# THE DYNAMIC IMPACT OF POST-SERVICE MANAGERIAL INTERACTION ON SATISFACTION, EWOM, AND LOYALTY

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THE DYNAMIC IMPACT OF POST-SERVICE MANAGERIAL INTERACTION ON SATISFACTION, EWOM, AND LOYALTY

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The importance of properly managing the post-service customer experience has been widely suggested in the service marketing literature. A popular post-service managerial practice in the hospitality industry is conducting a customer satisfaction survey (CSS) and responding to the customers who complete the survey. In this dissertation, I investigate the effect of conducting a CSS and responding to the customers who participate in the survey. First, I examine how customers would decide to post online reviews if the hotel does not examine the CSS. Then, using a panel data model, this dissertation empirically investigates how the post-survey managerial interaction can impact the customers' future satisfaction and online word-of-mouth behavior (i.e., eWOM). Finally, a Hidden Markov Model (HMM) is used to understand how customers' loyalty to the hotel that is measured by the booking channel selection (i.e., OTA vs. direct booking) can be improved as a function of the post-survey managerial interaction.

## BIOGRAPHICAL SKETCH

Saram Han was born of an economist and a pianist while they were studying in Mannheim, Germany. His parents were liberal enough to understand his decision not to enter high school and to study movies instead. However, later on, his natural interest in the services industry led him to study Tourism Management at Kyung-hee University in Seoul, Korea. He then went on to pursue a masters degree in Survey Methodology, specializing in market research at the University of Michigan, Ann Arbor, USA. In 2015, he entered the School of Hotel Administration at Cornell University and conducted his doctoral research under the guidance of Drs. Chris Anderson, Chris Forman, and Shawn Mankad. He majored in Services Marketing, with special interests in quantitative marketing, online reviews, service recovery, and Bayesian estimation.

This document is dedicated to all Cornell graduate students.

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Most importantly, I would like to take this opportunity to give my deepest thanks to my parents and my fiancée, You-Kyung Lee, for their endless emotional support whenever I was struggling with my research. This thesis is dedicated to them

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CHAPTER 1

# INTRODUCTION

## 1.1 Customer Satisfaction Survey and Objectives of this Study

This chapter introduces the main concept of the customer satisfaction survey (CSS) discussed in the literature, which outlines the goals that this study intends to achieve. It also describes the structure and content of the remaining chapters.

Customer engagement is known as an important resource that adds value to the company. A sizable amount of recent literature argues that the value generated by customers should not be limited to the output created at the transaction stage[52]. Kumar [47] suggests that in order to measure the right amount of customer value, studies should incorporate the customer values that are generated throughout the customer journey; the importance of the customer engagement with a firm or with other customers is often undervalued in the marketing literature. Previous studies have suggested that customer-firm interaction influences satisfaction, customer loyalty, and the online reputation of the company. Due to these findings, firms have recently started to invest more in creating an environment that allows customers to easily engage with the company. However, studies that estimate the value generated from these interactions are still limited. In this study, I will measure the externalities that a common customer relationship management practice can generate.

Specifically, this paper investigates the effect of conducting a customer satisfaction survey (CSS) and responding to the customers who provide feedback. I define CSS as a company practice that asks for feedback from customers who have recently purchased their product or service. A typical CSS also requests that the survey respondent posts an online review on one of the popular review websites upon completion. The entire process of CSS starts with the post-purchase evaluation by the customer. Once the firm requests the customer to participate in a survey through email, the customer can either ignore or respond to the survey. When the customer has a certain level of motivation to engage with the firm, there may be a higher chance that this customer will participate in the survey. If the customer responds to the survey and reaches the final question, he/she will be asked to rate the hotel and write a review that will be automatically posted on a travel review site. If the customer has a certain level of motivation to post a review on the assigned social platform, he/she will proceed and fill out the rating question and write a review. Otherwise, he/she may terminate the survey, and all feedback recorded so far is automatically sent to the manager. Once the manager receives that feedback, they can decide whether or not to respond to it. Managers can interact with the customers by responding to the email address which they used to send the survey to the customer. The goal of this dissertation is to fully understand the following:

- Customer baseline motivation to engage in online review posting (if the ratings are not collected through a CSS)
- The effect of customer-firm interaction followed by a CSS on future satisfaction
- The effect of customer-firm interaction followed by a CSS on future online review posting behavior
- The effect of customer-firm interaction followed by a CSS on future brand loyalty

## 1.2 Overview of chapters

Chapter 2 provides an overview of the online review environment and the selection bias that is caused by the posting motivation of the reviewers. By comparing the online review ratings of the self-motivated reviewers to the ratings of the CSS respondents, this study explores the impact of customer satisfaction and the level of difficulty involved in posting an online review on online review posting propensity. I demonstrate that post-purchase online customer ratings are likely to be biased unless they are collected through a survey sent by hotel managers to recent guests. I found that extreme and negative ratings are overly posted on TripAdvisor, which induces the underreporting bias. However, once customers become familiar with the online review process, the underreporting bias dissipates

Under such circumstances, firms may lose out on the online reputation if they rely only on the self-motivated reviewers. Chapter 3 shows how the presence of managerial response can dynamically influence customers future satisfaction and electronic word of mouth (eWOM) behavior. Specifically, this study deals with the effect of managerial email responses to completed post-service CSS on future customer satisfaction, and, in turn, customer online review posting. In this paper, I found that personalized apologies to dissatisfied customers increased future customer satisfaction and indirectly decreased customers motivation to post negative online reviews. This chapter implies that the relatively high ratings of the CSS respondents which I found in Chapter 1 might also partially be induced by private managerial responses.

Besides the impact of managerial response on satisfaction and online reputation, I found that this interaction strengthens the future loyalty of customers. In

Chapter 4, I investigate how customer feedback and managerial responses determine (i.e., increase or decrease) customers' future loyalty. For the purposes of this study, customer loyalty is measured through the booking channel that customers choose (i.e., Online Travel Agencies (OTAs) vs direct booking). In this chapter, I model direct booking using a hidden Markov model (HMM) where I can interpret the transition of the latent states as a loyalty improvement.

Chapter 5 summarizes the dissertation, discusses the limitations of this research, and provides potential future research directions.

CHAPTER 2

# CUSTOMER MOTIVATION AND RESPONSE BIAS IN ONLINE REVIEWS

## 2.1 Introduction

Search goods with pre-purchase product descriptions allows the potential customers to evaluate a products quality without actually purchasing it [67]. However, service in the hospitality industry is considered an experience good, meaning that pre-purchase product descriptions of hotels are not particularly informative and potential customers must actually visit a hotel in order to evaluate its quality [43]. Therefore, previous studies show that customers typically spend more time and energy learning from others' experiences when reading pre-purchase information on experience goods than when reading pre-purchase information on search goods [43]. Because the experiences of others have a strong impact on potential customers, online reviews are particularly important in the hospitality industry. [2] demonstrated the importance of online reviews to hospitality firms as he indicated an increasing frequency of visitation to review sites like TripAdvisor prior to hotel purchase as well as was indicating that a 1% increase in online reputation resulted in a 0.96% in hotel performance (RevPAR). However, while numerous recent papers discuss online reviews, little work has been done in hospitality research on to answering the fundamental question– are online reviews biased?

The goal of this study is to investigate how customers' intrinsic motivation to post reviews induces bias in the online review system and how this bias is reduced when individuals become familiar with the platform. In particular, we suggest that online review platforms are more likely to suffer from negative and extreme under-reporting biases when reviews are generated by customers who are unfamiliar with the platform. In contrast, customers who are familiar with a given review platform tend to equally post reviews across a variety of ratings, which reduces the under-reporting bias. This finding is explained using the benefit-cost theory [81].

Several researchers have empirically demonstrated the existence of systematic biases in online consumer product ratings. For example, studies show that only consumers with positive expected net utility will purchase a product and have the opportunity to review it, and thus the submitted ratings are likely to be positively skewed [41]. Therefore, product evaluations may not account for the net utility to those who have not yet purchased the product. As a result, the distribution of online product reviews is likely to be positively skewed [25, 40, 41]. Other studies focus on the temporal and sequential bias components in a platform. For instance, [53, 29, 64] show that posted product ratings become increasingly negative as rating environments mature.

Unlike traditional customer surveys that are collected randomly, consumers in online review platforms voluntarily decide to post their reviews. The customer's level of satisfaction or dissatisfaction is a key factor in the process of deciding whether or not to post a review. Previous studies show that given the same level of satisfaction, customers' motivation to post reviews may vary across different satisfactions. For example, [3] argues that customers engage with word-of-mouth (WOM) depending on the perceived utility of bragging or complaining to other people. Similarly, a more recent study [41] models customer review posting behavior based on the assumption that the need to express ones strong satisfaction or dissatisfaction is what incentivizes individuals to write reviews. Therefore, if there is a non-zero correlation between reporting motivation and satisfaction level, the review system is likely to suffer from an under-reporting bias [41].

However, there is limited empirical research linking customer motivation and the likelihood of posting a review (whether positive or negative). This study investigates which ratings customers are more motivated to post. Furthermore, previous studies tend to ignore the fact that customers' prior platform experience can determine their baseline reporting motivation. We suggest that customers who are familiar with a given review platform post different ratings than customers who are not familiar with the platform. It is particularly important to understand how customers' posting strategy changes as they become more familiar with a given review platform because it helps determine how we should evaluate the quality of the rating system. This study analyzes customer review posting behavior at each review-level to address the following research questions:

- Do customers have the same level of motivation to post a review across different satisfaction levels?
- Do customers who are familiar with the review posting process have similar posting motivation across different satisfaction ratings than those who are not?

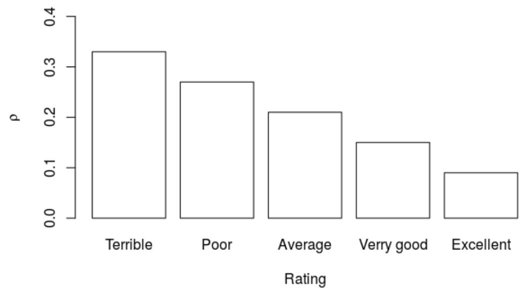
## 2.2 Customer Reporting Propensity and Bias

The under-reporting bias in any review platform becomes larger in a negative (positive) way when average customers become more motivated to report negative (positive) satisfaction. Throughout this paper, we will refer to the level of individual motivation to submit ratings to an online review platform as the reporting propensity. In this study, reporting propensity is used as a similar concept to survey response propensity, which refers to the likelihood that a selected individual in a sample will cooperate with a forthcoming survey request [49].

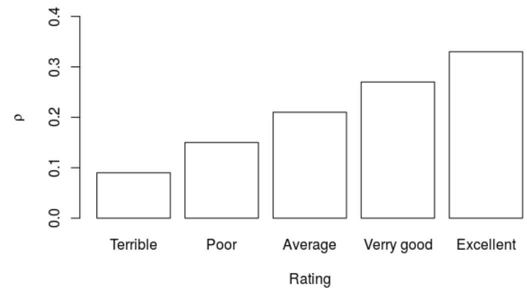
Likewise, reporting propensity is the likelihood that a customer who purchased a product/service will submit a rating or review to an online review platform. While there is a wealth of previous research that uses the reporting propensity to adjust statistical models, there are relatively few studies that discuss individual online review reporting propensity in itself. Under-reporting bias occurs as a function of the correlation between individual reporting propensity and post-purchase satisfaction. Stated formally, the under-reporting bias can be expressed using the same notation that is often used to calculate the non-response bias in survey methodology [32]:

$$\text{Bias}(\bar{r}) \approx \frac{\sigma_{r\rho}}{\bar{\rho}} \tag{2.1}$$

. This implies that the larger the population covariance between the rating, $r$, and the reporting propensity, $\rho$, the higher expected under-reporting bias. If the average online reviewer has a larger reporting propensity for lower satisfaction levels ($\rho_1$), the review platform suffers from a negative under-reporting bias which underestimates product satisfaction (Fig 2.1a). Likewise, if the average customer typically experiences positive satisfaction levels, the review platform suffers from a positive under-reporting bias which over-estimates product satisfaction (Fig 2.1b). In contrast, if customers have equivalent reporting propensities across all ratings (Fig 2.2a) or parallel reporting propensity for both positive and negative satisfaction (i.e., $\rho_1 = \rho_5$ and $\rho_2 = \rho_4$), the level of under-reporting bias becomes close to zero (Fig 2.2b and Fig 2.2c). Obviously, under-reporting bias can be eliminated altogether if the post-purchase evaluation is obtained from all customers or if reviews are collected through a well-designed survey where the non-response process is random. However, it is hard to imagine a scenario in which the under-reporting bias is close to zero in a typical online review platform because customers' posting intentions are often related to their level of satisfaction or dissatisfaction as displayed by Figures 2.1a and 2.1b [3, 41, 62].



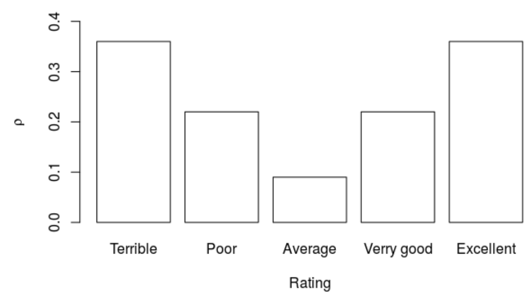

(a) $\rho_1 > \rho_2 > \rho_3 > \rho_4 > \rho_5$.



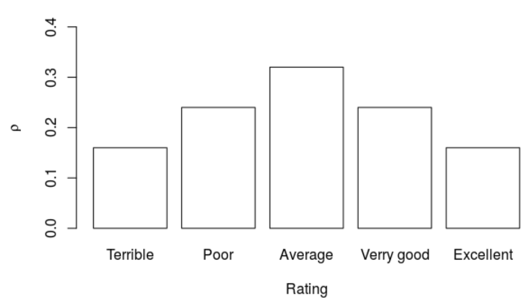

(b) $\rho_1 < \rho_2 < \rho_3 < \rho_4 < \rho_5$.

Figure 2.1: The relationship between satisfaction and reporting propensity when under-reporting biases are non-zero.


(a) $\rho_1 = \rho_2 = \rho_3 = \rho_4 = \rho_5$.




(b) $\rho_1 = \rho_5 > \rho_2 = \rho_4 > \rho_3$.




(c) $\rho_1 = \rho_5 < \rho_2 = \rho_4 < \rho_3$.

Figure 2.2: The relationship between satisfaction and reporting propensity when under-reporting biases are zero.

### 2.2.1 Background Theory and Hypotheses

Social exchange theory (SET) describes the consequences of every social interaction as costs and rewards [81]. Rewards are defined as the internal motivations that drive individuals to behave in a certain way whereas costs are factors that inhibit or deter individuals from performing certain behaviors. The higher the burden of action, the higher the costs will be. In the review posting context, an individual's decision to post a review is a function of the perceived reporting utility (benefit or reward) and the perceived reporting cost of completing the post-purchase evaluation. This approach is particularly useful in the online review posting context because previous studies focus mainly on why reviewers choose to post online reviews while ignoring the potential burdens that may deter customers from posting. For example, a customer may decide to submit their post-purchase evaluation even though they have never posted a review before. In this case, it is likely that the customer perceives a strong posting utility (i.e., motivation) that exceeds the perceived burden, leading them to post the online review. In contrast, posting reviews should be easy for a customer who is already familiar with the posting process on the same platform. This customer does not experience many of the costs that first-time reviews do, such as deciding which platform to use, creating a new account, understanding the questions and instructions and learning the platform's rules. Therefore, regardless of how motivated an experienced reviewer is, it is highly likely that they will complete a post-purchase evaluation simply because of how easy it is. Therefore, the ratings posted to online review platforms are the self-selected opinions of customers with high posting utility and low perceived posting cost. We are particularly interested in understanding whether customers perceive greater utility in posting positive or negative reviews (which would increase the under-reporting bias) and whether reducing the perceived burden mitigates the influence of the perceived utility.

**Perceived Posting Benefit and Customer Satisfaction**

Previous studies suggest that individuals with extreme opinions (either positive or negative) are more motivated (i.e., perceived greater utility) to post their opinions online than individuals with moderate opinions [19, 3, 62]. For example, using surveys conducted in the United States and Sweden, [3] found that extremely unsatisfied customers are most willing to share WOM opinions, followed by extremely satisfied customers. Therefore, [3] argues that the relationship between customer satisfaction and WOM follows an asymmetric U-shape that is greater for negative satisfaction. [62] use individual-level online product review data to test the nonlinear relationship between satisfaction and posting propensity. More recently, [41] demonstrate that there is a bimodal relationship between satisfaction level and self-reported WOM intention using a convenience sample collected via survey. While these studies have been insightful in enhancing our understanding of consumer review posting behavior, they are limited in their ability to directly measure posting propensity based on the behavior of real customers. These studies rely on self-reported measures of willingness-to-post, an exception being [62], which measured propensity by comparing the number of post-purchase product reviews on a particular online review platform to the number of product searches on Google. While this is a more direct measurement, it only provides a scaling factor, as Google searches are only a proxy for the number of purchases.

While previous studies agree that customers perceive greater utility in posting extreme ratings, there is some disagreement regarding whether satisfied or dissatisfied customers are more likely to complete a post-purchase evaluation. In the offline WOM literature, [3] found greater WOM among extremely dissatisfied customers than extremely satisfied customers. In contrast, other studies point to the overwhelmingly large quantity of positive online product ratings as evidence of larger WOM engagement among satisfied customers [17, 62]. Prospect theory, however, suggests that the marginal utility that consumers perceive from a positive gain is smaller than the negative loss [44]. Thus, given that the effort required for WOM activity is constant, customers with a negative experiences are more likely to post online reviews than customers with positive experiences. Therefore, consistent with [3], we predict that unsatisfied customers are more likely to post online reviews. Therefore, this study tests the following hypothesis, which has never before been tested in online WOM literature:

**Hypothesis 1** *Customers with extreme and negative opinions have a higher reporting propensity to post online reviews.*

**Perceived Cost of Posting**

A number of recent studies show that expert reviewers who frequently share their experience with others are different from novice reviewers in terms of their product taste. For example, [59] compare expert's and novice's reviews on a beer-rating website and show that the ratings of these two groups are different for most of the beers. [74] focus on differences between posters (those communicating their experience to others) and lurkers (those not posting their opinion), indicating that posters are influenced more by the negative ratings. However, all of these studies discuss the average of post-purchase evaluation (i.e., $E[r]$) or the probability of reporting a particular rating (i.e., $P(r)$), which is different from the reporting propensity given a particular satisfaction rating, $P(s|r)$, where $s$ is the binary indicator of whether the customer posted or not. Our focus is on the latter. In this section, we discuss how individual prior platform experience (familiarity) influences their reporting propensity. To the best of our knowledge, there is no study that discusses customer platform familiarity as an antecedent of the reporting propensity.

According to benefit-cost theory, in a online review context, the customer decision to post reviews cannot be just a function of the perceived utility of posting. As searching and visiting the review platform, creating a new account, figuring out the rules in the community, and understanding questions and instructions are possible factors that drive the costs of posting review online. However, considering that not all customers are equally familiar with posting, the amount of burden that each customer perceives will not be the same. While many studies incorporate the individual characteristics when predicting the customer reporting propensity, they tend to ignore the customer heterogeneity that comes from the individual familiarity with the online review platform. Since there is less posting utility required for the individual who is highly familiar with posting reviews (e.g. has an account on the platform) the reporting motivation that is correlated with the satisfaction does not play as strong a role as for those who are less familiar with the platform. Therefore, the novice reviewer needs to have a larger amount of reporting utility that can offset his/her perceived cost and allows this reviewer to have the same posting propensity as someone who has lower cost for posting reviews on the platform.

Formally stated, if the individual has no cognitive burden to post reviews on the platform, the reporting propensity, $\rho$, should be independent of the satisfaction rating, $r$ (i.e., $\sigma_{\rho,r} = 0$). However, if the customer posting process includes a large cognitive cost, the higher reporting utility causes the correlation between the rating and the reporting propensity to be nonzero (i.e., $\sigma_{\rho,r} \neq 0$). Therefore, we hypothesize that the correlation between the reporting propensity and the rating is only significant for those who are less familiar with the review posting process. However, for those who are familiar with the review posting process, their satisfaction does not influence their reporting propensity.

**Hypothesis 2** *The more customers become familiar with the review posting process, the less variation of reporting propensity across different ratings.*

## 2.3 Data

A critical distinction between our data set and those used by previous studies is that we (1) identify customer posting intention using a natural experimental design rather than customers' self-reported levels of WOM motivation and (2) use each reviewer's platform activity history prior to posting the review as a proxy for their familiarity with the platform.

Our empirical analysis uses hotel review data from the travel review website, TripAdvisor.com. We collected online reviews of 1,638 hotels in four U.S. states (New York, California, Nevada, and Florida), written between January 1, 2015 and December 31, 2017. We chose these states because of their higher volumes of consumer reviews. For each hotel, customers provided an overall satisfaction rating using a five-star scale in addition to a written review. For the purposes of this research, we use each consumer's posted overall rating out of five as a measurement of their opinion. We choose TripAdvisor as our primary data source because the platform indicates whether or not the data was collected via hotel/supplier invitation. Hotels are able to encourage post-stay review sharing through post-stay emails, which solicit guest feedback and then directly share customer opinions on TripAdvisor. Review collection by service firms can be facilitated directly within TripAdvisor using its Review Express service which allows service firms to upload a list of email addresses to which TripAdvisor will send invitations to review. TripAdvisor reviews collected through these post-stay surveys are flagged as having been collected ”in partnership” with the hotel.

### 2.3.1 Retailer-prompted vs. Self-motivated reviews

We refer to reviews collected via email prompted, post-stay guest satisfaction surveys as retailer-prompted reviews, differentiating these from reviews coming from self-motivated consumers that go to TripAdvisor.com directly to post reviews. The fundamental aspect of retailer-prompted reviews that allows us to answer our research questions is it enables customers with lower self-motivation to post a review. The most relevant study that utilizes this same data feature is the work of [5], which measures the social influence of multiple product ratings by comparing self-motivated and retailer-prompted consumer reviews. Our study makes the same distinction between self-motivated and retailer-prompted consumer reviews. With retailer-prompted reviews, hotels send email invitations to recent guests who provided their contact information. This email contains a link that enables respondents to easily post reviews on TripAdvisor. Self-motivated customers are also able to post reviews on TripAdvisor, without having received an email invitation. This hotel intervention encourages customers who may not have otherwise felt motivated to review the hotel to post a review online. This practice encourages customers who perceive less utility in writing a review and who are unfamiliar with TripAdvisor to review their hotel anyway, thus making online reviews more representative of the customer population as a whole. Therefore, if the ratings posted in retailer-prompted reviews differ greatly from those posted in self-motivated reviews, this difference is the result of the selection bias induced by varying levels of self-motivation and familiarity with TripAdvisor (in addition to other auxiliary variables related to the customer). In this study, we aim to estimate to what extent the baseline reporting utility (i.e., perceived benefit) induces a selection bias and how significantly this bias can be reduced by simplifying the posting process (i.e., perceived cost).

