the dependent variable. The model consists of *time-variant* variables and has two levels to allow for the heterogeneity among individuals. We gathered and calculated reviewer-related measures from what we observed on the accumulated behaviour of users at each data collection point. However, there are many unobserved characteristics on different reviewers, which we could not capture. Having a random effect in level two, which alters the coefficients in our main equation for each individual, takes care of unobserved reviewer-level measures. In addition, the $Sidedness_i$ measure is a time-invariant variable reflecting if on average individual rated books with higher sore compare to the population. On the other hand, the main level of the model consists of the *time-variant* measures that quantify reviewers' behaviour and have a different value on each time-period.

To develop our model, we assumed that the change in *review valence* is linear. As mentioned in section 3.4, conceptual modelling, the change in review valence can be explained by the components of the social theory of learning (Wenger, 1998). Hence:

$$AvgScore_{ij} = \pi_0 + \pi_1 Quarters + \pi_2 Friends_{i(j-1)} + \pi_3 VolumeQ_{ij} + \pi_4 LibrarianQ_{ij} + \pi_5 BookQuality_{ij} \\ + \pi_6\, ControlVariables + \varepsilon_{ij}$$

Where *control variables* consist of $BookQuality_{ij}$, $Sidedness_i$, $FiveStars_{ij}$, $ScoreSpread_{ij}$ $BestBook_{ij}$, $PlsntExp_{ij}$ , and $ReviewRatio_{ij}$. The level two is as follows:

$$\pi_0 = \gamma_{00} + \gamma_{01} Sidedness_i + \zeta_{0j}$$
$$\pi_1 = \gamma_{10} + \zeta_{1j}$$

The final model is a composite of level one and two:

$$AvgScore_{ij} = \gamma_{00} + \gamma_{01} Sidedness_i + \gamma_{10} Quarters + \pi_2 Friends_{i(j-1)} + \pi_3 VolumeQ_{ij} + \pi_4 LibrarianQ_{ij} \\ + \pi_5 BookQuality_{ij} + \pi_6\, ControlVariables + (\zeta_{0j} + \zeta_{1j} * Quarters + \varepsilon_{ij})$$

The random component of this model is as follows:

$$\varepsilon_{ij} \sim^{iid} N(0, \sigma_0^2)$$

In this model both level-one growth parameters have their own residuals ($\zeta_{0j}$ and $\zeta_{1j}$ ) which allows the parameters of the model to differ between individuals. $\sigma_0^2$ , $\sigma_1^2$ and $\sigma_{10}$ meausre the variance and covariance of the model for these residuals with the following distribution.

$$\begin{bmatrix} \xi_{0j} \\ \xi_{1j} \end{bmatrix} \sim^{iid} N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{10} & \sigma_1^2 \end{bmatrix}\right)$$

### 3.5.4. Analysis Result

#### *3.5.4.1. Analysis process*

We used Stata-14.1 as a general-purpose statistical software and we used the mixed-effect commands to fit a longitudinal model to our data set. For each analysis, we estimated the time relevant coefficients.

For the *review valence*, after running the simple growth model, we added independent variables, one by one, closely controlling the fitness-of-fit using AIC (Akaike information criterion) and BIC (Bayesian information criterion). Using this approach, as suggested by Singer & Willett (2003, p. p. 120), we could compare AIC and BIC fitted values in nested models (see models A, B, C, and D Table **3-3**). In Model A, we included variables associated with *self-selection bias* and *experience* along with all control variables. Then we added the variable associated with other hypotheses (H3-3, H3-4, and H3-5) one by one. We reported the goodness of fit measures in Table **3-3**, which is comparable as models are nested. We decided that the model D is the final model explaining the change in *review valence* with the lowest AIC and BIC. It has been shown in Table **3-3** that by adding explaining variables, our model is stable and all coefficients are consistent in their size and magnitude.

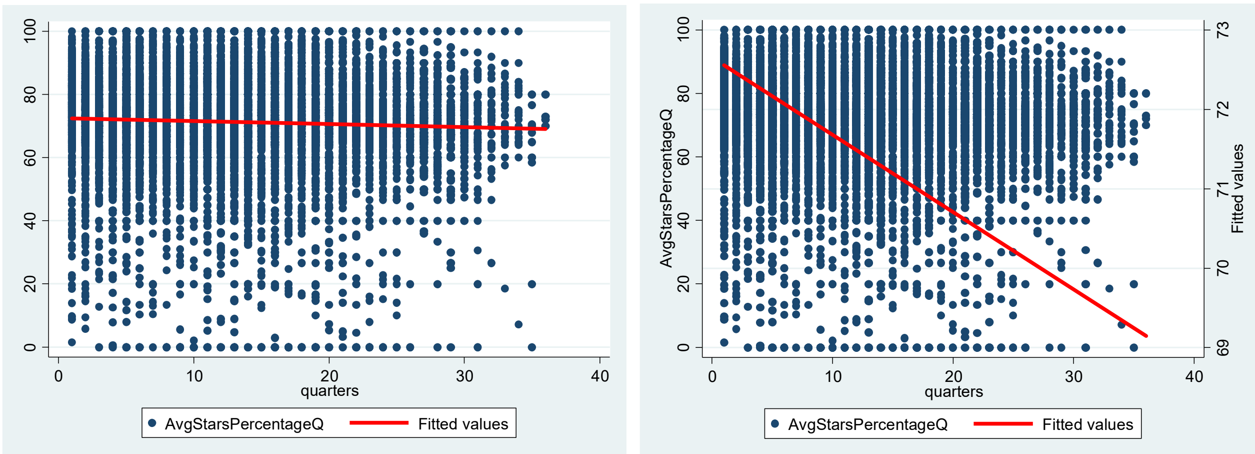
It worths mentioning that when we ran the model, we included the time interaction of all time invariant variables at the beginning. However, many of these interactions did not significantly explain the dependent variables and in the final model, we only kept significant measures. The coefficient associated with all explaining and control variables included in our model for review valence are highly significant.

#### *3.5.4.2. Estimation Results and Hypothesis Testing*

Concentrating on learning, we found evidence in Model D (Table **3-3**), as our final model, supports our hypotheses (H3-1 to H3-5). For the first hypothesis, the significant positive measure of ($\gamma_{00} =$ 18.21) for the intercept, confirms that reviewers are biased when they start to contribute in the eWOM community (H3-1). It also confirms the average valence score, at which users review books, decreases over time. The Coefficient for time measure (*quarters*) is significantly less than 0 (negative), confirming that over time frequent reviewers assign lower valence to books they review. This supports the second hypothesis (H3-2). As we argued, the early self-selection bias from the early stages, which is due to the reviewing the books from previous positive and memorable experience drops. A simple linear model on our data (Table 3-3; model A & B) illustrates the change trend of *Valence* over time.

Later reviews are written on books that the reviewer read right before writing the reviews, which has less chance of being positively self-biased based on the current research on the potential negative reaction of reviewers when they are expected to write a review (Ofir & Simonson, 2001). Another explaining reason for decline in the review scores over time is frequent reviewers' response to the social bias to negative reviews in the community (Goes, et al., 2014). Our result confirmed that frequent reviewers observe and learn in each quarter and lower their review valence as the result to stay in the attention-seeking game, which is alligned with Goes et al. (2014). On the other hand, our result is different from Goes et al. (2014) in a sense that they believe that the popularity of the reviewers puts them in a situation to respond with assigning lower score (valence) to products. They showed that the *review valence* decreases as their popularity increases. They assumed that the number of incoming friend requests is a proxy of the popularity of the reviewers and as the reviewer has an audience, they alter their behaviour towards a negative valence to maintain their popularity. Where we showed that the time itself and the experience that builds up when the time passes can easily describe the decline in the review valence. To sum up, although popularity in their model was shown to be effective in explicating the decreasing valence, it is not the only explaining variable. Frequent reviewers become better readers and reviewers and lower their valence along the way through a social learning mechanism. Their popularity on the other hand increases by the time and experience too, which could explain a portion of their behaviour change.

The analysis also showed that the coefficient for the $VolumeQ_{\mathrm{ij}}$ measure is significant and negative confirming the related hypothesis (H3-3). We observed that the more frequent reviewers write reviews, the more they might behave in response to the social tendency toward negative reviews and review with lower valence. We argue that publishing the result of reviewing practice in terms of reviews ($VolumeQ_{\mathrm{ij}}$), available to both public and your friends, increases the chance of a reviewer observes direct or indirect feedback. The feedback could be the confirming response agreeing with the point of view of the reviewer or a critique opposing. The indirect feedback could appear as more friend requests from other users with similar taste or generally people who might see and appreciated one's reviews in the community. Although the feedback is not always positive, it could be constructive (Tajfel & Turner, 1979). Getting no feedback or even negative feedback on one's current reviews could lead the reviewer to alter their behaviour, which will be towards posting more negative reviews (Goes, et al., 2014). Our result confirmed that for frequent reviewers, posting more reviews and higher *Volume* would result in more response to the social bias with more strict reviews and lower review *Valence.*




**(A)** **(B) – with the second Y axis**

**Figure 3-3: Scatter plot vs fitted LnVolume over time**

To investigate the effect of community recognition, we used the formal status of *Librarian* as be argued that taking up an extra role is a well-known way in our platform to build up an identity as book and website expert. The result of the analysis ($\pi_4 = 2.16$) in model D supports the associated hypothesis (H3-4). It confirms that although the intention of librarian is to build an identity, the job itself gives them opportunity to participate more in the eWOM community and communicate with more people. This could facilitate and intensify the learning effect of their contribution. They will become better readers compared to non-librarian and will select books with higher quality and closer to their taste, which result in higher review valence for them.

To investigate the effect of association with the community on the social learning process, we used measures of *Social Network Size*. Being a member of a big eWOM community could be helpful for reviewers to become better readers and better reviewers.

However, our analysis ($\pi_2 = 0.001 \sim$) does not support the hypothesis supported the associated hypothesis (H3-5). Based on the current literature and our argument we expected to observe a negative effect of social network size on the product evaluation (valence). The estimated coefficient for the $Friends_{i(j-1)}$ variable is positive with a large confidence interval. Our explanation is despite the significant effect of the *popularity* in the social network on the review *valence* (Goes, et al., 2014), frequent reviewers may suffer from associating with the big social network too. This adverse effect can be explained from different perspectives. **First** explanation is *time* as reviewers' limited resource. It is realistic to assume that reviewers have a limited time and energy for contributing in the community. When they spend a big part of time building connections to other members of the community and grow their social network, they have less time available to focus on the social feedback and observe the reaction of their peers towards their behaviour. This can slow down their social learning process. They also have to maintain their current social network, which is time and energy consuming. **Second** explanation is the slower social learning process as the result of *Information Overload* (Deuker & Albers, 2012; Zhang & Dellarocas, 2006; Malhotra & K., 1984; Park & Lee, 2009) for frequent reviewers with bigger social network. Before we argued that frequent reviewers, over time grasp the idea of the community's negative bias and lower their review valence. However, reviewers with a big social network are more likely to suffer from the *Information Overload*, which can slow down their social learning.

| Dependent variables | Measures | Coefficient | $\mathbf{AvgScore}_{ij}$ Models | | | |
|---|---|---|---|---|---|---|
| | | | A | B | C | D |
| Fixed effects | Intercept | $\gamma_{00}$ | 18.1 *** | 18.05 *** | 18.4 *** | 18.21 *** |
| | *Time (Quarter)* | $\gamma_{10}$ | -0.14 *** | -0.16 *** | -0.16 *** | -0.16 *** |
| | $Sidedness_i$ | $\gamma_{01}$ | 8.8 *** | 7.9 *** | 6.4 *** | 6.5 *** |
| | $VolumeQ_{ij}$ | $\pi_3$ | - | -0.04 *** | -0.14 *** | -0.14 *** |
| | $Friends_{i(j-1)}$ | $\pi_2$ | - | - | 0.001 ~ | 0.001 ~ |
| | $LibrarianQ_{ij}$ | $\pi_4$ | - | - | - | 2.16 * |
| | $BookQuality_{ij}$ | $\pi_5$ | 0.55 *** | 0.49 *** | 0.48 *** | 0.48 *** |
| | $BestBook_{ij}$ | $\pi_6$ | 0.14 *** | 0.22 *** | 0.23 *** | 0.22 *** |
| | $ReviewRatio_{ij}$ | | 0.07 ** | 0.07 * | 0.09 * | 0.09 * |
| | $PlsntExp_{ij}$ | | 6.5 *** | 7.0 *** | 5.14 *** | 5.14 *** |
| | $FiveStars_{ij}$ | | 0.02 *** | 0.12 *** | 0.56 *** | 0.56 *** |
| | $ScoreSpread_{ij}$ | | -0.14 *** | -0.14 *** | -0.13 *** | -0.13 *** |
| Random effects | Within-person | $\varepsilon_{ij}$ | 11.11 | 10.9 | 10.36 | 10.36 |
| | Initial Status (Constant) | $\sigma_0^2$ | 8.4 | 8.0 | 8.7 | 8.7 |
| | Rate of change | $\sigma_1^2$ | 0.63 | 0.62 | 0.59 | 0.59 |
| | Covariance | $\sigma_{01}^2$ | -.35 | -0.3 | -0.4 | -0.4 |
| Fitness | AIC | | 85857.27 | 85592.14 | 73488.43 | 73486.17 |
| | BIC | | 85952.17 | 85694.34 | 73595.84 | 73600.74 |

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

**Table 3-3: Analysis result; Review valence model**

It has been shown that due to the physiological characteristics of the human brain, the maximum number of friends that individuals can have personal connection with is 150 people on average (Hill & Dunbar, 2003). Size of the network and the amount of information from others that reviewers with big social network should handle, intensify the time and social pressure on them (Zhang & Dellarocas, 2006). They have to change either the *information load* or *information quality*, or at least the *concentration* by which they receive this information. The information overload results in a long list of updates on reading experience from connected friends. Based on the theory of bounded rationality (Simon, 1972), individuals decide with available information in their limited time frame the result of which is not necessarily optimal considering their limitations. We argue that reviewers who have a big social network and therefore a long list of reviews and updates from their friends, do not have enough time to receive and interpret the recommendations in a way that contributes in learning and becoming better readers. Therefore, they have a higher valence compared to the rest of the population.

Moreover, the *information overload* has an adverse effect on how frequent reviewers receive and interpret the social bias in the eWOM community which can slow down their learning process too. Having a very big social network decreases the chance of reviewers for observing the dominant social-bias in the community towards negative reviews. This decelerates their learning to become better reviewers. In addition, they have many updates from their friends to consider when they are deciding to select their next read. The information overload slows down their learning to become a better reader.

| **Hypothesis** | **Status** |
|---|---|
| *Hypothesis 1 (H3-1):* Due to the self-bias, frequent reviewers post positively inflated evaluations for books at the beginning of their contribution | Supported |
| *Hypothesis 2 (H3-2):* The average valence score, at which users review books, is likely to decrease over time | Supported |
| *Hypothesis 3 (H3-3):* The more frequent reviewers review books, the more it is likely for them to notice the social bias and have lower average valence. | Supported |
| *Hypothesis 4 (H3-4)*: Frequent reviewers who take extra role as the community expert (Librarian) will have a higher valence in reviewing books | Supported |
| Hypothesis 5 (H3-5)*: frequent reviewer with a larger social network will have a lower valence in reviewing books* | Not supported |

**Table 3-4: Summary of Hypotheses Testing**

To sum up, we showed that social learning components are effective for frequent reviewers' to become better readers and reviewers. Therefore, we believe that the social learning is one of the motivations of frequent reviewers to contribute. We conclude that frequent reviewers continuously contribute to the eWOM community hoping to find better recommendations on products (books) they might like and increase their chance for having a more pleasant (reading) experience. To maximize their exposure to the community, they connect to other reviewers as their friends and build a social network on the eWOM platform. Our analysis showed that the social network has an adverse effect on their learning. A bigger social network slows down their learning by building *information overload.* If the consequent overload becomes hard to handle and obstructs the benefits of the eWOM community, the reviewer might leave the community or stop their continuous contribution. Therefore, it is logical to assume that frequent reviewers, especially ones who expand their social network very fast during first quarters after joining the community, noticed the problem and altered their behaviour to respond.

Using our data set, we compared the rate of social network expansion rate for reviewers ($SNExRate_{i(t1)}$, $SNExRate_{i(t3)}$, and $SNExRate_{i(t5)}$) on each of those data points ($t_1$, $t_3$, and $t_5$). We used three sets of paired t-test to compare the mean rates pairwise. For all three tests, the H0 was testing if *Social Network Expansion Rate* has equal means in all three-time intervals. The H3-1 for each test is mentioned in the table. The result showed that the social network expansion rate decreases over time. This supports our argument that frequent reviewers have strong motivation to continue their contribution to the eWOM community. They notice the effect of *information overload* and will alter their behaviour to avoid minimizing the problem by reducing the incoming friendship relationship with other members of the community (Table 3-5).

| Parried measures | | H1 | t | obs[13] | df[14] | p (T<t) | Result |
|---|---|---|---|---|---|---|---|
| Array 1 | Array 2 | | | | | | |
| $\boldsymbol{SNExRate_{i(t1)}}$ | $SNExRate_{i(t3)}$ | $SNExRate_{i(t3)} < SNExRate_{i(t1)}$ | -11.64 | 10941 | 10940 | 0.000 | supported |
| $\boldsymbol{SNExRate_{i(t1)}}$ | $SNExRate_{i(t5)}$ | $SNExRate_{i(t5)} < SNExRate_{i(t1)}$ | -24.5 | 10941 | 10940 | 0.000 | supported |
| $\boldsymbol{SNExRate_{i(t3)}}$ | $SNExRate_{i(t5)}$ | $SNExRate_{i(t5)} < SNExRate_{i(t3)}$ | -19.24 | 10941 | 10940 | 0.000 | supported |

**Table 3-5: Study of Change in Social Network Expansion Rate**

### *3.5.4.3. Results for control variables*

In our analysis, we controlled for some literature-recommended factors. Our analysis confirmed what we expected as their determinant effect on the review valence, which demonstrate the validity of the model. First of all, from the literature we know that the review content is not all about the community, but the Product is important in the reviewing Results. Therefore, we controlled for the book quality in our model. Based on the result ($\pi_5 = 0.48 ***$), we conclude that frequent reviewers who read books with higher quality are less affected with the social bias effect over time and have higher evaluation on each quarter ( $AvgScore_{ij}$). We also included another control variable ($BestBook_{ij}$) to avoid the aggregation problem for using the average function in calculation. The result (0.22***) confirms that reviewers whose best book in a quarter has higher quality, has higher $AvgScore_{ij}$. A good consumption experience also affects two measures associated with *pleasant experience* in our model. The significant positive coefficient for $PlsntExp_{ij}$ ($5.1 ***$) and

[13] Observations
[14] Degree of Freedom

$FiveStars_{ij}$ $(0.56\ {*}{*}{*})$ shows that if a reviewer has a pleasant consumption experience with a book, it reflects on their review and weakens the effectiveness of the social bias. We also argue that when a reviewer likes a book the social bias towards less valence affects them less. They even might write textual reviews and discuss their opinion about the book in detail to justify their evaluation and avoid looking less competent or expert reviewers. Our result with a significant positive coefficient for $ReviewRatio_{ij}$ $(\pi_3 = 0.09\ *)$ confirms that. Another control variable with positive impact on the review valence is *sidedness*. The coefficient ($\gamma_{01}$ =8.8 ****) is significant and positive as expected controlling for the natural heterogeneity between strict and permissive reviewers.

We included the $ScoreSpread_{ij}$ measure in the analysis as a control variable to avoid the potential aggregation problem we might have using the average function. In addition, this measure represents the level of experimental reading each reviewer may do in each quarter. The experimental reading happens when reviewers experiment and read books with different quality in another language, from a different genre, so on and so forth. They may end up having a bigger spread in valence, as they are out of their favorite area and reading different books, which does not necessarily lead to having a better reading (consumption) experience. This is consistent with the observed result (-0.13 ***) of the negative coefficient for the measure.

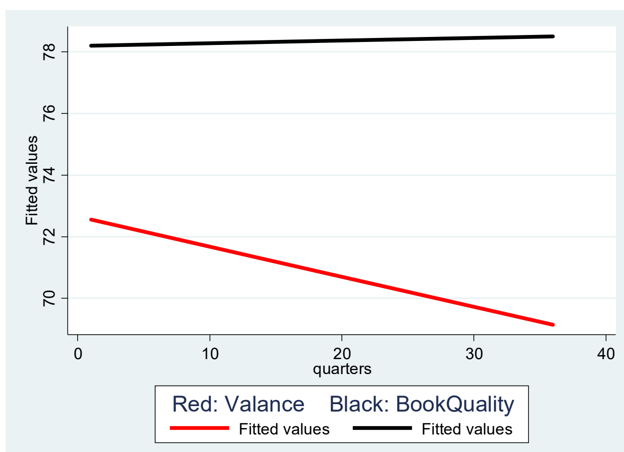



**Figure 3-4: Change in Book Quality and Valence Over Time**

## 3.6. Discussions

### 3.6.1. Estimation of time-variant measures

One of the challenges we faced during this research was measuring the history of some of time-variant variables. Some of the time-variant variables do not have time stamps on the website and only the current status is shown on reviewers' profile. We could not collect data on day-to-day change. Therefore, in our data set we have had snapshots of reviewers' social network size on five occasions of data collection. In this section, we summarize what we did for the estimation of *librarian status*, *book quality*, and *social network size*.

#### 3.6.1.1. Estimation of Librarian Status

As mentioned before, *Librarian* is a volunteer status that some reviewers have. After reviewing at least 50 books, reviewers apply for the status and, if granted, they will help with cataloguing books, updating or editing current catalogues, and organizing book's data in general. We have used a binary measure to capture the status, which is 1 if the user is a *librarian* on the platform. However, reviewers may change their status. They may apply or get approved at different stages in their reviewing history or some may not even be interested.

In our data set, we had five snapshots of the *librarian* binary measure. To estimate one time variant measure to include in our analysis, we assumed that the reviewer had the same status as they had at the end of each time interval on which we collected the snapshot value of *islibrarian* measure. This assumption is reasonable, as after submitting the application to show the interest to become a librarian, it may take some time for the status to be granted. We argue that during that time reviewers may start learning about the job, prerequisite and start behaving as they think they will be expected to act as *librarians.*

#### 3.6.1.2. Estimation of Social Network Size

In order to estimate a continuous measure of social network size, we assumed that the change in the size of social network is linear and estimated the rate and intercept for the linear change. We draw from literature on this assumption about mutual relationship in expertise-based communities (Barabâsi, et al., 2002). We do not claim that this is the most accurate possible estimation. However, it is close enough for our purpose which was not focusing on social network expansion strategies for frequent reviewers.

To estimate, we calculated a reviewer-quarter level measure for the social network size as $Friends_{ij}$. And we used three main rounds of data collection on which we did not have any missing data ($t_1$, $t_3$, and $t_5$) and assumed that:

$Friends_{ij}$=$\mathrm{a}_{0i} + SNExRate_{i(t1)} * Quarters$ (for any *j* between 0 and $t_1$)

For each individual $t_1$ has different value as they have joined the platform at different times. For the first interval, between *Quarter=0* and *Quarter=*$t_1$, we assumed that $\mathrm{a}_{0i} = 0$ as each individual must have joined the platform with no friends at the start and:

$$SNExRate_{i(t1)} = \frac{Friends_{i(t_1)}}{t_1}$$

For $t_3$, we used the observed measure of $Friends_{i(t_1)}$ as the intercept and calculated the rate as:

$$SNExRate_{i(t3)} = \frac{(Friends_{i(t_3)} - Friends_{i(t_1)})}{(t_3 - t_1)}$$

$Friends_{ij}$=$Friends_{i(t_1)} + SNExRate_{i(t3)} * Quarters$ (for any j between $t_1$ and $t_3$)

We used the same calculation method using $t_5$ and estimated the $Friends_{ij}$ for any *Quarters* between $t_3$ and $t_5$. As the number of friends should be an integer, we have used the *round* function at the end.

#### *3.6.1.3. Estimation of Book Quality*

We have used the measure of crowd-given score (valence) for each book as the proxy of the book's quality. To study reviewers' learning over time, book quality was a key measure in this research. Especially for books for which the time after the release is definitive on the overall of eWOM ratings (Hu & Li, 2011). Drawn from the literature we know that the average of crowd-given valence for books stabilizes after some time (Li & Hitt, 2008). Although the u-shaped distribution of online ratings (Hu, et al., 2008) makes it challenging to use the early rating scores as the product quality, the stabilized average of the ratings captured from a large set of ratings from different reviewers could be a good proxy for book's quality. Clemons et al. (2006) suggested that researchers use the mean of review ratings to study product differentiation strategies and product quality.

We draw on the Li and Hitt time-related model (Li & Hitt, 2008) to estimate the stabilized quality measure for books. Many of the books in our data set have thousands of reviews and it was not practical to crawl reviews within the limitations of the website's API. However, we collected a snapshot of crowds-given valence on each book on each data collection point.

First, we confirmed Li and Hitt's model (2008) for the crowds-given rating to books with our data set the details of which are available in Appendix A. The model (Li & Hitt, 2008) suggested that the accumulative valence of book ratings is a function of some of observable books' characteristics such as the release date. We collected supplementary data from amazon.com website including the release date of all books and then, estimated the quality measure for each book at the time that the user was posting their reviews. The model is as follows in which $AvgRating_{i,t}$ is the mean of currently posted ratings for book i at time t, $T_{it}$ is the time interval between the release date of book *i* and time *t.* $U_i$ is the book specific measure which includes all unobserved characteristics of each book.

$$AvgRating_{i,t} = 3.89 + 0.42 * e^{-0.156*T_{it}} * \cos(0.0001 * T_{it}) + U_i + e_{i,t}$$

To confirm the suitability of the model to our data set, first we used the released time for each book at $t_1$ (our first data collection point). We already crawled the measure of $AvgRating_{i,t1}$ from the website. We used the estimated measure the real measure ($AvgRating_{i,t_1}$) in the model above and calculated $U_i$ measure for each book. Then using $U_i$, we estimated the quality measure at $t_2$. The difference between the estimated measure ($\widehat{AvgRating}_{i,t_2}$) and real measure at $t_2$ is the representative of the random part of Li and Hitt model (2008) which we expect to be normal with a mean of zero and the same variance as $AvgRating_{i,t_2}$. The normality test confirmed that the error term has the same distribution as expected, validated our estimation method. We inferred that Li and Hitt model (2008) with our data set.

Then we draw on their conclusion from this model about the stability of the average rating score for books based on their quality after some time. Therefore, we used the latest observation of the accumulative valence for each book ($AvgRating_{i,t}$ ) as the proxy for $BookQuality_{ij}$.

### 3.6.2. Change in book quality over time

We argued that by frequently reviewing books on an eWOM community, as a community of practice, reviewers become better readers. It means that over time they select, read, and review books of higher quality. As this argument is critical in our conceptual model, we investigated it with modelling the change in $BookQuality_{ij}$ measure over time in the dataset. We used a multi-level and mixed-effect modelling approach (Singer & Willett, 2003) to account for the difference between unobserved difference between both individual reviewers and books. Here is a summary of the result:

Level one:

$BookQuality_{ij} = \Psi_0 + \Psi_1 Quarters + \varepsilon'_{ij}$

Individual level:

$\Psi_0 = \varphi_{00} + \xi_{0j}$

$\Psi_1 = \varphi_{10} + \xi_{1j}$

Composite model (Model A):

$$BookQuality_{ij} = (\varphi_{00} + \varphi_{10} Quarters) + (\xi_{0j} + \varepsilon_{ij} + \xi_{1j} Quarters) \quad \text{(Model E)}$$

Where we assumed that we have an unstructured covariance as follows:

$$\begin{bmatrix}\xi_{0j}\\ \xi_{1j}\end{bmatrix} \sim^{iid} N\left(\begin{bmatrix}0\\ 0\end{bmatrix}, \begin{bmatrix}\tau_0^2 & \tau_{01}\\ \tau_{10} & \tau_1^2\end{bmatrix}\right)$$

The result for the analysis for the *book quality* model is reported in Table 3-6.

### 3.6.3. Contribution over time and deviating from the crowd

Drawing on the Goes et al (2014) analysis, although the volume and valence of the reviews can be treated in the model separately, their change cannot be interpreted as independent phenomena. Both volume and valence shape reviewers' behaviour and are affected by the same personal and social factors. Therefore, we took a closer look to the contribution level of frequent reviewers. Table 3-7 and Table 3-8 summarize the result of the simple growth analysis.

**Table 3-6: Analysis Result; Book Quality Model**

| Dependent variables | Measures | Coefficient | $BookQuality_{ij}$ |
|---|---|---|---|
| | | | E |
| **Fixed effects** | Intercept | $\varphi_{00}$ | 77.9 *** |
| | *Time (Quarter)* | $\varphi_{10}$ | 0.04 *** |
| **Random effects** | Within-person | $\varepsilon'_{ij}$ | 2.97 |
| | Initial Status (Constant) | $\tau_0^2$ | 1.41 |
| | Rate of change | $\tau_1^2$ | 0.117 |
| | Covariance | $\tau_{01}$ | -0.15 |
| **Fitness** | AIC | | 56429.23 |
| | BIC | | 56473.03 |

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

The contribution, in terms of reviews' *volume,* decreases over time for an average frequent reviewer. This result is aligned with the current literature concerning the decreases in the level of users' contribution in online communities (Nov, et al., 2010).

We also observed that the amount reviewers elaborate in their reviews decreases over time. The review ratio, which represents the percentage of the reviews that include textual explanation, also decreases. As mentioned before, frequent reviewers might leverage on textual reviews to explain their point of view and justify their deviation from the crowd's opinion. Over time and by gathering reviewing experience, their identity as a reviewer is more established and they might try less appeal to others by following the crowd's opinion. They will be more confident to express their evaluation of books even when it is different from the average and they might feel less obliged to explain themselves. Therefore, as expected, we observed that the $ReviewRatio_{ij}$ measure decreases over time. The estimated negative slope in Table **3-7** and **Table 3-8** confirm that $Numrating_{ij}$ and $ReviewRatio_{ij}$ decrease over time.

**Table 3-7: Analysis Result; Review Volume Growth Model**

| Dependent variables | Measures | Coefficient | $\boldsymbol{Numrating_{ij}}$ F |
|---|---|---|---|
| **Fixed effects** | Intercept | $\varphi_{00}$ | 54.7 *** |
| | *Time (Quarter)* | $\varphi_{10}$ | -2.1 *** |
| **Random effects** | Within-person | $\varepsilon'_{ij}$ | 61.7 |
| | Initial Status (Constant) | $\tau_0^2$ | 36.1 |
| | Rate of change | $\tau_1^2$ | 1.53 |
| | Covariance | $\tau_{01}$ | -.98 |
| **Fitness** | AIC | | 121985.2 |
| | BIC | | 122029 |

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

**Table 3-8: Analysis result; Textual Review Growth Model**

| Dependent variables | Measures | $\boldsymbol{ReviewRatio_{ij}}$ G |
|---|---|---|
| **Fixed effects** | Intercept | 1.14 *** |
| | *Time (Quarter)* | -0.04 *** |
| **Random effects** | Within-person | 3.17 |
| | Initial Status (Constant) | 1.08 |
| | Rate of change | 0.04 |
| | Covariance | -1 |
| **Fitness** | AIC | 56704.06 |
| | BIC | 56747.86 |

To validate this argument, we took a closer look into the extent to which reviewers diverge from the average score of the rating of books. We computed variables using our current measures: $AvgDeviation_{ij}$ and $AvgABSDeviation_{ij}$. To calculate the $AvgDeviation_{ij}$, we take the rating score reviewer *i* assigned to book *k* and subtract it from the $BookQuality_k$ measure for each book. The result is stored as $AvgDeviation_{ik}$. Then we took the average value of this measure on all books rated by reviewer *i* during quarter (*j*) as $AvgDeviation_{ij}$. For the $AvgABSDeviation_{ij}$, we used the same logic, only instead of getting the average of all $AvgDeviation_{ik}$ during quarter *j*, we used the average function on the absolute value of deviations to mitigate the potential aggregation problem. Afterwards, we fitted a simple growth model on both measures over time to investigate our assumption. A summary of results is presented in Table 3-9 and Table 3-10.

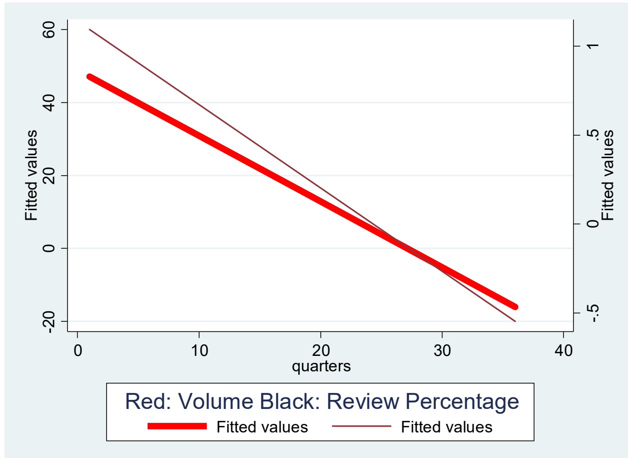



**Figure 3-5: Change in Volume and Review Percentage Over time**

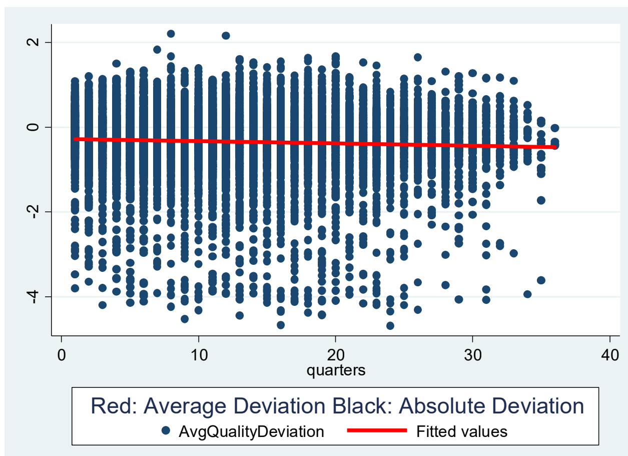



**Figure 3-6: Change in Average and Absolute Deviation from the Crowd**

Comparing two models illustrates an interesting point about the rating behaviour of reviewers. Where the average of deviation is decreasing it could seems that frequent reviewers start to evaluate products around the quality of books. However, this decline in addition to the observed increase in the average of the absolute value of deviations tells another story. It confirms that there are more negative deviations than positive ones in our data set. In other words, after gaining experience, frequent reviewers become stricter in evaluating books and it gets harder to satisfy them.

All considered, it seems that frequent reviewers lower their contribution over time while their reviews become more negative.

## 3.7. Robustness check report analysis

As stated before, the methodological approach for this research is a mixed effect, multilevel longitudinal modelling, which have been emphasized to better control for unobserved heterogeneity in longitudinal data. The *xtmixed* command we used is also computationally efficient for linear variance components (Rabe-Hesketh & Skrondal, 2008, p. pp. 62) such as our model.

| **Dependent variables** | **Measures** | $AvgDeviation_{ij}$ |
|---|---|---|
| | | **H** |
| **Fixed effects** | Intercept | -0.26 *** |
| | *Time (Quarter)* | -0.007 *** |
| **Random effects** | Within-person | 0.58 |
| | Initial Status (Constant) | 0.52 |
| | Rate of change | 0.033 |
| | Covariance | -0.34 |
| **Fitness** | AIC | 21734.98 |
| | BIC | 21778.78 |

**Table 3-9: Analysis Result; Average Deviation**

In this research, selecting the estimation method to fit the longitudinal model was critical. First of all, each estimation method has some pre-requisite assumptions without which the result is not to be trusted. In other words, the result of inference based on the estimation using different method is only rigor if the underlying assumptions of the method are met.

| **Dependent variables** | **Measures** | $AvgABSDeviation_{ij}$ |
|---|---|---|
| | | **I** |
| **Fixed effects** | Intercept | 0.89 *** |
| | *Time (Quarter)* | 0.003* |
| **Random effects** | Within-person | 0.44 |
| | Initial Status (Constant) | 0.36 |
| | Rate of change | 0.026 |
| | Covariance | -0.38 |
| **Fitness** | AIC | 15476.48 |
| | BIC | 15520.28 |

**Table 3-10: Analysis Result; the Magnitude of the Average Deviation**

Following, we explain our strategy to deal with potential issues that could have compromised the validity of our analysis. To validate the result of our analysis, first we revisited assumptions of estimation before estimating parameters including the *normality of the residuals, independency*, and the potential *serial autocorrelation* in data points. Then we explained the reasoning behind the selection of the estimated model. Later, after the analysis, we tested the stability of our model from different approaches the result of which is presented in the rest of this section.

### 3.7.1. Potential function problem

As mentioned in section 3.5.2, we used average function in computing some variables in our data set such as $AvgScore_{ij}$, $ScoreSpread_{ij}$, and $BookQuality_{ij}$. As mentioned before, using the average function could induce some aggregation problems to our measurement. To alleviate the possibility, we included some control variables in the model to differentiate between two different sets of measures with the same average. To include the range of scores, we include a reviewer-quarter level variable, $ScoreSpread_{ij}$ in our analysis. This measure, accounts for the interval between the lowest and highest score given by each reviewer in each quarter. We included the $ScoreSpread_{ij}$ measure following the current published work (Chen & Huang, 2013). However, in computing $ScoreSpread_{ij}$ we used an average function, which can cause the same issue. Therefore, we included $FiveStars_{\mathrm{ij}}$ as a control measure showing the number of books rated with high score. Finally, we added $BestBook_{ij}$ as the control variable to mitigate the same problem for the $BookQuality_{ij}$.

### 3.7.2. Testing the normality assumption of the residuals

We revisited assumptions of estimation before estimating parameters including the *normality of the residuals, independency*, and the potential *serial autocorrelation* in data points. Before fitting the model we did not have any evidence about the distribution of residuals. However, we had the real data on the dependent variable (*valence*). We plotted a histogram of valence and noticed that the distribution seems to be normal (Figure **3-7**). As our sample size is big enough (720 unique reviewers and 10,941 individual-quarters), we concluded that the valence is drawn from a normal distribution. On the other hand, each valence measure is the average of many reviews done by each reviewer on each quarter. Based on the *central limit theorem*, the mean of a sufficiently large number of iteration of random variables will be approximately normally distributed (Araujo & Giné, 1980). Figure **3-8** shows the observed versus estimated value for the dependent variable (Valence) and Figure **3-9** and Figure **3-10** shows the histogram of the residuals which looks like a normally distribution sample. The result of a t-test (Table **3-11**) shows that the normal distribution has a mean of zero.

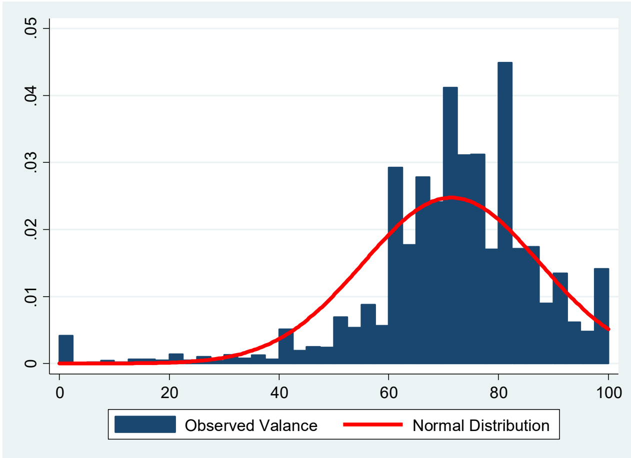



**Figure 3-7: Valence histogram vs Normal distribution with the same mean**

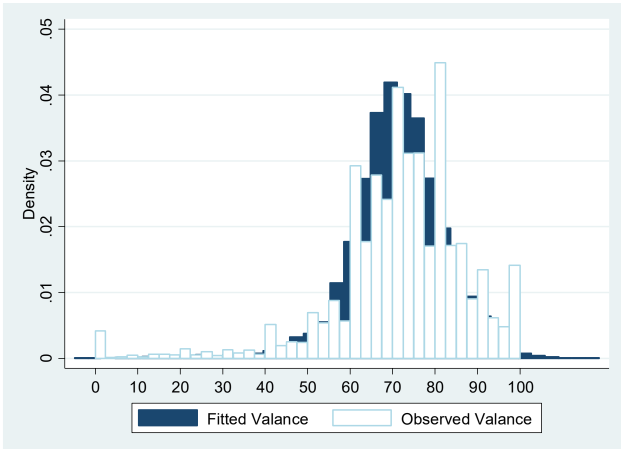



**Figure 3-8: Valence histogram**

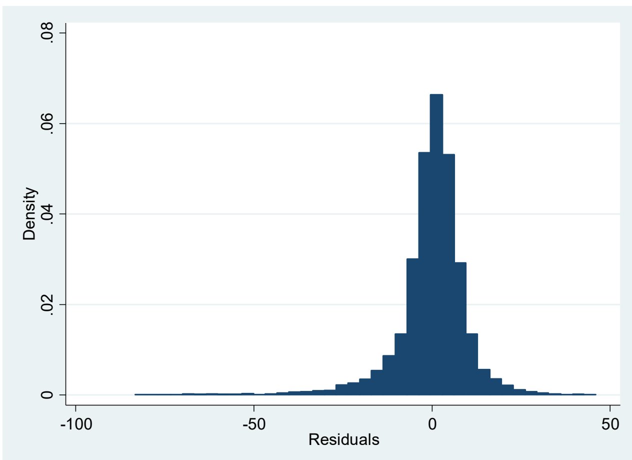



**Figure 3-9: the Residual Histogram**

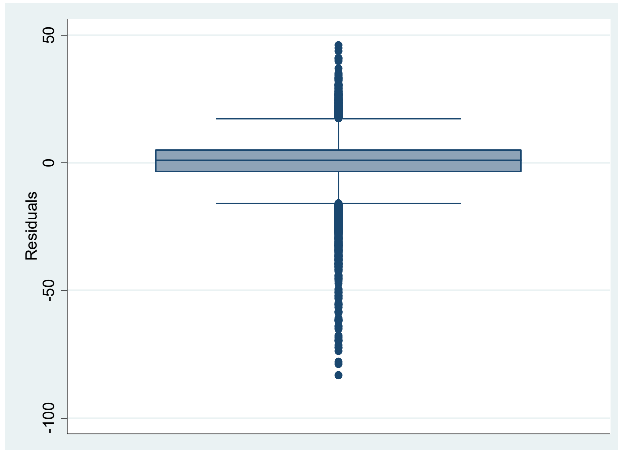



**Figure 3-10: Residual Normal test-1**

| H0 | H1 | t | Obs. | d.f. | P value |
|---|---|---|---|---|---|
| $\boldsymbol{Residual = 0}$ | $\boldsymbol{Residual > 0}$ | -0.000 | 9518 | 9517 | Pr(T>t)=0.5 |
| | $\boldsymbol{Residual <> 0}$ | -0.000 | 9518 | 9517 | Pr(\|T\|>\|t\|)=1 |
| | $\boldsymbol{Residual < 0}$ | -0.000 | 9518 | 9517 | Pr(T<t)=0.5 |

**Table 3-11: t-test on Residual's mean**

### 3.7.3. Estimation method

For a large unbalanced panel data sample, made it trickier to estimate unbiased coefficient and random effect. We selected our estimation model based on following discussion:

***Linear model***

To investigate hypotheses, we selected a linear fixed-effect multilevel model. Our theoretical argument led us to expect a change in frequent reviewers' behaviour. To be more specific we expected an average negative trend in the *review valence* over time. Based on our hypothesis, especially H3-1 and H3-2, our focus in data analysis was to investigate the population trend rather than fitting an accurate curve to the *valence* model for each individual. We also did not intend to use the mixed effect model to draw any predication of the *valence.* Therefore, we concluded that a linear combination between *valence* as dependent variable, and explaining measures was the most stable model to fit.

***Generalized Least Square (GLS) or Maximum Likelihood Estimation (MLE)***

There are many potential estimation methods to estimate the coefficient for our model. Singer and Willett (2003) suggested that GLS or Iterative GLS (IGLS) are preferable rather than OLS[15] as they

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allow the residuals to be auto-correlated and heteroscedastic (Singer & Willett, 2003, p. pp. 85). In panel data, each individual has more than one residual component and as these residuals contain unobserved personal characteristics, they are highly likely to be correlated. Therefore, the independency assumption between data points is not the case.

On the other hand, to estimate the coefficient of the linear model, we used the *xtmixed* command in STATA. The default estimation method for *xtmixed* is *Maximum Likelihood Estimation* (MLE), which we used in our analysis. MLE has three properties for big samples drawn from a well-defined population. It is asymptotically unbiased to the population true value, asymptotically normally distributed, and asymptotically efficient with smaller standard error (Singer & Willett, 2003, p. pp. 65). MLE has different assumptions than GLS about the distribution of random effects and uses a different procedure to estimate fixed and random effects. Singer and Willet (2003, p. pp 91) draw on previous studies and conclude that in practice both methods yield unbiased estimates and lead to the same inference for the same sample even though the estimates can differ.

The main difference between these two models is the assumption of the normality of residuals In MLE. If these assumptions hold, GLS and MLE procedures yield the same result for estimates. We already stablished our argument about the residual being drawn from a normal distribution. Therefore, we believe that MLE and GLS could be used interchangeably in our analysis. It also is expected that with normal errors (residuals), MLE and OLS estimate the same result too.

***Maximum Likelihood Estimation (MLE) or REstricted Maximum Likelihood (REML)***

In the MLE procedure, the software agent first computes the fixed effect of the model. Then with comparing these estimations with the real data, the random effect and error terms of the models are estimated (2003, pp. pp. 86-89). The estimation of the likelihood function is based on assessing the probability by which the joint observation for different individuals on different occasions could be observed. MLE, however, is negatively biased for errors, but this bias gets smaller for large samples, where REML gives a non-biased estimate.

Both MLE and REML estimation approaches use iterative algorithms to estimate fixed effect and random effects for given values. The difference between them is REML takes the number of estimated fixed effects into account and loss one degree of freedom for each (Harville, 1977). Therefore, REML is usually used specially when there are hypotheses about variance components not the fixed effects. However, when the sample size is big enough the difference in the degree of freedom in MLE and REML is not significant and it is to be expected that both estimation methods return same results.

We compared MLE and REML and checked the stability of the estimates with comparing estimates in a fixed effect model and mixed effect model. As presented in Table 3-12, we observed that the both the sign and the magnitude of coefficients is consistent in both models.

**Table 3-12: MLE and REML estimation method**

| Dependent variables | Measures | Coefficient | Estimation method | |
|---|---|---|---|---|
| | | | MLE | REML |
| | Intercept | $\gamma_{00}$ | 18.21 *** | 18.21 *** |
| Fixed effects | *Time (Quarter)* | $\gamma_{10}$ | -.16 *** | -.16 *** |
| | $Sidedness_i$ | $\gamma_{01}$ | 6.52 *** | 6.52 *** |
| | $VolumeQ_{ij}$ | $\pi_3$ | -.143*** | -.143*** |
| | $Friends_{i(j-1)}$ | $\pi_2$ | .001~ | .001~ |
| | $IdentityQ_{ij}$ | $\pi_4$ | 2.16 * | 2.16 * |
| | $BookQuality_{ij}$ | $\pi_5$ | .485 *** | .485 *** |
| | $BestBook_{ij}$ | $\pi_6$ | .228 *** | .228 *** |
| | $ReviewRatio_{ij}$ | | .09 ** | .09 ** |
| | $PlsntExp_{ij}$ | | 5.14 *** | 5.14 *** |
| | $FiveStars_{ij}$ | | .563 *** | .563 *** |
| | $ScoreSpread_{ij}$ | | -.135 *** | -.135 *** |
| Fitness | AIC | | 73486.17 | 73538.98 |
| | BIC | | 73600.74 | 73653.55 |

### 3.7.4. Endogeneity

Endogeneity occurs when error terms have a high correlation which one of the explaining variable (Greene, 2000), which could be a result of a hidden variable. Theoretically by including control variables from the literature (explained in 3.5.2.3), we do not expect a hidden variable in our model. Therefore, we do not believe that we have an endogeneity problem in our model potentially causing instability in our estimates. To illustrate that in a simple way, we calculated the residual between the predicted and actual *Valence* (dependent variable). The correlation between the residual and independent variables is given in Table **3-13**. We observed that there is no high correlation as an indication of possible endogeneity in our analysis.

| Variable | $AvgScore_{ij}$ | $Friends_{i(j-1)}$ | $VolumeQ_{ij}$ | $IdentityQ_{ij}$ | $ScoreSpread_{ij}$ | $BookQuality_{ij}$ | $BestBook_{ij}$ | $ReviewRatio_{ij}$ | $FiveStars_{ij}$ | $PlsntExp_{ij}$ | Sidedness | Quarters |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Residual* | 0.6876 | 0.0000 | -0.0000 | -0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | -.0000 |

**Table 3-13: Correlation matrix with residuals**

### 3.7.5. Autocorrelation effect

Based on the literature, the immediate experience of reviewers can affect their evaluation of products they are reviewing at the time. Therefore, it was highly likely that we have a first-degree autocorrelation in our model. We used the Wooldridge test for autocorrelation in panel data (Wooldridge, 2010, p. 118). We could not find evidence to reject the null hypothesis. Therefore, we assume there is an autocorrelation in our data, which is consistent with our data set. The Wooldridge test with the H0 as the existence of autocorrelation in panel data, yield *0.8506 as the F-test result.* We could not reject the null hypothesis. Therefore, we concluded that there is an autocorrelation in our data set.