### 2.3.2 Customer platform familiarity

TripAdvisor awards reviewers with "contribution points" to acknowledge their contributions to the platforms. Contribution points have no monetary value, so they do not give customers any economic incentive to post reviews. So, a customer's contribution points at the time they posted a given review can be used as a valid measurement of user familiarity with TripAdvisor. By utilizing this variable we are able to examine whether the variation of the reporting propensity across different ratings changes as the customer becomes more familiar with the posing process. As once reviewers reach a certain familiarity level, their marginal familiarity with the platform may not increase as much as the novice reviewers, we log-transform every reviewer's contrition points.

### 2.3.3 Descriptive statistics

To ensure that neither of the two review collection methods dominated our analysis, we only included data from hotels that receive a balanced combination of self-motivated and retailer-prompted reviews. To be included in our data set, hotels were required to receive no more than 70% of their reviews from either self-motivated or retailer-prompted customers. In other words, while some hotels included in our data set receive primarily retailer-prompted reviews, at least 30% of each hotel's reviews came from self-motivated customers. The same goes for hotel's that receive primarily self-motivated reviews. While the 30% was somewhat arbitrary, 30% was utilized to maintain our sample size (as higher would start to restrict the sample size) while lower would limit coverage across all potential satisfaction levels.

Our sample includes 189,212 reviews of 282 hotels. Given the computational challenge of our Bayesian approach, which involves a lengthy parameter estimation process when using such a large data set, we randomly sample 100 hotels for our analysis. This data consists of reviewer identification numbers, ratings (a scale ranging from one to five stars), travel year/month, reviewed time, contribution points, and whether reviews were self-motivated or retailer-prompted. For the control variables, we considered factors that previous research suggests are potential predictors of an individual's likelihood of reviewing a hotel. First, in order to control for the potential bias induced by the temporal process [29, 53], we formed the variable $STAY\_MONTH$, which captures the year and month when the customer stayed at the hotel. We define this variable as the number of months since the oldest stayed month in our data. Second, previous studies [29, 53, 94] demonstrate that the sequential processes of the online review is also an important predictor of the subsequent rating. Therefore, we included the $ORDER$, which captures the position of a review in the sequence of reviews posted on TripAdvisor. Lastly, recent studies indicate that an individual opinion in the online community is likely to be influenced by the majority's opinion [66, 51, 64, 94]. Thus, we included the $CUMM\_MEAN$, which is the average rating of the hotel at the time a given review was posted. A summary of the data used in this study is compiled in Table 2.1.

| Variable | Source of Data | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|---|
| **Sequential Review Position (ORDER)** | Slef-motivated | 75.83 | 42.19 | 27.00 | 264.00 |
| | Hotel-prompted | 104.33 | 52.84 | 25.00 | 410.00 |
| **Stayed Month (STAY_MONTH)** | Slef-motivated | 15.95 | 0.91 | 13.26 | 19.82 |
| | Hotel-prompted | 16.30 | 0.91 | 12.72 | 20.57 |
| **Average Rating until $t-1$ (CUMM_MEAN)** | Slef-motivated | 4.17 | 0.30 | 3.21 | 4.84 |
| | Hotel-prompted | 4.17 | 0.30 | 3.21 | 4.84 |
| **Satisfaction Rating (R)** | Slef-motivated | 4.05 | 0.37 | 2.71 | 4.73 |
| | Hotel-prompted | 4.24 | 0.38 | 2.68 | 4.89 |
| **Logarithm of Contribution Points (X)** | Slef-motivated | 7.29 | 0.50 | 5.57 | 8.12 |
| | Hotel-prompted | 5.33 | 0.27 | 4.84 | 6.04 |

Table 2.1: Data Summary by Data Source

## 2.4 Methods and Results

Two different models were used to understand the distribution of the under-reporting bias in online reviews. The first model investigates the relationship between customer reporting motivation and platform familiarity across each satisfaction level. The second model, used as a robustness check in 2.4.2, is applied to two different customer groups with differing levels of platform experience. For both models, we predicted the reporting propensity score based on [73]. A propensity score is defined as the conditional probability of receiving a treatment given the vector of the individual's covariates and is calculated for each individual [50]. In our reporting propensity model, we predicted each review's relative reporting propensity score by computing the probability that a given review was self-motivated or retailer-prompted given the covariates. To avoid possible multicollinearity, we standardized $ORDER$, $STAY\_MONTH$, $CUMM\_MEAN$, and $X$ for all our models. We explain each model and result in turn.

### 2.4.1 Reporting Propensity across ratings

U-shape relationships are usually estimated using polynomial regressions, but polynomial regressions also support a variety of distribution shapes besides the U-shape. For instance, one possible shape that can be drawn from the large negative linear coefficient and the relatively small positive quadratic coefficient that are consistently found in the previous studies [3, 41, 62] is a distribution where the willingness-to-post is greatest for the lowest satisfaction rating and diminishes quickly for the more positive satisfaction rating [12]. That is, without looking at the reporting propensity for each satisfaction rating, it is unclear what the actual distribution looks like. Therefore, we began our analysis by investigating customer reporting motivation at each satisfaction level. We modeled individual customer reporting propensity as a function of the contribution points and other covariates. Thus, we predicted the reporting propensity score using the following logistic regression model (which includes both random intercepts and slopes),

$$log\frac{P(s_{thr}=1)}{1-P(s_{thr}=1)} = \alpha_h + \delta_{1:3}z_{1:3} + \theta_r + \beta_r x_{th} \tag{2.2}$$

where $P(s_{thr} = 1)$ is the likelihood that the $t$'th review of the $h$ hotel was generated from a self-motivated reviewer who submitted a rating, $r$. Each $r$ is an element of vector $R \in \{1, 2, 3, 4, 5\}$ which is a discrete rating submitted by the customers. Here, $s_{th}$ denotes the dummy variable indicating whether the review is self-motivated (i.e., $s_{th} = 1$) or retailer-prompted (i.e., $s_{th} = 0$). Therefore, $P(s_{thr} = 1)$ is the reporting propensity, $\rho_{thr}$ that we want to estimate. $x_{th}$ denotes the logarithm of the TripAdvsior contribution point total of the reviewer $t$ who reviewed hotel $h$, which we use as a proxy of platform familiarity. We further assume that $\theta_r$ and $\beta_r$ can vary across different ratings. Therefore, we obtain different $\theta$ and $\beta$ for each rating, $r$. The random effects, $\theta_r$ and $\beta_r$, are identically distributed according to a multivariate normal distribution with mean vector 0 and variance-covariance matrix $I$, the identity matrix. Likewise, we allow the random intercept, $\alpha_h$, to vary across different hotels and follow a standard normal distribution with mean $\alpha_0$ and variance $\sigma^2$. Finally, $z_{1:3}$ denotes the three conditioning variables (i.e., $ORDER$, $STAY\_MONTH$, and $CUMM\_MEAN$).

To better understand this model, if the customer, $t$, has an average level of prior experience using the TripAdvisor platform and thus, our standardized $x_{th} = 0$, then the reporting propensity at each rating, $r$, is determined by $\theta_r$. As a customer's contribution points deviate from the average point total, the reporting propensities at each rating becomes a function of $\theta_r + \beta_r x_{th}$. Thus, $\beta_r$ measures the change in the probability that a self-motivated consumer will post a review at each satisfaction level, based on their familiarity with TripAdvisor. The value $\theta_r + \beta_r x_{th}$ for the novice reviewers, whose contribution points are at the lowest level and thus, $x_{th} < 0$ , indicates how much utility first time reviewers perceive in posting a review at each satisfaction level. If the online review platform has no under-reporting bias, then $\theta_r + \beta_r x_{th}$ should remain consistent regardless of the rating out of 5.

We adopt a Bayesian approach to estimate the parameters of the reporting propensity model. Unlike estimates in the frequentist framework, we can comfortably make probabilistic statements about the uncertainty associated with the parameters because the posterior is a probability distribution. In particular, a Bayesian approach is useful for simulating the predicted marginal probability and its uncertainty. For this purpose, we specify prior distributions for the model parameters and derive their posterior conditional distributions. In the hierarchical Bayes estimation, the first 2,000 iterations are provided as a burn-in period, and every $5^{th}$ iteration from the next 5,000 iterations is used to estimate the conditional posterior distributions and moments. Three chains are used in the sampling process. We use JAGS to code the Markov chain Monte Carlo (MCMC) algorithm and estimate the model.

| | M | SD |
|---|---|---|
| ORDER ($\delta_1$) | 0.256 | 0.062 |
| STAY_MONTH ($\delta_2$) | -0.191 | 0.021 |
| CUMM_MEAN ($\delta_3$) | -0.081 | 0.050 |
| $\theta_1$ | 0.497 | 0.134 |
| $\theta_2$ | 0.128 | 0.107 |
| $\theta_3$ | -0.211 | 0.079 |
| $\theta_4$ | -0.247 | 0.064 |
| $\theta_5$ | -0.406 | 0.058 |
| $\beta_1$ | 1.657 | 0.165 |
| $\beta_2$ | 1.973 | 0.127 |
| $\beta_3$ | 1.952 | 0.074 |
| $\beta_4$ | 1.796 | 0.048 |
| $\beta_5$ | 1.617 | 0.036 |
| $\sigma_\theta$ | 0.503 | 0.281 |
| $\sigma_\beta$ | 2.646 | 1.313 |
| $\sigma_\alpha$ | 0.477 | 0.043 |
| Number of hotels | 100 | |
| Number of reviews | 18,016 | |

Table 2.2: Reporting Propensity Model: Posterior Means (Posterior SD)

Table 2.2 shows the parameter estimates obtained for the reporting propensity model. The estimates represent the regression coefficients on the logit scale. These estimates are followed by the standard deviation (SD) of the 3,000 MCMC samples. The random intercept, $\theta$, of the reporting propensity model indicates that, on average, consumers are most motivated to post reviews when they are extremely unsatisfied ($\theta_1$ = 0.497), which is denoted as ″terrible″ on the TripAdvisor satisfaction scale. There was not a significant difference in the quantity of ″poor″ reviews posted by self-motivated and hotel-prompted reviewers (i.e., $\theta_2$ = 0.128). This indicated that self-motivated and hotel-prompted reviewers are equally motivated to post a ″poor″ review. However, consumers' self-motivation to post reviews drops significantly when they have a positive experience (i.e, ″Average″, ″Very good″, or ″Excellent″). The random slope, $\beta_r$, that captures the effect of platform familiarity on reporting propensity indicates that reviewers with fewer contribution points ($x_{th} < 0$) perceive greater utility in posting extreme and negative ratings than in posting moderate ratings. In contrast, as the reviewers' contribution points increase, the reporting propensity for the moderate satisfaction ratings increases as well. Therefore, our first hypothesis holds for novice reviewers.

To help the model interpretation, we show the average predicted marginal reporting propensity of the self-motivated reviewers. A marginal predicted reporting propensity allows us to see how the predicted probability of voluntarily submitting the five different ratings varies across different levels of TripAdvisor familiarity. Using the estimates obtained from Model 2.2, we predicted each reviewers' reporting propensity for each rating. However, instead of using each review's actual standardized logarithm of contribution points as $x$, we use the observed range of $x$ and take $k$ samples evenly spaced within the range. In our case, we select $k = 20$ out of the range of $x$, which is the 0th, 5th, 10th, ...90th, 95th, and 100th quantile (%). Figure 2.3 shows how customers' average reporting propensities of the five different ratings change as their platform familiarity increases. We can see that while novice reviewers tend to post primarily negative and extreme ratings, this variation across different ratings disappears as reviewers become more experienced. Specifically, as reviewers become more familiar with posting reviews on TripAdvisor, reviewers who have moderate satisfactions become more vocal and after a certain familiarity level, reviewers who have "poor" satisfaction tend to have even higher reporting propensities than those who have "terrible" satisfaction. Throughout the horizontal range, the unequal reporting propensity of novice reviewers, which causes the negative and extreme under-reporting bias in the online review system, disappears as reviewers become more familiar with the platform. This suggests that novice reviewers are

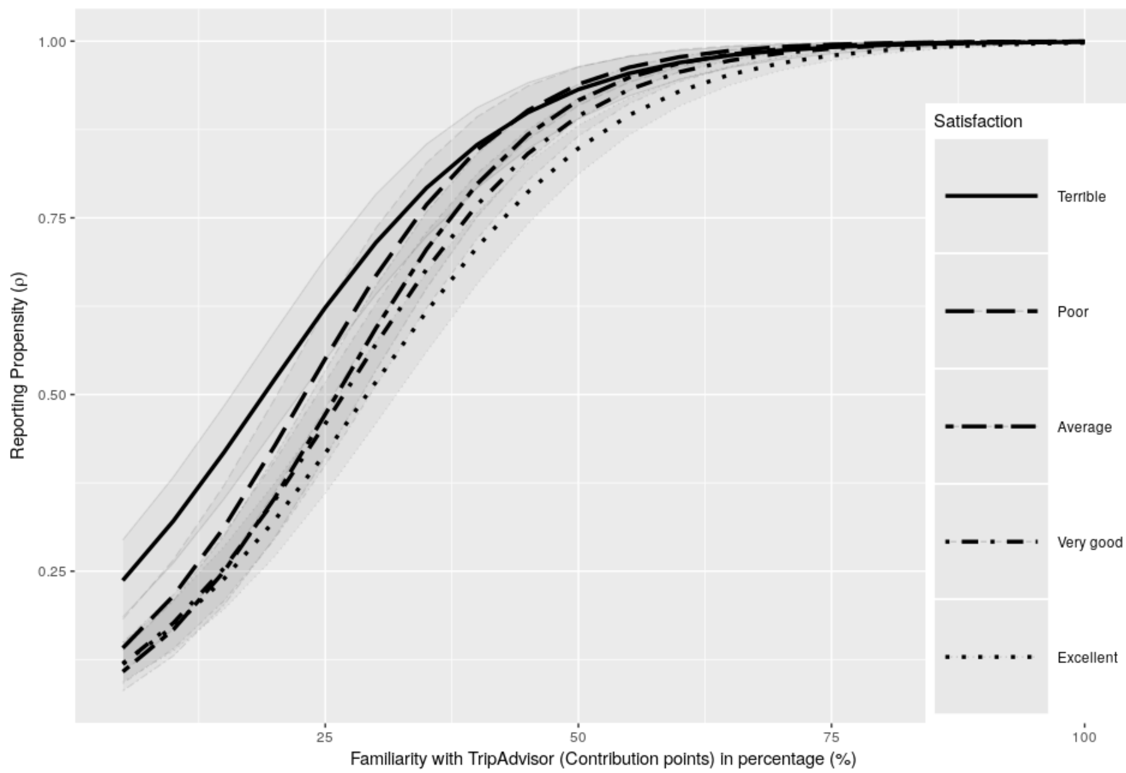



Figure 2.3: Average Reporting Propensity by TripAdvisor Familiarity (%).

strongly motivated to post reviews online when they have extreme and negative experiences, but that they are not particularly motivated to review positive and mediocre experiences. This causes the online review system to overestimate the quantity of extreme and negative customer opinions. However, as the reviewers become more familiar with a given platform, their reporting propensity becomes similar across all satisfaction levels, creating a less biased average opinion.

Table 3 presents the average predicted reporting propensities of the first-time reviewers (i.e., 0th quantile), median reviewers (i.e., 50th quantile), and expert reviewers (i.e., 100th quantile) along with their standard deviations The average predicted reporting propensity for the most negative rating (”terrible”) is about 10 percent higher than the other ratings when the review is generated from a first-time reviewer. While the reporting propensities of the other satisfaction ratings are similar, we find that the reporting propensity of the extremely satisfied reviewers (i.e., "Excellent") is higher than that of mildly satisfied reviewers (i.e., "Average" and "Very good"). This finding is partially consistent with [3], which found that extremely dissatisfied consumers engage most actively with WOM, followed by extremely satisfied customers. Mildly satisfied customers engage with WOM the least. Together, these results support for our first and second hypotheses: that the negative and extreme under-reporting bias disappears when consumers perceive a smaller burden in posting TripAdvisor reviews. The smaller the perceived burden, the more similar the reporting propensities will be across all satisfaction levels, causing the under-reporting bias to disappear. However, it is important to note that the zero under-reporting bias of expert reviewers does not guarantee that their opinions are free from any selection biases. What we are arguing is that while expert reviewers' opinions may cause other types of selection bias, the under-reporting bias specifically is small for the expert reviewers.

| | Terrible | Poor | Average | Very good | Excellent |
|---|---|---|---|---|---|
| First-time Reviewer | 0.237 (0.034) | 0.141 (0.024) | 0.108 (0.017) | 0.118 (0.018) | 0.120 (0.017) |
| Median Reviewer | 0.932 (0.023) | 0.939 (0.017) | 0.916 (0.015) | 0.894 (0.016) | 0.848 (0.021) |
| Expert Reviewer | 0.999 (0.001) | 1.000 (0.000) | 1.000 (0.000) | 0.999 (0.000) | 0.998 (0.001) |

Table 2.3: Average Reporting Propensity (SD) by TripAdvisor Familiarity.

### 2.4.2 Robustness

As a robustness check, our second model examines whether the relationship between consumer satisfaction and reporting propensity varies between novice and expert reviewers. We define novice (versus expert) reviewers by their TripAdvisor contribution point totals with those in the $70^{th}$ percentile and above experts and those whose point totals register in the $30^{th}$ percentile and below as novice. We once again use a reporting propensity model, because the dependent variable

| | Bottom 30% (Novices) | Top 30% (Experts) |
|---|---|---|
| $INTERCEPT$ ($\alpha_0$) | $-0.84$ $(0.38)^{*}$ | $1.98$ $(0.61)^{**}$ |
| $ORDER$ ($\delta_1$) | $0.12$ $(0.13)$ | $0.16$ $(0.09)$ |
| $STAY\_MONTH$ ($\delta_2$) | $-0.10$ $(0.06)$ | $-0.19$ $(0.05)^{***}$ |
| $CUMM\_MEAN$ ($\delta_3$) | $-0.33$ $(0.12)^{**}$ | $0.11$ $(0.08)$ |
| $RATE$ ($\beta_1$) | $-1.33$ $(0.25)^{***}$ | $0.30$ $(0.33)$ |
| $RATE^2$ ($\beta_2$) | $0.21$ $(0.04)^{***}$ | $-0.09$ $(0.04)^{*}$ |
| Log Likelihood | -1370.08 | -1566.47 |
| Num. obs. | 4,499 | 3,674 |
| Num. groups: hotel | 52 | 48 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 2.4: Comparing reporting propensity model of novice and expert reviewers

is the same binary variable, $s_{thr}$, as we used in the first model. However, instead of estimating the effect of platform familiarity at each satisfaction rating, we test the nonlinear relationship between the satisfaction rating and the reporting propensity. Therefore, we include consumer satisfaction rating, $r$, both as linear and quadratic terms in our model:

$$log \frac{P(s_{thr} = 1)}{1 - P(s_{thr} = 1)} = \alpha_h + \delta_{1:3} z_{1:3} + \beta_1 r_{th} + \beta_2 r_{th}^2 \tag{2.3}$$

where $\alpha$ and $\delta$ are the same in the first model. The parameters of interest in this model are $\beta_1$ and $\beta_2$, which are the linear and nonlinear slopes of the satisfaction rating, $r$, respectively. This model is similar to the models used in [3, 62] and [41], except that we are utilizing a natural experiment to estimate reporting intention instead of survey respondents' self-reported WOM intention. We apply this model to two distinct groups who have opposite platform familiarity. We compare novice reviewers, whose platform familiarity are among the bottom 30 percent, and expert reviewers, whose platform familiarity is in the top 30 percent of our data.

Table 2.4 displays the estimation results of the model 2.3. For novice reviewers, the significant negative value $\beta_1 = -1.33$ and the significant positive value of $\beta_2 = 0.21$ confirm our finding from Model 2.2 that novice reviewers are more likely to report extremely unsatisfying and extremely satisfying experiences than mildly satisfying experiences. On the other hand, even though the quadratic term of the expert reviewers is mildly significant, both the linear and quadratic terms are close to 0, which suggest that there is no significant relationship between expert reviewers' satisfaction with a hotel and their likelihood of posting a review. These findings suggest that the bimodal shape of WOM intention found from the survey results [3, 41] holds even in the online post-purchase evaluation system, causing an under-reporting bias. However, this bias only exists for reviewers with higher perceived burdens in using TripAdvisor than expert reviewers. For those whose perceived cost is less than that of novice reviewers, this relationship is weaker.

## 2.5 Results and Discussion

This paper addresses how consumers' motivation to post reviews causes an under-reporting bias in the online hotel review platform TripAdvisor. Consumer familiarity with the platform reduces this under-reporting bias. We address our research questions by leveraging a simple intervention of hotels through a comparison of hotel-prompted consumer ratings and self-motivated consumer ratings. This natural experiment allows us to test whether the self-reported WOM intention of consumers from previous studies is reflected in the online review system. We confirm that the decisions to post an online review are associated with the customers satisfaction level. Specifically, we find that customers who had bad and extreme experiences are more likely to post reviews than those who had positive or mild experiences. However, we also find that this pattern is strongest among first-time reviewers and that it disappears as consumers become more familiar with the online review posting process. Our findings suggest that varying levels of platform familiarity among consumers can influence the quality of the online rating system. This also suggests that while the asymmetric U-shape relationship between WOM intention and satisfaction found by [3] holds true for the first-time reviewers, this pattern diminishes as consumers gain online review posting experience.

Using the benefit-cost theory, we describe reviews submitted to hotel review websites both by the consumers who are unfamiliar with the online review posting process (i.e., high perceived cost) but perceive higher posting utility (i.e., perceived benefit), and by consumers who are already familiar with posting reviews and thus post reviews regardless of the benefit to them. Since posting utility is more strongly related to negative and extreme ratings, online reviews written by novice reviewers are more likely to cause a negative and extreme under-reporting bias. On the other hand, consumers who perceive a low cost in posting reviews demonstrate an equal average reporting propensity across all satisfaction ratings. This constitutes a low under-reporting bias. Thus, our study presents a different perspective that has not been expressed in previous studies, which typically present expert reviewers as being responsible for the selection bias in the online review system. Evaluating products using only the opinions of experts reviewers is also problematic, because these reviewers may have different preferences than novice reviewers. However, relying on opinions submitted by novice reviewers leads to a high under-reporting bias.

This research has important implications for industry practitioners as well. Online product reviews help potential customers set their expectations and decide which products they want to purchase [17, 22, 20]. Considering that potential service goods customers tend to rely more on online reviews, these underestimated ratings in the online customer review system have the potential to significantly reduce sales, particularly in the hospitality industry. In order to help potential customers set proper expectations for the products they are interested in and increase sales in the hospitality industry, we suggest making the posting process easier and more accessible to customers who have never posted reviews previously. This would stop the online review system from being dominated by customers with high posting utility and low posting familiarity, who are likely to be very unsatisfied with their hotel experience.

Our study clearly indicates the need for hotels and other product/service firms who partially rely on online WOM to aid consumers in purchase decisions to more actively engage in the review collection process. While our study focuses on the unique natural experiment created at TripAdvisor it clearly has implications for other social platforms - e..g Yelp, Amazon and Google. Our study also has implications for the review platforms themselves as aiding service firms in the collection of reviews provides a more representative view of service/product quality and further elevates the credibility of the platform. Service firms need to simplify review collection, removing any barriers to the posting process for consumers. Examples of this simplification might include moving from traditional email solicitation of reviews to text or app enabled solicitation through mobile devices as well as simplifying the questions asked - changing the focus from in-depth surveys of their stay to a few simple product and service questions of value to future customers.

This study is not without its limitations. First, our approach is predicated on the idea that the hotel-prompted reviewers' reporting propensity is similar across different rating levels, and thus we used it as reference data to estimate the reporting propensity. Future research in this area is required to obtain true customer satisfaction distribution that can be used as a proper benchmark. Second, we assume that the positive relationship between the contribution points and the moderate ratings is due to the reviewers' increasing familiarity with the posting process. However, we admit that this is a naive assumption that ignores the possibility that expert reviewers may simply have more moderate preference than the novice reviewers. Other research could overcome this limitation by obtaining and controlling our model with a variable that includes information about the reviewers' actual hotel room purchase experience.

CHAPTER 3

# THE DYNAMIC IMPACT OF MANAGERIAL RESPONSES ON CUSTOMER SATISFACTION AND EWOM BEHAVIOR

## 3.1 Introduction

It is common practice for businesses to reach out to recent customers as part of the post-purchase experience. One of the most frequent approaches to initiate the manager-customer interaction is encouraging customers who recently purchased a product or service to provide feedback through customer satisfaction surveys (CSS) [10]. A number of studies have investigated how businesses can best use this information [23, 39]. Other studies have shown the positive financial impact of conducting CSS [10]. However, instead of only soliciting feedback, many companies have started to respond to the customers who complete CSS. Such interactions are often outsourced to customer-relationship-management companies, which help firms handle customer complaints and improve their online reputation. Based on hotel review data that we collected from TripAdvisor in December 2018, 20.13% of hotels in California and 18.78% of hotels in New York state use CSS. The percentage of hotels that use CSS has increased every year since we started the data collection in 2015. In this study, we empirically investigate managerial efforts to interact with customers who responded to CSS as an antecedent that influences future satisfaction and electronic word-of-mouth (i.e., eWOM) intentions.

The existing body of literature on post-purchase managerial responses to customers can be divided into two streams: service recovery and eWOM motivation. The difference between these two camps lies in the outcome they are interested in. Service recovery refers to the actions an organization takes when a customer encounters a service failure [78]. Service recovery literature that is interested in the role of the managerial interaction uses satisfaction as the primary dependent variable. Effective managerial interaction should increase satisfaction among dissatisfied customers who have experienced service failure. While a successful recovery effort increases satisfaction beyond the satisfaction at the pre-failure level (i.e., service recovery paradox), disappointing and unsatisfactory service recovery efforts drop the satisfaction even further (e.g., double deviations) [58]. Therefore, the existing literature establishes the importance of post-purchase interactions with dissatisfied customers. Specifically, studies have found that managerial apologies are more effective than other widely known service recovery efforts in the service setting [26]. Since the main interest of this stream of research is how customer attitude changes as a function of managerial responses, behavioral outcomes such as WOM have been rarely used. Several recent studies have included positive/negative WOM intention questions in surveys and found a positive/negative relationship between service recovery efforts and the customers' attitudinal WOM intention variable [85, 26, 69]. As interesting as these findings are, they have not been extended to a study that looks into the observed customers' WOM behavior in a real-world setting.

Due to the fact that online reviews have the ability to influence future potential customers, another stream of research that examines the effect of managerial response investigates its impact on eWOM behavior. For example, [71] shows that, after managers respond to reviews on social review sites, the volume of total reviews increases while the number of negative reviews decreases. In contrast, [16] provides evidence that reviewers are more likely to share negative reviews in an attempt to negatively impact a firm after observing that managers are reading the customer reviews. Likewise, [55] suggests that managerial intervention encourages customers to voice their complaints. [15] demonstrates that managerial responses increase the volume of reviews, without significantly impacting review valence. [90] found that the average rating of a hotel increases after managers start to respond to negative reviewers, whereas the average rating decreases after managers begin responding to positive reviewers. Due to the difficulty of obtaining every individual's longitudinal data, however, this stream of research tends to be analyzed at the aggregate level rather than at the individual level. Thus, finding the causal relationship between the individual eWOM and the received managerial responses has often been challenging for these studies.

Relatively few studies in service research explain individuals' actual behavior, and to our knowledge, no study investigates the effect of the managerial response on both satisfaction and eWOM behavior. Therefore, we aim to add empirical evidence to bridge the gap between the two streams of the existing literature–service recovery which focuses on the attitudinal aspect and the eWOM studies which focus on the behavioral outcomes of the customers. Using a common post-purchase customer-manager interaction setting, where the manager interacts with the customer after receiving feedback, our study indicates that managerial apologies have a substantial impact on future customer satisfaction and online review posting motivation. However, this happens only with apologies that have certain specific qualities. In this study, we consider personalization as a response quality that measures the extent to which the managerial response is tailored to the customer's comment. We find that, in particular, personalized managerial apologies result in an increase in future satisfaction. While managerial apologies have no direct impact on future online review posting propensity, we find that they indirectly decrease the online review posting motivation of dissatisfied customers. We also find that online review posting motivation increases when customers receive timely responses.

Our research contributes to the recent academic literature in several ways.

- Our study integrates two separate streams of research into one model. That is, we longitudinally examine the whole causal chain of managerial response on individual satisfaction, which influences the eWOM behavior. This approach provides an empirically tested overall model that extends our understanding of the role of managerial responses.
- Next we estimate the dynamic effect of the post-purchase managerial interaction, which has rarely been done in service-marketing research. Although the effects of managerial post-purchase interactions are known to be iterative and dynamic, the customer outcomes following these interactions have been measured and assumed to be static [86]. Therefore, prior studies regarding the managerial response effect have primarily focused on the static effect, while the future customer outcome is assumed to be independent of the current customer outcome.
- We then examine the effect of the managerial interaction on the eWOM at the individual customer level. Prior empirical eWOM studies have primarily investigated how aggregate opinions on social platforms change when reviewers observe that managers have started to respond to reviews. While understanding managerial response at the macro level provides important insights, understanding how changes in the future attitudes and behaviors of customers happen at the micro-level provides important information that allows us to better understand the effect of managerial responses.
- Lastly, while many studies focus on how different customer-manager post-purchase interactions can lead to different customer outcomes, very few focus on the impact of post-purchase interactions over email. Considering that many organizations commonly interact with their customers over

email at the post-purchase stage, more studies need to examine the effectiveness of written communication on customer outcomes. Therefore, we study a common post-purchase customer-manager interaction setting, where the manager privately interacts with the customer after receiving feedback. As a result, we can extend the theories of service recovery and eWOM to a post-service interaction setting that uses written communication. We show how specific attributes of the managerial response can affect customer outcomes.

As shown in Figure 3.1, a typical CSS starts with a post-purchase evaluation from a customer who is contacted by the firm to provide feedback about their recent experience. Once the firm encourages the customer to participate in a survey through email, said customer can either ignore or respond to the survey, which gives the firm an opportunity to interact with the customer. Once a manager receives feedback, they can decide whether or not to respond. Managers can interact with customers by responding to the email address that they used to send the survey. The novel feature of our data is this: customers who reach the final question are asked to evaluate their experience and write a review that will be automatically posted on a review site (e.g. Google and TripAdvisor). If the customer has a certain level of motivation to post a review on the assigned social platform, he/she will rate their experience and write a review. Alternatively, the customer may choose not to post a review, in which case the manager will only receive feedback through the survey questions. In this way, we will be able to examine how both future customer satisfaction and publicly voiced eWOM intention are impacted by the private and public post-purchase interactions between managers and customers that has occurred after the prior hotel stay. It is the private post-purchase interactions that we are particularly interested in this study while controlling for the public online interactions.

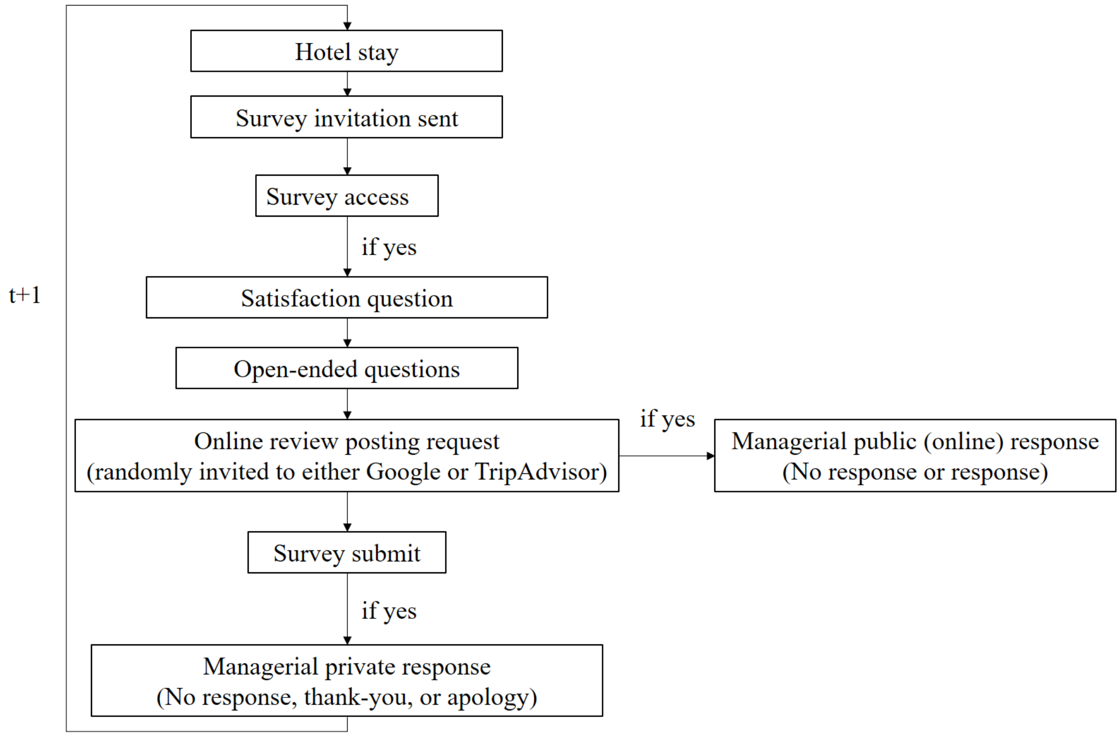



Figure 3.1: Flowchart Describing Customers' and Mangers' Sequence of CSS Steps.

There are two potential identification issues in this research. One of the challenges with the research arises from the self-selection of customers who respond to hotel survey requests. We account for this bias by modeling the latent survey response decision of each customer [35]. The other challenge comes from the dependence of the initial observation on unobserved individual characteristics, which is a common issue in a dynamic panel model. In specifying an explicit model for endogenous initial observations, we follow [36], which specifies an approximation for the latent observation.

To address all of these issues, we use unique customer-level hotel booking data. This data allows us to apply a dynamic panel model, in which an individual customer's past outcomes influence their current outcomes via a first-order Markov process [79]. This is ideal for this study for the following reasons: 1) the same customer repeats the evaluation for the same property, allowing us to capture individual preferences after ruling out measurement errors; 2) customers receive the survey request right after they visit the hotel and we can, therefore, test whether future evaluations and online review posting incidences are influenced by managerial responses received after the previous stay; 3) customer, hotel, and booking characteristics such as evolving loyalty membership level and check-in and check-out dates are available, enabling us to control for customer-, hotel-, and time-specific observed and unobserved heterogeneity; 4) customers can write additional comments in five different sections within the survey and managers can respond to this feedback. This feature allows us to measure managerial response quality, such as how tailored a managerial response is to the comments provided in the survey.

It is worth noting that [33]s study is similar to ours in that we both examine online reviews after customer-manager interaction at the individual level. This study investigates the effect of the managerial response on future customer satisfaction while accounting for self-selection bias in the data. Using data from two Chinese travel agencies, [33] found that managerial responses to dissatisfied customers increase customer satisfaction with respect to future hotel stays. However, dissatisfied customers who did not receive managerial responses, but saw that other customers were receiving responses, became even more dissatisfied. However, there are three critical limitations in this study. First, because the authors are unable to track every transaction point, the review posting propensity in the selection model is only a prediction based on the previous rating (versus the use of other individual-level covariates). In our study, we make use of all customers booking history even if they did not respond to the survey; thus, we were able to include multiple customer-level and transaction-level covariates in the selection model. This feature not only reduces self-selection bias but also uses the selection model to understand the relationship between managerial responses and future survey participation. Second, as stated by the authors, the reviewers are clearly exposed to other reviewers' opinions prior to evaluating the hotel, which makes it difficult to identify the degree to which their satisfaction changed as a result of the managerial response. Our data, on the other hand, comes from private interactions with consumers who were not exposed to other consumer opinions prior to posting their review. Using an open WOM research setting, it is difficult to track changes in individuals' satisfaction and distinguish the effects of managerial interaction from the effects of social influence caused by other reviewers. To avoid this, the participants in this study were invited to complete a survey via email. Because the entire survey and posting process was completed on a separate page, we are able to exclude the possibility that customers were influenced by external sources before evaluating the hotel and posting a review. Lastly, customers in our sample offered to provide voluntary feedback to the hotel. They were not encouraged to post online reviews for a chance to win a substantial prize from the company, as was the case with [33]s research. Therefore, the initial motivation of the customers in our sample is to engage with the hotel rather than seek an incentive. In the following section, we describe our hypotheses.

## 3.2 Conceptual Framework

In the following sections, we outline and develop hypotheses about the impact of managerial engagement in two broad areas – future guest satisfaction and the likelihood that guests will share opinions on social platforms. Our main interest centers on explaining satisfaction and eWOM intention following managerial responses to the CSS. Therefore, we formulate our hypotheses using satisfaction and eWOM incidence as our dependent variables. However, in order to account for the survey selection bias, we use the survey participation incidence as an additional dependent variable. This will be further explained in the next section. We examine the influence of nine different response attributes based on the previous literature in both service recovery and eWOM. Apology, compensation offers for the reported service failure, and speed of response (i.e., recency) are included because they are repetitively used in the service recovery literature as an effective method to affect interactional, distributive, and procedural justice, respectively. We also include managerial thank-you notes as a dummy variable, because many eWOM studies demonstrate that the effect of responding to satisfied customers is not negligible [90]. However, we also account for the quality of the apology and thank-you by using two measures that are used in eWOM studies – response length and personalization [15, 29, 90]. Finally, since managers are also able to respond publicly to online reviews, we include the dummy variable which indicates whether the manager provided online response in order to control for the bias that might be induced by this managerial activity. Figure 4.1 presents the framework of our study.

### 3.2.1 Increasing Customer Satisfaction with Managerial Responses

The impact of managerial post-purchase interaction on customer satisfaction has been widely studied in service recovery literature. According to perceived justice theory, once a customer encounters a service failure, he/she may perceive their own outcome-to-input ratio as being smaller than the service providers outcome-to-input ratio [89, 85, 26]. Because complaining customers have already expressed their concern through the survey response, their future satisfaction is based not

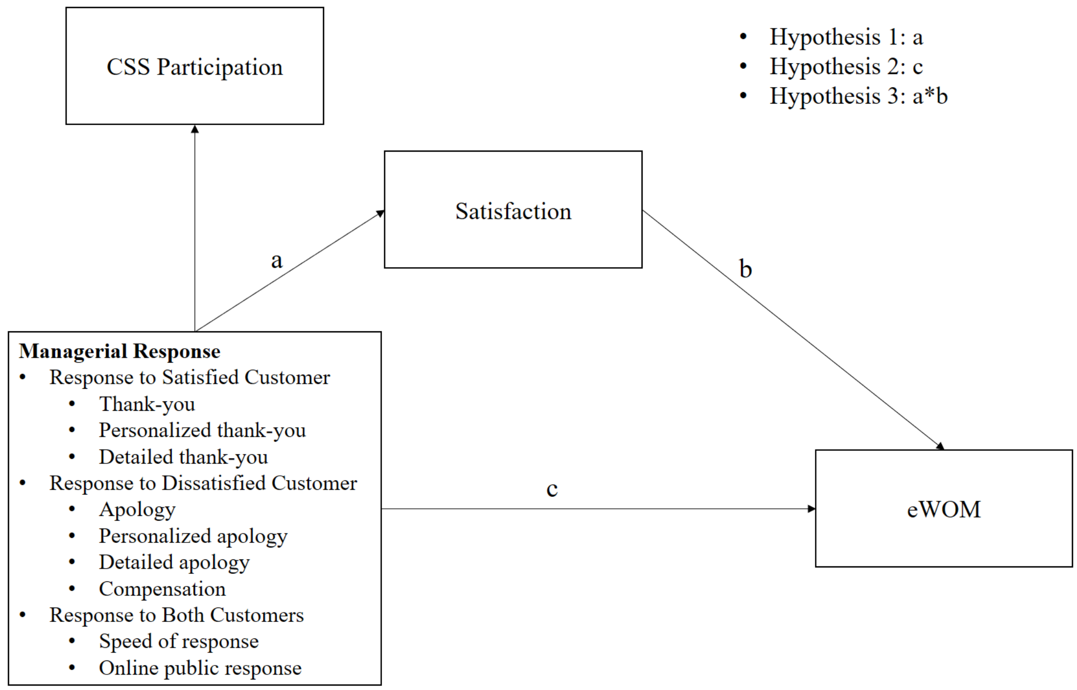



Figure 3.2: Conceptual Framework.

only on the quality of the service they relieved, but also on their perceptions of justice, which are determined based on how fairly their issue is handled. An appropriate recovery effort following a service failure is perceived as an investment to achieve a fair relationship, which becomes a perceived input to the customer. Prior studies have shown that customers evaluate the managerial input in three different justice dimensions–procedural, distributive, and interactional justice. Procedural justice involves the evaluation of the perceived fairness of the policies and procedures used by the manager in processing a complaint [9]. The speed of response has been identified as an important attribute that customers use to evaluate procedural justice [9, 78]. Distributive justice refers to the perceived outcome of the recovery. Compensation after the encountered service failure is the most important recovery dimension associated with customers' perceptions of distributive justice. Interactional justice refers to customer perceptions of the way they are treated during personal interactions with the firm throughout the recovery process. In a service setting, where more intense employee-consumer interactions are required, interactional justice plays a greater role than the other two perceived justice dimensions [26, 13]. An apology from the service provider has known to be a service recovery that is associated with the perceived interactional justice [78]. Therefore, an apology from the service provider in the event of failure increases the customers perception of interactional justice, which should enhance customer satisfaction [54]. In contrast, customers who do not voice dissatisfaction with the retailer cannot experience unfair justice that has to be recovered by the service provider. Therefore, the managerial response should have a greater impact after unsatisfactory customer experiences than after satisfactory experiences. In other words, a managerial apology should be more effective with respect to customer satisfaction than a thank-you message.

However, not all apologies will be equally influential. Especially, within the context of email communication, where customers know that managerial responses can easily be generated automatically, an apology that sounds generic may not give the impression that the manager is particularly concerned by the customer's encountered service failure. Marketing literature regarding the face-to-face manager-customer setting has repeatedly established that not all managerial interactions equally impact customer outcomes. For instance, inauthentic interactions between companies and customers yield lower levels of satisfaction than authentic interactions, thereby decreasing customer-employee rapport [38, 31]. By the same token, even in the written communication setting, customers evaluate the quality of the managerial apology. In experimental research, where the authors simulated a social media context by creating a fictitious website, [48] found evidence that all the significantly positive effects of the customer-company interaction disappear when customers are aware of the possibility that the companys response is automated. While measuring the extent of automation of the managerial text response appears to be rather complex, a recent study suggests using the extent of the text similarity between the customer comments and the managerial responses as an index for the relative personalization [90]. Here, we define personalization as the extent of the managerial response effort to tailor the individual's comment. If the received apology does not address the customer's specific problem and can be applied to any customers' complaint (as with automated responses), the customer may feel that his/her complaint was not heard by the manager. Therefore, such managerial apologies are likely less valuable to customers than personalized responses. Using the PersonalScale index, which we describe in the data section, we predict that, customer satisfaction will increase among dissatisfied customers who received personalized managerial apologies, because it increases the perception about the interactional justice.

**Hypothesis 3 (H3)** *Customer satisfaction with the same hotel increases after receiving personalized apologies from managers.*

### 3.2.2 Increasing Customer eWOM intention with Managerial Responses

Prior studies demonstrate that customers' eWOM motivation tends to increase when they recognize that their voice has an impact on the firm and other potential customers [95, 90, 15]. That is, customers tend to have greater motivation to post reviews when they feel that they can change the firm's future action. When customers feel that managers appreciate their CSS feedback, they also feel that their feedback has a great impact on the firm [15]. As a result, such managerial responses encourage customers to make a larger impact in the future by putting additional effort into CSS, which is posting an online review within the CSS context. Thus, we argue that managerial responses cause consumers to perceive the CSS as being important, so the motivation to post an online review at the end of the CSS after the next stay at the same hotel increases. Specifically, timeliness or speed of response has been identified as an important attribute that customers use to evaluate the communication process [9, 78]. A lack of response or an extremely late managerial response gives the impression that the feedback system is not important to the firm, causing the customer to put less effort into the CSS. In contrast, fast managerial responses give customers the impression that their feedback is important and that completing the CSS is worth the effort. As a result, we expect customers who receive timely managerial responses to have a greater motivation to post online reviews at the end of the CSS.