**Table 3-14: Modelling error covariance structure: unstructured and vs correlated**

| Dependent variables | Measures | Coefficient | Estimation method | |
|---|---|---|---|---|
| | | | unstructured | autocorrelated |
| Fixed effects | Intercept | $\gamma_{00}$ | 18.21 | 19.00 |
| | *Time (Quarter)* | $\gamma_{10}$ | -0.16 | -0.1703 |
| | $Sidedness_i$ | $\gamma_{01}$ | 6.5 | 6.359317 |
| | $VolumeQ_{ij}$ | $\pi_3$ | -0.14 | -0.143 |
| | $Friends_{i(j-1)}$ | $\pi_2$ | 0.001 | 0.001281 |
| | $IdentityQ_{ij}$ | $\pi_4$ | 2.16 | 2.01452 |
| | $BookQuality_{ij}$ | $\pi_5$ | 0.48 | 0.475 |
| | $BestBook_{ij}$ | | 0.22 | 0.23085 |
| | $ReviewRatio_{ij}$ | | 0.09 | 0.095278 |
| | $PlsntExp_{ij}$ | $\pi_6$ | 5.14 | 5.047591 |
| | $FiveStars_{ij}$ | | 0.56 | 0.565968 |
| | $ScoreSpread_{ij}$ | | -0.13 | -0.13622 |
| Random effects (unstructured covariance matrix) | Within-person | $\varepsilon_{ij}$ | 10.36 | 111.338 |
| | Initial Status (Constant) | $\sigma_0^2$ | 8.7 | 54.4 |
| | Rate of change | $\sigma_1^2$ | 0.59 | .24 |
| | Covariance | $\sigma_{01}^2$ | -0.4 | - |
| | Rho | $\rho$ | - | .098 |
| Fitness | AIC | | 73486.17 | 73474.13 |
| | BIC | | 73600.74 | 73588.7 |

In order to deal with the possibility, first we assumed we had an unstructured error covariance see (Table **3-14**). However, this model with unstructured random effect structure overlooks the likelihood of having autocorrelation in the model (Singer & Willett, 2003, p. P. 244). Therefore, in the next step, we estimated the model assuming to have an *Autoregressive Error Covariance Matrix* as suggested by Singer and Willett (2003, p. 262). In this model, the covariance structure is as follows (Singer & Willett, 2003):

$$\begin{bmatrix} \sigma^2 & \sigma^2\rho & \sigma^2\rho^2 & \sigma^2\rho^3 \\ \sigma^2\rho & \sigma^2 & \sigma^2\rho & \sigma^2\rho^2 \\ \sigma^2\rho^2 & \sigma^2\rho & \sigma^2 & \sigma^2\rho \\ \sigma^2\rho^3 & \sigma^2\rho^2 & \sigma^2\rho & \sigma^2 \end{bmatrix}$$

Comparing the goodness of fit (AIC and BIC), we observed that there is a slight improvement in the model with the autocorrelation covariance matrix. However, the sign and magnitude of all the independent and control variables are consistent which confirm the inference we did with our original model. However, we decided to stick to the original model.

## 3.8. Closing Remarks

### 3.8.1. Key findings

In this research, we focused on the online reviewers' evolution and analysed it with the Social theory of learning (Wenger, 1998) to study how the experience as frequent reviewer affects them. Using longitudinal data analysis method, we followed a random group of frequent reviewers on a non-retailer review-hosting website and studied the change in their behavior. We conclude that frequent reviewers do change over time and by gathering experience in the eWOM community as a Community of Practice, reviewers learn to become *better readers and reviewers*. We also observed that at the beginning, their reviews are boosted with the *self-selection bias*, which is due to the reviewing books from previous positive and memorable experience. Later, in response to the social bias towards negative reviews, they review books with lower valence even though on average they read books with higher quality score. As the time goes by, the early self-selection bias weakens and the valence score, at which reviewers evaluate books, decreases. The more they review books, the more is the potential effect and the lower the review valence will be. Moreover, current literature suggest that at first reviewers just participate in reviewing products but over time they may engage in other activities in the eWOM community too (Nov, et al., 2010). We observed that over time, frequent reviewers build an identity for themselves. They also closely monitor of their peers' behavior and feedback and alter their behavior to maintain or improve this identity. Taking an extra role in the community, strengthen their social identity and reinforce their social learning. As an example, we showed that librarian become better book readers over time.

As mentioned before, the social theory of learning (Wenger, 1998) suggested that belonging to the community facilitate the observational learning in members. This was confirmed by the result of recent studies about the effect of popularity of online reviewers on reducing the valence of their contribution (Goes, et al., 2014). However, we found that having a very big social network decelerate the social learning process for frequent reviewers. A big social network increases the chance of information overload (Deuker & Albers, 2012), which could be a barrier to observe the social bias. In addition, it may adversely affect effective receiving of book recommendations from friends. Therefore, *information overload* decreases the effectiveness of participating in the eWOM community on improving the consumption experience. Moreover, we showed that frequent reviewer notice the effect of *information overload* and will lower their social network expansion rate over time.

We also observed some effect of control factors in our study, such as *pleasant consumption experience* effect, which weakens the effectiveness of the social bias. On the other hand, if somebody explore and read more diverse books in the sense of the quality, even though they may find and read some good books, their average valence will be less, and they are more likely to get dissatisfied. Another observation was the effect of book quality on the effectiveness of social bias. We observed that reviewers who read books with higher quality are less likely to get affected by the social bias and have higher overall reviewing valence.

Interestingly, by looking closer into reviews and compare scores to the quality measure of the reviews (deviation), we saw that frequent reviewers become stricter in evaluating books and negatively deviate from the quality score of the book in their evaluations.

All considered, it seems that over time, frequent reviewers lower their contribution, in sense of Volume and textual reviews, while they become stricter and their reviews become more negative.

### 3.8.2. Research contribution

Our work is different than most of the published works in the literature. We added to the eWOM literature by adopting a theoretical foundation on social learning and explained the long term effect of an eWOM community on individual reviewers who frequently evaluate and review hobby-related products (books).

This study yields at least four important contributions: **First** of all, our theoretical contribution is drawing on the Social Theory of Learning (Wenger, 1998) in an eWOM community to explain the social process of learning of frequent reviewers, which drives the change in their behaviour. Although the theory was used before in the virtual and online environment (Lueg, September 2000; Wegener & Leimeister, 2012), this is the first time that it was applied to an eWOM community. The result of this research extends our knowledge of WOM mechanism, learning by practice in an online community and application of the Social Theory of Learning.

Most of the previous studies investigated user behaviour in eWOM communities and how they affect online environments. Whereas, in this study, we focused on the counter effect that the online environment (in the form of an eWOM community) has on individual reviewers in long run. We believe that, apart from the theoretical contribution, this is the main contribution of this research.

Our **third** contribution is confirming the current literature about the underlying reasons of online reviewers' behaviour. Qu and Lee (2011) suggested the reviewer behaviour is not solely about products and can be explained by both community-related and product-related factors. Our result showed that the reviews includes self-bias during early stages which will change to the social bias, a community-related factor, over time.

The **fourth** contribution is confirming the Li and Hitt (2008) model in estimating the overall average of rating scores for books. They suggested this model to study the self-selection bias in early adopters, readers, and reviewers for each book. However, after confirming the model in our data set (described in detail in appendix A), we draw on their finding and assumed that after some time, the average valence for each books stabilizes around a score, which could reflect the quality of the book. Therefore, we used the stabilized average valence for each book as the proxy of the book quality in our research. The result of our analysis added to their research (Li & Hitt, 2008), confirming that not only the self-selection bias exists in the product evaluation of early customers; they exist in the early reviews done by each reviewer when they freshly join an eWOM community.

Finally, we contributed in the literature of social networks and eWOM communities by spotting the information overload in general-purpose social networks and confirming that handling the eWOM community as a general-purpose social network, adversely affect the effectiveness of the community.

Recommendation systems supposed to help with the potential information overload in pubic social network (Shardanand & Maes, 1995) by focusing on a specific task that the community was designed around it (Johnson, 2001). We showed that this does not happen for individual who are connected to a big social network.

All said, our result is aligned to many studies in the current literature. However, our work is essentially different from the literature we drew on and add to them. First of all, our research on the belonging mechanism and social network is we are different than Goes et al. (2014). They focused on the effect of the popularity of online reviewers in their social network. Our work is different from theirs from two aspects; *the social network measure* and *the type of the community*.

***The social network measure***

Like Goes et al. (2014), we consider the social network as the *potential first hand audience* for the reviewers. Moreover, we believe that maintaining the social network as a source of cost for each reviewer. Therefore, we used *Social Network Size* measure by number of friends as the variable. Goes et al (2014) on the other hand, used the measure of incoming following request as the measure for the popularity in the community, which is the equivalent of the network development rate in our data set.

***The type of the community:***

The focused on a community of practice (CoOP) in which the reviewer and receivers of the reviews both have the same status in the community. The website of interest is a hobby community in which all members and reviewers are considered peers and nobody has the opinion leader role. Everyone has their own voice and media to share their opinion about books. In such a flat hierarchical community the relationship between people is a two-sided mutual friendship road. On the other hand, Goes et al (2014) used in epinion.com website in which the relationship between users is *following*, which implies that the reviewer has a higher hand in the conversation. Writing reviews and having followers were beneficial for individual reviewers as the platform used to pay reviewers compensation for writing helpful reviews. The extra monetary reward changes the motivation of reviewers and their reactions to the social learning process. Our website of interest (as an example of and eWOM community) is also different from the companies' social media pages, such as Facebook or Twitter pages. On the firms' pages, the community does not need the audience to contribute. As long as they have followers or people, who joined their pages, as an online customer base, the communication channel with customers is open and the purpose of the online community is satisfied. In such communities, the communication is mainly from the speaker the audience and resemble a one-to-many relationship. Unlike the relationship between individuals on eWOM or hobby communities which is a many-to-many relationship. The conversation has two sides and everyone has a voice and the chance to find their audience. The mutual conversation prepare the ground for reviewers to become affected by others too. Confirming the effectiveness of social learning process for frequent reviewers, we bold out the difference between the long-term effect of eWOM community on frequent reviewers.

### 3.8.3. The research implication

Our result also has practical implication for the eWOM communities. First, we showed that the reviews on the websites are biased. At the early stage, they are biased with the self-selection effect and later they are socially biased. As Goes et al. (2014) suggested the eWOM websites should address the potential “bias”. We believe that eWOM community can use this result to come up with indicators that can measure the bias or motivate the frequent reviewers to overcome this bias. The minimum response should be sharing the information on the potential bias with other users, so they account for it when adopting reviews in their consumption decisions. Some strategies could be designing some recognition or encouragement tools, so reviewers prove their capabilities in a way that they do not need to seem smart in their peers’ eyes and write negative reviews to become one.

We established that the participating in the community help reviewers to become better readers and better reviewers. eWOM hosting platforms could use this result to spot the implicit reviewers’ learning and exhibit it in a tangible way to members. It could positively affect frequent reviewers’ motivation to continue their participation and could help the platform to maintain their active members.

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# CHAPTER 4. The contribution dynamic of online reviewers (Paper 2)

## 4.1. Abstract

A huge body of research on online social media focuses on the behavior of individuals in the online environment or the effect of this behavior on the business or society. Some researcher also studied the effect of social media content on individuals. What is missing is the effect that contributing in the social media has on reviewers. Are they the same people who joined the social media and started contributing? Also we do not know if the participation in online communities affects people and changes them and what drives the change in their contribution. This research focuses on the evolution and change in online users in an electronic Word-of-Mouth (eWOM) community to explain how the social process of learning affects their contribution level (review volume).

Using longitudinal analysis, we studied historical reviewing behavior of frequent reviewers on a non-retailer review-hosting website. We concentrated on the social learning components to explain the drivers and obstacles of reviewers' contribution. We observed a decrease in reviewing volume over time as reviewers gain experience.  We concluded that reviewers whose motivation is to be recognized by the community or reviewers who perform community services have higher contribution volume. Also, reviewers who engage more with the features and function of the website have higher contribution volume. We also observed that where popularity (Baka, 2016), as the result of a big social network, is expected to initiate a rise in contribution volume (Goes, et al., 2014), the positive effect can be cancelled out by the interruption of cognitive learning in the social environment (Bandura, 1977). Social loafing and collective effort model (Karau & Williams, 2001) can explain this effect. We also conduct several robustness checks for potential issues to ensure the validity of our results.

**Keywords:** eWOM, Contribution Volume, Website Engagement, Online community, Social Theory of Learning, Social Loafing, Community of Practice (CoOP), Longitudinal Data Analysis

## 4.2. Introduction

With low-cost and general access to the internet, online customer reviews or eWOM are the best and the most economical way for customers to gather information about products before any purchase decision. The effectiveness of eWOM is stronger for experience goods such as books (Nelson, 1970). Some of eWOM hosting platforms have social networks embedded in them (e.g Yelp, FourSquare, and Goodreads). By facilitating the communication between customers (reviewers and readers), an online community of consumption may take form between users who share common consumption-related interests.

Online eWOM communities, like traditional communities, evolve over time and go through different stages in their life cycle (Iriberri & Leroy, 2009). While it is important to attract new members in early stages for creation and growth, retaining members during the maturity stage is no less critical to the long-term success and sustainability of these communities. At the maturity stage, only those communities survive and thrive that can maintain their members' commitments and contributions. To do so, they can develop mechanisms such as rewards or badges to encourage participants to maintain the same contribution level. Therefore, understanding the drivers of their members' ongoing contribution is vital for their sustainability where the contribution is a particular behavoiur.

Reviewers have different characteristics and motivations, which can explain different behavioral patterns to some extent. Some of those characteristics are, but not limited to, reviewing experience (Samiei & Tripathi, 2014), user characteristics such as specialized skills (Connors, et al., 2011), expertise (Mudambi & Schuff, 2010), and motivation toward social networks (Wasko & Faraj, 2005; Alexandrov, et al., 2013). Despite more than a decade of investigation of this phenomenon, current literature is scant in explaining reviewer's behavior and its change over time. What drives and steers such change is yet beyond our understanding. What we know is that product reviewing is a social process (Alexandrov, et al., 2013) during which frequent reviewers gain experience and learn. The learning reflects on their reviewing behavior. In this chapter, we focus on the online reviewers' contribution volume and use the Social theory of learning (Wenger, 1998) hoping to understand how the community affects frequent reviewers during their repetitive contribution.

The structure of the rest of this paper is as follows. Frist, we briefly mention the related literature on the eWOM and contribution in online communities. Then we draw on the social theory of learning to develop our hypotheses. Data, analysis, and the discussion follow. We report the robustness test results, followed by the conclusion section.

## 4.3. Literature review

### 4.3.1. Word Of Mouth (eWOM)

The current literature on eWOM has been summarized from different perspectives. As mentioned in chapter two some researchers use the general communication model to summarize the eWOM literature (Cheung & Thadani, 2012). Others use the stages of product/service adoption (Montazemi & Saremi, 2014), and the interaction of cause-effect with the communication model (King, et al., 2014). Following Goes et al. (2014), we categorize the current literature in two main streams. The *generation* and the *consequence* of WOM. The first stream, the generation of WOM, concentrates on two questions; the first question is *why people decide to contribute and what they share* (Moe & Schweidel, 2012). The answer to this question reveals incentives and motivation of reviewers (Mackiewicz, 2010; Cheung & Lee, 2012; Hennig-Thurau, et al., 2004; Munzel & Kunz, 2014). The second question focuses on the content of WOM. Content includes, but is not limited to, concepts such as the distribution of reviews (Hu, et al., 2006) and change in the reviews over time (Li & Hitt, 2008).

The second stream focuses on the *consequence* of reviews on others' opinions. Either on the product sale (Zhang & Zhu, 2010; Zhang & Dellarocas, 2006; Shen, 2009; Liu, 2006) or prospective customers' evaluation (Chen, et al., 2010) . Some studies investigated the effect of social interactions between reviewers and customers (Goes, et al., 2014; Huang, et al., 2012).

### 4.3.2. eWOM as an online community

As mentioned before, the majority of the online consumption community provide some level of social network functionality. This makes it easier for reviewers to connect to and keep track of their audience (Cheung & Thadani, 2012). This social network directly or indirectly affects the behaviour of online reviewers (Samiei & Tripathi, 2014). There are many studies in the current literature showing how the connected social network affects the reviewing behaviour (Schlosser, 2005; Samiei & Tripathi, 2014; Cheung & Thadani, 2012; Shen, 2009). We believe that the eWOM community has the characteristics and requirements of a *Community of Practice* (Wenger, 1998). Because it satisfies the premises suggested by Wenger (2009, p. 210) . an eWOM community also includes all components that Johnson (2001) suggested as the distinction between a community of practice (CoOP).

Online communities, like traditional communities, evolve over time and go through different stages in their life cycle (Iriberri & Leroy, 2009). While it is important to attract new members in early stages for creation and growth, retaining members during the maturity stage is no less critical to the long-term success and sustainability of these communities. At the maturity stage, those communities that can maintain their members' commitments and contributions survive. Poor participation of the members or having members with weak ties, undersupply of content, and unorganized contributors could lead an online community to its death phase. (Chen & Huang, 2013). Where recognition of the contributions and loyal contributors, as well as other success factors can increase the chance of the growth and maturity of an online review (Chen & Huang, 2013). Communities can develop mechanisms to encourage participation and engagement to maintain the same contribution level. Therefore, understanding the drivers of their members' ongoing contribution is vital for their sustainability.

### 4.3.3. Contribution in online community

Online communities of consumption thrive on voluntary contributions of users and reviewers. Therefore, the continuous contribution of reviewers is vital for their long-term success (Wei, et al., 2015). The contributions have different shapes and forms depending on the type of the community. In an eWOM community, members share their experience of the product or service consumed and their contribution is measured by *volume*, *valence*, and *textual reviews*. Contribution level can be explored from different perspectives such as *volume*, *frequency* and *continuity* (Cheung & Thadani, 2012)[16].

The desire and commitment of the members to maintain their level of contribution (Wang, et al., 2012) is critical to sustain these communities. However, in reality, many reviewers gradually lower their level of contribution and become inactive. Explicit recognition, visibility of contributions, and granting rewards for the expertise, loyalty and commitment are some successful policies through which communities maintain their frequent contributors (Iriberri & Leroy, 2009).

In an eWOM community, reviewers share their opinions with other people in the community and get feedback. We expect them as rational agents to modify their behaviour hoping to get more and better attention. Recent studies have found that, over time, reviewers gain experience, learn, and change their reviewing behaviour and level of their contribution (Li & Hitt, 2008). This is also in line with the well-established Hawthorne effect (Adair, 1984), which shows that the presence of observers affects the behaviour of people. Current literature suggested that the presence of the audience and their actions such as friend requests and helpful votes[17] affect the volume of the

[16] Reviewers' comments and feedback on others in the eWOM community are considered contribution too. However, we did not include them in this research because of some limitations in our context website.

[17] In some eWOM communities, users who read any reviews can leave their evaluation of the review's quality or helpfulness with *like* or *helpfulness* vote.

reviews and also the type of review content (Goes, et al., 2014). However, existing research is not conclusive about the direction of the effect.

To sum up, in the current literature we know that the *contribution volume* changes over time in all online communities and specifically in an eWOM community. However, we do not know enough about the direction of the change, and factors and mechanisms that drive this change. We intend to answer to this question in this research.

## 4.4. Conceptual modelling

Using the social theory of learning (Wenger, 1998), we empirically investigated the change in the contribution of frequent reviewers in an eWOM community. After briefly discussing the underpinning theory, we focus on four main *components* of the theory. To explain the learning and behaviour change in frequent reviewers, we discuss the social learning process. We also introduce our arguments and hypotheses for each component. Figure 4-1 summarize the research model.

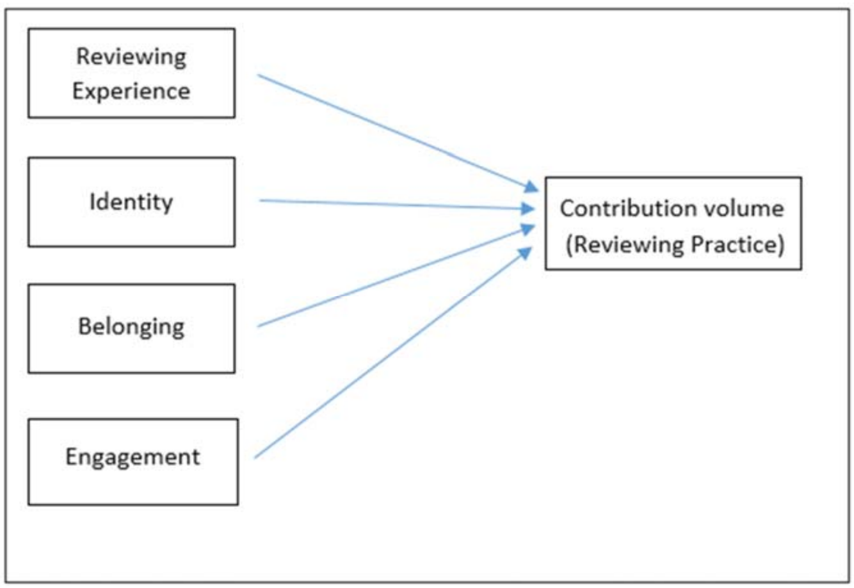



**Figure 4-1: the research model**

### 4.4.1. The social theory of learning

To answer the research question, we build our model on the Social Theory of Learning (Wenger, 1998). Many researchers believe that learning is not just a cognitive process in an isolated environment (Lave, 2009; Bandura, 1977; Wenger, 1998). Focusing on people as social beings, social-oriented theories of learning (Bandura, 1977; Wenger, 1998) suggest that learning is a social process, as well as a cognitive one. The Social Theory of Learning (Wenger, 1998) explains how learning and knowledge acquisition happens when individuals perform activities in a Community of Practice (CoOP), observe, and interpret the feedback from the environment they are working in.

In an eWOM community, frequent reviewers repeatedly practice their activity (rating products and writing textual reviews). They also observe others' reactions to their reviews and receive social feedback. By interpreting their observations, they gather experience and adjust their future behavior accordingly, hoping to attract more attention. We believe that frequent reviewers constantly revisit their motivation to continue through a social learning process through the process of *retention*, *reproduction*, and *motivation* (Bandura, 1977) which is the basic idea of social learning theory. As we believe that an eWOM community is a Community of Practice (CoOP), we draw on the *social theory of learning* (Wenger, 1998) to investigate the change in reviewers' contribution.

We draw on Johnson's work (2001) to argue that the eWOM community is a community of practice (CoOP). He suggested that there are three characteristics that differentiate between a community of practice (CoOP) and any other community **First**, the community initially starts as a designed platform, but it will evolve by later members' contribution in the form of the main task for around which the community was designed for in the first place. **Second**, there is a legitimate task-oriented reason, which community members are motivated to engage with. In addition, the **last**, but not the least characteristic of a CoOP is the structure of the community, which consists of people with different levels of expertise who work together (Johnson, 2001, p. p. 53). The community of interest satisies all three characteristics for a CoOP (details described in section 3.4.1).

The learning happens when individuals digest the meaning of their experience with their engagement in the society (Wenger, 2009). Wenger (1998) explains that the learning process has four main components: Learning by ***practice, identity, meaning,*** and in the ***community.*** The comprehension happens when, during and after the *practice*, people extract the collective *meaning* out of their experience. They also observe and understand their *identity* in the *community* they are practicing in. The main characteristics of the Wenger's theory (Wenger, 1998) is the centrality of the practice in the learning process. The direct and indirect feedback, community members get during and after their practice is the new data for them to process and contemplate. It helps them to understand their position in the community and evaluate their performance as a community member. A member is supposed to contribute in the core task of the community (Johnson, 2001). If they believe they cannot do the core activity of the community right, or good enough, they are more likely to leave the community or stop their contribution. Drawing from Wenger's theory (Wenger, 1998), we believe that the learning process is in place to help them to observe, interpret, and enjoy their learning as an extra motivation to continue their contribution over time. They learn through the social learning process how to keep doing the practice and focusing on the progress.

### 4.4.2. Reviewing books as practice

Wenger introduced *practice* as the first component of the social theory of learning (Wenger, 1998). He later defined *practice* as a component of his theory as "a way of talking about the shared historical and social resources, frameworks, and perspectives that can sustain mutual engagement in action" (Wenger, 2009). Johnson (2001), in a survey of research on online community of practice suggested that having a "completely authentic task" to build the community around is an inseparable component of a task-oriented community of practice. Members of the community are learning partners who do not necessarily support each other's practice (Wenger, 2010). They may criticize or comment on other members' practice, which will be a big opportunity for them to learn. For some members their practice may not be aligned with the community. Therefore, learning result in the behaviour change in members towards the realignment with others and with the task agenda of the community (Wenger, 2010).

In our context, reviewing books is the main activity or *Practice* that the eWOM community shapes around. Different individuals have their own practice experience, reflecting on their practice. However, what all have in common is a willingness to expose themselves and their evaluation of books by writing frequent reviews. Later by observing and gathering the reaction of other members towards their practice, they learn to adjust their behaviour.