**Hypothesis 4 (H4)** *Customer online review posting motivation about the same hotel increases after receiving timely responses from managers.*

Extant research demonstrates that an individual's post-purchase satisfaction is one of the primary antecedents driving the customers decision to complete the CSS and post a review [19, 17, 3, 63]. [3] shows that extremely dissatisfied customers are more likely to share their experience with others, which derives the asymmetric relationship between customer satisfaction and self-reported offline WOM intention. [63] found that this behavior also exists in the online review community, where satisfied customers are more likely to post online reviews than dissatisfied customers. While there are several ways to explain this behavior, the most plausible one for us is prospect theory [45]. According to this theory, the marginal utility that consumers perceive from a positive gain is smaller than the negative loss. Thus, given that the effort required for eWOM activity is constant, customers with a negative experience are more likely to post online reviews than positive customers. Therefore, the satisfaction that is influenced by the perceived interactional justice may have an indirect effect on the online WOM decision. In other words, current satisfaction mediates the effect of the perceived interactional justice that is either recovered or worsened following the manager's post-purchase interaction. Considering that dissatisfied customers are more likely to engage in WOM activity, complainants are likely to become angrier and thus engage in negative eWOM if appropriate service recovery is not served. Therefore, we argue that appropriate service recovery methods increase customer perceptions of interactional justice and therefore reduce eWOM intention. That is, personalized managerial apology will increase current satisfaction, which decreases the motivation to post a negative online review at the end of the survey. As a result, we hypothesize the following moderated mediation effect of the current satisfaction:

**Hypothesis 5 (H5)** *A personalized managerial apology indirectly decreases customer's future review posting motivation about the same hotel.*

## 3.3 Data

Our data is comprised of a customer satisfaction survey from 515 randomly selected hotels from one of the largest middle-scale international hotel chains in the world. In lodging, the managerial interaction through CSS is one of the main customer post-stay interfaces. Our data contains the customers hotel visit information and any self-reported satisfaction ratings submitted by the customer regarding their recent stay experience with the hotel. The data was collected over a period of 48 months, from Jan 2015 to Dec 2018. Immediately following check out, the hotel chain's CSS provider automatically emails a survey request to all customers who chose to provide their contact information. Every respondent receives a maximum of 20 questions, and the number of questions varies depending on the services each customer received. Each customers decision to open the email and complete the survey is purely based on their self-motivation, because there are no financial incentives provided by the hotels.

Our data comprise over $544,194$ unique customers and $334,538$ survey responses. Unfortunately, not all customers in our dataset have the full link between the survey and the online review postings. While some customers have the identification that links the survey response and the posted online review, others lack this information. Thus, in our analysis, we only include customers whose identification is available, and thus we can track the full process, from booking a hotel room, to responding to the CSS, to deciding whether or not to post an online review. Next, because the purpose of this paper is to understand the causal effect of the previous period's managerial response to the CSS on the subsequent period's satisfaction and online review posting intention, we discarded all visit information that precedes each customer's first feedback to each hotel. This approach allows us to track how survey participation, satisfaction, and online review posting intention change after customers submitted the first survey. Of course, this strategy also means that our final dataset does not include customers who never answered the survey. Then, due to the significantly large size of the original dataset, we subsample customers to accelerate our Bayesian estimation. As shown in Table 3.3, however, the number of customers who posted online reviews at least one time is relatively small as compared to the number of customers who never posted an online review (i.e., posted at least one time: $2,529$, never posted: $541,665 = 544,194 - 2,529$). Therefore, rather than randomly sampling from the entire customer pool and further reducing the number of customers who posted online reviews, we employed the propensity score matching strategy [73] to subsample customers who never posted. Using propensity score matching, we selected customers who had never posted, but who had similar loyalty levels and a similar number of total bookings to customers who had posted reviews at least once. Note that because we include all these variables in the final regression analyses as well, the main purpose of the propensity score matching in our study is merely to reduce the dataset while providing a sufficient number of online reviews posting incidences rather than controlling for selection bias. Hence, our final result is the same even if we randomly sample the never-posted customers instead of employing the propensity score matching approach. Table 3.3 provides summary statistics of the $544,194$ customers from the original data set and the $5,058$ customers that we used in our main analysis. Consequently, in the final dataset used for this main analysis, the total number of customers who posted at least once remains the same as in the original dataset, and the number of non-posting customers becomes the same as the number of customers who posted at least once after propensity score matching. As a result, we are left with information from a total of $22,682$ customers, where customers responded to the survey after 88% of these bookings. Note that the survey response rate is high in the data we used for our analysis because we discarded all transactions which occurred prior to each customers first hotel survey response. Managers responded to approximately 35% of these surveys, which is a slightly higher proportion than the original data indicates.

### 3.3.1 Dependent Variables

Table 3.4 summarizes both dependent and independent variables that we used in our models. Since we have three different models (which we will describe in the next section) we introduce the dependent variables for each model. Firstly, for the selection model, we use the survey response incidence as the dependent variable, which is a binary indicator variable of whether or not the customer completed the survey after receiving the CSS request email. Second, for the satisfaction model, we need to find a valid perceived satisfaction measure as a dependent variable. The survey that every customer receives includes more than 15 satisfaction-related questions, but the number of questions that each customer answers may vary depending on the type of services they experienced during their stay. Among these satisfaction questions, we choose one as the key-dependent variable for our satisfaction model: "How satisfied were you with the OVERALL experience?". The rationale behind our decision to select this variable as a satisfaction measure is: 1) it measures the same general satisfaction with the hotel experience as the online review rating question and 2) this satisfaction question is the first satisfaction question that customers receive, an approach which averts the potential measurement bias caused by the question order effect [11]. Table 3.1 shows the distribution of the number of customer satisfaction and manger responses. Customer satisfaction is highly skewed towards positive ratings, which is a common distribution in general online product reviews [42]. The managerial response rate towards customers of each satisfaction level shows that managers tend to respond to positive customers more frequently than negative customers. While 23.63% of the extremely satisfied customers (i.e., 10) received manager responses, only 11.38%of extremely negative customers received manager responses. Finally, for the posting model, we used the binary posting incidence as the dependent variable. This variable indicates whether the survey respondent answered the final two questions that ask the respondent to evaluate the hotel on a 5-point scale and write a review that will be automatically posted on either TripAdvisor or Googles online review platform. It is worth noting that the ratings posted online are highly correlated with the customer satisfaction ratings reported to CSS as shown in Table 3.2 (Pearson correlation coefficient: 0.83, $p < 0.001$). Therefore, in the posting model, we confidently assume that the online reviews posted after customers completing the CSS are not different from the satisfaction they reported in CSS.

Table 3.1: Manager responses by Customer satisfaction

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Number of CSS Responses | 1,424 | 912 | 1,971 | 3,299 | 3,525 | 5,426 | 15,596 | 45,557 | 80,643 | 176,186 |
| Number of Managerial Responses | 162 | 104 | 225 | 450 | 361 | 606 | 2243 | 7,894 | 16,034 | 41,625 |
| Manager Response Rate | 11.38% | 11.4% | 11.42% | 13.64% | 10.24% | 11.17% | 14.38% | 17.33% | 19.88% | 23.63% |

Table 3.2: Cross Table of CSS Satisfaction Ratings by Online Ratings

| | Posted Online Ratings | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| CSS Satisfaction Ratings | | | | | |
| 1 | 44 | 0 | 0 | 0 | 0 |
| 2 | 13 | 11 | 0 | 0 | 0 |
| 3 | 27 | 24 | 0 | 0 | 0 |
| 4 | 28 | 41 | 50 | 0 | 0 |
| 5 | 0 | 31 | 43 | 0 | 0 |
| 6 | 0 | 17 | 52 | 62 | 0 |
| 7 | 0 | 0 | 70 | 110 | 0 |
| 8 | 0 | 0 | 62 | 170 | 231 |
| 9 | 0 | 0 | 0 | 262 | 409 |
| 10 | 0 | 0 | 0 | 445 | 1,267 |

### 3.3.2 Independent Variables

The nine managerial response predictors through which we aim to measure the causal impact on future satisfaction and posting decision are: thank-you, personalized thank-you, lengthy-thank-you, apology, personalized apology, lengthy-apology, public-response, compensation offers, and speed of response. Among these managerial response variables, personalized apology and the speed of response are the key predictors that we use to test our hypotheses. First, we describe how we identify the thank-you and apology responses and how we measure the degree of personalization. It is not easy to distinguish a thank you message from an apology, since a lot of managerial responses are a mixture of thank you and apology. All manager responses in our data set start with a message thanking customers for taking the time to provide feedback. We classify any manager response that includes the word ”sorry”, ”apology”, or ”apologize” as an apology message (i.e., APOLOGY = 1) and all other messages as pure thank you messages (i.e., ThankYou = 1). We include both APOLOGY and ThankYou variables and keep all satisfied and dissatisfied customer samples in our model for the following reasons; First, while the satisfaction model tests service recovery, the posting model tests the effect of general managerial response (i.e., response to both negative and positive feedback). Since our moderated mediation model has to use the same sample for both satisfaction and posting models, we included both samples. Second, including the ThankYou variable is necessary for a statistical reason. Since managers in our research setting can respond to both positive and negative customer feedback, it is necessary to control for the main effect of responding to any customer feedback as shown in prior eWOM studies. Third, however, instead of simply including the general managerial response variable as a dummy, we included the Thank-you identifier as a dummy, which changes the interpretation of the intercept but yields the same results. Part of the reasoning behind this decision was that we wanted to highlight the importance of apologizing for service failure by showing that the same effect does not hold when responding only thank-you to customer feedback. Fourth, since we are analyzing a state-dependent model using panel data, only utilizing data from customers that experienced failure in the previous stay will lose the power to control for the hotel-customer unobserved heterogeneity. For example, a customer at a given hotel may have an average tendency to answer the CSS, average satisfaction, and average tendency to post an online review. If we remove all satisfied cases, then these intercepts may lose the statistical power. Lastly, we assume in the dynamic-latent-ordered-probit model that the latent satisfaction formed from the previous stay affects future satisfaction. Thus, the previous satisfaction included in the right-hand side of the model is a predicted value from the previous stay. However, if we only use data from customers that experienced service failure, we cannot take advantage of the dynamic-latent-ordered-probit model. This is because if the customer was satisfied with the previous hotel stay, the latent satisfaction of this stay can only be estimated when the satisfied cases are not removed from the sample.

The alerts sent by the CSS system to notify managers that a customer has completed the survey also display the average satisfaction rating from that survey. As a result, managers can choose to reply to customers simply based on the average satisfaction rating included in the alerts without carefully scrutinizing the answers in the survey. Therefore, a manager's decision to reply with a thank you message or apology does not necessarily indicate how carefully they read the customer's response. To measure the degree of personalization, we use a metric based on [90]s approach. [90] converts manager responses and customer reviews into a numerical topic distribution vector and defines managerial responses that are highly correlated with the customer's review vector as having high response tailoring. Since we aim to estimate the effect of not being sound as a generic response (i.e., tailoring or personalizing), the text similarity measure, which has been used recently in marketing journals, is an effective method of accomplishing this goal. However, the cosine similarity used in [90]s paper is often criticized as performing worst among the popular inter-document similarity measures [92]. Moreover, we find that using the LDA topic distribution as a vector fails to capture the unique information contained in each individuals specific comment. This might be because online reviewers write general information targeting other customers who want general information about the hotel, whereas CSS feedback that is targeting the staff of the hotel includes more specific issues or interactions from the hotel stay. Therefore, the general topics of LDA are not able to capture specific details of the CSS communication to the same extent as the Jensen-Shannon document similarity measure. Jensen-Shannon similarity [18] is a measure for inter-document similarity which is known to perform more effectively than other similarity metrics [92]. We first compute a vector for each customer comment and manager response using TF-IDF. TF refers to term (i.e., word) frequency in a document. The higher the frequency of a term, the higher the chances that the document is relevant to that term. IDF refers to the inverse of the number of documents in which this term occurs. Thus, every word in each customer comment and manager response can be represented as a term frequency divided by the document frequency (i.e., $\frac{tf}{df}$). The metric scales down the weight given to words that occur in all documents and increases the weight given to terms occurring in a lesser number of documents. Since every single word has now been assigned a value, we can represent every customer comment and managerial response as the same length of the vector. We then apply our similarity measure to the document vectors as follows,

$$\begin{aligned}\text{PersonalScale}_{iht} = 1 - \frac{1}{2}[&\sum_{w=1}^{N} \text{GC}_{ihtw}(log\text{GC}_{ihtw} - log\text{M}_{ihtw}) \\ &+ \sum_{w=1}^{N} \text{MR}_{ihtw}(log\text{MR}_{ihtw} - log\text{M}_{ihtw})]\end{aligned} \tag{3.1}$$

where $\text{GC}_{ihtw}$ and $\text{MR}_{ihtw}$ refer to the normalized TF-IDF value for each word $w$ in the guest comment of customer $i$ for hotel $h$ in time $t$ and its corresponding manager response, and $\text{M}_{ihtw} = \frac{\text{GC}_{ihtw}+\text{MR}_{ihtw}}{2}$. Due to the fact that we now have document vectors for each guest comment and its corresponding manager response that has the same length of $N$, $\text{PersonalScale}_{iht}$ refers to the document similarity between these two documents relative to the other documents. As a result, PersonalScale is a measurement of the manager's effort to personalize their response. The measurement ranges from 0 to 1, where 0 is the lowest level of personalization while 1 is the highest level of personalization. Besides the numerical satisfaction ratings for each survey question, survey respondents are also asked to submit open-ended questions:

(Comment 1) Please tell us what it would take for you to give this hotel a stronger recommendation.

(Comment 2) Please share with us how we can improve the speed of check-in for your next stay.

(Comment 3) How can we make your next stay even better?

(Comment 4) Please tell us about employee(s) who went out of their way to make your stay more enjoyable.

(Comment 5) Please share any additional comments here.

After concatenating each customer's responses to these five open-ended questions, we computed the PersonalScale for each managerial response. Examples of managerial responses with particularly high and particularly low levels of personalization are displayed in Figure 3.3. We also confirmed that no managerial responses simply copy the customer's comment by checking all 438 managerial responses that have extremely high PersonalScale values. As a measure of how detailed the manager response is, we use ResponseLength, which is the log of word count for each managerial response. Although by normalizing the TF-IDF our PersonalScale already accounts for the length of the text, we chose to include this variable to further understand the role of the managerial responses detailedness. eWOM literature demonstrates that detailedness is an important antecedent of online review posting motivation [15, 29]. Here, we use the multiplied variables ThankyYou$\times$PersonalScale and ThankyYou$\times$ResponseLength as a measure for the personalized and detailed thank-you, and the Apology$\times$PersonalScale and Apology $\times$ ResponseLength as a measure for personalized and detailed apology, respectively.

Another activity we consider is OnlineMngResp, which measures managers' decision to respond or not respond to reviews posted online. Although the effect of this activity is not the main interest in our research, we include this variable in our model since prior studies of eWOM suggest that omitting this variable may cause potential bias in our estimates driven by the social influence [90]. Because our model outcomes may be influenced by the presence of any financial compensation offers as an effort to recover the encountered service failure, we include COMPENSATION which refers to whether or not complainants were offered a monetary compensation offer which can be applied in their next hotel stay. This indicator variable becomes 1 if either the manager response or the interaction log data contains any of the following words: discount, refund, coupon or reward. Lastly, SpeedResponse is a measure of managerial response speed. Here, we use the log of the number of days between the customers completion of the CSS and the managerial reply. Therefore, the larger this value, the longer it took for the manager to respond to the customer's feedback.

In addition to the managerial interaction activities, we include transaction-level covariates to control our model. Since customers' prior purchase experience is considered to be an antecedent of customer satisfaction, firm-engagement, and WOM intention, we include the number of prior bookings for each customer (Number of Visits) as a control variable [52]. The number of nights per stay (Stayed Nights) is considered because previous studies have shown that the ex-

1) Non-personalized

> Dear XXX,
> Thank you for completing the survey regarding your recent stay at our property. Your business is very important to us and we value your feedback. By telling us what you liked about your stay and how we can improve, you are helping us deliver a superior experience for you and other guests in the future. We hope you will come back and see us again soon. If I can be of assistance in the future, please don’t hesitate to contact me at XXX. Thank you again for taking to time to complete the survey. We appreciate your loyalty to our brand.

2) Fully-personalized

> Dear XXX,
> Thank you for completing the survey regarding your recent stay at our property. Firstly, on behalf of our entire team, I would like to express our condolences on the loss of your father. W are sorry for your loss. Secondly, I want to apologize to for the cleanliness issues in your room. It is obvious that we did not clean your room or inspect it the way we should have. The issues you reported should never have been an issue. Your satisfaction is important to us and we will be using the feedback you gave us to implement improvements to ensure we offer a better experience for guests in the future. I hope that you will consider staying with us again so that we can have another chance to provide you with a superior experience. I can provide any assistance, please don't hesitate to contact me directly at XXX.

Figure 3.3: Example of non-personalized vs. personalized manager response.

tent to which customers are invested in the hotel-client relationship is an important antecedent of satisfaction and WOM intention [70]. Likewise, membership level when visiting the hotel (Membership Level) which we treat a categorical variable (i.e., Membership Level $\in \{Blue, Gold, Platinum, Diamond\}$) as a continuous 5-point variable is included in our model. This variable controls for the potential bias that may be induced by the time and money that the customer invested while building the relationship with the hotel. The length of customer comments (Comment Length) is included since managers may write a longer response when the customer writes a lengthy comment. The number of days since the last time the customer provided feedback $h$ (Number of Days since last CSS) is included to control for the possible memory decay regarding the last customer-manager interaction [46]. That is, more recent memory about the last purchase experience should have a stronger effect on future outcomes, which has to be accounted for in our model. Since prior studies suggest that each of the three dependent variables is likely to be associated with the above-mentioned variables, we include all managerial response variables and transaction-specific variables in all three models (i.e., survey selection, satisfaction, and posting model) equally [47]. Due to our real-world study design, however, the posting model accounts for three additional variables that are not included in the other two models. Specifically, we consider the fact that the decision to post a review may be influenced by to which online review platform (i.e., TripAdvisor or Google) the survey respondent was randomly assigned to and whether or not the customer received the survey request through Gmail, a factor which may reduce the burden of posting Google reviews. These two variables are included in our model in order to control for the systematic burden that each survey taker may perceive before posting an online review due to the different email account and platform assignment [76]. That is, for example, if the survey taker is assigned to write a review on Googles platform and is already logged into the Gmail account when he/she received the CSS invitation, then the posting process should be easier than other possible scenarios. We call these two indicator variables Random Posting and Gmail, respectively. When Random Posting = 1, it means that the respondent is assigned to Google, otherwise they were assigned to TripAdvisor. If Gmail = 1, the customer received the survey request through a Gmail account, otherwise they received it through a different email account. Lastly, as we further describe in the hypotheses section, it is widely known that WOM intention is strongly associated with the customers current satisfaction with the hotel [3]. Therefore, it is necessary to include current satisfaction which is our mediator as a predictor in the posting model. However, unlike with the dependent variable in the satisfaction model ($S$), we treat the satisfaction as a continuous variable ($S'$) so that we can more easily interpret our mediation model, which we describe in the next section. All control variables are standardized before our main analysis by subtracting the mean and dividing by the standard deviation.

Table 3.3: Summary Statistics for the Original VS. Analysis Data

| | Original data | Data in our analysis |
|---|---|---|
| Number of hotels | 515 | 515 |
| Number of customers | 544,194 | 5,058 |
| Number of bookings | 1,737,410 | 22,682 |
| Number of survey responses | 334,538 | 20,012 |
| Number of monetary compensation offers | 11,083 | 723 |
| Number of manager responses to CSS | 98,746 | 7,142 |
| Number of online review postings | 2,589 | 2,589 |
| Number of customers who posted at least one time | 2,529 | 2,529 |
| Number of customers who never posted | 541,665 | 2,529 |
| Number of manager responses to reviews | 308 | 308 |

## 3.4 Models and Analysis

The multilevel structure of our data set creates several benefits to our study. First, at the individual customer level, we can appropriately control for observed and unobserved individual customer heterogeneity. Similarly, we can also control for hotel level unobserved heterogeneity. In addition to the managerial interaction and control variables, for each model, we included prior survey participation event ($z_{t-1}$), satisfaction ($\theta_{t-1}$), and online review posting event ($\text{post}_{t-1}$) as state dependent variables to control for the heterogeneity across customers with respect to the persistence of behavior and preference [28]. This is because customers' perception and behavior in the past relationship are strong determinants of the future perception and behavior which the model has to control [88]. All of these three lagged dependent variables have to be included in each of the three models since the managerial response effects are supposed to be conditional on customers' past survey participation, satisfaction, and online review posting incident.

With respect to the main interest variables which contain information about the manager post-survey interaction, $\boldsymbol{x}$, we included the following nine lagged variables in each of the three models as we described in the previous section: (1) $\text{SpeedResponse}_{t-1}$: a logarithm of the number of days between the

Table 3.4: Data Descriptive Statistics

| Variable | Description | Mean | Min | Max |
|---|---|---|---|---|
| ***Outcome Variables*** | | | | |
| $z$ | Dummy for survey participation | 0.84 | 0 | 1 |
| $S$ | Categorical satisfaction rating | 7.60 | 1 | 10 |
| post | Dummy for online review posting | 0.15 | 0 | 1 |
| ***Managerial Responses*** | | | | |
| ThankYou | Dummy for managerial thank-you | 0.26 | 0 | 1 |
| Apology | Dummy for managerial apology | 0.03 | 0 | 1 |
| PersonalScale | Extent of response tailoring | 0.42 | 0 | 0.65 |
| ResponseLength | Logarithm of the number of words included in the managerial response | 1.41 | 0 | 6.11 |
| COMPENSATION | Dummy for monetary compensation offer | 0.03 | 0 | 1 |
| SpeedResponse | Logarithm of the gap of the number of days between the customer survey submit and the managerial response | 0.20 | 0 | 5.15 |
| OnlineResponse | Dummy for managerial public response to the online review | 0.02 | 0 | 1 |
| ***Transaction Level Variables*** | | | | |
| Number of Visits | The number of times the customer visited the hotel $h$ | 2.69 | 1 | 23 |
| Membership Level | Continuous membership level | 2.91 | 1 | 5 |
| Stayed Nights | The number of stayed nights for the particular stay at time $t$ | 1.75 | 1 | 146 |
| Comment Length | Logarithm of the number of words included in the customer comments | 0.88 | 0 | 6.37 |
| Number of Days since last CSS | The number of days since the most recent date when provided feedback to the hotel $h$ | 72.11 | 0 | 830 |
| ***Posting-model Specific Variables*** | | | | |
| Random Posting | Dummy for Google review platform invitation | 0.46 | 0 | 1 |
| Gmail | Dummy for receiving CSS through Gmail | 0.27 | 0 | 1 |
| $S'$ | Continuous satisfaction rating | 7.60 | 1 | 10 |

date of the customer survey submit and the date of the managerial response, (2) $\text{COMPENSATION}_{t-1}$: an indicator variable if a financial compensation offer that can be applied in the future hotel stay was made, (3) Online $\text{Response}_{t-1}$: an indicator variable of whether manager response is provided to the customer's online review, if a review is posted by the customer, (4) $\text{ThankYou}_{t-1}$: an indicator variable of whether the manager sent a "Thank you" message, (5) $\text{APOLOGY}_{t-1}$: an indicator variable of whether the manager response includes an "Apology" message, (6) $\text{ThankYou}_{t-1} \times \text{PersonalScale}_{t-1}$: the extent of personalizing the managerial thank you message, (7) $\text{APOLOGY}_{t-1} \times \text{PersonalScale}_{t-1}$: the extent of personalizing the managerial apology message, (8) $\text{ThankYou}_{t-1} \times$

ResponseLength$_{t-1}$: the number of words of the managerial thank you message, and (9) APOLOGY$_{t-1}$ × ResponseLength$_{t-1}$: the number of words of the managerial apology message.

### 3.4.1 Satisfaction Model

Given the discrete and ordered nature of the satisfaction variable, we employ the ordered probit model to capture the categorical nature of the survey-based preference measure, in which a continuous latent preference variable generates observed survey responses. Our model incorporates the dynamic features including the satisfaction reflected in the previously submitted survey and the manager response. Thus, the model deals with the dynamic process by involving the lagged values of the dependent variable as explanatory factors. In a categorical dynamic panel model, it is recommended to specify feedback from previous preferences to current ones as a continuous latent preference rather than as categorical because it is an unrealistic assumption that current continuous preferences are influenced by past categorical survey responses [72, 79]. In other words, instead of including the lagged satisfaction value as the observed indicator, $S_{t'-1}$, which is a common approach in the traditional state dependence model, it is more appropriate to include the continuous latent variable of the dependent variable, $\theta_{iht'-1}$, as an explanatory variable (for detail see [72]). We thus model the latent satisfaction $\theta_{iht'}$ as customer $i$'s perceived quality of hotel $h$ at time $t'$ when responding to the survey:

$$\theta_{iht'} = \zeta_{ih} + \phi_2\theta_{iht'-1} + \beta'\boldsymbol{x}_{iht'-1} + \omega_2'\boldsymbol{v}_{iht'} + \nu_2 z_{iht-1} + \varrho_2\text{post}_{iht'-1} + \rho_1\hat{\lambda}_{iht'} + \epsilon_{2,iht} \tag{3.2}$$

where $\zeta_{ih}$ is the baseline satisfaction of customer $i$ toward hotel $h$. We capture each customer's heterogeneous preference for hotels by including $\zeta_{ih}$ because every customer has different baseline preferences for different hotels. $\phi_2$ denotes the auto-correlation between perceived satisfaction at $t'-1$ and $t'$ of the same customer $i$ toward the same hotel $h$. $\beta'$ is a vector of regression parameters for matrix $\boldsymbol{x}_{iht'-1}$ that captures the effects of manager responses on future satisfaction. $\omega'_{2:5}$ is a vector that controls for the observed heterogeneity. We control the survey participation at the previous visit in time $t-1$ by including $z_{iht-1}$ and the previous online review posting incidence after the previous survey participation at time $t'-1$ by including $\text{post}_{t'-1}$. Thus, $\nu_2$ and $\varrho_2$ capture how the previous survey participation and the online review posting decision are correlated to the current satisfaction. The term $\epsilon_{2,iht'}$ is the error that follows a standard normal distribution. Because the survey ratings are submitted on a 10-point scale, we model the latent satisfaction score, $\theta_{iht'}$, as follows:

$$P(S_{iht'} = s | z_{iht} = 1) = P(\kappa_{s-1} < \theta_{iht'} < \kappa_s) \tag{3.3}$$

where $s \in \{1, 2, \ldots, 10\}$ is the rating scale. The variable $S_{iht'}$ is the satisfaction rating submitted by customer $i$. The $\kappa_s$ denote cut points for rating category $s$. The condition $z_{iht} = 1$ indicates that the respondent completed and submitted the survey at his/her $t$'s visit at hotel $h$ while $z_{iht} = 0$ indicates that the visited customer ignored the survey.

### 3.4.2 Posting Model

**Direct Effect of Managerial Response on Posting** In the same manner as for the satisfaction model, we conceptualize the survey respondents' online review posting decision as a function of the prior interaction with the manager as well as individual and booking specific constructs. Additionally, we capture the effect of the current satisfaction about the hotel experience $S_{iht'}$ with $\phi_3$ and the posting-specific conditions ($\boldsymbol{w}$) with $\delta_{2,1:2}$. Specifically, we consider the fact that the posting decision may be influenced by to which online review platform (i.e., TripAdvisor or Google) the survey respondent is randomly assigned and whether the customer received the survey request through Google email (i.e., Gmail), a factor which may reduce the burden of posting Google reviews. We name these two indicator variables as Random Posting and Gmail, respectively. When Random Posting = 1, it means that the respondent is assigned to Google, otherwise to TripAdvisor. If Gmail = 1, the customer received the survey request through the Google account, otherwise through any other accounts. [63] suggests modeling an individual's decision to submit an online review with the customer experience with the product, varying individual baseline tendency for posting online reviews, the current state of the rating environment, and the post-purchase evaluation [51]. In our research setting, there is no need to contain the social interaction between reviewers because customers post an online review within the survey response page rather than after being explicitly exposed to other reviewers' opinions. Thus, the only social factor that can influence the rating environment is the manager interaction that customers may receive after the previously submitted survey. Therefore, we model the customer $i$'s latent utility $U^*_{iht'}$ of posting an online review for hotel $h$ at time $t$ after filling out the survey:

$$\begin{aligned} U^*_{iht'} = \alpha_3 + \xi_{ih} + \varphi_{2,1} S'_{iht'} + \phi_3 S'_{iht'-1} + \beta'_3 \boldsymbol{x}_{iht'-1} + \omega'_3 \boldsymbol{v}_{iht'} \\ + \nu_3 z_{iht-1} + \varrho_3 \text{post}_{iht'-1} + \delta_{2,1:2} \boldsymbol{w}_{iht'} + \rho_2 \hat{\lambda}_{iht'} + \epsilon_{3,iht} \end{aligned} \tag{3.4}$$

where $\alpha_3$ is the general customers' baseline online review posting propensity, while $\xi_{ih}$ is the baseline for the individual customer $i$ for hotel $h$. As in the selection and satisfaction models, the term $\epsilon_{3,iht'}$ is an idiosyncratic error and $\epsilon_{3,iht'} \sim N(0, 1)$. However, note that unlike $S_{iht'}$ which is the submitted discrete satisfaction variable that we used to create the latent variable, $\theta_{iht'-1}$, $S'_{iht'}$ is a variable that we treat $S_{iht'}$ as a continuous scale. We further standardize the 10-point continuous satisfaction variable, $S'_{iht'}$, by subtracting the mean and dividing it by the standard deviation. Thus, $\varphi_{2,1}$ is the parameter that estimates the relationship between the standardized current satisfaction and the online review posting event, which allows us to test the Hypothesis 5. Likewise, $\phi_3$ estimates how the prior standardized satisfaction at time $t'-1$ influences the posting incidence at time $t'$. Then, the probability that customer $i$ submits an online review at the end of the survey is given by the following probit model:

$$\begin{aligned} Pr(\text{post}_{iht'} = 1 | z_{iht} = 1) = \Phi(&\alpha_3 + \xi_{ih} + \varphi_{2,1} S'_{iht'} + \phi_3 S'_{iht'-1} + \beta'_3 \boldsymbol{x}_{iht'-1} + \omega'_3 \boldsymbol{v}_{iht'} \\ &+ \nu_3 z_{iht-1} + \varrho_3 \text{post}_{iht'-1} + \delta_{2,1:2} \boldsymbol{w}_{iht'}) \end{aligned} \tag{3.5}$$

where $\Phi(.)$ denotes the standard normal cumulative distribution function (c.d.f.). The vector $\beta'_3$ captures the effect of managers' post-survey interaction and $\varrho_3$ captures the auto-correlation between the current posting and the previous posting on the same hotel. Unlike the satisfaction model, we use the observed binary variable $\text{post}_{iht'-1}$ as the explanatory variable rather than the latent continuous variable $U^*_{iht'-1}$ because the online review posting incidence is not a subjective preference but is the event that we can directly observe from the posting behaviors. Therefore, the posting model is simply a standard state dependent model, where individuals' previous posting experience for the hotel $h$ is correlated with the current posting decision of the same hotel. As same as the satisfaction model, the condition $z_{iht} = 1$ indicates that we observe online review posting incidence given that the respondent completed the survey. We discuss in the following section how we control for the potential effect of self-selection bias that can be caused by the individuals' survey participation decision.

**Indirect Effect of Managerial Response on Posting** Mediation analysis is widely used in marketing and other social science areas because of its power of testing the causal sequence from the independent variable (X) to the mediator (M) to the outcome. It is often known that to perform a mediation analysis the model has to fulfill the following three conditions. First, the independent variable must affect the mediator in the first equation ($a$); second, the independent variable must be shown to affect the dependent variable in the second equation ($c'$); and third, the mediator must affect the dependent variable in the third equation ($b$). The significance of the coefficients $a$,$b$,and $c'$ are tested and estimated using the equations 3.6, 3.7, and 3.8:

$$M = i_1 + aX + e_1 \tag{3.6}$$

$$Y = i_2 + c'X + e_2 \tag{3.7}$$

$$Y = i_3 + cX + bM + e_3 \tag{3.8}$$

where each $i$ denotes the intercept of the linear equation [98, 75]. While the original Baron and Kenny's mediation test [6] is known for requiring to meet all of these three conditions, more recent studies point out the flaws of the original paper and demonstrate that only one requirement is sufficient to establish mediation [98, 56, 57, 75]. They suggest that showing the indirect effect $a \times b$ to be significant is sufficient and even recommended to show the presence of the indirect effect. Thus, in this paper, we estimate the indirect effect of the manager responses on the online review posting decision using the recently updated mediation test. In the next section, we illustrate that the managerial post-survey apology significantly influences customer's current satisfaction ($a$) and that current satisfaction significantly influences online review posting behavior ($b$). Consequently, the multiplication between the coefficients of the managerial interaction effect on current satisfaction (i.e., $\beta_{2,1:9}$) and the coefficient of current satisfaction on posting decision (i.e., $\varphi_2$) is the amount of the indirect effect of the managerial interaction on that posting decision. Note that, however, since some of the managerial response predictors are interaction variables, our model is a moderated mediation model (i.e., PersonalScale$_{t-1}$ $\times$ ThankYou$_{t-1}$, PersonalScale$_{t-1}$ $\times$ Apology$_{t-1}$, ResponseLength$_{t-1}$ $\times$ ThankYou$_{t-1}$, and ResponseLength$_{t-1}$ $\times$ Apology$_{t-1}$). Thus, using the moderated mediation model, we show that providing personalized apology to the complainants indirectly decreases their future online review posting propensity due to their increased current satisfaction. In other words, the probability of a customer posting negative online reviews in the future may drop when responding to the complainants with a personalized apology. A typical challenge in classic mediation analyses is to obtain standard errors of the mediated effects ($a \times b$), since the distribution of the product of two normally distributed coefficients is often unknown. However, with our Bayesian analysis, this is not a concern anymore since we can easily calculate the standard deviation of the product of the two coefficients $a$ and $b$ which we obtain throughout the MCMC estimation process [97].

### 3.4.3 Controlling for Selection Biases

Our dynamic panel data model comprises two selection problems that may induce potential biases of the estimates. In this section, we describe how our model accounts for both the initial condition problem and the survey selection bias.

**Controlling for Initial Condition Problem** When formulating a dynamic panel data model where the lagged dependent variable also appears on the right-hand side of the model, it is necessary to initialize the process because of the *initial conditions problem* [77]. This problem occurs if the customers who we observe the reported satisfaction and online review posting incidence is a non-random sample of the population. For instance, when unsatisfied customers decides to switch to other hotel, the remaining customers may those who are consistently happy with the hotel. In this case, the satisfied customers may be over-represented in the sample (for detail see [77]). A realistic strategy that we follow is the solution first suggested by Heckman [36, 37] which considers that the initial values are endogenous variables with a probability distribution conditioned on the unobserved individual effects. Thus, to capture the dependence of the initial observation on unobserved characteristics, we specify an arbitrary correlation between the initial preference $\theta_{ih1'}$ and the customer-hotel specific effect $\zeta_{ih}$ as,

$$\theta_{ih1'} = \eta_1 \zeta_{ih} + \psi'_{1,1:2} \boldsymbol{v}_{ih1'} + \epsilon_{2,ih1} \tag{3.9}$$

Likewise, we specify the correlation between the initial online review posting propensity the customer-hotel specific effect $\xi_{ih}$ as,

$$U^*_{ih1'} = \alpha_1 + \eta_2 \xi_{ih} + \varphi_{1,1} S'_{ih1'} + \psi'_{2,1:2} \boldsymbol{v}_{ih1'} + \delta_{1,1:2} \boldsymbol{w}_{ih1'} + \epsilon_{3,ih1'} \tag{3.10}$$

where $\epsilon_{2,ih1}$ and $\epsilon_{3,ih1'}$ are the random disturbance terms at the initial period and are assumed to be uncorrelated with the future error terms, $\epsilon_{iht}$ and $\epsilon_{3,iht'}$. Using Heckman's specification, the scale factors $\eta_1$ and $\eta_2$ allow for a different effect magnitude of unobserved characteristics on initial preferences and posting incidence.

**Controlling for Survey Selection Bias** However, even after controlling for the initial condition problem, the individual decision to participate in the survey after every hotel stay may be non-random as well. Because the satisfaction and posting models rely on the attitude and behavior that are observed only when the customer completes the survey, a potential self-selection bias of the estimates may result. Specifically, if customers' survey response propensity is correlated to their satisfaction or review posting intention, the observed satisfaction or posting propensity will be biased. A common econometric approach widely used in eWOM literature [33, 51] that allows to correct the self-selection bias is termed the Heckman's two-step selection model [35]. In the first step, we model the survey response tendency of a customer $i$ responding to the survey requested by a hotel $h$ using a binary probit model. Thus, we model that customer $i$ responds to the survey which is requested by hotel $h$ after his/her visit at time $t$ if

$$Z^*_{iht'} = \alpha_2 + \gamma_i + \phi_1 S'_{iht'-1} + \beta'_1 \boldsymbol{x}_{iht'-1} + \omega'_1 \boldsymbol{v}_{iht} + \nu_1 z_{iht-1} + \varrho_1 \text{post}_{iht'-1} + \epsilon_{1,iht} > 0 \quad (3.11)$$

where $\alpha_2$ is the overall baseline survey participation rate and $\epsilon_{1,iht}$ is an idiosyncratic error that follows a standard normal distribution (i.e., $\epsilon_{1,iht} \sim N(0, 1)$). Given that the same survey requests are sent to all customers, the survey response decision is mainly driven by the individual's choice. Therefore, unlike in the satisfaction and positng models, we model $\gamma_i$ to vary only at the customer level. Although our purpose of specifying the selection model is to control for the effect of potential self-selection bias, we include the same variables used in the satisfaction model to investigate whether manager interaction influences future survey participation of the customers. Thus, $\beta'_1$ is a vector that estimates the effect of hotel $h$'s manager response toward the customer $i$ at time $t-1$, which influences the future survey participation at time $t$. $\omega'_1$ is a vector that captures the effect of the same covariates that are included in both satisfaction and posting models. Then, the probability that customer $i$ responds to a survey is given by the following probit model:

$$P(z_{iht} = 1) = \Phi(\alpha_2 + \gamma_i + \phi_1 S'_{iht'-1} + \beta'_1 \boldsymbol{x}_{iht'-1} + \omega'_1 \boldsymbol{v}_{iht} + \nu_1 z_{iht-1} + \varrho_1 \text{post}_{iht'-1}) \quad (3.12)$$

where $\Phi$ denotes the standard normal cumulative distribution function (c.d.f).

In the second step, we use the predicted value from the probit model to calculate the inverse Mill's ratio for each customer's visit by estimating the equation 3.12 such as,

$$\hat{\lambda_{iht}} = \frac{\phi(\hat{\alpha}_2 + \hat{\gamma}_i + \hat{\phi}_1 \hat{S'}_{iht'-1} + \hat{\beta}_1' \boldsymbol{x}_{iht'-1} + \hat{\omega}_1' \boldsymbol{v}_{iht} + \hat{\nu}_1 z_{iht-1} + \hat{\varrho}_1 \text{post}_{iht'-1})}{\Phi(\hat{\alpha}_2 + \hat{\gamma}_i + \hat{\phi}_1 \hat{S'}_{iht'-1} + \hat{\beta}_1' \boldsymbol{x}_{iht'-1} + \hat{\omega}_1' \boldsymbol{v}_{iht} + \hat{\nu}_1 z_{iht-1} + \hat{\varrho}_1 \text{post}_{iht'-1})} \tag{3.13}$$

where $\phi$ is the probability density function (p.d.f).

Therefore, $\hat{\lambda_{iht'}}$ in the satisfaction and the posting models controls the potential self-selection bias that comes from the correlation between the decision to respond to the survey and the submitted satisfaction rating as well as the correlation between the decision to respond to the survey and online review posting propensity. Therefore, each of the self-selection bias is captured in $\rho_1$ and $\rho_2$. We jointly fit the satisfaction model, posting model and the selection models using the Bayesian estimation approach.

## 3.5 Results and Discussion

We describe results obtained by estimating the models described in the previous section. We adopt the Bayesian approach due to its straightforward interpretation of the standard error and its ease of estimating all three models' parameters simultaneously. Results are obtained by MCMC sampling using three parallel chains run with 20,000 iterations each. We thinned the iteration by a factor of 10 and 10,000 previous iterations are discarded as burn-in. We implemented the model using Stan [14] and we confirmed that the model converged using [27]'s potential scale reduction factor (PSRF). Due to the space limitation, the estimate of the intercepts $\alpha_1$, $\alpha_2$, $\alpha_3$, and the cut points ($\kappa_s$) of the ordered probit model are not displayed in the tables.

### 3.5.1 Satisfaction Model Results

The column on the left-hand side of Table 3.5 displays the results of the satisfaction model while considering the dynamics of customer preference persistence. We provide posterior means and 95% highest posterior density regions (HPD). Here, we use the dynamic latent ordered probit model as described in the model description.

The parameter estimates of $\beta_{2,1:9}$ show the influence of the manager post-survey interaction at the previous stay (i.e., $t-1$) on the customer's current satisfaction (i.e., $t$). The effect of PersonalScale$_{t-1}$ × APOLOGY$_{t-1}$ shows that when managers apologize for service failures with personalized written responses, customer satisfaction increases during the next visit ($\beta_{2,7} > 0$). In a dynamic panel model, usually the central interest is the long-run or steady-state effect of the target variables taking preference persistence into account, we calculate the long-run marginal effect of the manager responses by calculating $\frac{\beta'}{1-\phi_2}$ [79]. In Table 3.7, we provide the long-run marginal effects of managerial responses in the predicted probability. The results reflect that when a complainant receives the maximum level of personalized managerial apology, the probability that they will rate this property as $S_t = 10$ rather than any other ratings following their next stay increase by about 19.6%. Note that when calculating the marginal effect, we predict the amount of probability change due to the increase in the focal variable from zero to the maximum (e.g., PersonalScale$_{t-1}$ × APOLOGY$_{t-1}$ = 0 vs. PersonalScale$_{t-1}$ × APOLOGY$_{t-1}$ = 0.65), while holding everything else as constant. However, these effects are hard to expect from other managerial interactions. These findings suggest that future customer satisfaction tends to increase following a personalized managerial apology for the reported complaint. Therefore, we conclude that our results are consistent with Hypotheses 1, and find strong evidence of the recovery paradox that exists in the post-survey written interaction.

### 3.5.2 Posting Model Results

In Figure 4.1, we present the effects of managerial interaction following posting behavior at two levels: direct effects and indirect effects through moderated mediation analysis.

**Results of Direct Managerial Effects on Posting** The column on the right-hand side of Table 3.5 shows the effect of managerial post-survey interaction and current satisfaction on online review posting decisions. The estimate of $\beta_{3,1}$ in the posting model of Table 3.5 is negative and statistically significant. This result implies that the survey respondent's online review posting motivation increases once they receive a quick response from the manager. Providing support for Hypothesis 2.

Other managerial response effects on the online review posting motivation provide interesting insights as well. Our results show that while the estimate of $\beta_{3,4}$ in the posting model is positive and statistically significant, the estimate of $\beta_{3,5}$ is not significantly greater than zero. These results have different implications regarding the managerial responses towards satisfied and dissatisfied customers. In regards to the managerial responses to satisfied customers, these results imply that the survey respondents' online review posting motivation increases once they receive any type of thank you message from the manager and realize that their voice has been heard. While the thank-you message does not necessarily have to be personalized or detailed, a speedy response should increase the customers' online review posting motivation even further. The managerial apology to unsatisfied customers, however, has no effect on future online review posting motivation unless it includes a compensation offer (i.e., $\beta_{3,2} > 0$) or is very quick. We find that customers who are dissatisfied with the current stay ($S_t'$) are more likely to post an online review in both the initial ($\varphi_1 < 0$ in Table 3.9) and the following surveys ($\varphi_2 < 0$ in Table 3.5). Therefore, consistent with prior studies in WOM literature, we conclude that the negative customers are more likely to post an online review after completing the survey [3].