### 4.4.3. Contribution experience

Reviewers on a book-reviewing website are people who read books and share their opinion and evaluation of books with other readers. They change their behaviour over time as they gather experience on the website. Wenger suggested that members of a CoOP extract meaning from feedback they get from other members of the community. This collective meaning shapes and changes their future experience and affect their learning and it may reflect in their behaviour (Wenger, 2010). According to this definition, the experience accumulates over time and can lead to the change in the participants' behaviour. We believe that the change in frequent reviewers' behaviour could be seen in a decreasing pattern in their contribution volume due to two different mechanisms. **First**, when reviewers join the platform and create a profile to begin reviews of books, everything is new and novel which leads to excitement. We argue that the early novelty and affection of reviewers for both the community and the activity (reviewing) diminish over time (Homburg, et al., 2006). This results in *arousal reduction* and a decrease in their motivation (Karau & Williams, 2001, p. 135) and could lead to a decreasing level of contribution level; i.e. posting less number of book reviews by frequent reviewers. In extreme cases, the excitement about the platform might diminish very quickly so they stop contributing to the community. Irriberi and Leroy (2009) suggested that people might leave the community if they do not perceive any useful outcome out of their contribution after having experience the result of their contribution. The **second** mechanism is the way that frequent reviewers select books to review. At the beginning, most of the books they review are the books that they have read before and recall them from memory. This means a large inventory of books to discuss in early stages. Another potential way of selecting books to review is exploring the website, visiting different lists of books, genres, authors' profiles and recalling if they have read some of those books. When time passes, it is more likely for them to be done with reviewing their previous read list and moving on to reviewing books that they are reading currently. Replenishment inventory is harder to come by, given that frequent reviewers at this stage must first read and review books compared to remembering a book title, searching for that and assign numerical score and/or textual review. Therefore, over time, by moving from reviewing previous reads to the current ones, the contribution volume of frequent reviewers decreases.

***Hypothesis 1 (H4-1)****: The volume of the contribution of frequent reviewers decreases over time*

### 4.4.4. Building social identity

Building and maintaining an identity is one of the learning mechanisms for participants in a community of practice. Community members build and identity by contributing to the community and "become someone in the context of our [the] community" (Wenger, 1998). In a community of practice, the ongoing participation is the most important way for building an identity (Yoo, et al., 2013; Tajfel & Turner, 1979). By repetitive participation in the eWOM community, frequent reviewers might feel attached to the community and it can positively affect the *becomin*g process for them and strengthen their collective identity as active, consistent and/or credible reviewers with a personal history (Qu & Lee, 2011).

#### *4.4.4.1. Engaging in community service*

In addition to the identity development by belonging and participating in the community, other strategies can lead to the development of an identity. Some might take an extra role in the community. Drawing on the literature, Yoo et al. (2013) suggested that more commitment to the community by taking an extra role can facilitate the identity building process. The volunteer contribution of reviewers is the key component of the community's sustainability and long-term success. Therefore, at the maturity level of their life cycle, communities design some mechanisms to maintain the excitement of the contribution, alleviate the risk of contributors getting bored and leaving the community. Iriberri and Leroy (2009) summarized the literature and suggested that encouraging forming subgroups, which are organized and managed by volunteers, are strategies that online communities follow to ensure the sustainability of their platforms. Also, establishing reward systems to recognize volunteers' extra effort is one of the success factors for the sustainability (Iriberri & Leroy, 2009). Encouraging volunteer members to take extra roles such as running activities, managing subgroups or managing data, distinguishes volunteers from the members' pool, facilitates and strengthens their identity.

On our selected platform, volunteer members manage and organize the data about books. After reviewing at least 50 books reviewers can apply for the badge and engage in extra activities such as creating, editing book profile pages, and so on. The status of volunteer members who help with such tasks changes to *Librarian.* These people are not librarians in real life. However, in the eWOM community, they act as community experts on books.

We believe that *librarians* have a higher contribution volume than other reviewers. First of all, they may be interested in the book reading more than others are and have a higher contribution level at the start. That is aligned with the fact that they have satisfied the prerequisite contribution level to become a *librarian*. They are likely to be motivated to assert their familiarity with books or their book specific experience (Mackiewicz, 2010). To maintain the status and the identity they most probably intend to build, they may feel obliged to keep up with the image of a knowledgeable person about books. Moreover, over time, *librarians* are less likely to find the eWOM community useful and as Irriberi and Leroy (2009) suggested they might leave the community if it loses its usefulness for them. To do their job, *librarians* deal with different books and related reviews, even the books that they have not or do not intend to read. Hence, we argue that being a librarian will give them a very special opportunity to research a broad range of books and make a more well-informed decision when selecting their next read, and could lead to a better reading experience. Because such involvement keeps the platform useful for librarians, we do not expect them to lower their contribution to the platform. To investigate if this explains their behaviour we hypothesize if:

**Hypothesis 2 (H4-2)**: *Librarians have a higher contribution volume compared to other frequent reviewers*

#### *4.4.4.2. Desire to be recognized*

Online WOM communities are considered helpful when they host many reviewers and products, maximizing the probability of prospective customers to rely on them for their purchase decision. Like any other communities, eWOM communities need to maintain their contributing members to stay sustainable. Particularly in the maturity stage, where the early contributors may lose their interest or motivation; the sustainability of the community could be at real risk. The primary success factor at this stage is recognizing the contribution of active participants (Iriberri & Leroy, 2009), which helps to maintain their motivation. Their volunteer contribution should be acknowledged and rewarded with tangible or intangible, but still positive, rewarding feedback (Iriberri & Leroy, 2009). Iriberri and Leroy (2009) suggested that recognizing the uniqueness, helpfulness, and loyalty has a similar effect compared to any tangible recognition such as as physical, or monetary gifts or any extrinsic reward. Assigning an identity status is a form of social benefit, and the more active reviewers are, the more it is likely for them to get affected (Shen, 2009). The identity status gives reviewers visibility and will mainly help to keep those users motivated who wish to have a unique contribution or be distinctive from others (Cheema & Kaikati, 2010). One way to build and identity and earn the status is by comparison with other members (Tajfel & Turner, 1979), which is known to be more effective instead of earning badges or status that some platforms assign to users just because of their contribution (Chen, et al., 2010).

In our selected platform, reviewers may get six different badges as the recognition of their outstanding contribution. The badges are *top reviewer*, *top user*, *top librarian*, *top reader*, *most followed*, and *best reviewer*. Reviewers get a badge if their contribution is ranked withing the first 200 people in each category. Achieving and retaining any of these badges requires a lot of effort and hard work from individuals who have the motivation to be recognized with a remarkable effort. Therefore, we believe that frequent reviewers who earn better ranks for these badges are very likely to have higher contribution level than others. Maintaining the ranking is hard to do as there are always new reviewers joining the platform who offer fresh and motivated competition. Therefore, reviewers with badges should keep up their contribution to maintain their place within the top 200 rankings. To test this argument, we investigate if:

> **Hypothesis 3 (H4-3)**: *frequent reviewers, who earned a better-ranked recognition badge, are more likely to have a higher contribution level*

### 4.4.5. Association with the community (belonging)

In general, individuals need to belong to others as this need gives them motivation to maintain their relationships with others. The frequent encounter with others in a community give people a sense of belonging (Alexandrov, et al., 2013) and help them to build an identity (Yoo, et al., 2013). That is how the participation in a community strengthens their sense of belonging. The feeling of belonging is one important component of the social learning process (Wenger, 1998). In a community of practice, *belonging* was defined by Wenger (2009). Sense of belonging is a way that members feel that their participation is recognized and they are qualified and accepted in the community. In this theory, belonging to the community and building a social identity are closely related (Wenger, 2009). We argue that being part of the embedded social network in the eWOM community facilitates the learning mechanism for frequent reviewers and helps them to stay motivated and not be affected by the decrease in their contribution.

In the previous chapter (Chapter3), we inferred that connecting to a big social network affects reviewers' behaviour through the social learning process. Goes et al. (2014) suggested that a larger online audience naturally motivates reviewers to contribute more and have a higher volume (Goes, et al., 2014, p. 4) which is aligned with the early studies such as the Hawthorne experiments (Adair, 1984). It is established that people modify and improve their behaviour when being observed. Therefore, we expect that being part of a social network in an online consumption community influences the reviewing contribution. With a bigger connected social network, reviewers have a big potential audience to get feedback from or prove their credibility to. The bigger the social network of one be, the more s/he can reach to the audience with the same amount of time and energy to write a review. Therefore, with the same review volume, reviewers with bigger social networks achieve higher visibility and feedback. As the friendship relationship on our platform is two-sided, for reviewers a larger number of friends means a bigger potential audience and more opportunities to get feedback. It also could be translated as more people who are interested to see one's evaluation of different books. We know from the literature that if the reviewer feels that their contribution is not useful, they are likely to leave the community or lower their contribution (Iriberri & Leroy, 2009). We argue that frequent reviewers might interpret the size of their social network as a signal of their participation to be recognized as competent and helpful. These reviewers are less likely to get affected from the natural decrease in their behaviour. Besides, the expansion rate of the network might be interpreted the same which is aligned with previous results of the effect of incoming social ties on the contribution volume (Goes, et al., 2014). Overall, we hypothesize that:

**Hypothesis 4 (H4-4)**: *for frequent reviewers, bigger audience (larger social network) result in a higher contribution volume. Also a higher social network expansion rate has the same effect*

### 4.4.6. Engagement with the platform

Social engagement is one of the main success factors of a sustainable online community. It is always a challenge for community designers to inaugurate mechanisms in the community to improve member engagement. The engagement can be divided into two categories: *community engagement* and *transactional engagement* (Gummerus, et al., 2012). In this research, we considered the *belonging* as the *community engagement*, which is being engaged with other members of the community. We also believe that in our context, the *transactional engagement*, as Gummerus et al. (2012) has defined, covers the reviewers' engagement with the website, its features, and functionalities. When community members are engaged with the online platform, it is more probable that the main mission of the community is achieved. It is not guaranteed, but research in different areas (Leslie, et al., 2005) showed that users of the website are likely to meet their goals of the contribution if they engage with the platform.

In an eWOM community, the primary purpose is the contribution and reviewing of books. We believe that higher engagement will increase the contribution level. When the main activity for reviewers is reviewing books, their learning by practice is significant. As shown in the previous chapter (chapter 3), the favourable consequence of learning, for frequent reviewers reflected in their future consumption experience. Therefore, we will test if:

**Hypothesis 5 (H4-5)**: *frequent reviewers who are more engaged with the eWOM community are more likely to have higher contribution volume*

## 4.5. Data and analysis

To investigate the aforementioned set of hypotheses, we used a data set, which included the history behaviour of book reviewers on a publicly available book reviewing community. We selected our platform for two reasons: **first**, in order to study the contribution level of reviewers we need to control some aspects. The current literature has determined that the product type affects review quality and perceived helpfulness (Mudambi, et al., 2014) which can affect the direct or indirect feedback from reviewers' peers. We decided to control the effect of product type by collecting our data on an eWOM community that only includes reviews for one particular product type. We also wanted to minimize the possibility of having fake reviews in our data set. Therefore, we selected a platform, which is neither a vendor, nor a retailer platform.

Although our data covers almost 9 years for some reviewers, we started collecting data from July 2012. At that point of time (first wave of data collection), our crawler agent stored all the reviewing history of all reviewers. Later, in December 2015, we went back to the website and collected incremental data about reviewers' behaviour from the last data collection time. Therefore, we assure that we have complete reviewing history of 719 reviewers in 2012. In the first round of data collection, we selected a set of 500 random books. The crawler agent followed hyperlinks to the profile page of users who wrote reviews on those books. Then the complete reviewing history of those users were collected. In the next iteration, all books reviewed by visited reviewers were added to the book list, the same iteration was followed to the reviewers of those books, and new reviewer profile pages were visited. After cleaning the data set at the end of the first wave of data collection, we had a complete data set of reviewing history for 719 reviewers. In the next data collection waves until December 2015, we tracked down these reviewers to capture all their new activities and profile changes. As a result our data set consists of 719 reviewers, 81.233 books, 10 reviews and 10,941 quarter-reviewer records

At the book level, we have a ccumulative crowds-given score for on each data collection wave. We also used a separate crawling agent to collect complementary data on books from the Amazon.com website. The complementary dataset includes basic data on all books in our dataset such as author and publisher name, time of release, and a number of pages. We have used the supplementary data on books in calculating control variables discussed in previous chapter (section 3.6.1.3).

### 4.5.1. Measures and constructs

In order to investigate our hypotheses empirically, we are studying the change in constructs, we need a time clock, which is comparable for different reviewers who joined the platform at different times. Therefore, we defined the time for each reviewer as the number of days after s/he reviewed the first book. The time units are 90 days or a quarter. Then we aggregated daily data records for each reviewer and re-calculated all behaviour based on this time clock. On the other hand, as we believe that the contribution of each reviewer is affected by their behaviour and the feedback they have from the last time period, we included a lagged variable of time as *LagQuarters* in our model as the time variable.

To study the hypotheses, we used the current literature to extract related constructs. The main theoretical argument is the social theory of learning (Wenger, 1998), and in the research model (Figure 4-1), we have five main constructs to focus on. Each of these constructs reflects one social learning mechanism in the eWOM community and we measure them as follows:

#### *4.5.1.1. Outcome variable*

Researchers use different quantitative metrics for online communities such as size (number of members), participation (number of visits, or hits), contributions (number of posts), or relationship developments (contact between users) (Iriberri & Leroy, 2009). In this research, according to Wenger's model (Wenger, 1998), we believe that the centre of the Community of Practice (CoOP) is the practice itself. The practice is the core activity that the community shapes around (Johnson, 2001). All community members, no matter if they are contributors or lurkers (Munzel & Kunz, 2014) are somehow interested in this core activity. Where contributors are keen on the reviewing activity, lurkers are interested in the product of the activity. In an eWOM community such as our platform, the main *practice* is reviewing products (books in our case). Contributors are frequent reviewers who write reviews about different books and share them with others, where lurkers (Munzel & Kunz,

2014) are members who mostly joined the eWOM community to receive recommendations and have access to helpful reviews written by others. All considered, we measure the *contribution volume* as the proxy for the *practice* in our eWOM community. We measured this value with $volume_{ij}$ measure. The Figure 4-2 shows the scatter plot of the contribution volume over time for the sample population (all 719 reviewers). However, due to the higher contribution volume in early quarters, and also the huge difference between the contribution volume for different users, we decided to use the *natural logarithm transformation* and use the measure of $LnVolume_{ij}$ as the outcome variable.

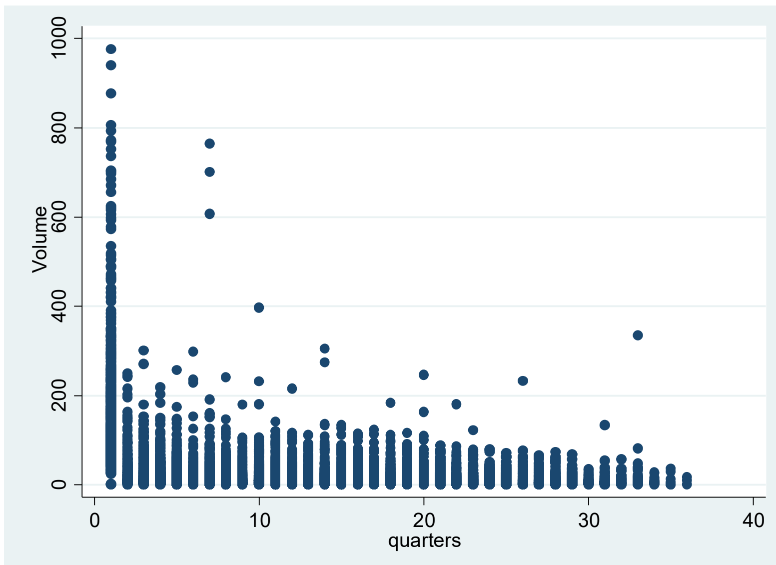



**Figure 4-2: Contribution volume over time for the population**

### *4.5.1.2. Constructs under study (independent measures)*

***Experience***

The focus of this study is on drivers of the change in the contribution volume for frequent reviewers. In order to study the effect of previous experience on the *contribution level (volume)*, we included the *LagQuarter* measure. We also believe that prior experience in an eWOM community have two parts: the *reviewing experience* and the *consumption experience*. The *consumption experience* is the reflection of the extent to which the consumer is satisfied with the product (book, in our case).

Drawing on Goes et al. (2014) analysis, we know that even though the volume and valence of the reviews can be analysed separately, they are highly correlated and their changes cannot be interpreted as independent phenomena. Both volume and valence shape reviewers' behaviour and are affected with the same personal and social factors. Therefore, we took a closer look at the contribution level of frequent reviewers. Our first hypothesis (H4-1) solely focuses on the reviewing experience where we needed to control for the *consumption experience.* Therefore, we included the measure of $AvgScore_{ij}$. This measure is the aggregated measure of the rating score each reviewer assigned to a book on each quarter and can reflect the reviewer evaluation of books they read on each quarter (consumption experience).

***Identity***

To investigate H4-2 and H4-3, we wanted to focus on the ways frequent reviewers build an identity in the eWOM community by doing community service as a *librarian* or gaining the community's *recognition badge*.

To capture the *librarian* status, we used a binary measure as $Librarian_{ij}$ which is equal to 1 if the reviewer is a *librarian* at the time. Frequent reviewers may apply or attain the title anytime in their contribution life cycle and it is a time-variant status. Unfortunately, we only had the data about this status at the times of data collection. Therefore, we estimated the $Librarian_{ij}$ measure with a step-wise function assuming that it stays constant for quarters between two data collection points.

Members of online communities can build identity based on their desire to be recognized compared to their peers (Tajfel & Turner, 1979) or the uniqueness of one's contribution to the community (Goes, et al., 2014). To capture the result of gaining such status in the eWOM community, we calculated the $BestBadge_{ij}$ measure. $BestBadge_{ij}$ measures the value of the best ranking each individual reviewer has achieved during her/his reviewing history. Moreover, the current literature established that online reviews are considered more helpful when product experts write them, even if the expertise is self-declared. Higher helpfulness might lead to better social feedback, which we believe is likely to increase the contribution of the expert reviewer. To control for such effect in our research, we added the binary $Author_i$ measure representing if the frequent reviewer is a published or self-published author. Authors can create an *author profile* for themselves on the book review platform. The $Author_i$ measure is 1 if the reviewer has an author profile and is 0 for other reviewers.

***Belonging***

To investigate the hypotheses on the effect of belonging on the contribution volume (H4-4), first we used the size of the social network each reviewer is connected to as friends. We captured the effect of belonging with the lagged measure of Social Network Size ($Friends_{i(j-1)}$), which is the reviewers' number of friends in the previous quarter as we believe that a big part of the effect of social network on the contribution of frequent reviewers is by receiving their feedback as the audience. It is worth mentioning that although the feedback can come from anyone on the community that can see the reviews, but still it is more likely for direct friends to provide feedbacks as they see all the reviews and contribution of their friends before reviews from the community. All considered, it is sensible to assume that the effect comes with a lag. On the other hand, using the connected social network size (as $Friends_{ij}$), does not capture all information on how reviewers satisfy their need of belonging. It shows how big the community that reviewers belong to is, but does not capture the rate by which reviewers connect to others. People may have different strategies in expanding their ties to the eWOM community. Some may expand their social network very fast during first quarters after joining the community whereas other may develop their relationships gradually. The latter group may focus on reviewing products first and later form social ties. These strategies cause the heterogeneity in reviewers (Samiei & Tripathi, 2015). To capture data on such strategies we calculated the rate of social network expansion for each individual by dividing the change in $Friends_{ij}$ measure to Quarters on three data points of our data collection and assumed that the rate stayed constant between two waves of data collection. We stored this step-wise rate in the $SNExRate_{ij}$ variable.

***Engagement***

In the current literature, the concept of *website engagement* was measured using different variables. For measuring the engagement, researchers used variables such as log time, click-through rates, number of page views or website visits, *dwell time* (Millen & Patterson, 2002). Among these *dwell time*, was proven to be a robust measure for the website engagement. The web analytics communities used online behavioural measures over time. One of the reasons that behavioural measures are used as proxy is that they are scalable to millions of users and do not measure the behaviour of a controllable and limited number of users (Millen & Patterson, 2002). We are also interested in the behavioural aspect of reviewers' engagement with the eWOM community. To capture the behavioural measures, we used some of the built in functions in the community, which can be categorized as the *designed elements* of the website (Millen & Patterson, 2002) to improve user engagement.

The current literature suggests that not every reviewer has extrinsic motivation to help or warn new customers when they write online reviews. The intrinsic motivations such as fun and enjoyment do play an important role for many reviewers and drive their contribution (Hennig-Thurau, et al., 2004; Munzel & Kunz, 2014). In the section 4.4.6, we suggested that the *engagement* with the eWOM community has a positive effect on the contribution *volume* (H4-5). To investigate this hypothesis, we argue that the engagement with the platform affect the consumption experience of frequent reviewers at two levels. The retrospective engagement will affect what they take from their *previous readings* (consumption experience). At the same time, it can help them to plan for their future consumption or the *next books* to read.

To consider the retrospective engagement, we used number of *bookshelves* for each reviewer as the proxy. In our platform of interest, members have three pre-defined *bookshelves* including *read, currently reading,* and *want to read* books*.* Reviewers also can add new shelves to their collection to the maximum number of 100 shelves. We argue that a *higher number of shelves* shows the reviewer's stronger motivation to use the eWOM platform as a tool to document their personal consumption experience. On our platform, each reviewer has three default book shelves and they can add as many shelves they want up to 100 shelves to categorize books they reviewed.

Documenting personal consumption experience was proved to be a strong motivation of contribution in online communities (Gummerus, et al., 2012). If the motivation of self-documenting is high, we expect that users to review all books they have read already. They are less likely to be affected by either the *purchase bias* and *underreporting bias* (Hu, et al., 2009). With purchase or underreporting bias only reviewers with extreme experiences (either positive or negative ones) will write reviews. People who have average experience do not bother to spend time and energy to write about it. Without these biases, we expect reviewers with a larger list of shelves to have higher contribution volume. We calculated the measure of $Self\_document_{ij}$ as on the number of shelves for each reviewer. Then we centralized the measure around the minimum predefined number of shelves (three).

The platform engagement engenders prospective motivations to improve future consumption. Reviewers who have such motivation are likely to engage with the eWOM community more. They would contribute to the platform more and at the same time use the platform to find recommendations and information on new books. In addition, being engaged with the community can help them to reduce the search cost for the new products, which we know is high for the experience products (Nelson, 1970) such as books.

in our selected platform , there is a mechanism for reviewers to use if they want to increase the number of books they read, and supposedly review. Reviewers can set a personal reading challenge for themselves for each year. The challenge function was introduced in the website in 2011. We used the binary time-variant measure of $Challenge_{ij}$ to capture reviewers' use of this feature. We assumed that it was 0 for all reviewers before 2011 and during the quarters of each year was 1 for reviewers who have set a personal reading challenge for themselves.

### *4.5.1.3. Control variables*

**Product characteristics**

We know that the likelihood of someone writing an online review is dependent affected by their evaluation of the product's quality. Hue et al. (2006) suggested that the distribution of the online reviews is binomial (u-shaped) as people are more likely to share their reviews with others if the product has very high or very low quality. It is natural to assume that one's perception of the book quality is dependent on the actual book quality. In another word, if somebody just select to read books with very low quality scores, s/he is more mostly probable to rate them with very low score and is expected to write a high number of reviews compared to someone who select books with random quality. Therefore, we decided to include the quality of the book (as $BookQuality_{ij}$) as a control variable in our analysis. We used the crowds-given quality measure of books in modeling the learning to control for the product quality. We calculated the measure as the average quality score of all books that reviewer *i* selects to read and review in quarter *j.* To mitigate the possible aggregation issue when using the average function, we included another control variable ($WorstBook_{ij}$), which specifies the quality score range. The $WorstBook_{ij}$ measure is the quality score of the book with the lowest quality score read by each reviewer ($i$) on each quarter ($j$). In the appendix of the last chapter (Chapter 3-Appendix A), we explained in detail how we estimated the unobserved measure of book quality with a crowd-given score in our platform.

**Reviewing effort**

Another control variable we included in our analysis model is the $\#TextReview_{ij}$, which is the number of textual reviews each individual may write supporting their numerical score rating of books. The ration behind having $\#TextReview_{ij}$ as a control variable is the limited time (as the reviewer resource) to allocate to the reviewing effort. Naturally, a reviewer will divide his reviewing time between allocating the numerical score ($AvgScore_{ij}$) and writing textual comments to express their opinion and justify their evaluation of the book. The more they write textual reviews leaves them with less time on the eWOM platform to review different books. However, when they express their opinion in detail for a larger number of their reviews, their reviews are more likely to get the attention of their followers and leave them with better feedback from their peers. This could eventually strengthen their motive and makes them expect higher social benefits. The effect would be moderated if their evaluation of books' quality deviated from the crowd's average. Therefore, we include $AvgABSDeviation_{ij}$ in our analysis.

| Construct | Variable | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| **Contribution volume (outcome)** | $Volume_{ij}$ | 26.18` | 62.6 | 1 | 2789 |
| | $LnVolume_{ij}$ | 2.38 | 1.26 | 0 | 7.93 |
| **Experience** | $LagQuarters$ | 11.50 | 8.04 | 0 | 35 |
| **Belonging** | $Friends_{i(j-1)}$ | 117.47 | 396.41 | 0 | 5668 |
| | $SNExRate_{ij}$ | 8.63 | 34.53 | -47.57 | 673 |
| **Identity** | $Librarian_{ij}$ | .10 | .30 | 0 | 1 |
| | $BestBadge_{ij}$ | .074 | .249 | 0 | .998 |
| **Engagement** | $Self\_document_{ij}$ | 14.22 | 22.9 | 0 | 97 |
| | $Challenge_{ij}$ | .230 | .421 | 0 | 1 |
| **Control Variables** | $BookQuality_{ij}$ | 78.31 | 3.50 | 40.1 | 100 |
| | $WorstBook_{ij}$ | 68.21 | 9.77 | 0 | 100 |
| | $Author_{i}$ | .103 | .304 | 0 | 1 |
| | $\#TextReview_{ij}$ | .149 | 1.07 | 0 | 52 |
| | $PlsntExp_{ij}$ | 0.222 | 0.415 | 0 | 0 |
| | $AvgScore_{ij}$ | 71.42 | 16.18 | 0 | 100 |
| | $AvgABSDeviation_{ij}$ | 0.907 | 0.58 | 0 | 4.69 |

**Table 4-1: Descriptive Statistics**

### Pleasant experience

It is obvious that having a pleasant experience in reading books could affect the social learning process. The customer's satisfaction has a cognitive component (Homburg, et al., 2006). The cognitive evaluation is the result of comparing the expectations and the real quality of the product (book). Having that in mind, having a pleasant experience can affect the reviewer evaluation of the book. As the customer's satisfaction/disappointment is the main driver of writing reviews (Hu, et al., 2009), we argue that $PlsntExp_{ij}$ can affect the contribution *volume*. Therefore, we control for it.