Table 3.5: Posterior summary of managerial response effects in satisfaction and posting Models

| Description | Parameters | Satisfaction Model ($S_t$) Mean [95% HPD] | Parameters | Posting Model ($post_t$) Mean [95% HPD] |
|---|---|---|---|---|
| ***Managerial Post-survey Interactions*** | | | | |
| SpeedResponse$_{t-1}$ | $\beta_{2,1}$ | 0.005 [-0.045, 0.055] | $\beta_{3,1}$ | **-0.161 [-0.223,-0.100]** |
| COMPENSATION$_{t-1}$ | $\beta_{2,2}$ | -0.030 [-0.210, 0.137] | $\beta_{3,2}$ | **0.229 [ 0.029, 0.429]** |
| OnlineResponse$_{t-1}$ | $\beta_{2,3}$ | -0.051 [-0.285, 0.193] | $\beta_{3,3}$ | 0.214 [-0.184, 0.614] |
| ThankYou$_{t-1}$ | $\beta_{2,4}$ | 0.020 [-0.758, 0.829] | $\beta_{3,4}$ | **0.833 [ 0.008, 1.665]** |
| APOLOGY$_{t-1}$ | $\beta_{2,5}$ | -0.729 [-1.981, 0.486] | $\beta_{3,5}$ | 0.024 [-1.340, 1.392] |
| PersonalScale$_{t-1}$ × ThankYou$_{t-1}$ | $\beta_{2,6}$ | 0.035 [-0.253, 0.319] | $\beta_{3,6}$ | -0.024 [-0.345, 0.286] |
| PersonalScale$_{t-1}$ × APOLOGY$_{t-1}$ | $\beta_{2,7}$ | **0.474 [ 0.074, 0.871]** | $\beta_{3,7}$ | -0.182 [-0.652, 0.292] |
| ResponseLength$_{t-1}$ × ThankYou$_{t-1}$ | $\beta_{2,8}$ | 0.000 [-0.171, 0.166] | $\beta_{3,8}$ | -0.076 [-0.253, 0.102] |
| ResponseLength$_{t-1}$ × APOLOGY$_{t-1}$ | $\beta_{2,9}$ | 0.192 [-0.063, 0.447] | $\beta_{3,9}$ | 0.046 [-0.236, 0.327] |

Table 3.6: Posterior summary of control variables in satisfaction and posting Models

| Description | Parameters | Satisfaction Model ($S_t$) Mean [95% HPD] | Parameters | Posting Model ($post_t$) Mean [95% HPD] |
|---|---|---|---|---|
| ***Current Satisfaction*** | | | | |
| $S'_t$ | | | $\varphi_2$ | **-0.056 [-0.088,-0.024]** |
| ***Control Variables*** | | | | |
| Number of Visits | $\omega_{2,1}$ | 0.003 [-0.026, 0.033] | $\omega_{3,1}$ | 0.033 [-0.007, 0.075] |
| Stayed Nights | $\omega_{2,2}$ | **0.044 [ 0.012, 0.077]** | $\omega_{3,2}$ | **-0.260 [-0.299,-0.221]** |
| Membership Level | $\omega_{2,3}$ | -0.002 [-0.041, 0.040] | $\omega_{3,3}$ | **0.059 [ 0.022, 0.094]** |
| Comment Length$_{t-1}$ | $\omega_{2,4}$ | 0.024 [-0.007, 0.056] | $\omega_{3,4}$ | **0.064 [ 0.029, 0.098]** |
| Number of Days since last CSS | $\omega_{2,5}$ | **-0.039 [-0.069,-0.009]** | $\omega_{3,5}$ | **0.267 [ 0.237, 0.297]** |
| Random Posting | | | $\delta_{2,1}$ | -0.021 [-0.090, 0.048] |
| Gmail | | | $\delta_{2,2}$ | **0.104 [ 0.025, 0.182]** |
| Prior Survey Participation: $z_{t-1}$ | $\nu_2$ | 0.018 [-0.024, 0.059] | $\nu_3$ | **0.153 [ 0.078, 0.231]** |
| Prior Online Reivew Posting: post$_{t-1}$ | $\varrho_2$ | 0.009 [-0.027, 0.044] | $\varrho_3$ | **-0.239 [-0.298,-0.182]** |
| Prior Satisfaction: $\theta_{t-1}$ (Satisfaction Model)<br>Prior Satisfaction: $S'_{t-1}$ (Posting Model) | $\phi_2$ | **0.680 [ 0.533, 0.761]** | $\phi_3$ | 0.026 [-0.015, 0.067] |
| ***Selection Biases*** | | | | |
| Survey Selection Bias | $\rho_1$ | 0.034 [-0.086, 0.154] | $\rho_2$ | **0.451 [ 0.272, 0.633]** |
| ***Unobserved hotel-customer variance*** | | | | |
| % of Variance from Customers | $\frac{\sigma_\gamma^2}{1+\sigma_\gamma^2}$ | 0.226 [ 0.154, 0.362] | $\frac{\sigma_\xi^2}{1+\sigma_\xi^2}$ | 0.001 [ 0.000, 0.002] |

Table 3.7: Long-run (steady-state) marginal effects of managerial responses

| | $\text{SpeedResponse}_{t-1}$ | $\text{COMPENSATION}_{t-1}$ | $\text{OnlineResponse}_{t-1}$ | $\text{ThankYou}_{t-1}$ | $\text{APOLOGY}_{t-1}$ | $\text{PersonalScale}_{t-1}$ $\times\text{ThankYou}_{t-1}$ | $\text{PersonalScale}_{t-1}$ $\times\text{APOLOGY}_{t-1}$ | $\text{ResponseLength}_{t-1}$ $\times\text{ThankYou}_{t-1}$ | $\text{ResponseLength}_{t-1}$ $\times\text{APOLOGY}_{t-1}$ |
|---|---|---|---|---|---|---|---|---|---|
| ***Satisfaction Model*** | | | | | | | | | |
| Pr(s = 1) | -0.000 (0.000) | 0.000 (0.000) | 0.000 (0.001) | 0.008 (0.046) | 0.176 (0.300) | 0.000 (0.000) | **-0.000 (0.000)** | 0.020 (0.094) | 0.005 (0.052) |
| Pr(s = 2) | -0.000 (0.000) | 0.000 (0.000) | 0.000 (0.001) | 0.003 (0.011) | 0.024 (0.032) | 0.000 (0.000) | **-0.000 (0.000)** | 0.005 (0.016) | 0.001 (0.008) |
| Pr(s = 3) | -0.000 (0.000) | 0.000 (0.001) | 0.000 (0.002) | 0.006 (0.020) | 0.038 (0.048) | 0.000 (0.001) | **-0.000 (0.000)** | 0.010 (0.027) | 0.002 (0.013) |
| Pr(s = 4) | -0.000 (0.002) | 0.001 (0.002) | 0.001 (0.005) | 0.010 (0.029) | 0.051 (0.058) | 0.000 (0.002) | **-0.001 (0.001)** | 0.016 (0.037) | 0.003 (0.018) |
| Pr(s = 5) | -0.000 (0.002) | 0.001 (0.003) | 0.001 (0.005) | 0.008 (0.021) | 0.033 (0.036) | 0.000 (0.002) | **-0.001 (0.002)** | 0.012 (0.025) | 0.002 (0.013) |
| Pr(s = 6) | -0.001 (0.004) | 0.001 (0.004) | 0.003 (0.008) | 0.012 (0.027) | 0.040 (0.042) | 0.000 (0.003) | **-0.002 (0.003)** | 0.016 (0.032) | 0.001 (0.017) |
| Pr(s = 7) | -0.003 (0.012) | 0.004 (0.012) | 0.008 (0.019) | 0.024 (0.052) | 0.065 (0.070) | 0.001 (0.010) | **-0.008 (0.011)** | 0.030 (0.059) | -0.002 (0.033) |
| Pr(s = 8) | -0.006 (0.049) | 0.014 (0.037) | 0.023 (0.053) | 0.035 (0.106) | 0.074 (0.128) | 0.000 (0.035) | **-0.045 (0.039)** | 0.036 (0.117) | -0.040 (0.077) |
| Pr(s = 9) | 0.017 (0.089) | 0.013 (0.057) | 0.019 (0.079) | -0.045 (0.151) | -0.076 (0.174) | -0.013 (0.062) | **-0.139 (0.079)** | -0.065 (0.162) | -0.187 (0.126) |
| Pr(s = 10) | -0.006 (0.151) | -0.034 (0.101) | -0.056 (0.144) | -0.061 (0.316) | -0.425 (0.350) | 0.011 (0.104) | **0.196 (0.121)** | -0.081 (0.370) | 0.216 (0.261) |
| ***Posting Model*** | | | | | | | | | |
| Pr(post = 1) | **0.231 (0.057)** | **0.053 (0.038)** | 0.056 (0.069) | **0.227 (0.147)** | 0.069 (0.224) | -0.019 (0.035) | -0.010 (0.054) | -0.085 (0.156) | 0.078 (0.249) |

**Results of Indirect Managerial Effects on Review Posting** In Table 3.8, we describe the indirect effect of post-survey interactions on the online review posting decision, which is equal to $\beta_{2,1:9} \times \varphi_2$. Note that while the values in parenthesis are the standard error, we highlighted the estimates based on the 95% HPD. As we confirmed from the estimate $\varphi_2 < 0$ in Table 3.5, unsatisfied customers perceive higher utility in posting online reviews than satisfied customers. Considering that we found that customers' satisfaction increases after receiving a personalized managerial apology, the utility of posting online reviews may drop after receiving such a response. As shown in the significant value in $\beta_{2,7} \times \varphi_2$ from Table 3.8, current satisfaction mediates the effect of the personalized managerial apology. This result implies that when the customer reported negative satisfaction in the survey and received a personalized apology from the manager, he/she becomes less likely to post online reviews due to their increased satisfaction. This result is consistent with Hypotheses 3. While previous studies focused on how managerial response can change the posting behavior of aggregated opinions in online review platforms, we demonstrate at a micro level that managerial apology indirectly influences individuals' posting motivation through satisfaction, but only when the apology is sufficiently personalized.

Table 3.8: Posterior summary of Mediation Effects of Post-survey interactions

| Description | Parameters | Mean | Mean [95% HPD] |
|---|---|---|---|
| $\text{SpeedResponse}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,1} \times \varphi_2$ | -0.000 | [-0.003, 0.003] |
| $\text{COMPENSATION}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,2} \times \varphi_2$ | 0.002 | [-0.008, 0.012] |
| $\text{OnlineResponse}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,3} \times \varphi_2$ | 0.003 | [-0.012, 0.017] |
| $\text{ThankYou}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,4} \times \varphi_2$ | -0.001 | [-0.050, 0.043] |
| $\text{APOLOGY}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,5} \times \varphi_2$ | 0.041 | [-0.026, 0.125] |
| $\text{PersonalScale}_{t-1} \times \text{ThankYou}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,6} \times \varphi_2$ | -0.002 | [-0.019, 0.015] |
| $\text{PersonalScale}_{t-1} \times \text{APOLOGY}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,7} \times \varphi_2$ | **-0.026** | **[-0.059,-0.002]** |
| $\text{ResponseLength}_{t-1} \times \text{ThankYou}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,8} \times \varphi_2$ | 0.000 | [-0.009, 0.010] |
| $\text{ResponseLength}_{t-1} \times \text{APOLOGY}_{t-1} \rightarrow S'_t \rightarrow \text{post}_t$ | $\beta_{2,9} \times \varphi_2$ | -0.011 | [-0.029, 0.003] |

### 3.5.3 Selection Model results

While the initial condition and survey selection model are used mainly for controlling the selection biases, we also report the parameter estimates of these models to understand the bias components.

**Initial Selection Bias Results** A specification test for the independence of initial conditions and unobserved hotel-customer effects is obtained by testing whether $\eta_1$ or $\eta_2$ is equal to zero. The significantly positive observation $\eta_1 > 0$ suggests that individuals who decide to participate in the CSS panel are likely already substantially satisfied with the property at the start of the panel. This is an interesting finding as it provides insight into who decides to engage with the firm. Our findings suggests that customers are more likely to provide consistent feedback to the firm if they are satisfied with the service and wish to continue their relationship with the firm. Therefore, consistent with the prior literature, this result indicates that the sorting effect (in which the most dissatisfied customers drop out of the customer base) plays a strong role in our panel data [46]. Specifically, customers who frequently visited the same property ($\psi_{1,1}$) and stayed longer at the hotel ($\psi_{1,4}$) already have a significantly higher preference for the hotel at the start of the survey panel. All these initial selection bias estimates confirm the previous literatures conclusion that customers who are particularly engaged with a given firm are also more loyal to that brand [83]. In contrast, $\eta_2$ indicates that the association between the hotel-customer-specific unobserved condition and the initial online review posting decision is close to zero. Therefore, for the posting model, there is no strong reason to model the initial conditions as endogenous to customer-hotel specific unobserved characteristics. However, observed customer covariates such as Number of Visits, Stayed Nights, and Gmail are correlated with the initial online review posting decision of the property.

Table 3.9: Posterior summary of Initial Biases

| Description | Parameters | Satisfaction Model ($S_t$) Mean [95% HPD] | Parameters | Posting Model ($post_t$) Mean [95% HPD] |
|---|---|---|---|---|
| Initial Selection Bias | $\eta_1$ | **2.854 [ 1.949, 3.498]** | $\eta_2$ | -0.051 [-1.707, 1.586] |
| ***Control Variables*** | | | | |
| Random Posting | | | $\delta_{1,1}$ | 0.011 [-0.032, 0.054] |
| Gmail | | | $\delta_{1,2}$ | **0.085 [ 0.039, 0.131]** |
| Number of Visits | $\psi_{1,1}$ | **0.188 [ 0.081, 0.304]** | $\psi_{2,1}$ | **0.105 [ 0.025, 0.184]** |
| Stayed Nights | $\psi_{1,2}$ | **0.052 [ 0.023, 0.081]** | $\psi_{2,2}$ | **-0.094 [-0.117,-0.072]** |
| Membership Level | $\psi_{1,3}$ | 0.014 [-0.017, 0.045] | $\psi_{2,3}$ | 0.015 [-0.004, 0.034] |
| ***Current Satisfaction*** | | | | |
| $S'_t$ | | | $\varphi_1$ | **-0.097 [-0.109,-0.085]** |

**Survey Selection Bias Results** Table 3.10 shows the results of the parameter estimation from our selection model. The results from the selection model account for managers' post-survey interactions, which allows us to describe how the managerial response effort can influence customers' future survey participation decisions. Interestingly, as shown in the estimates of the $\beta_{1:1:9}$ parameters, none of the manager's post-purchase interaction efforts have a significant impact on future survey participation. The result shows that customer-to-firm engagement motivation is driven by other intrinsic factors, such as customer or transaction level characteristics. At the transaction level, customers who were highly satisfied with their last stay $S'_{t'-1}$ are more likely to participate in the survey in the future ($\phi_1 > 0$), confirming findings in the previous literature which suggest that satisfied customers are more likely to engage with the firm [47]. We also found that customers who stayed at a hotel for a long period of time were more likely to participate in the survey ($\omega_{1,2}$). Customers who recently provided feedback are less likely to offer secondary feedback within a short time period ($\omega_{1,6} > 0$). Lastly, the positive value of $\nu_1$ indicates that there is a positive auto-correlation between previous survey participation at time $t-1$ and current survey response propensity at time $t$. Therefore, customers' tendency to engage with the same hotel tends to persist.

Table 3.10: Posterior summary of Selection Model

| Description | Parameters | Satisfaction Model ($S_t$) Mean [95% HPD] |
|---|---|---|
| ***Managerial Post-survey Interactions*** | | |
| SpeedResponse$_{t-1}$ | $\beta_{1,1}$ | -0.038 [-0.096, 0.022] |
| COMPENSATION$_{t-1}$ | $\beta_{1,2}$ | 0.154 [-0.043, 0.351] |
| OnlineResponse$_{t-1}$ | $\beta_{1,3}$ | 0.069 [-0.142, 0.286] |
| ThankYou$_{t-1}$ | $\beta_{1,4}$ | 0.284 [-0.533, 1.096] |
| APOLOGY$_{t-1}$ | $\beta_{1,5}$ | -0.282 [-1.559, 0.947] |
| PersonalScale$_{t-1}$ $\times$ ThankYou$_{t-1}$ | $\beta_{1,6}$ | 0.290 [-0.015, 0.611] |
| PersonalScale$_{t-1}$ $\times$ APOLOGY$_{t-1}$ | $\beta_{1,7}$ | -0.315 [-0.768, 0.122] |
| ResponseLength$_{t-1}$ $\times$ ThankYou$_{t-1}$ | $\beta_{1,8}$ | 0.004 [-0.172, 0.176] |
| ResponseLength$_{t-1}$ $\times$ APOLOGY$_{t-1}$ | $\beta_{1,9}$ | 0.103 [-0.153, 0.366] |
| ***Control Variables*** | | |
| Number of Visits | $\omega_{1,1}$ | **-0.177 [-0.213,-0.140]** |
| Stayed Nights | $\omega_{1,2}$ | **0.134 [ 0.092, 0.177]** |
| Membership Level | $\omega_{1,3}$ | 0.016 [-0.020, 0.054] |
| Comment Length$_{t-1}$ | $\omega_{1,4}$ | -0.001 [-0.035, 0.032] |
| Number of Days since last CSS | $\omega_{1,5}$ | **0.087 [ 0.057, 0.119]** |
| Prior Survey Participation: $z_{t-1}$ | $\omega_{1,6}$ | **0.204 [ 0.163, 0.245]** |
| Prior Online Review Posting: post$_{t-1}$ | $\nu_1$ | **-0.071 [-0.100,-0.040]** |
| Prior Satisfaction: $S'_{t-1}$ | $\phi_1$ | **0.101 [ 0.066, 0.137]** |
| ***Unobserved hotel-customer variance*** | | |
| % of Variance from Customers | $\frac{\sigma_\zeta^2}{1+\sigma_\zeta^2}$ | 0.580 [ 0.545, 0.614] |

### 3.5.4 Model Comparison

As stated in the introduction, we hypothesize that customers' future satisfaction and online review posting decisions may be affected by hotel managers' post-survey interactions. Therefore, we argue that by accounting for managers' post-survey interactions in the model, the model explains our data more accurately. Therefore, it is necessary to compare the two models where managers' post-interaction is not included in the reduced model, but is included in the full model. In other words, we compare the full model, which includes the vector $\boldsymbol{x}$ in each selection, satisfaction, and posting models; with the reduced model which assumes that there is no post-survey interaction. Our results show that after accounting for the post-survey responses, the predictive accuracy of our model increased significantly. Following the guideline of [87], we use WAIC (Watabe-Akaike or widely applicable information criterion; [91]) and leave-one-out cross-validation (LOO), which are recommended as a Bayesian model selection criterion. As shown in Table 3.11, both WAIC, and LOO indicate that the full model has significantly smaller values. Consequently, we conclude that the full model fits the data better than the reduced model. The results imply that the post-survey managerial interactions provide important information to for understanding customer dynamics.

Table 3.11: WAIC and LOO for Model Comparison

| | Reduced Model | Full Model | Full Model vs. Reduced Model |
|---|---|---|---|
| WAIC | 66291.67 (362.21) | 66013.83 (360.99) | 138.92 (11.82) |
| LOO | 68763.84 (379.09) | 68550.85 (378.09) | 106.5 (16.46) |

## 3.6 Summary

Our comprehensive model expands on prior studies of service recovery and eWOM that have examined the effect of the managerial response from different areas. Our study demonstrates that the managerial response is a promising tool for service recovery and encouraging customers to post an online review – thereby sharing feedback with potential future guests. We demonstrate that, when customers who complained in the survey received a personalized managerial apology, their future satisfaction increased because they were able to assess the quality of the written service recovery. This result implies that it is not the managerial apology itself that recovers the service failure, but rather the quality of the response that gives the impression that the manager cares about customers complaints. Therefore, we conclude that an appropriate managerial apology is perceived as the service provider's investment in the relationship in question, which reduces the inequity perception of the interactional justice of the customer.

This result suggests that the service recovery paradox also exists in the context of written communication, but only when the manager puts additional effort into the apology rather than providing a response that appears to have been generated by automated software. This finding may also explain why the customer loyalty of the complaining customers increases after receiving an authentic service recovery as found in prior literature [82]. While the extent of managerial response personalization has no direct effect, we find that this response feature indirectly reduces the online review posting motivation of negative customers which supports the findings of prior studies [10, 30, 80]. In contrast, if the complainant has received an automated managerial apology, and thus becomes more dissatisfied with future stays, he/she is more likely to post a negative online review. While the quick response may not influence customer satisfaction, such managerial responses may give customers the impression that their feedback is important to the hotel, which increases the probability that the customer will be motivated to put in the effort to post an online review following the CSS. This finding implies that, if a customer is aware that a manager is closely reviewing feedback and responding quickly, then they will be motivated to write a review in the future.

These findings have significant implications for firms that have an interactive feedback system where managers can respond individually and privately to customers following consumer feedback. In contrast to the traditional customer survey, where the only purpose of conducting the survey is to understand customer perception at the aggregate level, the interactive features of more recent CSS systems allow firms to have an intimate relationship with individual customers. Additionally, this system also allows more customers (who otherwise might not be included in the sample) to voice their opinions in online review communities. Making full use of this system allows firms to improve their own value by improving customer satisfaction and their online reputation. Our findings contribute to practitioners by advancing the understanding of the effect of managerial written responses to customer feedback, which have often been completed without clear guidelines. A typical problem that managers suffer from has to do with deciding whether it is worth investing in responding to customers. Because writing a timely and personalized response requires extra effort, this can be understood as the same capacity constraint problem that firms encounter from any resource allocation. Thus, firms either send a simple automated thank-you message to every customer or invest time in responding to every single survey comment. However, our findings suggest that personalization has a greater impact among complainants who are expecting a managerial apology. Responding to these customers not only increases their future satisfaction, but also reduces the chance that negative opinions will be posted online in the future. It is also important to note that, however, a personalized apology is a tool that reduces the chance of posting negative reviews rather than increasing the chance of posting positive reviews. According to our mediation model, once satisfaction is increased due to a successful service recovery (i.e., personalized apology), customers are less likely to post positive reviews that reflect their satisfaction. In contrast, however, if satisfaction has decreased due to service failure, customers are more likely to post reviews about their negative experiences. To make the personalized response work as a tool to increase the chance of posting a positive review, current customer satisfaction should be positively associated with the posting incidence, which allows the satisfaction to work as a positive mediator. However, as our results demonstrate, satisfied customers are less likely to post online reviews, which does not allow the firms personalized managerial response to be utilized as a tool for increasing the chance of posting positive reviews. Therefore, managers should note the role of the personalized managerial response, which is more effective in discouraging negative reviews than encouraging positive reviews. However, it is still worth responding quickly to all customers with either a thank-you or an apology, because this gives the impression that managers appreciate customer responses to the CSS. Therefore, if increasing the number of online reviews is one of the goals of the firm, managers should develop a system that allows to respond quickly to the customers who provide feedback. This may include alerting managers about incoming customer feedback or hiring more employees to respond to customers. Offering compensation to unsatisfied customers in particular might give customers the impression that the manager cares about the CSS, which increases future online review posting motivation.

Several results that are not related to the core of this paper are also worth mentioning. We found that responding to public reviews from customers who went through the CSS has neither attitudinal ($\beta_{2,3} = 0$) nor behavioral ($\beta_{3,3} = 0$) impact for the focal customer. It may change the opinion of other reviewers in the community, but, if a manager wants to recover from a service failure and increase the review posting motivation of the focal customer, then a private response has a greater impact. The negative posting persistence estimate $\varrho_3$ indicates that customers who posted online reviews at the prior visit are less likely to post another online review about the same hotel after the next hotel stay (see Table 3.6). Considering that customers have significantly positive persistence over time for both survey participation (i.e., $\nu_1$) and satisfaction (i.e., $\phi_2$), this result reveals an interesting eWOM behavior that differs from other customer outcomes. That is, while customers tend to recurrently engage with the same hotel by providing feedback, their eWOM behavior regarding the same hotel rarely occurs more than one time. This finding suggests that once a customer writes an online review, it is less likely that the same customer posts another review even after his/her satisfaction has been updated. Thus, while managers have to make sure that the customer is satisfied with their service before soliciting for posting online reviews, potential customers who read the online reviews should be aware that the opinions are rarely updated. We also found that the longer the customer stays at the hotel, the more likely they are to participate in CSS and post an online review. These findings suggest that customers tend to invest more effort in providing feedback to the firm and sharing their experience online when they spend a significant amount of time at a hotel. Therefore, to adjust for the possible selection bias of these customers, studies that utilize the CSS or online review data should account for the time that customers spent at the hotel. Finally, the estimates of the survey selection bias ($\rho_2$) provide interesting insights into the survey participants' posting motivation, which differs from the posting motivation of non-participants. We find that the individual customer's survey response decision is significantly correlated with his/her posting motivation, which is captured by the parameter $\rho_2$ in the posting model. The observation $\rho_2 > 0$ suggests that individuals with a high propensity to participate in the survey are more likely to post online reviews at the end of the CSS. This finding is consistent with the customer engagement literature where customer-to-firm engagement is positively associated with customer-to-customer engagement [47]. By allowing customers to easily provide feedback to the firm, the service provider can expect even more online review postings, since the participants are self-selected customers who are likely to post online reviews.

Several limitations of our study call for further research. First, our sample only includes the opinions of those who want to provide feedback to the firm. Although our selection model controls for the potential selection bias, it may be useful to compare our results with data from customers who post reviews online without taking the survey. Second, our data is from a single chain hotel brand. While said data is sufficiently large enough to generalize and the hotel brand used is one of the most popular chains in the world, customer behavior with respect to other hotels, which have different standards of quality or reputations, might be different. Third, we did not include many other managerial response quality dimensions in our model. For instance, customers may change their attitudes and behaviors based on the politeness of the managerial response. Fourth, while we explicitly accounted for the potential selection biases in our model, the natural experiment research design may not be ideal for controlling all endogeniety. In the future it might be helpful to conduct a longitudinal experiment, which would allow researchers to observe online review posting behavior in a restricted laboratory setting. Lastly, although we took into account customer-hotel level heterogeneity, it may be particularly useful for future research to account for the varying expectation level due to price changes.

CHAPTER 4

# THE IMPACT OF MANAGERIAL RESPONSE ON BOOKING CHANNEL SELECTION

## 4.1 Introduction

The importance of maintaining long-term relationships with existing customers has been extensively emphasized in marketing literature. Prior studies have investigated the factors that determine customer loyalty behaviors. Studies have found that enhancing the relationship commitment, which is the customers desire to maintain a relationship with the firm, promotes customer loyalty behaviors. To enhance customer loyalty, firms endeavor to interact with their existing customers.

A typical business situation in which such customer-firm interactions take place is when hotels ask their recent customers to provide feedback about their experiences. This feedback request is sent to the customers as an email that includes a customer satisfaction survey (CSS), which is comprised of a mixture of open-ended and close-ended satisfaction-related questions. Once the firm encourages a customers participation in a survey through an email, said customer can either ignore or respond to the survey, which gives the firm an opportunity to interact with him or her. Once a manager receives feedback, he or she can decide whether to respond. Managers can interact with customers by sending emails to the same address as the one used for the survey. Although this is a prevalent managerial practice in the hospitality industry, our understanding of the impact of the communication process on customer loyalty is lacking. In this article, we are specifically interested in the dynamic effects of both customer feedback and managerial response on customer loyalty to the brand.

## 4.2 Background

Prior relationship marketing studies have investigated the link between customer feedback behavior and loyalty. For example, [60] showed that when customers feel a strong tie to their service provider, they are less likely to provide negative feedback (i.e., complaints). Though customers with strong ties hesitate to complain because they are concerned about harming their relationships with their service providers, those with weak ties do not have relationships to preserve. As an extension of [60], a recent study has argued that customers complaining behaviors create loyal relationships with the firm, given that they perceive strong ties with their service provider [82].

Several studies in services marketing have shown that managerial post-purchase interactions also drive customer brand loyalty. The major focus of these studies is the role of the managerial response as a means of service recovery [21, 4, 84]. Service recovery refers to the actions that an organization takes when a customer encounters a service failure [78]. Thus, these studies used to conduct cross-sectional surveys of noncustomers if they encountered service failures, and this was followed by questions asking about the respondents self-reported loyalty intentions. As interesting as these findings are, they have not been extended to a study that looks into loyalty behavior in a real-world setting. Moreover, due to the cross-sectional survey design, these studies have primarily focused on the static effect, which ignores the dynamic effect of customer loyalty. Considering that customers update their loyalty levels using the information they gather from past experiences, a dynamic analysis with longitudinal data is appropriate for capturing the pure amount of loyalty that is updated after customers provide feedback and receive a managerial response. Therefore, cross-sectional data are often criticized because they cannot establish causal relationships in loyalty research [88, 61]. To the best of our knowledge, the dynamic of loyalty behavior as a function of both customer feedback and managerial response has not yet been investigated.

Behavioral loyalty metrics with longitudinal data have been more often used in other business areas than they have in hospitality. The most typical behavioral loyalty metrics that have been used in marketing literature are customer retention and share of wallet [88]. Customer retention is defined as repurchase activity, which is the opposite of customer churn (i.e., the likelihood that the customer will stop buying from the company). Share of wallet is usually defined as the percentage of a customers expenses for a specific product that goes to a given supplier among his or her whole expenses in that category. Although these metrics are a powerful way to understand customer loyalty dynamics, both retention and share of wallet cannot be used in most of the hospitality transaction settings. For example, to observe the retention of hotel bookings for hotel A, it is necessary to track all purchase histories whenever a customer stays at a hotel. Since tracking purchase behavior is not possible in most hospitality databases, retention is the primary behavioral loyalty metric that has been used in the subscription business, where firms can track whether a customer churns. Likewise, to calculate a customers share of wallet in the hospitality industry, it is necessary to compute the number of hotel bookings purchased during the same period. However, it is rare for customers who book at one hotel to book at another during the same period. Therefore, services marketing literature, in which retention and share of wallet are not attainable, has been using self-reported loyalty intention measures rather than behavioral loyalty metrics for a long time [21, 93, 24]. To overcome this challenge and extend our knowledge about customer loyalty behavior, we make use of common customer behaviors in the hospitality industry that allow researchers to infer customers loyalty dynamics.

Though it is not easy to observe customer loyalty behavior in the hospitality industry, there is a unique opportunity to observe a reflection of loyalty: namely, the selection of a reservation channel. Aside from hotels official websites, booking via online travel agencies (OTAs) has become very popular. Once OTAs started to emerge, hotels were keen on listing their properties on these OTAs to create visibility, which generated a higher reservation volume. However, because OTAs comprise a large portion of the channel distributions, their services began to threaten the hotels revenues due to the high commissions. For instance, it has been reported that OTAs receive a 15% to 20% commission fee for bookings in the US. For this reason, some hotels have tried to reduce their reliance on OTAs by investing more in direct booking channels. Although several studies have argued that OTAs provide little value while siphoning off significant revenue that would otherwise accrue to the hotels, there are significant difficulties associated with hotels relying on direct booking channels. First, the hotels are required to invest a considerable amount in their direct booking channels. Second, there is a limited number of potential customers who are within the reach of direct booking; only customers who have a strong loyalty to a particular hotel or those who expect to gain greater benefits from direct booking will have the motivation to visit a hotels website to search for information. However, due to the rate parity agreement between hotels and OTAs, in which the hotels guarantee to use the same rate and terms for a specific room type, regardless of the distribution channel, customers cannot expect to gain any financial benefits from direct booking. Thus, the only motivation that drives customers to direct booking channels is their loyalty to the brand. Although hotels are still suffering from a low number of visitors, there are no marketing strategies that are known to increase direct booking. Thus, the goal of this paper is to investigate how managerial interactions can influence customers future brand loyalty, which is reflected by their channel selection.

Specifically, we identify how both the customer activity of providing feedback and managerial email responses can influence the future loyalty of a customer. Though the popular state-dependent model [36], in which a customers observed previous choice constitutes his or her future choice, can identify a causal relationship, such models have a limitation. If the state-dependent model fails to include important variables, the estimation from the observed variables is likely to be biased. To overcome the defects of the state-dependent model, we use the hidden Markov model (HMM), in which the observed dependent variable is the consequence of an unobserved state. The HMM allows the customers to transition between these states and understand the factors that move the customer from one loyalty state to the other. Therefore, this model allows us to capture the different latent loyalty states of customer behavior (i.e., high and low loyalty states).

Using our model, we suggest that brand loyalty increases after low loyalty state customers give negative feedback to a firm. This finding implies that the complaints of low loyalty customers act as a signal that these customers are ready to leverage their loyalty. We also find that managerial apologies have a greater impact on future brand loyalty when they are sent to customers who are currently at a high loyalty state. This result suggests that to keep their loyal customers, firms need to direct their email apologies to high loyalty customers.

A better understanding of customer loyalty dynamics is essential for both researchers and practitioners. This article contributes to the current customer loyalty literature in four important ways: 1) we explore both customer feedback and managerial response as drivers of customer loyalty; 2) we demonstrate how the effects of customer complaining behavior and managerial apologies on future brand loyalty have different impacts depending on the customers loyalty state; 3) instead of relying on the loyalty intention data collected from customer survey answers, we investigate latent loyalty states from behavioral outcomes using the HMM; and 4) we apply the loyalty model to the hospitality industry by introducing channel selection behavior as a loyalty behavior. By providing specific guidelines on how managers can enhance customer loyalty, this study helps managers in the following ways: 1) we interpret the implication of customers complaints, which may show managers how to increase these customers loyalty states ; 2) we provide specific decision recommendations to managers regarding the customers with whom they should interact by predicting the customers latent loyalty states based on their transaction historyestimating the impact of managerial responses allows for an assessment of which customers brand loyalty can be increased in the future by interacting with them; and 3) we provide an estimate of the cost reduction a firm can expect by increasing customer loyalty. By utilizing a unique data set in which the price of each hotel room is available, we can calculate the expected commission fees that hotels can save by interacting with their customers.

## 4.3 Predictors of Direct Booking

Although a customer may purchase a hotel room through the hotel's website, this behavior does not necessarily mean that the customer is highly loyal to a firm. The transaction-specific attributes (e.g., price and display promotions) may influence the customer's decision of direct booking. Therefore, it is important to distinguish the attributes that have enduring effects and short-term effects on customers' booking behavior.

### 4.3.1 Enduring effects

Customers develop their loyalty to a brand based on what kind of relationships they have with a firm. A typical customer–hotel post-purchase interaction occurs when hotels send a feedback request to the customers who recently stayed at their hotels.

**Customer feedback** Offering feedback to a firm requires time and effort; thus, doing so must have a reason. Therefore, customers' feedback to the firm is likely to contain a signal of how willing they are to change their loyalty level to a firm. Predicting customers' loyalty status in advance allows managers to react proactively. Therefore, understanding which customers voice is the most likely to be a signal that predicts an increase in future loyalty is important for both marketing researchers and managers. There is disagreement over whether positive or negative customer voices are associated with increases in loyalty to service providers [61]. Though the majority of studies argue that there is a positive relationship between customer satisfaction and loyalty, recent studies have demonstrated that customers complaining behavior may act as a signal that indicates their interest in continuing a relationship with the service provider [82, 60, 8]. In the context of service failure, they suggest that offering negative feedback is one way of signaling that the relationship is so important that the customers are willing to rectify it. To have a better understanding of the signal of each customer feedback behavior, we include four different customer feedback behaviors as customer-side relationship predictors that induce enduring effects: No feedback, which means the customer ignored the CSS request received by email, negative, neutral, and positive feedback which are defined based on the satisfaction ratings offered by the customers.

**Managerial responses** Under a typical interactive CSS system, managerial responses to customer feedback may also play an important role in how customers perceive their relationship with the hotel brand. Such managerial responses provide additional information to the customers when evaluating their relationship level with the hotel. While some customers offer feedback to express their emotions, others expect some type of follow-up from the managers. Prior service recovery studies have found that customers who complain about their encountered service failure are likely to seek redress from the manager [55]. Customers evaluate managerial service recovery efforts in three different justice dimensions: procedural, distributive, and interactional justice. Procedural justice involves the evaluation of the perceived fairness of the policies and procedures used by a manager in processing a complaint [9]. The speed of response has been identified as an important attribute that customers use to evaluate procedural justice [9, 78]. Distributive justice refers to the perceived outcome of the recovery efforts. Compensation after the encountered service failure is the most important recovery dimension associated with customers perceptions of distributive justice. Interestingly, however, we could rarely find managerial apologies that include any type of compensation offered in our data. Therefore, we do not include any variables that can be used as a proxy for the distributive justice dimension in our model. Interactional justice refers to customer perceptions of the way they are treated during personal interactions with the firm throughout the recovery process. In a service setting, which requires more intense employee–consumer interactions, interactional justice plays a greater role than the other perceived justice dimensions [26, 13]. An apology from a service provider has been known to be a service recovery effort that is associated with perceived interactional justice [78]. In the context of our study, an email apology aims to act as a recovery effort by rectifying the impaired interactional justice dimension. To account for the quality of the managerial response, we also account for the length of the text responses of the managers in our model.

### 4.3.2 Short-term effects

While the interaction between the customer and the manager may transfer the customers' loyalty state to the firm to a different level, there are transaction-specific attributes that have short-term effects on customers' purchase decisions. Among the many attributes, the displayed price of the hotel room may have the biggest impact on which channel the customer uses to book the hotel. Because the longer the customer schedules to stay at the hotel, the more expensive the hotel room will be, the number of days the customer stayed at each booking is also considered as a predictor inducing short-term effects. In the next two sections, we describe how we defined both the enduring and short-term variables and how we account for them in our HMM model.

## 4.4 Data

Our data comprises all hotel booking transactions of customers of a large hotel chain, which is one of the largest mid-range international hotel chains in the world. The data contains every customers hotel visit information, such as check-in/out date and the price they paid for their room. Once guests provide their email address during the transaction process, the hotel system automatically sends a survey request through this email immediately after the guest checks out. Every respondent receives a maximum of 20 questions, and the number of questions varies depending on the services each customer received. Each customers decision to open the email and complete the survey is purely based on their self-motivation because there are no financial incentives provided by the hotels. Thus, our data consists not only of whether the customer participated in the survey, but also their self-reported satisfaction ratings about the recent experience with the hotel if they participated in the survey.

First, we describe how we identify customer feedback. While there are several different satisfaction questions in the questionnaire, we chose one that measures the general satisfaction, which contains the feedback information that we need: "How satisfied were you with the OVERALL experience?". The rationale behind our decision to select this variable as a satisfaction measure is: 1) this satisfaction question is the first satisfaction question that customers receive, an approach which averts the potential measurement bias caused by the question order effect [11], and 2) for the same reason, the survey drop-out rate is relatively lower, which reduces the risk of item-nonresponse bias. We collapsed the 10-point satisfaction scale into a 3-point scale (i.e., Negative: 1-5, Neutral: 6-9, and Positive: 10) since the distribution of the ratings is highly skewed towards positive. Finally, we create the categorical variable $FeedBack \in$ {No feedback, Negative feedback, Neutral feedback, Positive feedback}, which identifies customer withheld behavior and of which valence the feedback consists.

This data also includes whether the manager responded to the customer survey or not, and other characteristics of this managerial response. Managerial response variables included in our model are the dummy for managerial response (ManagerResponse) and apology (APOLOGY). We classify any manager response that includes the words "sorry", "apology", or "apologize" as an apology message (i.e., APOLOGY = 1). As a measure of how detailed the manager response is, we use ManagerResponseLength, which is the log of the word count for each managerial response. Lastly, SpeedResponse is a measure of managerial response speed. Here, we use the log of the number of days between the customers completion of the CSS and the managerial reply. Therefore, the larger this value, the longer it took for the manager to respond to the customer's feedback.

In addition to the customer-managerial interaction variables, we also included the price that customers paid for each hotel room at the time $t$ (Price), and the number of nights per stay (Stayed Nights). Customer's reward membership level at the time they visited the hotel (Membership Level) was also included as a categorical variable (i.e., $\text{Membership Level} \in \{\text{No Membership}, \text{Membership Tier 1}, \text{Membership Tier 2}, \text{Membership Tier 3}\}$).

The unique feature of this data is that it contains the information about which distribution channel the customer purchased the hotel room through. Since the widely used behavioral loyalty metrics, customer retention, and share of wallet are often not available in hospitality transaction settings, we use the channel selection as an alternative. Therefore, we use the booking channel as a binary dependent variable – one, if booking directly from the hotels' website, zero otherwise. The data covers a period of 30 months, from July 2015 to December 2018.

As the objective of our research is to analyze the effect of email communication between customer and manager, we reduced the data set to one that only included the customers who responded to the CSSs at least once throughout the data range. In addition, we excluded customers who have a limited history of hotel bookings (less than three repeat purchases). As a result, the dataset contains 84,917 booking transactions from 515 hotels and 32,707 unique customers. Given the computational challenge of our Bayesian approach, which involves a lengthy parameter estimation process when using such a large data set, we randomly sampled 2000 individuals for our analysis. The descriptive statistics are reported in Table 4.1.

Table 4.1: Data Descriptive Statistics

| Variable | Description | Mean | Min | Max |
|---|---|---|---|---|
| ***Dependent variable*** | | | | |
| $m$ | Dummy for direct booking | 0.62 | 0 | 1 |
| ***State transition variables (Predictors for the enduring effects)*** | | | | |
| FeedBack | Response event and ratings as a categorical variable | 4.00 | 1 | 4 |
| ManagerResponse | Dummy for managerial response | 0.69 | 0 | 1 |
| Apology | Dummy for managerial apology | 0.14 | 0 | 1 |
| ManagerResponseLength | Logarithm of the number of words included in the managerial response | 4.72 | 3.22 | 6.81 |
| SpeedResponse | Logarithm of the gap of the number of days between the customer survey submit and the managerial response | 0.78 | 0.69 | 4.94 |
| ***State dependent variables (Predictors for the short-term effects)*** | | | | |
| Member | Membership program as a categorical variable | 2.16 | 1 | 4 |
| Hotel | Hotel ID as a categorical variable | 274.79 | 1 | 506 |
| Quarter | Every three-month period as a categorical variable | 6.07 | 1 | 10 |
| Price | Price for a single night | 106.91 | 21.71 | 359.10 |
| Nights | The number of stayed nights for the particular stay at time $t$ | 1.62 | 1 | 25 |

## 4.5 Model

We use a hidden Markov model (HMM) to investigate the effectiveness of managers' post-purchase interactions on customers' channel selection in a dynamic manner. HMM has been widely used in marketing to understand the transition process of finite sets of hidden states. Interestingly enough, despite its benefit as introduced in [68, 7], this model has rarely been used in the service research. The transition process is affected by a number of time-varying covariates, which includes the customer feedback information and the managerial responses. The probability of the customer deciding to book directly depends on which state the customer belongs to at the moment he/she books a hotel room.

We consider a set of customers, each of whom repeatedly booked from the same chain hotels in our data. We estimate the direct-booking decision of the customer from a conditional likelihood in each state, which is a typical setting in an HMM. Both the customer feedback and the managerial response to those who participated in the CSS affect the latent state of a customer in a stochastic way. The probability of direct booking is dependent on the latent state of a customer. In the following section, we describe the main components of our HMM.

**Loyalty State Evolution**

$$Q_{i,t-1\to t} = \begin{pmatrix} q_{it11} & \cdots & q_{it1S} \\ \vdots & \ddots & \vdots \\ q_{itS1} & \cdots & q_{itSS} \end{pmatrix} \tag{4.1}$$

where $q_{itss'} = P(S_{it} = s'|S_{it-1} = s)$ is the conditional probability of individual $i$ moving from state $s$ at time $t-1$ to state $s'$ at time $t$ and $S$ is the number of latent states in the model.

$$\begin{aligned} P(s_{it} = 1|s_{it-1}) &= \frac{exp(\mu(1)_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})}{1 + exp(\mu(1)_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})} \\ P(s_{it} = 2|s_{it-1}) &= \frac{exp(\mu(s')_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})}{1 + exp(\mu(s')_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})} \\ &\quad - \frac{exp(\mu(s'-1)_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it}a_s})}{1 + exp(\mu(s'-1)_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})} \\ &\cdots \\ P(s_{it} = S|s_{it-1}) &= 1 - \frac{exp(\mu(S-1)_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})}{1 + exp(\mu(S-1)_{is} - \omega_{s,FeedBack_{it-1}} - \boldsymbol{x'_{it-1}a_s})} \end{aligned} \tag{4.2}$$

The customer feedback-specific parameter $\omega_{s,FeedBack_{it-1}}$ and the managerial response-specific vector of parameters $\boldsymbol{a_s}$ are the intercept and coefficients that we are particularly interested in. It is worth noting that the variables that predict the state transition probabilities should have an enduring impact (as compared to immediate impact). Customers' memory of the relationship with the manager is long-lasting and forms the perception about the brand, which, in turn, influences all subsequent transactions. Therefore, both the customer's feedback and the managerial email response are considered to induce a long-term effect on customer brand loyalty. The feedback intercepts $\omega_{s,FeedBack_{it-1}}$ capture the average state-transition propensity of each of the prior feedback (i.e., No feedback, Negative feedback, Neutral feedback, and Positive feedback) from customer $i$ at the given loyalty state $s$. The set of lagged variables in vector $\boldsymbol{x'_{it-1}}$ defines the attributes of hotel managers' email responses after customer $i$'s prior hotel stay. These variables include whether the manager responded to the customer feedback (ManagerResponse), whether the response includes an apology (Apology), the length of managerial response (ManagerResponseLength), and the speed of managerial response (SpeedResponse). It should be noted that our modeling approach assumes that these customer-hotel interactions occur, and are observed, prior to the next hotel room booking.

For the initial state distribution $\pi$, we follow [68]. Initial distribution is defined as the stationary distribution of the transition matrix if the transition matrix of an HMM is time-homogeneous. However, since our HMMs transition matrix is time-variant, we set all covariates to zero to calculate the stationary distribution. This approach has been found to be similar to setting all covariates to their mean and calculating the stationary distribution.

**State Dependent Channel Selection** Customers' decision for direct booking is independent, given the customer's loyalty state. Thus, the probability of customer $i$ booking directly from the hotel's website at time $t$, given the loyalty state $s$, could be modeled as the following binary logit model,

$$m_{it|s} = \frac{exp(\tilde{\beta}_{0s} - \varphi_{Quarter} - \vartheta_{Hotel} - \gamma_{Memeber} - \boldsymbol{z}'_{it}\boldsymbol{\beta}_s)}{1 + exp(\tilde{\beta}_{0s} - \varphi_{Quarter} - \vartheta_{Hotel} - \gamma_{Memeber} - \boldsymbol{z}'_{it}\boldsymbol{\beta}_s)} \tag{4.3}$$

where $\tilde{\beta}_{0s}$ is the state-specific coefficient for state $s$ and $\boldsymbol{\beta}_s$ is a vector of state-specific coefficients for the post-survey interactions and $z'_{it}$ is a vector of time-varying covariates associated with the booking channel selection of customer $i$ at time $t$. Contrary to the state transition matrix, these state-dependent choice probability estimates should include the variables having a direct and immediate impact on the choice of observable outcomes. In the hotel booking context, price (Price) and the number of nights the customer stayed (Nights) are variables with short-term influence on the decision of booking channel. Furthermore, we also consider the hotel-specific ($\vartheta_{Hotel}$), time-specific ($\varphi_{Quarter}$), and reward-membership-specific ($\gamma_{Memeber}$) intercepts to capture the heterogeneity at each level. The intercepts $\vartheta_{Hotel}$ and $\varphi_{Quarter}$ are included to control for the effect of promotions done by certain hotels or during certain periods. While we argued that the price listed in OTAs and hotels' own websites are the same due to the rate parity agreement, we found that sometimes hotels offer lower prices to customers who register for a reward membership program and log in to the hotel website using the created account. Thus, the intercept $\gamma_{Member}$ controls for the possible increase in the direct booking propensity due to the advantages for each membership level. To ensure identification of the states, we restrict the choice probabilities to be nondecreasing in the relationship states. Thus, the restriction $\tilde{\beta}_{01} \leq \tilde{\beta}_{02} \leq \cdots \leq \tilde{\beta}_{0S}$ is operationalized as,

$$\tilde{\beta}_{0s} = \beta_{01} + \sum_{s'=2}^{s} exp(\beta_{0s'}) \tag{4.4}$$

### 4.5.1 Empirical Results

We describe the results obtained by estimating the models described in the previous section. We estimated the parameters using a MCMC hierarchical Bayes procedure, as suggested by [68]. We ran three parallel chains that each had 2,000 iterations. After discarding the first 1,000 iterations as a burn-in period, we used the last 1,000 iterations to estimate the conditional posterior distributions. We implemented the model using Stan [14], and we confirmed that the model converged using [27]s potential scale reduction factor.