To measure the $PlsntExp_{ij}$, we used a binary variable at the reviewer-quarter level ($PlsntExp_{ij}$). As people are different in their interests, expectations, and tastes in reading books, we normalized this measure for reviewers based on their own experience. The measure is 1 if their good experience in one quarter is higher than their overall experience. In this definition, we consider reading a book a good experience if the reviewer evaluates the book with a five star score. We summarized the dependent, independent, and control variables in the Table 3-1, which includes the descriptive statistics of the variables too. We also presented the pairwise correlation between those variables in the Table 4-2.

**Table 4-2: Correlation Matrix**

| Variable | $LnVolume_{ij}$ | LagQuarters | $Friends_{i(j-1)}$ | $SNExRate_{ij}$ | $Librarian_{ij}$ | $BestBadge_{ij}$ | $Self\_document_{ij}$ | $Challenge_{ij}$ | $BookQuality_{ij}$ | $WorstBook_{ij}$ | $Author_i$ | $\#TextReview_{ij}$ | $PlsntExp_{ij}$ | $AvgScore_{ij}$ | $AvgABSDeviation_{ij}$ | $Volume_{ij}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $LnVolume_{ij}$ | 1.00 | | | | | | | | | | | | | | | |
| LagQuarters | -0.1677 | 1.00 | | | | | | | | | | | | | | |
| $Friends_{i(j-1)}$ | 0.0597 | 0.0970 | 1.00 | | | | | | | | | | | | | |
| $SNExRate_{ij}$ | 0.0808 | -0.1184 | 0.4821 | 1.00 | | | | | | | | | | | | |
| $Librarian_{ij}$ | 0.1197 | 0.0543 | 0.0606 | 0.0455 | 1.00 | | | | | | | | | | | |
| $BestBadge_{ij}$ | 0.1027 | 0.0174 | 0.1353 | 0.1099 | 0.0752 | 1.00 | | | | | | | | | | |
| $Self\_document_{ij}$ | 0.2436 | 0.0930 | 0.1463 | 0.0791 | 0.3393 | 0.1160 | 1.00 | | | | | | | | | |
| $Challenge_{ij}$ | 0.2373 | 0.0776 | 0.1357 | 0.0917 | 0.1118 | 0.1374 | 0.1815 | 1.00 | | | | | | | | |
| $BookQuality_{ij}$ | -0.0180 | 0.0338 | 0.1015 | 0.0513 | -0.0162 | 0.0283 | -0.0003 | 0.0382 | 1.00 | | | | | | | |
| $WorstBook_{ij}$ | -0.5109 | 0.0800 | 0.0125 | -0.0146 | -0.0616 | -0.0756 | -0.1358 | -0.1168 | 0.5379 | 1.00 | | | | | | |
| $Author_i$ | -0.0065 | -0.0105 | 0.2506 | 0.2439 | -0.0658 | 0.1032 | 0.0031 | -0.0020 | 0.0120 | -0.0542 | 1.00 | | | | | |
| $\#TextReview_{ij}$ | 0.1647 | -0.1805 | -0.0376 | 0.0395 | 0.0323 | 0.0064 | 0.0187 | -0.0190 | -0.0036 | -0.0642 | -0.0072 | 1.00 | | | | |
| $PlsntExp_{ij}$ | 0.3985 | -0.1445 | -0.0219 | 0.0322 | 0.0145 | 0.0095 | 0.0286 | 0.0197 | 0.0695 | -0.1619 | 0.0132 | 0.1468 | 1.00 | | | |
| $AvgScore_{ij}$ | -0.0099 | -0.0396 | 0.0264 | 0.0882 | -0.0099 | 0.0342 | -0.0394 | 0.0405 | 0.2069 | 0.1527 | 0.0567 | 0.0188 | 0.159 | 1.00 | | |
| $AvgABSDeviation_i$ | 0.0044 | -0.0158 | 0.1011 | 0.0393 | -0.0283 | -0.0312 | 0.0232 | -0.0241 | -0.0250 | -0.0499 | 0.0600 | -0.0156 | -0.028 | -0.754 | 1.00 | |
| $Volume_{ij}$ | 0.075 | -0.139 | 0.058 | 0.09180 | 0.115 | 0.115 | 0.216 | 0.17 | -0.004 | -0.39 | -0.014 | 0.18 | 0.39 | -0.017 | 0.024 | 1.000 |

## 4.5.2. Data analysis and results

### *4.5.2.1. Analysis model*

As in the previous chapter of the thesis, we have used a mixed effect longitudinal data analysis method. The nature of our data set is a panel data, as we have reviewing activity of individuals over time. We intended to study the contribution volume of frequent reviewers over time. Thus, *time* (measured by Quarters) is the main independent variable in our data set. As mentioned before, we needed to use the lagged time variable.

After a closer look at our hypotheses, we needed a model with two levels: population and individual level. We also have to account for the within and between individual differences. Therefore, we need a multi-level model with random effects. We adopted the longitudinal data analysis method suggested by Singer and Willett (2003) for contribution volume (*LnVolume*).

We used the multi-level, mixed effect longitudinal analysis method (Singer & Willett, 2003). We developed a longitudinal model with the $LnVolume_{ij}$ as the dependent variable. The model consist of *time-variant* variables and has two levels to allow for the heterogeneity among individuals. However, there are many unobserved characteristics on different reviewers, which we could not capture. Having a random effect in level two, which alters the coefficients in our main equation for each individual, takes care of unobserved reviewer-level measures. In addition, the $BestBadge_i$ and $Author_i$ are time-invariant variables reflecting on the individual level measures. The main level of the model consists of the *time-variant* measures that quantify reviewers' behaviour and have a different value on each time-period. The model is as follows:

$$LnVolume_{ij} = \pi_0 + \pi_1 LagQuarters + \pi_2 Friends_{i(j-1)} + \pi_3 SNExRate_{ij} + \pi_4 Librarian_{ij} + \pi_5 Engagement_{ij} + \pi_6\, ControlVariables + \varepsilon_{ij}$$

Where *control variables* consists of:

$$ControlVariables = \begin{bmatrix} WorstBook_{ij} \\ \#TextReview_{ij} \\ PlsntExp_{ij} \\ AvgScore_{ij} \\ AvgABSDeviation_{ij} \\ BookQuality_{ij} \end{bmatrix}$$

And

$$Engagement_{ij} = \begin{bmatrix} Self\_document_i \\ Challenge_{ij} \end{bmatrix}$$

And the second level is as follows:

$$\pi_0 = \gamma_{00} + \gamma_{01} BestBadge_i + \gamma_{02} Author_i + \zeta_{0j}$$

$$\pi_1 = \gamma_{10} + \zeta_{1j}$$

Using the Singer and Willet (2003) approach, the composite, multi-level is:

$$LnVolume_{ij} = \gamma_{00} + \gamma_{01} BestBadge_i + \gamma_{02} Author_i + \gamma_{10} LagQuarters + \pi_2 Friends_{i(j-1)} + \pi_3 SNExRate_{ij} + \pi_4 Librarian_{ij} + \pi_5 Engagement_{ij} + \pi_6\, ControlVariables + (\zeta_{0j} + \zeta_{1j} * Quarters + \varepsilon_{ij})$$

The random component of this model is as follows:

$$\varepsilon_{ij} \sim^{iid} N(0, \sigma_0^2)$$

In this model both level-one growth parameters have their own residuals ($\zeta_{0j}$ and $\zeta_{1j}$ ) which allows the parameters of the model to differ between individuals. $\sigma_0^2$ , $\sigma_1^2$ and $\sigma_{10}$ meausre the vaiance and covariance of the model for these residuals with the following distribution.

$$\begin{bmatrix}\xi_{0j}\\ \xi_{1j}\end{bmatrix} \sim^{iid} N\left(\begin{bmatrix}0\\0\end{bmatrix}, \begin{bmatrix}\sigma_0^2 & \sigma_{01}\\ \sigma_{10} & \sigma_1^2\end{bmatrix}\right)$$

#### *4.5.2.2. Analysis process*

To analyse the data and investigate our hypotheses, we also used the same tools as the previous chapters. We used Stata-14.1 as a general-purposed statistical software and used the mixed-effect commands (*xtmixed*) to fit a longitudinal multi-level model to the data model.

| Dependent variables | Measures | Coefficient | $LnVolume_{ij}$ Models | | | |
|---|---|---|---|---|---|---|
| | | | A | B | C | D |
| Fixed effects | Intercept | $\gamma_{00}$ | 0.81 *** | 0.76 *** | 0.7 *** | .89 *** |
| | *Time (LagQuarters)* | $\gamma_{10}$ | -0.03 *** | -0.03 *** | -0.039 *** | -.028 *** |
| | $BestBadge_{ij}$ | $\gamma_{01}$ | - | 0.19 * | 0.12 *** | .179 ~ |
| | $Author_i$ | $\gamma_{02}$ | - | -0.15 * | -0.14* | -.129 ~ |
| | $Friends_{i(j-1)}$ | $\pi_2$ | - | - | - | .0003 |
| | $SNExRate_{ij}$ | $\pi_3$ | - | - | - | .00006 |
| | $Librarian_{ij}$ | $\pi_4$ | - | 0.3 *** | 0.166 ** | .242 *** |
| | $Self\_document_{ij}$ | $\pi_5$ | - | - | 0.006 *** | .0064 *** |
| | $Challenge_{ij}$ | | - | - | 0.077** | .113 *** |
| | $BookQuality_{ij}$ | $\pi_6$ | 0.08*** | 0.08 *** | 0.08 *** | .0706*** |
| | $WorstBook_{ij}$ | | -0.05 *** | -0.05 *** | -0.05 *** | -.047 *** |
| | $\#TextReview_{ij}$ | | 0.09 *** | 0.09 *** | 0.09 *** | .215 *** |
| | $PlsntExp_{ij}$ | | 1.09 *** | 1.09 *** | 1.09 *** | .768 *** |
| | $AvgScore_{ij}$ | | -0.01 *** | -0.01 *** | -0.011 *** | -.0107 *** |
| | $AvgABSDeviation_{ij}$ | | -0.22 *** | -0.21 *** | -0.21 *** | -.195 *** |
| Random effects | Within-person | $\varepsilon_{ij}$ | 0.68 | 0.68 | 0.68 | 0.61 |
| | Initial Status (Constant) | $\sigma_0^2$ | 0.51 | 0.506 | 0.47 | 0.55 |
| | Rate of change | $\sigma_1^2$ | 0.028 | 0.028 | 0.027 | 0.029 |
| | Covariance | $\sigma_{01}^2$ | -0.28 | -0.3 | -0.33 | -0.44 |
| Fitness | AIC | | 24257.32 | 24232.37 | 24178.56 | 19172.1 |
| | BIC | | 24344.68 | 24341.57 | 24302.31 | 19307.72 |
| P<0.001*** | - P<0.01 ** -P<0.05 * -P<0.1 ~ | | | | | |

**Table 4-3: Analysis result; Contribution volume**

For the contribution *volume* ($LnVolume_{ij}$), after running the simple growth model, we added independent variables and the *experience* measures. Then, following the approach suggested by Singer & Willett (2003, p. p. 120), we added the measures for each construct one at a time. By closely controlling the fitness-of-fit using AIC (Akaike information criterion) and BIC (Bayesian information criterion) measures, we compared fitness values in nested models (see models A, B, C, and D in Table 4-3). In Model A, we included variables associated with reviewing *experience* with all control variables (Model A). Then we added the variable associated with other hypotheses one by one. Model B covers the *identity* measures, where Model C has both *identity* and *engagement* related measures. Finally, in Model D we added the measures associated with the *belonging*. We reported the goodness of fit measures in Table 4-3), which is comparable as models are nested. We decided that model D is the final model explaining the change in *review volume* with the lowest AIC And BIC. It has been shown in Table 4-3) that by adding explaining variables, our model is stable and all coefficients are consistent in their size and magnitude.

It is worth mentioning that when we ran the model, we had included the time interaction of all time invariant variables at the beginning. However, many of these interactions did not significantly explain the dependent variables and in the final model, we only kept significant measures. The coefficient associated with all explaining and control variables included in our model for review valence are highly significant.

#### *4.5.2.1. Estimation Results and Hypothesis Testing*

Using the analysis results, we can discuss our inference on hypotheses. We focused on the *social learning* process assuming that being a part of a *Community of Practice* gave frequent reviewers a unique opportunity to learn and become better reviewers. We argued that with this process, their reviewing behaviour and their contribution level changes too. To investigate this argument, we deduced that the contribution *volume* decreases for frequent reviewers but the social learning mechanisms can explain the heterogeneity in different reviewers' behavioural pattern.

| **Hypothesis** | **Status** |
|---|---|
| *Hypothesis* 1 (H4-1): The volume of the contribution of frequent reviewers decreases over time | Supported |
| *Hypothesis 2 (H4-2)*: Librarians have a higher contribution volume compared to other frequent reviewers | Supported |
| *Hypothesis* 3 (H4-3): frequent reviewers, who earned a better-ranked recognition badge, are more likely to have a higher contribution level | Supported |
| Hypothesis 4 (H4-4): for frequent reviewers, bigger audience (larger social network) result in a higher contribution volume. Also a higher social network expansion rate has the same effect | Not supported |
| Hypothesis 5 (H4-5): frequent reviewers who are more engaged with the eWOM community are more likely to have higher contribution volume | Supported |

**Table 4-4: Summary of hypotheses testing**

Investigating the first hypothesis showed that the contribution volume of the contribution for frequent reviewers decreases over time, which supports H4-1. The relevant coefficient ($\gamma_{10}$ =-.028 ***) is negative and significant confirming that the contribution volume decreases over time. With a negative exponential rate over time, we expect the negative rate for $Volueme_{ij}$ decrease too. This is consistent with our argument on the reason for declining contribution. Therefore, we conclude that as time passes by, the novelty of the eWOM community, website, and practicing the new role as book reviewer diminishes for reviewers. This reflects on the decline in the contribution volume.

Figure 4-3 shows the linear change in the transformed *volume* over time along with the scatter plot of the transformation.

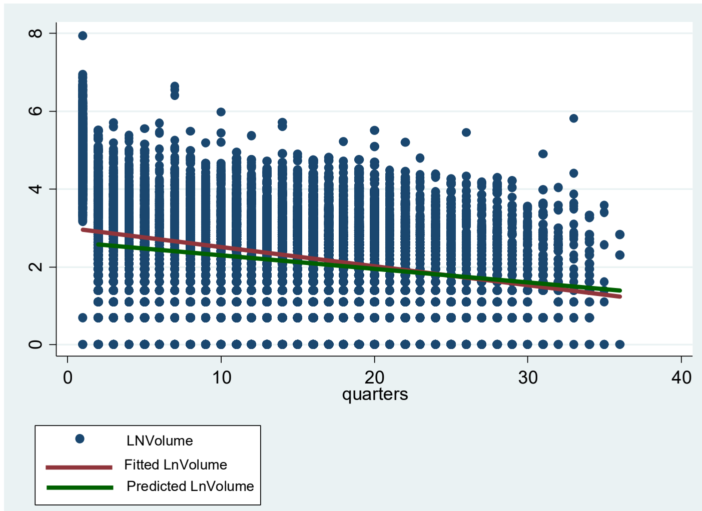



**Figure 4-3: Observed, fitted and predicted LnVolume over time**

We also aimed to study the effect of the social identity process on the contribution level of online reviewers. Our result showed that engaging in the community service positively affects the reviewing volume ($\pi_4$ =.242 ***). Especially when the required qualification for being accepted as the community volunteer (librarian) is directly related to the contribution of reviewers. A closer look at our data set about the consistency of the motivation for community service showed that reviewers who earned the librarian position do not lose that status[18]. All considered, we conclude that Librarians have higher contribution volume compared to the population (H4-2 supported).

Some frequent reviewers also focus on achieving the recognition of the community with their performance. Our analysing the result in the eWOM community of interest ($\gamma_{01}$ =.179 ~) showed that these reviewers have higher contribution *volume.* This supports the argument of the positive effect of motivation for being recognized on the contribution *volume.* Hence, after investigating H4-3, we conclude that frequent reviewers, who earned a better-ranked recognition badge, are more likely to have higher contribution level. Figure 4-4 shows the difference in the contribution volume for badge owners and the rest of the sample.

[18] A few users become authors instead and one reviewer becomes the website official employer.

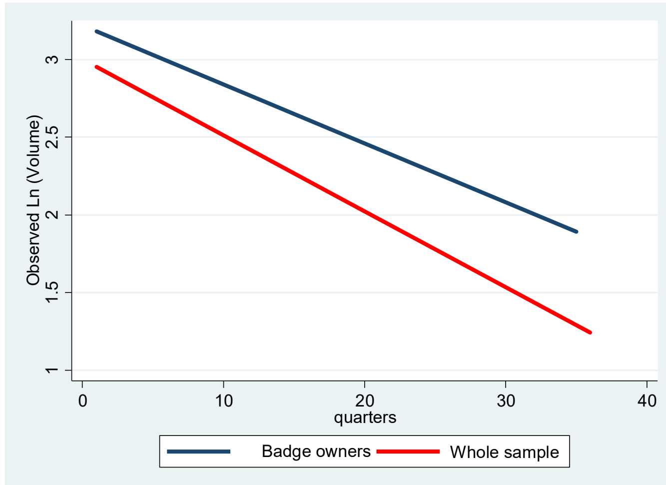



**Figure 4-4: Contribution volume; comparing badge-owners with the sample**

Investigating H4-4, we drew from the current literature and expected to see that a larger online audience naturally motivates reviewers to contribute more and have a higher volume (Goes, et al., 2014, p. 4). Theoretically speaking, we should observe the significant effect of the *social network size* on the contribution *volume*. However, the analysis does not meet our anticipations and the estimated coefficients ($\pi_2$ =.0003; $\pi_3$ =.00006) are not significant. We believe that the *Collective Effort Model* (CEM) (Karau & Williams, 2001) and the cognitive side of social learning (Bandura, 1977) can explain the underlying reason of such observation. We will discuss it in detail in the discussion section (4.6.1).

The last, but very important hypothesis to investigate is the effect of website engagement on the contribution level. We focused on the *transactional engagement* (Gummerus, et al., 2012) which feeds either *retrospective* or *prospective* motivations. The significant coefficients, $\pi_5 = \begin{bmatrix} .0064 *** \\ .113 \ \ *** \end{bmatrix}$, confirm that regardless of the type of the motivation for engagement with the platform, frequent reviewers who have a higher engagement level with the eWOM community are more likely to have higher contribution volume. This result supports the related hypothesis (H4-5).

### *4.5.2.2. Result for control variable*

In our analysis, we controlled for some literature-recommended factors. Our analysis confirmed what we expected as their determinant effect on the review volume, which demonstrate the validity of the model. First of all, frequent reviewers who read books with better quality (with higher $BookQuality_{ij}$ and $WorstBook_{ij}$) may end up with higher $PlsntExp_{ij}$ and end up with higher $AvgScore_{ij}$. Based on the current literature, with an expected u-shaped distribution for reviews, it is more likely for individuals to write reviews if they have a very good or very bad experience (Hu, et al., 2009). However, in the special case of reading books, reviewers do not have to consume the product or finish reading the book. As reading books as a hobby, one who does not like a book at all will not continue to read and are less likely to write a review. The positive coefficient for $BookQuality_{ij}$ and $PlsntExp_{ij}$ and a negative coefficient for $AvgScore_{ij}$ and $WorstBook_{ij}$ are consistent with this argument.

We also controlled for reviewers who created an author profile and claimed to publish a book themselves, either a commercial publication or a self-publication. We believe that the authorship status signals others with the expertness of the reviewer about the books. Authors obtain their credibility with their expertness, not the reviewing activity. Drawing from the literature, the *expertise "*implies an in-depth mastery of a field of knowledge" (Mackiewicz, 2010). Therefore, we expect them to be less influenced with the social learning process and stick to their professional and expert reviewing behaviour. This is consistent with the significant negative coefficient that we observed ($\gamma_{02}$ =-.129 ~). The Figure 4-5 illustrates the difference in slope and intercept in *volume* change over time between authors and the samples.

The main reason that being a book expert (author) will ennhance the negative rate of change in contribution level is the effect of complacency (Goes, et al., 2014, p. 4) . For reviewers, developing a credible identity in the community is a big motivation. Reviewers with *author* status already are considered *book expert* and they might have less motivation to have high contribution to achieve the expertness status. So, it less likely for them to engage in the eWOM community. On the other hand, for book experts the group size is not as effective as normal reviewer. Authors already have the expert status or if they do not feel like it, they have to act as such. Therefore, they are more likely to get affected by the complacency effect and be less motivated to review books (Goes, et al., 2014, p. 4). Therefore, we cocluded that authors started with a lower contribution, got less affected by their experience, and over time decreased their contribution with a shallower rate.
Another important control variable is $AvgABSDeviation_{ij}$. The analysis result with significant negative coefficient (-.195 ***) shows that the more reviewer deviate from the crowd's opinion, the more they are likely to contribute less to the community. Product reviewers want to know if their contribution is unique (or at lease useful) or not and if they do not come across any evidence of the usefulness of their shared experience, they may leave the community (Iriberri & Leroy, 2009). Having a completely different opinion with the community, reviewers might conclude that they are not in the right community and lower their contribution. Moreover, the current literature established that "although posting a differentiated rating can attract more attention, it usually brings more negative feedback" (Shen, 2009). Therefore, higher deviation from the crowds give

quality score for books may demotivate frequent reviewers and consequently lower their contribution volume over time.

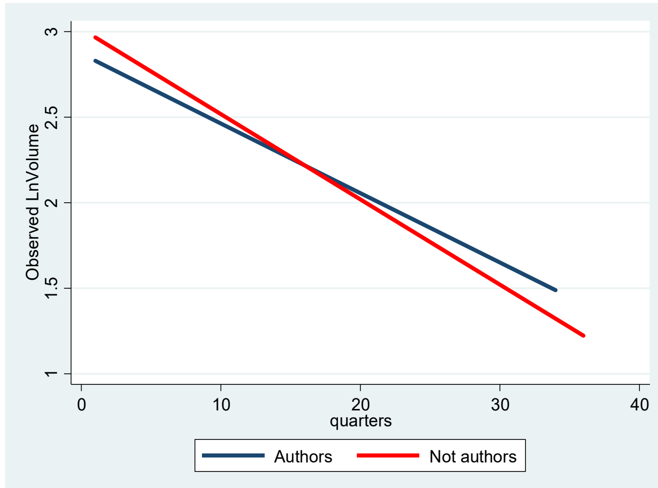



**Figure 4-5: Contribution volume; comparing authors with the samples**

## 4.6. Discussions

### 4.6.1. The interruption of the cognitive learning process

As discussed before, in an eWOM community, the group size (Zhang & Zhu, 2010) is expected to have a positive effect on the contribution. Receiving friendship requests, which happens when the social network is growing, should encourage reviewers to contribute more as they may signal the importance of one's contribution in the community (Goes, et al., 2014). This effect is more significant for frequent reviewers who repeatedly share their opinion with the community and are very likely to have a reputation of seeking and structural embeddedness motives (Wasko & Faraj, 2005) for their contribution. Therefore, we expected to observe the significant effect of the *social network size* on the contribution *volume*. However, we could not find evidence of such observations. We believe that there are two reasosn for such effects as follows:

***Interruption in cognitive learning process***

We believe that the cognitive side of social learning theory explains the underlying reason. The theory of social learning (Bandura, 1977) suggests that the behaviour is the interactive function of one's *cognitive* drives, enacted *behaviour*, and the *environment*. In our community of interest, the *environment* is the eWOM platform as a community of practice and the *behaviour* is repetitive and frequent acts of reviewing books. The process of *learning by meaning* (Wenger, 1998) can explain the *cognitive* mechanism. A closer look to the cognitive factors of social learning can explain the reason of not significant effect of the social network size on the contribution volume.

The most important part of the cognitive analysis is a result of comparing the expectations with real feedback from the environment (Homburg, et al., 2006). According to the social learning theory triangle (Bandura, 1977), expectation can be about *self-efficacy* or *outcome expectations.* We believe that the cognitive interpretation of self-efficacy and outcome expectations can explain the underlying reason that the positive affect of social networks was not observed on the contribution volume.

*Self-efficacy* refer to the extent to which one believes that they perform an action. We argue that having a very big social network may adversely affect the motivation and consequently the intention of book readers to share their reviews with others. The reason could be:

- *Social loafing:* Individuals who work in groups are expected to make effort less than their full potential as they are hoping that other group members will cover needed effort for the team to meet the performance goals (Karau & Williams, 2001, p. 134). This effect can increase over time with the potential arousal reduction (Karau & Williams, 2001, p. 135). The bigger the group is, the more likely for individuals to be demotivated to contribute to help the overall performance. This will result in the negative effect of social network size on the contribution volume.
- *Fear of sharing with unknown crowd:* Research shows that one individual physiologically can handle to be related to around 150 people (Hill & Dunbar, 2003). Reviewers who have a social network bigger than this threshold would not feel as safe as someone who shares her/his opinion with friends or acquaintances. Sharing content with a big group of people may feel like sharing your opinion with the public. At first, it seems that the feeling should not change the sharing behaviour as these reviewers already selected to share their reviews publicly[19]. However, talking to the public and sharing content with a no-face crowd may bring up some concern. First of all, one may not similarly trust everyone in a her/his friend list. Reviewers may know people in their social network in the community from different places. There could be family members, colleagues, neighbours, etc. between your friends. We argue that reviewers are unlikely to share all of their reading experience with everyone. They are more likely to only review books and share their opinion that can share with the people in their friends list that can trust the least.

[19] The ethics approval for this research only let us collect publicly available data. To meet this requirement, we only tracked and collect data on internet users who have shared their reviews publicly.

- *Fear of sharing too much:* having a big social network makes it possible to be friends with many people that one may not be comfortable to share your experience with. As reading books is a way of dealing with everyday life, frequent reviewers may not be comfortable to share their entire reading list with everyone. For example, you may not want your colleagues to know that you are struggling to improve your *self-confidence*. We believe that the bigger the social network, the more these types of concerns and trust issues. This can cancel out the augmenting effect of a social network on the reviewing *volume*.

The *outcome expectation* can cancel out the positive effect of social networks on the contribution volume. According to the expectancy-value models of effort, individuals seek to maximize the expected utility of their effort, which will be their motivation to continue their contribution (Karau & Williams, 2001, p. 137). We argue that for frequent reviewers with a big social network, anticipating the outcome of their reviews is harder, which weaken their motivation due to:

- *Hardship of anticipate the outcome:* With a bigger social network, it is harder to imagine and anticipate the reaction of the audience to your reviewing behaviour
- *Hardship of sharing something worthy or unique:* According to the current research on the Homophily in social media (McPherson, et al., 2001) individuals have the tendency to connect to people with similar tastes and interests. Being connected to other members with similar taste in reading books, makes it harder for reviewers to contribute significantly different from others. This can reduce the extent of attention and feedback they get and may result in demotivating them.
- *Information overload:* having a big social network may result in a huge pile of information to process. This can cause information overload, which most probably will consume most of the time and energy that reviewers have. Understanding and interpreting the book recommendation, reviews from friends, and direct or indirect feedback on one's contribution might take a huge portion of time.

All these reasons lead to a higher contribution cost and lower benefit from the contribution for reviewers with bigger social networks. Current research showed that community members who do not find the contribution in the community useful, are more likely to lower their contribution or leave the community (Iriberri & Leroy, 2009). Therefore, we believe that with higher cost and lower benefit, reviewers who have a bigger social network may be less interested to continue their contribution.

We can sum up by concluding that a big social network in an eWOM community, can adversely affect the social learning process by intervention with the cognitive factors. This is aligned with the

*Collective Effort Model* (Karau & Williams, 2001, p. 137) which suggests that reviewers may lower their effort when they do not expect to be recognized or rewarded for their individual effort. However, if they are very interested and enthusiastic about the reviewing, they may prefer to work in a smaller group and have smaller social network in the eWOM community.

### 4.6.2. Robustness of analysis

Based on validation literature in Information systems research (Straub, 1989) , this study is confirmatory research as a quantitative empirical study with statistical techniques for theory testing. As stated before, the methodological approach for this research is mixed effect, multilevel longitudinal modelling. The *xtmixed* command we used, is also computationally efficient for linear variance components (Rabe-Hesketh & Skrondal, 2008, p. pp. 62) such as our model.

First, drawing from Goes et al. (2014), in our robustness tests, we remove those with extremely high numbers of incoming ties, to ensure that these outliers or influential observations do not make our result bias.
Moreover, knowing the significance of the selected estimation method on the inference result, we focused on its robustness. Each estimation method has some prerequisite assumptions that the result is not to be trusted without. In other words, the result of inference based on the estimation using different method is rigor only if the underlying assumptions of the method are met.

In the following, we explain our strategy to deal with potential issues that could have compromised the validity of our analysis. To validate the results of our analysis, first we compared our estimation method. Then we revisited assumptions of parameter estimation including the *normality of the residuals, independency*, and the potential *serial autocorrelation* in data points. To overcome the potential serial autocorrelation, we used different error structure and the result of which is presented in the section 4.6.2.3. At the end, we dealt which the potential endogeneity between explaining variables and showed (section 4.6.2.4) that the estimated coefficients in Table 3-1 Table 4-3 are consistent and robust.

#### *4.6.2.1. Estimation method*

A large unbalanced panel data sample made it more difficult to estimate unbiased coefficient and random effect. We selected the MLE method to estimate the coefficient. However, to reassessing the robustness of the model, we compared the MLE estimation result with REML estimation method.

As mentioned in the previous chapter, for the MLE procedure, the software agent first computes the fixed effect of the model. Then comparing these estimations with the real data, the random effect and error terms of the models are estimated (Singer & Willett, 2003, pp. 86-89). The estimation of the likelihood function is based on assessing the probability that the joint empirical distribution different individuals on different occasions could be observed. The MLE, however, is negatively biased for errors, but the bias gets smaller for large samples whilst REML gives a non-biased estimate.

| **Dependent variables** | **Measures** | **Coefficient** | **Estimation method** | |
|---|---|---|---|---|
| | | | **MLE** | **REML** |
| **Fixed effects** | Intercept | $\gamma_{00}$ | .89 *** | .89 *** |
| | Time (LagQuarters) | $\gamma_{10}$ | -.028 *** | -.028 *** |
| | $BestBadge_{ij}$ | $\gamma_{01}$ | .179 ~ | .18~ |
| | $Author_i$ | $\gamma_{02}$ | -.129 ~ | -.129 ~ |
| | $Friends_{i(j-1)}$ | $\pi_2$ | .0003 | .0003 |
| | $SNExRate_{ij}$ | $\pi_3$ | .00006 | .00006 |
| | $Librarian_{ij}$ | $\pi_4$ | .242 *** | .24 *** |
| | $Self\_document_{ij}$ | $\pi_5$ | .0064 *** | .0064 *** |
| | $Challenge_{ij}$ | | .113 *** | .112 *** |
| | $BookQuality_{ij}$ | $\pi_6$ | .0706*** | .0706*** |
| | $WorstBook_{ij}$ | | -.047 *** | -.047 *** |
| | $\#TextReview_{ij}$ | | .215 *** | .215 *** |
| | $PlsntExp_{ij}$ | | .768 *** | .768 *** |
| | $AvgScore_{ij}$ | | -.0107 *** | -.0107 *** |
| | $AvgABSDeviation_{ij}$ | | -.195 *** | -.195 *** |
| **Fitness** | AIC | | 19172.1 | 19301.6 |
| | BIC | | 19307.72 | 19437.23 |

**Table 4-5: MLE and REML estimation method**

Both MLE and REML estimators use iterative algorithms to estimate fixed effect and random effects for the given values. The difference between them that REML takes the number of estimated fixed effects into account and lose one degree of freedom for each (Harville, 1977). Therefore, REML is usually used when there are hypotheses about variance components not the fixed effects. However, when the sample size is big enough the difference in the degree of freedom in MLE and REML is not significant and it is to be expected that both estimation methods return the same results.

We compared MLE and REML, and checked the stability of the estimates with comparing estimates in fixed effect model and mixed effect model. As presented in Table 4-5, we observed that the both the sign and the magnitude of coefficients is consistent in both models.

#### *4.6.2.2. Testing the normality assumption of the residuals*

Both estimation methods we used (MLE and REML) assume that the underlying distribution of the residual is norma. To investigate if the residuals satisfy the assumption, first we predicted the residuals using the predicted dependent variable (LnVolume). Figure 4-6 shows the histogram of the observed LnVolume versus its predicted value.

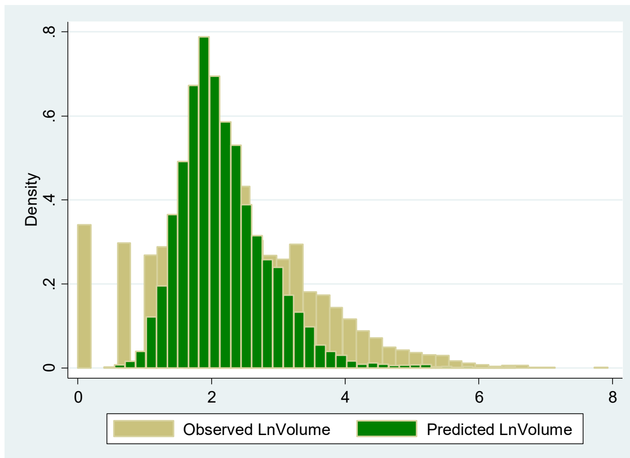
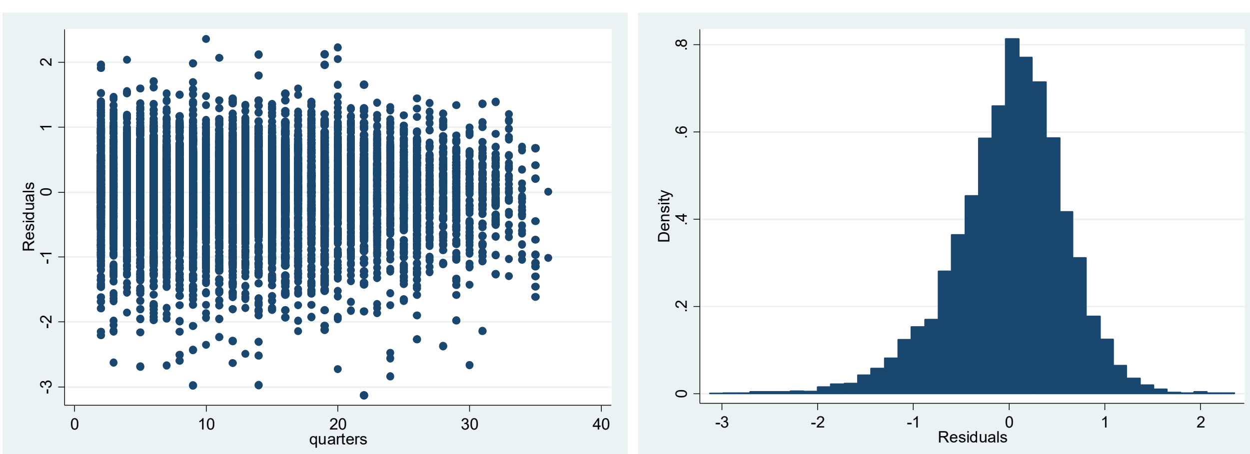



**Figure 4-6: Observed and predicted LnVolume histogram**

Our hypothesis is that the residuals are scattered around 0 (as residual's mean). Therefore, first we checked if we could reject the hypothesis of residual's mean being different from zero with a simple t-test. Figure 4-7 shows the histogram of the residuals which looks like a normally distributed sample and Figure 4-7 shows the box plot for the residual. The result of a t-test (Table 4-6) shows that the normal distribution with zero mean too.




**(A)** **(B)**

**Figure 4-7: the Residual scatter and histogram**

| H0 | H1 | t | Obs. | d.f. | P value |
|---|---|---|---|---|---|
| $Residual = 0$ | $Residual > 0$ | -0.000 | 9303 | 9302 | Pr(T>t)=0.5 |
| | $Residual <> 0$ | -0.000 | 9303 | 9302 | Pr(\|T\|>\|t\|)=1 |
| | $Residual < 0$ | -0.000 | 9303 | 9302 | Pr(T<t)=0.5 |

**Table 4-6: t-test on Residual's mean**

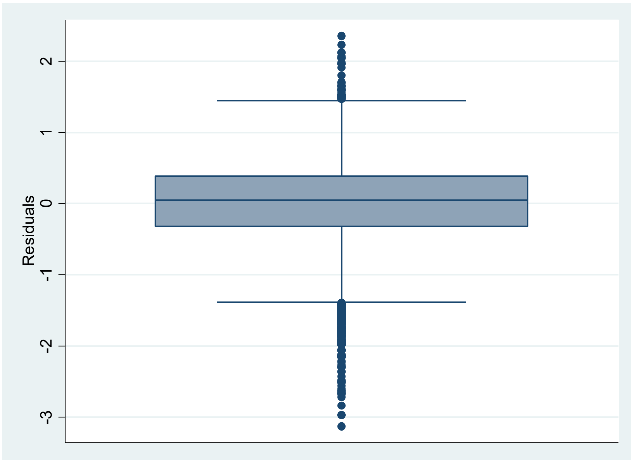



**Figure 4-8: Residual Normal test**

### *4.6.2.3. Error structure*

Another assumption that we need to address to ensure that our estimation method results in solid and robust, is the dependency between data sample. Unlike the cross sectional data that the independency should hold for all sample points in panel data, we expect dependency between reviewing records for each individual.

In order to deal with the possibility, first we assumed we have an un-structured error covariance see (Table 4-7 ). However, this model with unstructured random effect structure overlooks the likelihood of having autocorrelation it the model (Singer & Willett, 2003, p. P. 244). Therefore, in next step, we estimated the model assuming to have an *Autoregressive Error Covariance Matrix* as suggested by Singer and Willett (2003, p. 262). In this model, the covariance structure is as follows (Singer & Willett, 2003):

$$\begin{bmatrix} \sigma^2 & \sigma^2\rho & \sigma^2\rho^2 & \sigma^2\rho^3 \\ \sigma^2\rho & \sigma^2 & \sigma^2\rho & \sigma^2\rho^2 \\ \sigma^2\rho^2 & \sigma^2\rho & \sigma^2 & \sigma^2\rho \\ \sigma^2\rho^3 & \sigma^2\rho^2 & \sigma^2\rho & \sigma^2 \end{bmatrix}$$

| Dependent variables | Measures | Coefficient | Estimation method | |
|---|---|---|---|---|
| | | | unstructured | autocorrelated |
| Fixed effects | Intercept | $\gamma_{00}$ | .89 *** | .921 *** |
| | Time ($LagQuarters$) | $\gamma_{10}$ | -.028 *** | -.0273 *** |
| | $BestBadge_{ij}$ | $\gamma_{01}$ | .179 ~ | .169 ~ |
| | $Author_i$ | $\gamma_{02}$ | -.129 ~ | -.134 ~ |
| | $Friends_{i(j-1)}$ | $\pi_2$ | .0003 | .000037 |
| | $SNExRate_{ij}$ | $\pi_3$ | .00006 | .000555 |
| | $Librarian_{ij}$ | $\pi_4$ | .242 *** | .234** |
| | $Self\_document_{ij}$ | $\pi_5$ | .0064 *** | .0068 *** |
| | $Challenge_{ij}$ | | .113 *** | .1271 *** |
| | $BookQuality_{ij}$ | $\pi_6$ | .0706*** | .069 *** |
| | $WorstBook_{ij}$ | | -.047 *** | -.0466 *** |
| | $\#TextReview_{ij}$ | | .215 *** | .215 *** |
| | $PlsntExp_{ij}$ | | .768 *** | .746 *** |
| | $AvgScore_{ij}$ | | -.0107 *** | -.0105 *** |
| | $AvgABSDeviation_{ij}$ | | -.195 *** | -.1985 *** |
| Random effects (unstructured covariance structure) | Within-person | $\varepsilon_{ij}$ | 0.68 | .6355446 |
| | Initial Status (Constant) | $\sigma_0^2$ | 0.47 | .4623815 |
| | Rate of change | $\sigma_1^2$ | 0.027 | .0199129 |
| | Covariance | $\sigma_{01}^2$ | -0.33 | - |
| | Rho | $\rho$ | - | .2009735 |
| Fitness | AIC | | 19172.1 | 18996.57 |
| | BIC | | 19307.72 | 19132.2 |

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

**Table 4-7: Modelling error covariance structure: unstructured vs autocorrelated**

Comparing the goodness of fit (AIC and BIC), we observed that there is a slight improvement in the model with the autocorrelation covariance matrix. However, the sign and magnitude of all the independent and control variables are consistent which confirmed the inference we employed by our original model. However, we decided to stick to the original model.

### *4.6.2.4. Endogeneity*

The presence of endogeneity in the model can compromise the robustness of the analysis. To investigate the consistency of the estimation value for the model parameters, we examined the potential endogeneity in our analysis. We want to ensure that the probability selection of samples varies for the outcome variable even when we condition the explanatory variables.

In our analysis, we have considered the literature recommended control variables within the limitations of our data collection. We do not expect a serious endogeneity problem in the model that can affect our inference.

On the other hand, it is reasonable to assume that the contribution *volume* has an effect on two of our variables. To check the robustness of our parameters (estimated coefficients), we re-estimated the final model assuming that these two measures are endogenous. The first potential endogenous variable is $\#TextReview_{ij}$. In some cases the number of textual reviews ($\#TextReview_{ij}$) can be affected by the magnitude of the dependent variable, *volume*. In addition, the $Librarian_{ij}$ measure can also have a reverse causality with the *volume* as it is a status that reviewers may apply for after reaching to some level of contribution on the platform.

To address the issue we tested the parameter estimations for all coefficient using the *Hausman-Taylor test* (Hausman & Taylor, 1981) for random effects with the *xthtaylor* command in Stata. The test is a step-by-step estimation in which, first, the fixed effects are calculated and the time variant coefficients and error variances are estimated. In the second step, using the instrument variable(s), the between-effects for time invariant measures are estimated. At the end, the instrumental regression will be estimated the final prediction for all coefficients and error terms.

***The importance weight***

We know that if the sampling method is exogenous, we do not need to use any weight especially in our regression modelling. When the sampling is endogenous, meaning that DV has a correlation with error term or even explaining variable has such relationship, we can use weights to reach to a consistent estimation. Methods use inverse probability to find an unbiased estimation (Solon, et al., 2015).

In this research, we have used a crawler agent to collect the data. The way a crawler agent work is, by obtaining the URL address of all hyperlinks in one page and visits those pages one by one. We believe that reviewers' profile link with higher contribution volume are more likely to be visited by the crawler agent and they are more likely to end up in our sample. Therefore, the contribution is endogenous in our data set and we used the LNVolume, the dependent variable, as the weight in the importance weight analysis of this research.

To sum up, we have used the *xthtaylor* command in Stata to run the Hausman-Taylor test. Then we compared the estimated coefficients with the result of Model D ( Table 4-3). The result shows that the magnitude and sign of all coefficients are still in the same range as the original model which the validity of our inference on hypotheses.

## 4.7. Conclusion

### 4.7.1. Key findings

Using the social theory of learning (Wenger, 1998), we empirically investigated the change in the contribution of frequent reviewers in an eWOM community. As the measure of the contribution, we used *volume* and studied its change over time. Then we investigated the effect of social learning components on this change.

We concluded that the contribution volume for frequent reviewers decreases over time. It confirms the argument that as time passes, the novelty and affection of the eWOM community, website, and practicing the new role as book reviewer diminishes for reviewers. Our result also confirmed that participating in the community service (being a *librarian*) has a positive *e*ffect on the reviewing volume. In our community of interest, Librarians have a higher contribution volume compared to the population.

In addition, we showed that the mechanism which the review-hosting implements to encourage reviewers to continue is effective, especially when they address one of reviewers' motivation to contribute; for example, reviewers who have earned a recognition badge for their reviews have a higher contribution volume. We also concluded that regardless of the motivation for engagement with the platform, frequent reviewers who have a higher engagement level with the eWOM community are more likely to have higher contribution volume.

On the other hand, reviewers who follow their personal agenda in the community, or claim their product expertise, will be less influenced by the social learning process and stick to their professional and expert reviewing behaviour due to the *complacency* effect (Zhang & Zhu, 2010). Therefore, we cocluded that authors start with lower contribution, gets less affected by their experience, and over time decrease their contribution with shallower rate.

Based on Goes et al. (2014), we expected to see a positive effect of the social network size on the *volume.* However, the analysis did not meet our anticipations and the estimated coefficient is not significant. The main reasons are the *social loafing* and *Collective Effort Model (CEM)* (Karau & Williams, 2001), and the cognitive side of the social learning (Bandura, 1977). In brief, the burden of a big social network negates the encouraging effect of a big audience.

### 4.7.2. Research contribution

This research is totally related with the current literature on eWOM and at the same time is unique in several ways. Our main contribution is using the *community of practice* literature and applying the social theory of learning in explaining the change in frequent reviewers' behaviour. For the first time we concluded that sharing opinion with a big social network could have an adverse effect on the contribution as it triggers the *social loafing* and the *collective effort model* could explain it.

### 4.7.3. Implications

This research has both theoretical and practical implication for reviewers and review-hosting platforms. The main theoretical result of the whole thesis is to contribute to the WOM literature by suggesting a model explaining the reviewers' contribution through their learning. Understanding factors that shape online reviews could have an implication for review-hosting platforms. They can alter their design to influence reviewers to continue their contribution. The volunteering contribution of reviewers is the key component of their success in the marketplace.

Our result also has practical implication for the eWOM communities. First, we showed that at the beginning reviewers are more enthusiastic with their contribution. Over time, their contribution volume decreases, which is a result of reviewing books in a community of practice. The learning mechanisms will change them and this change reflects on their *contribution volume.*

The result of this research can help reviewers to understand how their contribution in reviewing books frequently affects their social learning. Moreover, our discussion on the effect of social network size (section 4.6.1) could help reviewers to identify and understand their desire to be influential and be recognized within the community to continue their contribution. Knowing this, reviewers could adopt different strategies to absorb more attention and contribute in a more effective way. An example of such strategy is reviewing books that have fewer number of reviews on the website so that the review has more chance to be read and stand out (Shen, 2009). Such strategy could reduce the *Collective Effort Model (CEM)* and will result in a higher total contribution volume in the eWOM community.

This research also has implications for eWOM communities where our result can be used in designing more practical and effective eWOM platforms and implementing support processes during the maturity stage of the community's life cycle to maintain their members' contribution volume and mitigate the potential death. This research showed that the engagement mechanisms on our community of interest work fine. They will cancel out the expected decrease in reviewing *volume*. Millen and Patterson (2002) studied the drivers of the social engagement in an online community and concluded that three different mechanisms encourage the social engagement in an online community: various selection criteria for members, designed elements such as conversation channels and even notifications and facilitating specific discussion topics. All said, we showed that websites' mechanisms to encourage social engagement in frequent reviewers are working and increase the contribution volume.

### 4.7.4. Limitations and future research

The main limitation of this research, in the design phase was the availability of stable, complete and balanced data. The community of the interest in this research started as a start-up company and was not this popular at start. Many of the features, functionalities of the community were developed over time. Based on the longitudinal nature of our study, we collected data of the whole reviewing history of selected members. However, many of the sections of the website were not launched during the first quarters when many of our reviewers started reviewing books on the website. This makes it very hard to use unbalanced data. As an example, we did not measure *social feedback* in for of likes or comments on reviews on the website. Because this feature was introduced in the middle of our data collection time interval and there were no data on the feedback for a significant portion of the longitudinal study.

For the future research, we have some suggestions. In our investigation, we have used arguments about the change in reviewers' motivations. However, we did not the data on their motivations and only relied on some behavioural evidences, which could be interpreted as the indication of such motivation. We suggest that the next step of this research could be including the same reviewers in the dataset and studying their motivations over time. This could verify our findings and arguments.

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# CHAPTER 5. Are Online Reviewers Leaving? Heterogeneity in Reviewing Behaviour (Paper 3)

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## 5.1. Abstract

Online consumption communities evolve over time and go through different stages in their life cycle (Iriberri & Leroy, 2009). The key factor of the sustainability of the community is members' ongoing contribution. This study examines the factors affecting the ongoing contribution of online reviewers for different types of users. Drawing from theory on communities of consumption (Kozinets, 1999) and popularity effect (Goes, et al., 2014); we propose a conceptual model of drivers of ongoing contribution. We observed that social ties, sidedness, and consumption activity could explain the heterogeneity of ongoing contribution level for different users. We studied a community of book reviews. We showed that the effect of sidedness on contribution prediction is stronger for reviewers with extreme behaviour. We also concluded that consumption activity has more predictive information about the contribution compared to social ties and sidedness.

**Keywords:** eWOM, Social ties, Consumption activity, User Type, Community of Consumption, Sidedness

## 5.2. Introduction

Online consumption communities, are groups structured around consumption experiences (Kozinets, 1999, p. 254) and like traditional communities, evolve over time and go through different stages in their life cycle (Iriberri & Leroy, 2009). Although attracting new members during early stages, such as creation and growth, is important, retaining members during the maturity stage is no less critical for a community's long-term success and sustainability. Communities are sustainable if they can maintain members' commitments and contributions over time. To achieve this goal, they develop mechanisms to encourage participants to maintain their contribution levels. These mechanisms will be more productive if the online community detects and understands the drivers of members' ongoing contribution.

A community providing electronic Word-of-Mouth (eWOM) is a form of online community of consumption in which previous customers share their consumption experience with prospect customers (Brooks, 1957). eWOM community reduces the information search cost for potential customers. *Source credibility* is an important factor, affecting the decision of the receiver/reader of a review, whether or not to trust and adopt a review. On retailer-sponsored, customer-to-customer review platforms, such as

Amazon.com, most of the users do not know each other. The only information they have about the source credibility (Cheung & Thadani, 2012) is what is shared on the platform about the reviewer. Online communities of consumption that are shaped around the consumption of a product type (e.g., Goodreads.com for books), attract hobbyists and have strong connections among members. In these communities, with so many product experts and ongoing discussions on reviews and comments, it is not easy for members to write a review before consuming the product (e.g., reading a book). Therefore, reviewers try to share well-thought reviews with others to maintain their image as a credible source.

In an online community of consumption (Kozinets, 1999), members have some expertise or experience with the same product type. Even when the expertise is self-reported, it has an effect on the helpfulness and adoption of the review (Mudambi & Schuff, 2010). The experience and reviewer's history is usually available, and the eWOM receiver can explore them to decide if the reviewer shares a point of view or taste with her/him. We argue that these communities offer more value to prospective customers compared to the reviews posted on retailer websites (e.g. Amazon), where a reviewer may have reviewed different kinds of products, challenging the reviewer's expertise in one particular area.

Online communities of consumption thrive on voluntary contributions of users and reviewers. The continuous contribution is vital for reviewers' long-term success (Wei, et al., 2015). However, many communities fail to attract or retain enough experts and experienced reviewers, and therefore, are unable to sustain their activity in the long run.

Reviewers have different characteristics and motivations, which can explain their behavioural patterns to some extent. Some of these characteristics are *reviewing experience* (Chen & Huang, 2013), *motivation* toward the social networks (Wasko & Faraj, 2005; Alexandrov, et al., 2013), and *individual characteristics* such *as specialised skills* (Connors, et al., 2011) and *expertise* (Mudambi & Schuff, 2010).

In this research, we intend to understand these behavioural patterns and we focused on reviewers' *ongoing contribution*. We aim to explore the factors that drive the heterogeneity in ongoing long-term contribution from reviewers to these communities of consumption (Kozinets, 1999). We proposed a model drawn from the literature on e-tribalized marketing (Kozinets, 1999), to uncover the drivers of this heterogeneity. We concluded that *social ties* and reported *consumption activity* are the primary drivers of different behavioural patterns. Reviewers with stronger social ties may become popular in their community, and a recent research showed that the reviewers' popularity affects reviewing behaviour including the sidedness of the reviews (Goes, et al., 2014). Following that, we argue that the valence is likely to influence the reviewers' reviewing behaviour.

The paper is structured as follows: we begin with a brief overview of the relevant literature and then we explicate our argument to develop hypotheses. The proposed research model is followed by analysis and results. We conclude with discussions of our results and implications of our work.

## 5.3. Previous work and literature review

Electronic Word-of-Mouth or eWOM is an informal information exchange in which former customers share their experience with prospective customers (Brooks, 1957). Current literature can be categorised in two main streams. The **first stream** focuses on the generation of eWOM and concentrates on why and how customers share their reviews on online platforms (Moe & Schweidel, 2012). Studies on the incentives and motivation of reviewers (Munzel & Kunz, 2014; Cheung & Lee, 2012; Hennig-Thurau, et al., 2004) and the content of reviews (Hu, et al., 2006; Li & Hitt, 2008) are some examples. The **second stream** focuses on the consequences of eWOM. Some examples are the effect of eWOM on sales (Zhu & Zhang, 2010; Zhang & Dellarocas, 2006; Shen, 2009). In this area, some researchers focused on the effect of reviews on the prospective customers and the social interactions between reviewers and customers (Goes, et al., 2014; Huang, et al., 2012). The eWOM literature has also been summarised from different perspectives. From the Products/Services Adoption Process perspective, Montazemi & Saremi (2014) proposed a conceptual model in which they have categorised eWOM into five dimensions: *receiver, source, eWOM content, response, and focal product/service.* They have classified the effect of these five dimensions on the three stages of product/service adoption. These five dimensions are consistent with the summary of eWOM literature by Cheung and Thadani (2012). They have considered eWOM as a communication process, which includes a *sender, receiver, message,* and *response.* Later King et al. (2014) consolidated the eWOM literature using a framework of the interaction of two factors: the *unit of analysis* and *cause-effect.* As the unit of analysis, they suggest sender and receiver. For addressing the cause and effect, they focused on the antecedence (as the cause) and consequence (as the effect) of eWOM.

From the current eWOM literature, we know that reviewers and participants in online communities of consumption are heterogeneous in their behaviour (Munzel & Kunz, 2014; Ridings, et al., 2006; Takahashi, et al., 2002). Different factors shape this heterogeneity. Demographic attributes, personal characteristics and motivations are some of these factors. Munzel et al. (2014) summarised the motives of online reviewers for their contributions and studied different reviewing behaviours. They observed three distinct patterns of behaviour, which resulted in three reviewer types: *creators, multipliers,* and *lurkers. Creators* are the users interested in first order activities such as reading and writing reviews. *Multipliers* are users who are primarily interested in contributing to amplify the content generated by others in the community. They may be interested in first or second activities such as writing comments or re-share the online content generated by *creators*. The last reviewer type is *lurkers* who are not interested in creating or sharing content. They are only interested in highly passive activities such as reading reviews (Munzel & Kunz, 2014). Other researchers have also found these different behaviour patterns or user types for online reviewers. As an example, they studied lurking versus general participation (Li & Lai, 2007; Hartmann, 2015), and lurkers versus posters (Ridings, et al., 2006; Takahashi, et al., 2002). Some researchers also investigated the dynamics of different user types over time and examined their motivations. As an example, Preece and Shneiderman (2009) suggested that reviewers and participants in eWOM communities change from readers to *contributors*. If they engage in interaction with other reviewers, they become *collaborators* and if they continue to provide content (reviews) and share it with others, they are likely to become opinion *leaders* in the community.

In the current literature, we know about this behaviour heterogeneity. However, we still cannot explain it. We try to focus on this gap and answer the question of what drives the heterogeneity in the ongoing contribution of online reviewers.

## 5.4. Theory and hypotheses development

### 5.4.1. Online community of consumption:

The Internet facilitates the emergence of online communities. In the online environment, millions of people form groups around different subjects. They share information, develop group identities and engage in social interaction with others. With the vast spread of creating and using eWOM, many of these communities are structured around consumption experiences (Kozinets, 1999, p. 254). Some communities may shape around a favourite brand or a theme such as the community of Star Treck fans (Kozinets, 2001). In addition, communities may form around a specific product type; Goodreads.com for books, IMDB.com for movies, CNET.com for tech products, tripadvisor.com for travel, and BoardGameGeek.com for board games are some examples.

There are a countless number of online communities out there. However, most of them are not sustainable. They may fail to engage enough expert members or experienced reviewers in the first place. They also may fail to keep their members motivated to continue their contribution and lose them over time. Therefore, sustainability of an online community is an indicator of the success of a community (Butler, 2001). Referring to previous works, Butler (2001) believed that a sustainable community should have access to the pool of resources to support its social processes. He argued that a community with access to enough resource can provide the promised benefits to its members over time in exchange for the membership cost, and whoever stays longer will get these promised benefits

(Wang, et al., 2012). Maintaining membership can lead to the commitment to the community. Members are constantly evaluating the community to check if it is rewarding enough to continue. This evaluation is affected by their commitment, and it determines the likelihood of remaining in the community with the same level of contribution (Wang, et al., 2012).

### 5.4.2. Contribution and continuity:

In an online community of consumption, reviewers share their consumption story with others. As this is a volunteer activity most of the time, a reviewer can stop posting content without even informing the platform. Many reviewers gradually lower their level of contribution and become inactive. In the *maturity* stage of a community, poor participation, especially from members with weak ties, can be the initiator of the *dying* stage of the community (Iriberri & Leroy, 2009). Therefore, it is vital for online communities to know their members and their members' behaviour patterns, and understand the triggers of these patterns. They can use this understanding to design mechanisms to maintain members and increase the members' commitment and contribution to avoid the *dead* stage.

That shows the importance of understanding reviewers' behaviour and their contribution for review hosting websites. As mentioned before, this research aims to study factors that drive long-term and ongoing contribution to an online consumption community.

Over time, reviewers gain experience, learn, and change their reviewing behaviour and the level of their contribution (Chen & Huang, 2013). However, existing research is not conclusive about the direction of this change. A few studies have found that time, to be exact, the length of the membership, has an effect on reviewers' contributions through two mechanisms (Nov, et al., 2010). First, we expect the contribution to drop over time as the novelty and affection of the community decreases. Reviewers get bored or disappointed with the community and lower their participation. However, another mechanism works in a very different way. Reviewers share their opinions with other people in the community and get feedback about the quality of their opinion. We expect reviewers, who are supposedly rational agents, have a desire to receive pleasant and satisfying feedback. To receive such feedback, reviewers may modify their behaviour hoping to get more favourable and better feedback.

### 5.4.3. Types of consumption community members:

To study the reviewer heterogeneity, we draw on the types of online community members in e-tribalized marketing. Kozinets (1999) explained the identity formation of a member in an online community of consumption. This model is comprehensive and can explain the different aspects of reviewing behaviour patterns: patterns drawn from the literature such as lurkers, posters, multipliers, opinion leaders, and followers and so on (Schlosser, 2005; Ridings, et al., 2006; Preece & Shneiderman, 2009; Takahashi, et al., 2002).

Kozinets (1999) categorised the contribution behaviour of community members using two factors: *consumption activity* and *intensity of social relationships (social tie strength).* Although these two factors affect one another.

*Consumption activity* is the relationship of the user to the product, and it shows how using that particular product is central and essential in one's psychological self-image. This importance may increase the frequency of using the product. Assuming that writing a review is a consequence of use, the number of reviews written by an individual might reflect the importance of the product for her/him. On the other hand, *social ties* represent the intensity and number of mutual relationships each user forms with other members of the community. Kozinets (1999) suggested that members belong to one of *Tourist, Mingler, Devotee,* and *Insider* groups. *Tourist*s are users with low consumption activity and lack strong social ties. They show a narrow interest in the consumption (product) and their relationship to the community is minimal and casual. Many users act as *Tourists* when they join an online community and only engage in information browsing and lurking activities. If an online community grabs their attention, they are likely to become *Minglers* or *Devotees*. If they like the product, better than their audience they will turn into a *Devotee*.

If *Tourists* become interested in the social relation and information/knowledge sharing, they are likely to engage in more relationships, develop social ties with others, and join *Minglers*, who only share a few opinions. In general, it is possible for any *Minglers* or *Devotees* to upgrade to *Insiders* if they strive to maintain strong social ties and engage in high consumption activity. If they form more friendship relationships with other members and review more products, they may become an *Insider.*

As aforementioned, Nov. et al. (2010) concluded that the contribution of reviewers in online communities will decrease as the affection and excitement weakens over time unless users receive social feedback which keeps them interested in the community. We believe that if reviewers in an online community of consumption (eWOM platform) do not show interest in either social engagement or consumption activity (product), they are likely to lose interest and consequently their contribution level will drop even more. Hence, we hypothesize:

> ***Hypothesis 5-1****: In an online community of consumption, members with weaker social ties and weaker consumption activity (Tourists) are more likely to have a lower ongoing contribution compared to other members.*

On the other hand, there is some research showing that a member's contribution level—measured by the number of reviews posted by the member—is expected to decrease over time as they gain experience (Samiei & Tripathi, 2013). Reviewers may choose to spend more time to write a fewer number of reviews with higher quality. Based on Kozinets (1999), we also believe that the consumption activity reflects the importance of the product for the reviewer. For example, an interest one has in technological gadgets and electronic devices can be very close to the heart for some reviewers on technical review hosting websites (e.g. CNET.com). Despite this argument, we believe that the effect of the centrality of the consumption activity in one's life and reviewer interest in that particular product will lead to a different behaviour for different individuals.

Similarly, many members at the website of interest could be passionate book readers as a hobby. We argue that for many of these reviewers on the website, reading books and reviewing them can be the primary activity in the community compared to their social ties. Therefore, the importance of the consumption activity trumps the effect of the social ties for them. These users stick to their ongoing contribution no matter what the social feedback they get is. To explore this effect, we hypothesize that:

> ***Hypothesis 5-2:*** *In an online community of consumption, with a similar level of social ties and a high level of consumption activity, members are more likely to continue their ongoing contribution*

### 5.4.4. Social network and popularity effect

The current literature on the social network and its impact on eWOM can be categorised in two main streams. The first stream concentrates on the effect of the eWOM on the social network of the reviewers through the *Social Influence* concept (Xu, et al., 2013; Huang, et al., 2012). In this stream, the researcher focused on the fact that adopting reviews written by someone in their social network during the pre-purchase or consuming phases affects her/his product evaluation significantly (Samiei, 2014). This effect can be bigger if the review writer is a friend of the adoptee (Huang, et al., 2012). The second stream is the effect that being in a social network has on the reviewer, and consequently, her/his reviewing behaviour (Chen & Huang, 2013; Goes, et al., 2014; Samiei & Tripathi, 2013; Wei, et al., 2015).

In this research, we draw on Goes et al. (2014) who also studied the popularity effect of the reviewer on their reviewing behaviour. They showed that being popular in the online community of consumption (eWOM social network) increases the chance of getting feedback from other members and can drive an increase in the number of reviews and the number of negative reviews one member posts. The popularity also affects the objectivity and readability of reviews. We draw on this effect of popularity on volume and valence (sidedness) of the reviews captured and explain the dynamics by which members in an online eWOM network change their behaviour over time (e.g. from being a *Mingler* or *Devotee* to an *Insider*, and so on).

This result is in line with the social feedback mechanism of Nov et al. (2010). The size of the social network a reviewer is connected to indicates the size of her/his potential audience. Having a bigger audience can justify the cost and time needed to write a review (Goes, et al., 2014) (assuming that there exists some social motivation). With this mechanism in place, we suspect that *Insider* reviewers, who have strong connections with other members, have a big audience and have more chance to get social feedback on their contributions. They also share more about their consumption experience. With more opinions posted and more content generated and shared with others, they may get more feedback. This feedback may result in increasing their contribution. Therefore, our hypothesis is:

> ***Hypothesis 5-3****: In an online community of consumption, members with stronger social ties and higher consumption activity (Insiders) are more likely to have a higher ongoing contribution compared to other reviewers.*

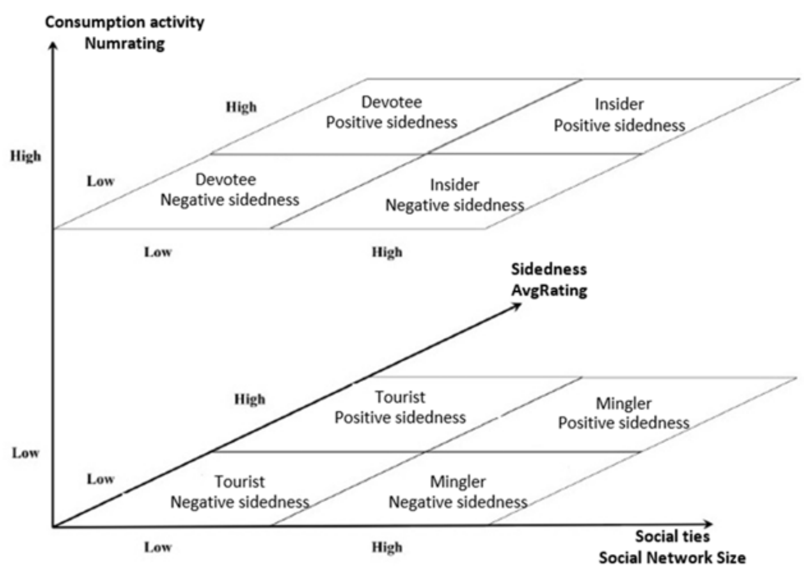


**Figure 5-1: The conceptual model of reviewer behaviour patterns**

Goes et al. (2014) also used a negative bias in the social network to explain how popularity can systematically affect the product evaluation result and lead to negative valence of reviews. This negative bias exists in social feedback, as people perceive that the negatively-valence review shows unfavourable feelings and the failure of the product in meeting the reviewer's expectation. They usually perceive that the reviewer is more knowledgeable or has higher standards (Schlosser, 2005) which lead to our conceptual model of online customer reviewer behaviour patterns in which we suggest that we need three axes to explain the different behavioural patterns of online reviewers. (Figure 5-1)

> ***Hypothesis 5-4****: In an online community of consumption, for members with similar consumption activity levels, their level of ongoing contribution will be driven by the strength of their social ties.*

Based on the proposed conceptual model (Figure 2-1), we believe that sidedness can explain some of the heterogeneity of reviewers in their behaviour patterns.

> ***Hypothesis 5-5****: In an online community of consumption, members with negative overall sidedness are more likely to have a higher ongoing contribution compared to other reviewers.*

**Table 5-1: Measures of interest**

| Variable | Definition | Calculation |
|---|---|---|
| $\boldsymbol{Continuity_{i2}}$ (As a proxy for reviewing continuity) | Did person i rate any book between $t_1$ and $t_2$? | 1----if $(numrating_{i2} - numrating_{i1})$ >0<br>0----if $(numrating_{i2} - numrating_{i1})$ =0 |
| $\boldsymbol{LowActivityRatio_{i2}}$ (As a proxy for review frequency) | Low activity of person *I* between $t_1$ and $t_2$, compared to her/his rating history | $= 1 - \frac{(numrating_{i2} - numrating_{i1})}{expectedRatings_{i2}}$ |
| $\boldsymbol{AverageDaysBetweenRatings_{i1}}$ | The average number of days person i posts a new review, based on her/his rating history | $= \frac{numrating_{i1}}{(t_1 - t_0)}$ |
| $\boldsymbol{ExpectedRatings_{i2}}$ | Number of ratings we expect done by person i between $t_{i1}$ and $t_{i2}$, based on her/his average behaviour at $t_{i1}$ | $= \frac{(t_2 - t_1)}{AverageDaysBetweenRatings_{i1}}$ |
| $\boldsymbol{AvgRating_{i1}}$ | The average of rating scores done by person *i* to different books between $t_0$ and $t_1$ (between 1 and 5) | Collected from reviewers' profiles |
| $\boldsymbol{AvgRatingSidedness_{i1}}$ | A binary value representing the average sidedness of evaluation for person *i* at $t_1$ compared to the median of sidedness of our dataset | For reviewer k<br>1---if $AvgRating_{k1}$>Median($AvgRating_{i1}$)<br>0--- if $AvgRating_{k1}$<Median($AvgRating_{i1}$) |
| $\boldsymbol{NumRating_{ij}}$ | The number of rated books by person *i* between $t_0$ and $t_j$ | Collected from reviewers' profiles |
| $\boldsymbol{NumRatingLevel_{i1}}$ | A binary value representing the volume of ratings done by person i at $t_1$ compared to the median of others' activity | For reviewer k<br>1---if $Numrating_{k1}$>Median($Numrating_{i1}$)<br>0---if $Numrating_{k1}$<Median($Numrating_{i1}$) |
| $\boldsymbol{SNSize_{ij}}$ | The number of two-sided friendship relations that each person *(i)* has with other reviewers, between $t_0$ and $t_j$ | Collected from reviewers' profiles |
| $\boldsymbol{SNSizeLevel_{ij}}$ | A binary value representing the size of Social Network person *i* at $t_1$ is connected to compared to other reviewer | For reviewer k<br>1---if $SNSize_{k1}$>Median ($SNSize_{i1}$)<br>0--- if $SNSize_{k1}$<Median ($SNSize_{i1}$) |

## 5.5. Data and analysis

### 5.5.1. Data

To answer our research questions, we have proposed a conceptual model (Figure 2-1). In this model, we studied the interaction of *Sidedness*, *social tie strength,* and the *consumption activity*. We also investigated how these interactions can explain different behaviour patterns of online reviewers.

We have selected books to control the effect of product type in our research. Books are considered experience goods. Experience goods, as opposed to search goods, are products that a customer can only evaluate after purchasing and using (Zhu & Zhang, 2010) or by gathering information in another costly way. Online reviews can immensely decrease the information-seeking cost for prospective readers (customers) and could have a huge effect on their purchase decision. Therefore, the selected online community has a major role in the market-place for this product.

**Table 5-2: Descriptive Statistics**

| Variable | Mean | Median | SD |
|---|---|---|---|
| $\boldsymbol{Continuity_{i2}}$ | 0.65 | 1 | 0.47 |
| $\boldsymbol{LowActivityRatio_{i2}}$ | 0.65 | 0.79 | 0.46 |
| $\boldsymbol{AverageDaysBetweenRatings_{i1}}$ | 6.6 | 4.6 | 12.1 |
| $\boldsymbol{ExpectedRatings_{i2}}$ | 31.76 | 23.12 | 31.33 |
| $\boldsymbol{AvgRating_{i1}}$ | 3.82 | 3.79 | 0.39 |
| $\boldsymbol{AvgRatingSidedness_{i1}}$ | 0.5 | 0.5 | 0.5 |
| $\boldsymbol{NumRating_{ij}}$ | 430.5 | 307 | 395.1 |
| $\boldsymbol{NumRatingLevel_{i1}}$ | 0.49 | 0 | 0.5 |
| $\boldsymbol{SNSize_{ij}}$ | 127.6 | 38 | 381.1 |
| $\boldsymbol{SNSizeLevel_{ij}}$ | 0.49 | 0 | 0.5 |

For data collection, we used an online crawler and collected data from an eWOM social platform which hosts book reviews. Our data set includes 620 randomly selected reviewers and their reviewing history. We collected data in several waves between June 2012 and July 2014. However, we have treated *Time* as a dynamic phenomenon. $t_0$ is when each reviewer started reviewing products on the website which is a specific date and differs from reviewer to reviewer. $t_1$ is the time we collected data of the previous reviewing history, which is a specific date for all reviewers. As we wanted to investigate if the previous reviewing pattern affected the ongoing contribution, we collected data again at $t_2$ to determine our dependent variable.

We have calculated our measures of interest. For the categorisation of reviewers based on their historical behaviour, we used three measures. First, as the indicator of the social tie strength, we have $SNSize_{ij}$: the number of two-sided friendship-bound formed between person i and other reviewers between $t_0$ and $t_j$. Then we categorised reviewers into two groups with larger and smaller social networks using its Median ($SNSizeLevel_{ij}$). As the consumption activity we have used the number of rated books by person *i* between $t_0$ and $t_1$ ($NumRating_{i1}$). We have used the same method to categorise reviewers ($NumRatingLevel_{i1}$). As the measure of sidedness, we used the average of all rating scores given by person i to different books between $t_0$ and $t_1$ and used its median to categorise reviewers ($AvgRating_{i1}$ and $AvgRatingSidedness_{i1}$).

Contribution level is our dependent variable. We Draw on Chen and Huang's work (2013) in which they quantified contribution level using review frequency and reviewing continuity. We have defined $Continuity_{i2}$ as a binary variable with a value of 1 if the reviewer rated any book between $t_1$ and $t_2$. In contrast, for review frequency, we have defined a continuous variable showing low activity of the reviewers. To calculate that we have calculated the average days between each pair of reviews (which is a unique value for each reviewer based on their history). Then we calculated the expected activity of that reviewer assuming that they will continue to contribute at the same pace. Table 5-1 and Table 5-2 include definition, calculation method, and descriptive statistics of all measures.

### 5.5.2. Analysis result

To investigate our hypotheses, we needed to compare reviewers with different behaviour to each other. First, we calculated the binary value for three categorical measures: $NumRatingLevel_{i1}$,$SNSizeLevel_{ij}$, and $AvgRatingSidedness_{i1}$ (detail is presented in Table 5-1). Then we clustered reviewers into four main clusters and labelled them based on the conceptual model (Figure 2-1) as *Insider, Devotee, Mingle*r, and *Tourist*. Each cluster has two sub-clusters for reviewers with positive and negative sidedness. Table 5-3 includes summary data on contribution measures for all clusters. Overall, we have 620 reviewers in eight clusters. In this study, we do not have any data about the distribution of the dependent variables, neither $Continuity_{i2}$ nor $LowActivityRatio_{i2}$. The reason is that we clustered reviewers in different clusters and the number of users in each cluster is not necessarily enough for the assumption of having a normal sample in each cluster. As we cannot assume normality of their distribution, we cannot use any parametric statistical analysis methods. Therefore, we have used two nonparametric statistical tests to compare the distribution of dependent variables (DVs) between clusters and evaluate our hypotheses.

| Cluster name | Cluster | $Continuity_{i2}$ (average) | | $LowActivityRatio_{i2}$ (average) | |
|---|---|---|---|---|---|
| Insider | Cluster1 (Insider -)* | 0.83 | 0.8 | 0.53 | 0.55 |
| | Cluster3 (Insider +) | 0.76 | | 0.59 | |
| Devotee | Cluster5(Devotee+) | 0.73 | 0.78 | 0.67 | 0.61 |
| | Cluster7(Devotee -) | 0.81 | | 0.57 | |
| Mingler | Cluster2(Mingler +) | 0.705 | 0.61 | 0.64 | 0.69 |
| | Cluster8 (Mingler -) | 0.47 | | 0.76 | |
| Tourist | Cluster4 (Tourist -) | 0.52 | 0.46 | 0.73 | 0.76 |
| | Cluster6(Tourist +) | 0.41 | | 0.79 | |

***: Insiders with overall negative sidedness**

**Table 5-3: Measures of interest and descriptive statistics for each cluster**

We used *two-samples Kolmogorov–Smirnov* (KS) (Stata.com, 2015) to compare the distribution of DVs. This test examines the empirical distribution of two independent samples. The $H_0$ is that both samples are coming from an identical distribution, and the calculated p-value is based on asymptotic distributions and represents the confidence interval (CI) under which we can reject H0. This test only compares distributions and does not include any information about the distribution themselves.

We could not solely rely on the *KS test* because of its limitation. This test is very conservative. The approximations of asymptotic distributions are not to be fully trusted in two situations: small samples and continuous variables (Stata.com, 2015). We believe that we still can use the test, but we have double-checked the conservative results with another test, the Wilcoxon rank-sum test.

The *Wilcoxon rank-sum test* compares the distribution of two unmatched independent samples, which are drawn from the same population. The assumptions for this non-parametric test are having “continuous variables with ordinal response”, and “independency of two samples”. The outcome of the test is a p-value which represents the confidence interval (CI) under which the H0 of the same distribution for two samples can be rejected. The test also gives back a probability under which the average of the DV for the sample is greater than the second sample (Huang, et al., 2010). We used two non-parametric tests (KS and Wilcoxon test), and we observed consistent results from both methods. We also made sure that all assumptions for these tests are met in our dataset. It is worth mentioning that as we calculate all independent variables at $t_1$ and dependent variables between $t_0$ and $t_1$, we mitigate the problem of heterogeneity in our analysis.

## 5.6. Discussion

In this study, we studied the heterogeneity in product reviewing behaviour. The analysis result showed the significance of this heterogeneity on frequent reviewers’ ongoing contribution.

The KS and Wilcoxon rank-sum test result (3rd, 5th, and 6th rows in Table 5-4) support our first hypothesis. It shows that contribution measures for *Tourists* are drawn from a significantly different distribution from *Insiders* and *Devotees* (with a high CI). However, this distribution difference between *Tourists* and *Minglers* is only significant with a CI of 90%. The Wilcoxon probability also shows that *Tourists* are more likely to show lower activity compared to *Insiders* (68%), *Minglers* (58%), and *Devotees* (66%)[20]. We conclude that *Tourists*, who have a weak social tie to the community and less interest in the product, are more likely to decrease their contribution over time.

**Table 5-4: Ksmirnov (KS) and Wilcoxon run-sum test, comparing reviewer types**

| Row | 1st Cluster | 2nd Cluster | KS p-value (Continuity) | KS p-value (Low Activity) | Wilcoxon run-sum p-value (Low Activity) | Wilcoxon Probability |
|---|---|---|---|---|---|---|
| **1** | Insider | Devotee | 1 | 0.07~ | 0.13 | P(Devotee >Insider)=0.55 |
| **2** | Insider | Mingler | 0.008 ** | 0.002 ** | 0.0003*** | P (Mingler>Insider)=0.62 |
| **3** | Insider | Tourist | 0.0*** | 0.0 *** | 0.0 *** | P(Tourist>Insider)=0.68 |
| **4** | Devotee | Mingler | 0.05 ~ | 0.03 * | 0.02* | P(Devotee>Mingler)=0.41 |
| **5** | Devotee | Tourist | 0.0 *** | 0.0 *** | 0.0 *** | P(Devotee>Tourist)=0.34 |
| **6** | Mingler | Tourist | 0.06 ~ | 0.02 * | 0.01* | P(Mingler>Tourist)=0.42 |

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

The second hypothesis (H5-2) focuses on the centrality of the consumption activity for reviewers. We believe that consumption activity, itself, can drive the contribution of reviewers, as their interest in the product is not a function of time or social feedback. The result of our analysis (2nd and 5th rows in Table 5-4, supports this argument for reviewers with strong social ties at a CI of 99.99 %. The same result also supports the hypothesis for reviewers with weak social ties at 99%. However, the result does not fully support H3 (1st, 2nd, and 3rd rows in Table 5-4). We expected that *Insiders*, who have a high level of consumption activity and strong ties to the society, maintain significantly higher contribution than all other members do. We showed that *Insiders'* ongoing contributions are significantly different from that of *Minglers* and *Tourists* (with the probability of 0.62 and 0.68). Yet their difference with ongoing contributions by *Devotee*s is not significant. This result is in line with the result of H2, which emphasises the consumption activity as the driver of ongoing contribution. We have built our hypothesis on the previous literature (Goes, et al., 2014; Chen & Huang, 2013) based on which we expected to observe the effect of popularity as the principal driver of reviewing volume. We also can see the same effect in the analysis for H4 (1st and 6th rows in Table 5-4). We cannot reject the null hypothesis that the contribution of *Insiders* and *Devotees* is coming from different distributions. However, we observed that *Minglers* and *Tourists* are performing differently at the CI level of 90%.

[20] 100*(1-0.42) for Minglers and 100*(1-0.34) For Devotees

| Row | Description | cluster | # of reviewers | KS test p-value | Mean (0-1) | KS p-value low Activity | Wilcoxon p-value | Wilcoxon Probability |
|---|---|---|---|---|---|---|---|---|
| **1** | Tourist with positive sidedness | 6 | 112 | 0.00 *** | 0.41 | 0.0*** | 0.000 *** | 0.33 |
| **2** | Insider with negative sidedness | 1 | 108 | 0.001** | 0.83 | 0.0 *** | 0.0 *** | 0.6 |
| **3** | Tourist with negative sidedness | 4 | 85 | 0.068 ~ | 0.52 | 0.04 * | 0.02 * | 0.42 |
| **4** | Insider with positive sidedness | 3 | 85 | 0.194 | 0.76 | 0.002** | 0.005 ** | 0.59 |
| **5** | Devotee with negative sidedness | 7 | 72 | 0.030 * | 0.81 | 0.02 * | 0.018 * | 0.58 |
| **6** | Mingler with positive sidedness | 2 | 68 | 0.991 | 0.7 | 0.76 | 0.57 | 0.521 |
| **7** | Mingler with negative sidedness | 8 | 46 | 0.069 ~ | 0.47 | 0.035 * | 0.011 * | 0.39 |
| **8** | Devotee with positive sidedness | 5 | 45 | 0.924 | 0.73 | 0.59 | 0.75 | 0.51 |

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

**Table 5-5: KS and Wilcoxon run-sum test, comparing each cluster with the whole sample**

It is more complicated to examine H5. We intended to study the effect of sidedness in changing the ongoing contribution. To do so, first we ran both KS and Wilcoxon tests for each cluster at a time, and then compared the contribution level of that cluster to the rest of our reviewers (Table 5-5). We have observed that the contribution of *Insiders* with negative sidedness (1$^{st}$ row in Table 5-5) and *Tourists* with positive sidedness come from different distributions with very high CI (99.99 %). This effect is not as strong for any other clusters. Therefore, we concluded that the effect of sidedness on ongoing contribution is significant for extreme reviewers.

| Hypothesis | Status |
|---|---|
| *Hypothesis 5-1:* In an online community of consumption, members with weaker social ties and weaker consumption activity (Tourists) are more likely to have a lower ongoing contribution compared to other members. | Supported |
| *Hypothesis 5-2*: In an online community of consumption, with a similar level of social ties and a high level of consumption activity, members are more likely to continue their ongoing contribution | Supported |
| *Hypothesis 5-3:* In an online community of consumption, members with stronger social ties and higher consumption activity (Insiders) are more likely to have a higher ongoing contribution compared to other reviewers. | Partially supported |
| *Hypothesis 5-4:* In an online community of consumption, for members with similar consumption activity levels, their level of ongoing contribution will be driven by the strength of their social ties. | Partially supported |
| Hypothesis *5*-5: In an online community of consumption, members with negative overall sidedness are more likely to have a higher ongoing contribution compared to other reviewers. | Partially supported (only in extreme situations) |

**Table 5-6: Summary of analysis results**

We know that *insiders* have high consumption activity. We showed that members who have negative sidedness have more chance to receive negatively biased social feedback. Therefore, they may have more incentives to continue their contribution which is entirely in line with Goes et al. (2014) and the popularity effect. On the other extreme, *Tourists* have less chance to receive social feedback as they do not have a large audience and did not expose many of their opinions. However, *Tourists* who have positive sidedness are less likely to receive any social feedback, which we know is negatively biased (Schlosser, 2005), and it is more likely for them to leave the community sooner. Also, *Tourists* with negative sidedness may have extra motivation to write about their negative consumption experience and consequently, stay longer than other *Tourists* (second row in Table 5-5).

The summary of the hypotheses investigation result is presented in Table 5-6.

## 5.7. Conclusion and Implication

We have used the theory of e-tribulized marketing (Kozinets, 1999) and different member types in an online community of consumption to study an eWOM community of book reviews. We confirmed some driving factors of ongoing reviewing contribution. We proposed a three-dimensional conceptual model to cluster different reviewing behaviour patterns. We showed that the heterogeneity in reviewing pattern, especially in leaving the platform, could be predicted by these three dimensions: s*trength of social ties, the level of consumption activity*, and *reviewer's sidedness.* We showed that the effect of sidedness on contribution prediction is stronger for reviewers with extreme reviewing behaviour. We also concluded that consumption activity has more predictive information about the contribution compared to the social tie and sidedness. Our results are aligned with both Kozinets' work (Kozinets, 1999) and the popularity effect of eWOM (Goes, et al., 2014).

This research, like any other research, has limitations. The main limitation is the static nature of the analysis, which does not cover the time-related dynamics of changing behaviour in reviewers. Moreover, the effect of product type was controlled in this research, and we will continue this research removing that limitation in the next step.

This result can have a huge implication for online review hosting platforms. These platforms must have some tailored policies, rewards, and other mechanisms to attract and retain their members and endeavour to host a sustainable online community. We believe that using the result of this research these mechanisms can be tailored for individual members based on their historical reviewing behaviour to maximise the likelihood of their continuous contribution.

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# CHAPTER 6. Conclusion

In this multi-paper thesis, we explored the evolution of online reviewer over time in a community of practice. We used the social theory of learning (Wenger, 1998) to explore the effect of the social learning components on the contributions of frequent product reviewers. We observed that the social learning process changed reviewers and consequently the volume and valence of their reviews. We also used the theory of e-tribulized marketing (Kozinets, 1999) to study the heterogeneity of the reviewers in the continuity of their contribution. In this section, we summarize the overall contribution of the thesis. In addition to explaining research limitations and our strategy to overcome them, we suggest some research directions to continue this project.

## 6.1. Research objective and research question

The objective of this research is *to investigate the evolution of online reviewers in an eWOM community as a community of practice.* In attempt to achieve this objective, we narrowed down the research within the boundaries of this study to three research questions, which are different but closely related.

Inspired by the Goes et al. (2014) who treated the volume and valence separately, we considered each research question separately. The findings of each research were discussed in detail in chapters 3-5.

## 6.2. The research results

In this section, first, we summarize the research results for each research question and at the end we consolidate the results.

### 6.2.1. Paper 1- reported in chapter 3

In this paper, we focused on the following research question.

***Research question 1***: Do reviewers change over time in how they review or evaluate the product/services, and does their association with the eWOM community explain this change in reviewing behaviour?

We concluded the following results:

- Frequent reviewers change over time and learn to become *better readers and reviewers* by gaining experience in the eWOM community as a community of practice.
- At the beginning, reviews posted by new members are boosted by the *self-selection bias.*
- Over time, and in response to the social bias towards negative reviews, frequent reviewers evaluate books with lower valence even though they read books with higher quality score on average.
- Over time, the early self-selection bias weakens and the valence score, at which reviewers evaluate books, decreases.
- Taking an extra role in the community, strengthens reviewers' social identity and reinforces their social learning (e.g. librarian became better book readers over time)
- Despite the expected positive effect of the social network on the reviewers' learning, we observed that a big social network decelerate the social learning process for frequent reviewers as it increases the chance of information overload (Deuker & Albers, 2012). The information overload decreases the effectiveness of participation in the eWOM community on improving the consumption experience.
- Frequent reviewers notice the effect of *information overload* and lower their social network expansion rate over time.
- Reviewers who read books with higher quality are less likely to get affected by the social bias and have higher overall reviewing valence.
- Frequent reviewers become stricter in evaluating books and negatively deviate from the quality score of the book in their evaluations

### 6.2.2. Paper 2- reported in chapter 4

In this paper, we concentrated on the following research question.

> ***Research question 2****: How does the contribution level of reviewers change over time, and can reviewers' association with the eWOM community this change?*

Using the social theory of learning (Wenger, 1998), we empirically investigated the change in the contribution of frequent reviewers in an eWOM community. As the measure of the contribution, we used volume and studied its change over time. Then we investigated the effect of social learning components on this change. We concluded that:

- The frequent reviewers' contribution volume decreases over time as the novelty and affection of the eWOM community diminish.

- Taking extra role and performing community service positively affect the frequent reviewers' contribution (i.e. librarians have higher contribution volume compared to the population)
- Engagement mechanisms, policies, or badges that eWOM websites use to keep frequent reviews interested and maintain their contribution are effective and decreases the decline in the contribution volume
- Reviewers who have personal agenda or goal in contributing to the community do not get affected by the community as much as the others, and may have different behavior patterns (i.e. authors start with lower contribution, gets less affected by their experience, and over time decrease their contribution with shallower rate)
-

### 6.2.3. Paper 3- reported in chapter 5

We have designed and implemented the paper 3 to answer this research question.

> ***Research question 3****: what drives the heterogeneity in the ongoing contribution of online reviewers?*

To answer this research question, we examined the factors affecting the on going contribution of online reviews for different types of users. Drawing from the theory of communities of consumption (Kozinets, 1999) and popularity effect (Goes, et al., 2014), we proposed a conceptual model to cluster reviewers by their behavioural patterns. We used this model to explain the heterogeneity in reviewers' on going contribution. As the result, we concluded following:

- The heterogeneity in leaving the platform could be predicted by three dimensions: the s*trength of social ties, the level of consumption activity*, and *reviewer's sidedness.*
- For members with similar consumption activity, the strength of the social ties is determinative in explaining the level of ongoing contribution will be driven by the strength of their social ties.
- The consumption activity has more predictive information about the contribution compared to the social ties and sidedness.
- The sidedness effect on contribution prediction is stronger for reviewers with extreme reviewing behaviour.

### 6.2.4. Research summary

Frequent reviewers learn by contributing to the eWOM community. Over time, they read and review less number of books but they books with higher quality. They become stricter in evaluating books in response to the social bias. They also lower the average of the *valence* of their evaluation. By an improved consumption experience (reading better books), they obtain higher standards. The higher the quality of the books, the higher the quality of reviewers' benchmarks would be. We also showed that the interaction of s*trength of social ties, the level of consumption activity*, and *reviewer's sidedness* could explain different behaviour in leaving the platform. We showed that the consumption activity has more predictive value about reviewers' on going contribution compared to the social tie and sidedness.

We also showed that the mechanisms, policies, or badges that eWOM websites use to engage their frequent reviews and maintain their contribution are effective and decreases the decline in the contribution volume. We also showed that such engagement tools only affect the contribution *volume,* not the *valence.* Therefore, they do not affect the reviewer evaluations or judgments about the products.

## 6.3. Research contribution

This thesis yields in following contributions (but not limited to):

- **The theoretical contribution:** We drew on the Social Theory of Learning (Wenger, 1998) in an eWOM community to explain the social process of learning of frequent reviewers, which drives the change in their behaviour. Although the theory was used before in the virtual and online environment (Lueg, September 2000; Wegener & Leimeister, 2012), this is the first time that it was applied to an eWOM community. The result of this research extends our knowledge of WOM mechanism, learning by practice in an online community and application of the Social Theory of Learning.
- **Contribution to the online community literature.** We investigated the counter effect of contribution in online communities on individuals. Most of the previous studies investigated user behaviour in eWOM communities and how they affect online environments. Whereas, in this study, we focused on the counter effect that the online environment (in the form of an eWOM community) has on individual reviewers in long run. We believe that, apart from the theoretical contribution, this is the main contribution of this research.
- **Contirbuiting to the social network literature:** We contributed to the literature of social networks and eWOM communities by spotting the *information overload* (Malhotra & K.,

1984) general-purpose social networks and confirming that handling the eWOM community as a general-purpose social network, adversely affect the effectiveness of the community. We also borrowed from the literature on the *social loafing* (Karau & Williams, 2001, p. 134) , *complacency* (Goes, et al., 2014, p. 4), and *collective effort model* (Karau & Williams, 2001, p. 137) to explain the unexpected result about the effectiveness of the social network in increasing the contribution in eWOM communities.

- **Contirbuiting in eWOM literature:** We have contributed to the eWOM literature in many ways. Some of them are:
  - We confirmed the Li and Hitt (2008) model in estimating the overall average of rating scores for books. They suggested this model to study the self-selection bias in early adopters, readers, and reviewers for each book. However, after confirming the model in our data set (described in detail in Appendix A), we drew on their finding and assumed that after some time, the average valence for each book stabilizes around a score, which could reflect on the quality of the book. Therefore, we used the stabilized average valence for each book as the proxy of the book quality in our research. The result of our analysis added to their research (Li & Hitt, 2008), confirming that not only the self-selection bias exists in the product evaluation of early customers; they exist in the early reviews done by each reviewer when they freshly join an eWOM community.
  - We studied changes in reviewers' behaviour and showed that the components of social learning drive the change in reviewers' behaviour (volume, valence, and continuity) over time.
  - We have confirmed the current literature about the underlying reasons of online reviewers' behaviour. Qu and Lee (2011) suggested the reviewer behaviour is not solely about products and can be explained by both community-related and product-related factors. Our result in chapter 3 confirmed the potential self-bias during early stages, which will change to the social bias, as a community-related factor.

## 6.4. Research implications

In addition to the theoretical contribution, this thesis could have implication on reviewers, eWOM communities, and other researchers.

### 6.4.1. For reviewers:

The result of this research can help reviewers to understand how their contribution in reviewing books frequently affects their social learning. Moreover, our discussion on the effect of social network size could help reviewers to identify and understand their desire to be influential and be recognized within the community to continue their contribution. Knowing this, reviewers could adopt different strategies to absorb more attention and contribute in a more effective way. An example of such strategy is reviewing books that have less number of reviews on the website so that the review have more chance to be read and standout (Shen, 2009). Such strategy could reduce the *Collective Effort Model (CEM)* and will result in a higher total contribution volume in the eWOM community.

Using the results of chapter 3, reviewers can recognize the effect of self-selection and social bias in their reviews and modify their behaviour to satisfy their motivations.

### 6.4.2. For eWOM communities:

First of all, the eWOM community can use our results on the self or social bias to develop indicators to measure the bias to motivate frequent reviewers to overcome it. An example could be sharing the information on the potential bias in reviewers' behaviour so that the review receiver account for it before adopting reviews in their consumption decisions. Some strategies could be designing some recognition or encouragement tools, so reviewers prove their capabilities in a way that they do not need to seem smart in their peers' eyes and write negative reviews to become one.

This research also has implication on eWOM communities who can use our result can be used in designing more practical and effective eWOM platforms and implementing support process during the maturity stage of the community's life cycle to maintain their members' contribution volume and mitigate the potential death. This research showed that the engagement mechanisms on our community of interest are effective. They will cancel out the expected decrease in reviewing *volume*. Millen and Patterson (2002) studied the drivers of the social engagement in an online community and concluded that three different mechanisms encourage the social engagement in an online community: various selection criteria for members, designed elements such as conversation channels and even notifications and facilitating specific discussion topics. All said, we showed that websites' mechanisms to encourage social engagement in frequent reviewers are working and increase the contribution volume.

Moreover, the result of chapter 5, can be used by eWOM platforms, to categorize their frequent contributors based on their historical reviewing behaviour and estimate the likelihood of them leaving the platform. EWOM platform designers could use such segmentation to develop personalized and more effective mechanisms, features, and plans. This could help them to maintain the contribution of their members.

### 6.4.3. For other researchers:

The results, theoretical approach, and contributions presented in this thesis can be used by researchers different disciplines such as Marketing and Information Systems. The list of proposed future research could be used to serve other researchers.

## 6.5. Challenges and limitations

Like any other research, this study had limitations and encountered some obstacles, which we describe in this section. Then in Table 6-1, we listed strategies or actions we undertook to either overcome or minimize their effect on the research project.

### 6.5.1. Time

Such as all other PhD projects, time was the main limited resource in this study. The objective of this research is very vast and very broad that made it hard to address properly. Coming to this understanding, in the early stages of the PhD, we designed this thesis to be based on publications. Using this structure, we designed the research program to address the research objective as modular research plan with different research questions. The biggest part of the research has been addressed in the presented three papers (and some conference papers with primary results, which were not addressed in this report). However, there are still smaller research questions or gaps that we need to address later. These research opportunities are listed as the future research suggestions.

### 6.5.2. Technical limitations of data collection

At the beginning, we designed this research based on collecting a data set including all the history of reviewing behaviour in condition to the quality of each book. To have the quality measure for books, we intended to collect a complete set of reviewing contribution of all users and the full review history for each book. Later we found out that the selected website has some technical limitation for vising crawler agents to control the website’s traffic. Sticking to the same data set design was only possible if we have dramatically lowered the crawler’s speed. This would have solve the situation but time and cost of the data collection would have increased remarkably.

### 6.5.3. Ethical limitations

Our data was secondary data (Management_Study_Guide, 2016). We also wanted to avoid the potential Hawthorn effect (Adair, 1984) in the behaviour of online reviewers knowing that their behaviour is observed. On the other hand, based on the ethical approval number 8426, we had to use publicly available data. Therefore, we could not interfere in any way with the website, contact the reviewers, or meddle with any individual on the website.

### 6.5.4. Dynamic website and unbalance data

The community of interest in this research started as a start-up company and was not this popular when they started. Many of the features, functionalities of the website were developed over time. Based on the longitudinal nature of the sample for our study, we collected data of the whole reviewing history of selected members. However, many of the sections of the website were not launched during the first quarters that many of our reviewers started reviewing books on the website, which makes it very hard to use the unbalanced data.

| Limitation | Strategy to overcome | The effect |
|---|---|---|
| **Time** | • Thesis by publication<br>• Designing a modular research program | Solved |
| **Technical issues** | • Optimizing the crawler software<br>• Altering the data set design<br>• Using the supplementary data from other websites for each paper | Somehow solved |
| **Ethical limitations** | • Using the aggregated and de-identified data set to ensure individual's privacy | solved |
| **Dynamic website and unbalanced data** | • Using instrumental variables with the value of 0 before the lunching of new functionalities<br>• Centering or transforming<br>• Defining a unified clock to use the data of users who started their contribution on different data | Solved |
| **Not accessible data** | • Using proxy variables instead of measuring the construct<br>• Estimating the missing variables and validating the estimations | Solved |

**Table 6-1: Research limitations and strategies to overcome them**

### 6.5.5. Not accessible data

As we wanted to have the whole reviewing history of reviewers from the data they joined the website[21], we had to collect retrospective data on their reviews. The website of interest store the reviewing contribution with a time stamp. Therefore, it was possible to collect data on reviewers' previous contributions. However, the historical values of some other parts of the data were not stored. For example, at the time of posting a review, user will see the current *average valence* of the

[21] We assumed that reviewers joined the website on the date that they posted their first contribution. As before that, they did not have any contribution, this assumption does not affect any part of our analysis.

book based on the scores given by all reviewers to the very same book. However, at the time of data collection, we cannot see they exact number that each reviewer saw. We needed this measure as the proxy for the book quality. Eventually, we used the literature to estimate the estimated average rating for all the books at any time of their life cycle (see Appendix A- Chapter3).

## 6.6. Future research

Considering the contribution of this research to the literature and mentioned limitations, we would like to suggest the following subjects as the future research ideas to strengthen or extend our results.

- The current literature suggested (Qu & Lee, 2011) that the reviewer behaviour is either product-related or community-related. We believed that reviewers' change due to the social learning (Wenger, 1998) could deepen our understanding of their behaviour. In this research, we controlled for the product type, and we focused on a single eWOM community, to be able to investigate the social learning process and reviewers' evolution. This research can be extended to include more product types, more eWOM communities.
- Learning effectiveness is highly correlated with personal characteristics and motivations. However, due to the data collection limitation, we only focused on the behavioural factors about reviewers. Such factors were not within the boundaries of this research. We recommend to future researchers to collect supplementary data from reviewers on their characteristics and motivation and revisit conclusions of this study. Moreover, in the present research, we have used arguments about the change in reviewers' motivations, where we did not data on their motivations and only relied on some behavioural evidence. Based on the literature we assumed that such evidence could be interpreted as the indication of such motivations. Collecting data and analysing reviewers' motivations over time could verify our findings and arguments further.

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