The interpretation of the two states was determined by the state-specific intrinsic propensity for direct booking (the parameters $\beta_{01}$ and $\beta_{02}$). We confirmed that with a 100% chance, the estimate of the high loyalty intercept $\beta_{02} = -0.34$ was greater than the low loyalty intercept $\beta_{01} = -0.96$. For ease of interpretation, we set the covariates price and nights at zero and calculated the conditional probability of each state. The conditional probability of direct booking given state 1 was 45.99%, and the conditional probability of direct booking given state 2 was 50.71%. Accordingly, we labeled these respective states as low loyalty and high loyalty states. Obviously, managers may want their customers to belong to the high loyalty state which has higher direct booking probability. We assume that while customer feedback and managerial responses contribute to the change in loyalty-state transition probabilities, all other variables may have short-term effects that change the probability of direct booking given their loyalty states at time $t$. Figure 4.1 presents the framework of our study.

**Customer feedback on loyalty state transition** In Figure 4.2 and Figure 4.3, we plot the posterior distributions of the customer feedback parameters (i.e., $\omega$) for each low and high loyalty customers, respectively. The parameter estimates of the

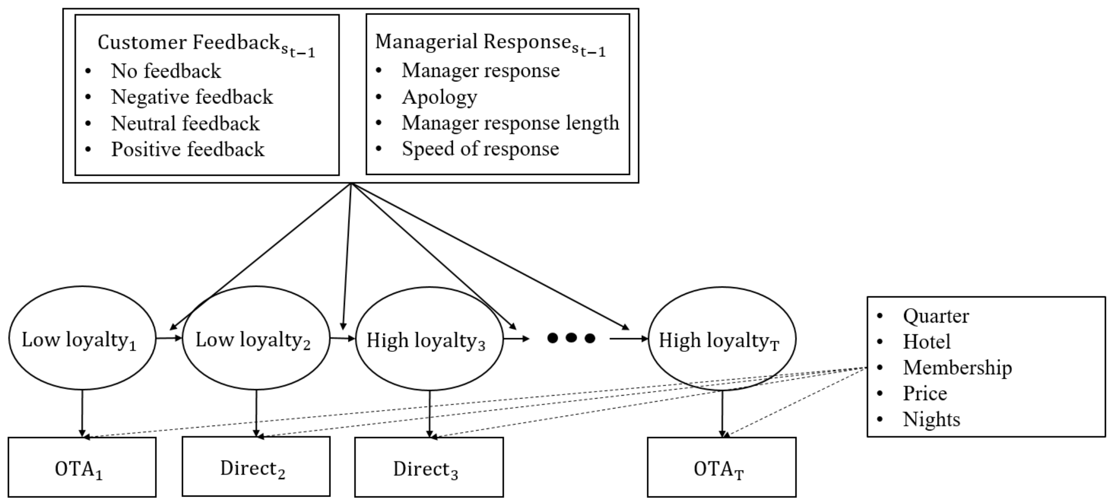



Figure 4.1: Conceptual Framework.

low loyalty customers in Table 4.2 which is plotted in Figure 4.2 demonstrate that except for complaining, all other feedback behaviors, which include withholding and providing neutral or positive feedback, had a significantly low tendency to transition to a higher loyalty state. We confirmed that with a 97.2% chance, the estimate of complaining (i.e., $\omega_{12}$) was greater than the estimate of withholding (i.e., $\omega_{11}$). With 96.4% and 96.3% chances, respectively, the estimate of complaining was greater than the estimates of neutral and positive feedback. Therefore, we confirm that, once we observe the low loyalty customers' complaining behavior, it is highly likely that they are willing to transfer their loyalty state to a higher level. This is a robust and quantitative observation which conforms with recent studies that suggest negative customer voices are associated with increases in loyalty [82, 60, 8]. However, such effect difference was not found from the high loyalty customers (see Figure 4.3). No matter what feedback we observe from the high loyalty customers, those behaviors strongly signal that the customer is willing to transfer to a high loyalty customer in the future again.

Table 4.2: Posterior Means of the Effect of Customer Feedback

| | | State | |
|---|---|---|---|
| | Parameters | Low loyalty | High loyalty |
| No feedback | $\omega_{\cdot 1}$ | **-1.31 [-1.95, -0.68]** | **3.70 [3.24, 4.21]** |
| Negative feedback | $\omega_{\cdot 2}$ | -0.10 [-1.21, 0.99] | **3.69 [3.03, 4.38]** |
| Neutral feedback | $\omega_{\cdot 3}$ | **-1.15 [-1.79, -0.52]** | **3.83 [3.41, 4.27]** |
| Positive feedback | $\omega_{\cdot 4}$ | **-1.18 [-1.87, -0.55]** | **3.90 [3.46, 4.35]** |

**Managerial apology on loyalty state transition** Table 4.3 reports how customers transition between loyalty states. None of the estimates except the apologies to the high loyalty state customers were significantly different from zero. The email apologies after service failures significantly increased customer future brand loyalty, but this was only the case for the high loyalty customers (i.e., $a_2 = 0.75$). We did not find evidence of similar benefits for low loyalty customers. This result suggests that only customers who have certain level of trust about the brand, may perceive the apology as an effective tool to recover the damaged relationship.

Table 4.3: Posterior Means of the Effect of Managerial Responses

| | | State | |
|---|---|---|---|
| | Parameters | Low loyalty | High loyalty |
| ManagerResponse | $a_{\cdot 1}$ | -0.05 [-1.94, 1.87] | -1.30 [-2.87, 0.40] |
| Apology | $a_{\cdot 2}$ | 0.75 [-0.20, 1.70] | **0.75 [0.08, 1.46]** |
| ManagerResponseLength | $a_{\cdot 3}$ | -0.01 [-0.44, 0.41] | 0.15 [-0.22, 0.50] |
| SpeedResponse | $a_{\cdot 4}$ | 0.44 [-0.01, 0.90] | 0.01 [-0.24, 0.29] |

**Transaction-specific Short-term Effects** Table 4.4 evaluates the average direct booking tendency of each of the membership tiers. The average direct booking tendency was lowest for those who were not enrolled in the reward membership program of the hotel brand in our study (i.e., −6.06). Once the customers enrolled in the reward membership program, their direct booking tendency became close to zero, which was significantly higher than those who had no membership. As

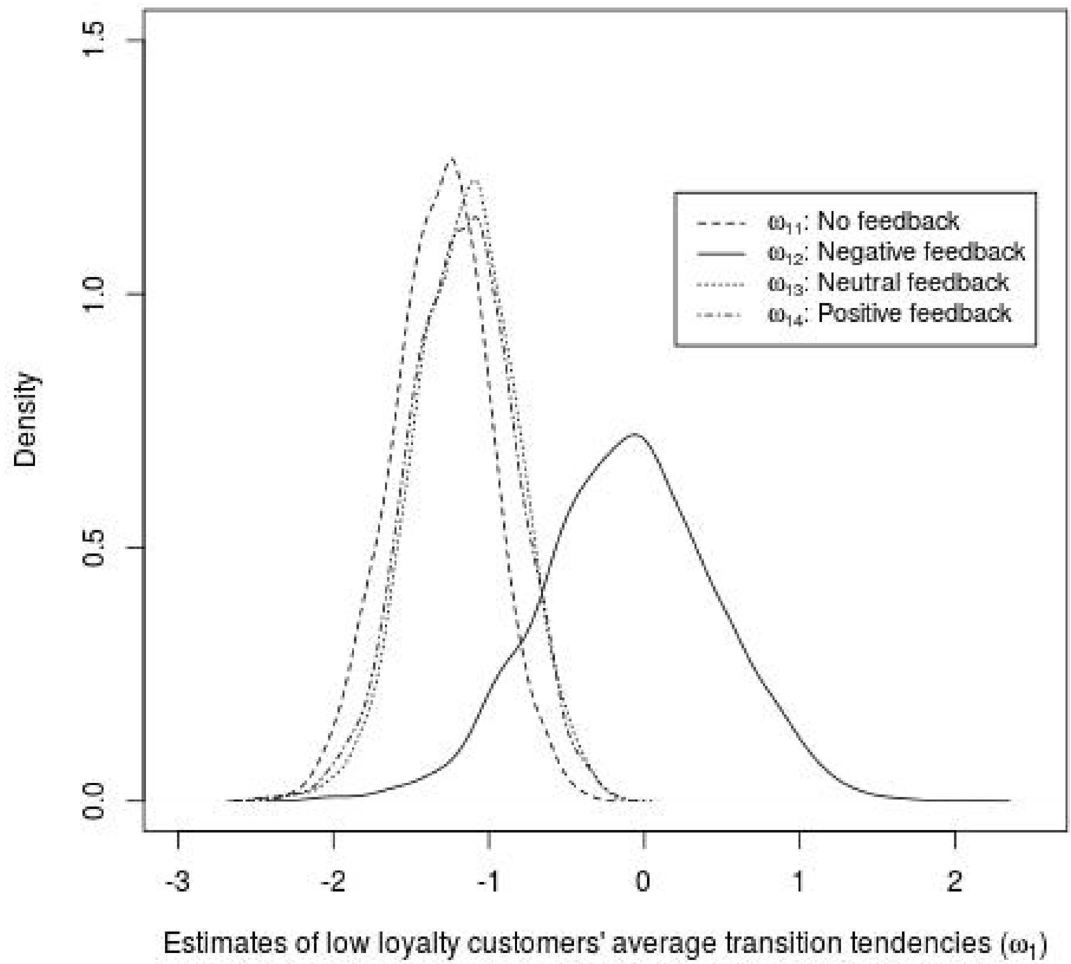



Figure 4.2: Posterior distribution of low loyalty customers' feedback on loyalty transition.

the customers earned higher membership levels, the average tendency to book directly increased as well. This result suggests that a hotels reward membership program has a significant effect on direct booking tendencies. All other parameters in our model were estimated conditional on the unobserved heterogeneity caused by these different membership levels. Given that our model captures the consumer behavior that customers who had higher membership levels were more likely to book directly to take advantage of their membership statuses, we sug-

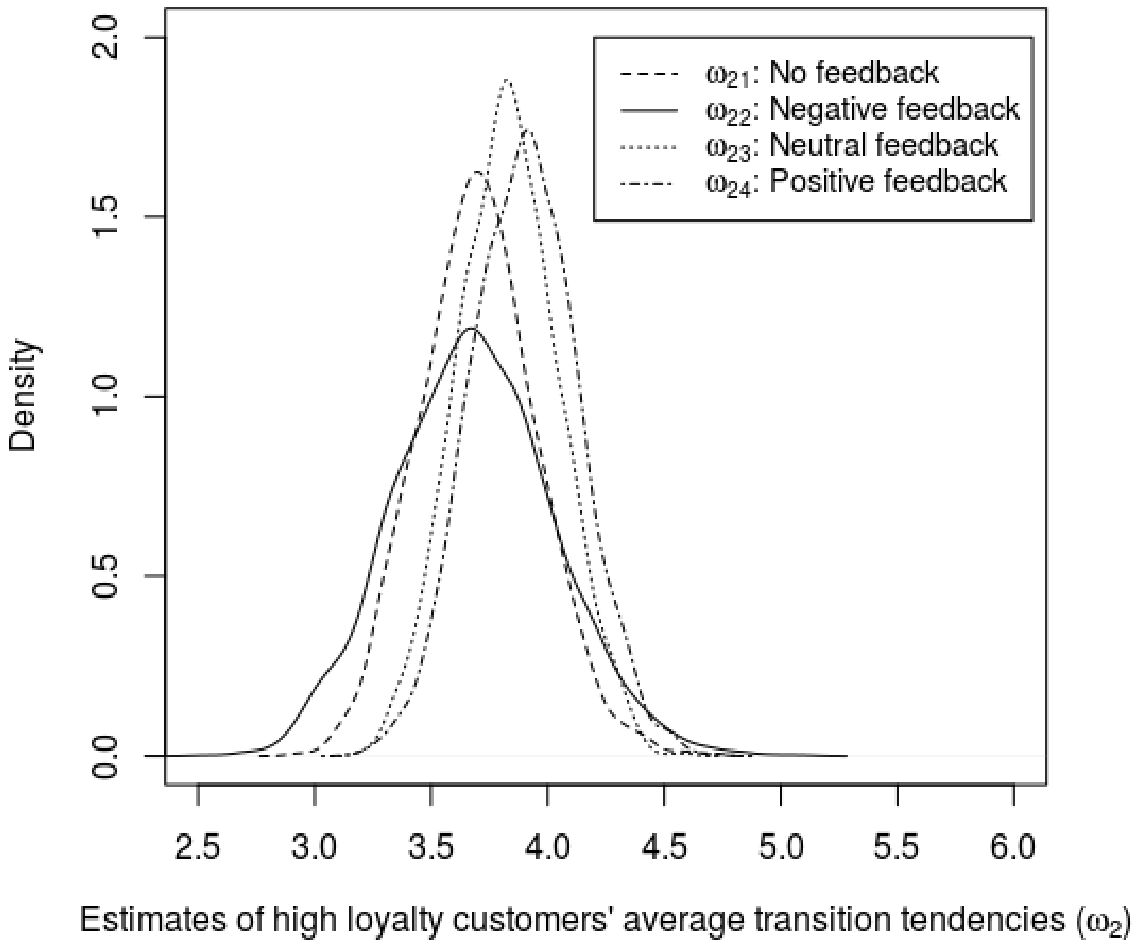



Figure 4.3: Posterior distribution of high loyalty customers' feedback on loyalty transition.

gest that our binary direct booking variable is valid for investigating the actual customers loyalty behavior.

Due to the rate parity agreement, prices on both OTA and hotels website are supposed to be the same unless the customer creates a reward membership account and login the hotel website using this account. Therefore, this result may indicate that the higher the price, the higher the probability that customers visit

Table 4.4: Posterior Means of the Effect of Membership Program

| Variables | Parameters | Intercepts |
|---|---|---|
| No Membership | $\gamma_1$ | **-6.06 [-7.21, -4.88]** |
| Membership Tier 1 | $\gamma_2$ | 0.82 [-0.21, 1.81] |
| Membership Tier 2 | $\gamma_3$ | **2.09 [1.07, 3.08]** |
| Membership Tier 3 | $\gamma_4$ | **2.19 [1.17, 3.20]** |

to the hotel website to search for lower options. Although the customers realize that the prices are not different across the two channels, they end up booking at the hotel website rather than going back to the OTAs. The higher price effect of the low loyalty customers (i.e., $\beta_{11} = 0.98$) than the high loyalty customers indicates that low loyalty customers are more price sensitive for direct booking than the high loyalty customers (i.e., $\beta_{21} = 0.02$).

Table 4.5: Posterior Means of the Effect of State Dependent Probabilities

| | | State | |
|---|---|---|---|
| | Parameters | Low loyalty | High loyalty |
| Price | $\beta_{\cdot 1}$ | **0.98 [0.22, 2.42]** | **0.02 [0.02, 0.02]** |
| Nights | $\beta_{\cdot 2}$ | 0.17 [-1.51, 2.06] | **-0.26 [-0.33, -0.18]** |

**Effects of complaints and apology on loyalty state transition** We now describe the effect of past managerial email responses on loyalty state transition probability. As shown in Table 4.6, we investigated the effects of time-varying covariates on transitions between states. Specifically, we compared the effect of customers complaining behavior and managerial email apologies. The No feedback case in Table 4.6 corresponds to the transition matrix in which we assumed that none of the customers had replied to the CSS request. In the second scenario, we randomly selected 50% of all the transactions and assumed that those were followed by the negative feedback of the customers, though the manager had not responded to any of these complaints. As shown in the transition matrix under the second scenario in Table 4.6, the customer complaints made low loyalty customers more likely to transition to a high loyalty state. The fact that the average transition probability increased from 25.5% to 35.55% is statistically significant at the 5% level. The right-hand matrix in Table 4.6 demonstrates the average effect of the managerial apologies on the loyalty state transitions. We assumed that the managers responded to all the negative feedback of the customers that we assumed in the second scenario. Writing an email apology made the already highly loyal customers 1% more likely to stay in a high loyalty state. These results suggest that both customer complaints and managerial apologies significantly increase future brand loyalty, depending on the current loyalty state.

Table 4.6: The Mean Posterior Transition Matrices

| | No feedback | | Complaints without apology | | Complaints with apology | |
|---|---|---|---|---|---|---|
| | t | | t | | t | |
| t-1 | Low loyalty | High loyalty | Low loyalty | High loyalty | Low loyalty | High loyalty |
| Low loyalty | 74.5 % [ 33.3 %- 96.37 %] | 25.5 % [ 3.63 %- 66.7 %] | 64.45 % [ 23.42 %- 93.87 %] | 35.55 % [ 6.13 %- 76.58 %] | 58 % [ 20.92 %- 90.28 %] | 42 % [ 9.72 %- 79.08 %] |
| High loyalty | 4.09 % [ 0.52 %- 14.93 %] | 95.91 % [ 85.07 %- 99.48 %] | 4.15 % [ 0.51 %- 15.31 %] | 95.85 % [ 84.69 %- 99.49 %] | 3.25 % [ 0.38 %- 12.22 %] | 96.75 % [ 87.78 %- 99.62 %] |

**Monetary Effect of Managerial Response** A related managerial question might be as follows: how much of the OTA commission fees could be saved by sending apologies to those who voiced negative feedback? Since a typical commission rate in the industry is 15% [96], we can easily predict the commission fees that the hotel brand would have to pay under different scenarios. To calculate the predicted marginal commission fee, we multiplied the commission percentage by the hotel price that the customers paid for each booking. We then multiplied this by the predicted probability that the booking was made through an OTA under specific conditions. The filtering probability that individual $i$ is in state $s$ at time $t$ conditioned on the individuals history of choices is given by [68].

$$\begin{aligned} &P(S_{it} = s|Y_{i1}, Y_{i2}, \ldots, Y_{it}) = \\ &= \boldsymbol{\pi \tilde{m}_{i1} Q_{i,1\to 2} \tilde{m}_{i2} \ldots Q_{i,t-1\to t.s}} \tilde{m_{it|s}} / L_{it} \end{aligned} \tag{4.5}$$

In Table 4.7, we report the total commission fees that the hotel brand would have to pay under three different scenarios. For the default scenario, we assumed that the manager had never responded to the current negative and neutral feedback of the customers. Then, the first, second, and third scenarios assumed that 50%, 75%, and 100% of these voices had received apology emails, respectively. As shown in the second row of Table 4.7, the additional commission fees that hotels can save by apologizing for the service failure were relatively small for our 2,000 individual samples (i.e., 1st scenario: 268.14 dollars; 2nd scenario: 401.57 dollars; and 3rd scenario: 491.55 dollars). However, once we applied this amount to all 84,917 transactions of 32,707 individuals that we filtered after cleaning the data, the amount became meaningful to the hotel brand. Moreover, this amount becomes even larger as the number of customer visits to the hotel brand increases.

Table 4.7: Predicted savings under each apology scenario

| | Scenario 1 (50%) | Scenario 2 (75%) | Scenario 3 (100%) |
|---|---|---|---|
| 2,000 individuals in our analysis | $268.14 | $401.57 | $491.55 |
| All 32,707 individuals | $2,921.47 | $4,375.15 | $5,355.55 |

## 4.6 Discussion

In this paper, we examined the dynamic effect of customer-hotel post-survey email communications on customer brand loyalty. Specifically, we investigated how customer complaints and managerial apologies within post-service interactions affected future customer loyalty. As a loyalty behavior in our hospitality context, we used the booking channel that the customers chose as our dependent variable. However, to account for the endogeneity problem in the longitudinal model, we used the HMM. We used this model to examine how the customers post-purchase feedback and the managerial email responses dynamically transitioned individual loyalty states.

We demonstrated that the complaints of low-loyalty customers have a greater impact on future brand loyalty. Therefore, once low-loyalty customers' complaints are observed, this might be a strong signal they are likely to transition to a higher loyalty level. While email apologies have no significant effect on future loyalty for low-loyalty customers, we find that sending these apologies has a greater impact on future loyalty when they are sent to high-loyalty customers. Therefore, we suggest that these apologies are more effective if the customer has a damaged relationship that needs to be recovered. While the customer–manager post-survey interaction changes the customers' brand loyalty state, there are also transaction-specific attributes that have short-term effects on customers' booking behavior. Specifically, we found that the reward membership program and higher price of the hotel room strongly attract customers to book directly.

This research is particularly relevant for firms that allow customers to purchase either through their own channels or through an agency in which they have to pay a commission fee. Because the commission fees become larger as the agencies grow, many firms have been looking for a way to convert the customers who make purchases through the agencies to their own channels instead. We approached this problem by making a rational assumption that channel selection is driven by customer loyalty. Thus, increasing the chance of a customer booking directly from a firms distribution channel is the same as increasing customer loyalty. Specifically, our study provides strong evidence that post-service email communications increase customer loyalty.

The managerial implication for hospitality marketers who want to empirically understand their customers loyalty is also noteworthy. Prior loyalty studies have predominantly used behavioral metrics that are hardly applicable to hospitality industries, such as retention and share of wallet. As an alternative, we suggest that the booking channel through which the customers choose to purchase services can be used as a behavioral loyalty metric. For managers, we suggest that this metric is superior to the other two behavioral loyalty metrics because it allows them to detect a loyalty decrease before a customer entirely churns.

This research has implications for firms that have interactive feedback systems in which managers can respond individually to customers following consumer feedback. As our proposed HMM model requires only the customers channel selection data from the booking records, managers can easily apply this model to evaluate how effectively they can communicate with the customers who provided feedback through the CSS.

Several limitations should be acknowledged and addressed in future research. First, given the limitations of the data, we did not include the hotel price difference between the OTAs and the hotels website. Although we accounted for the customers reward memberships, which is the only factor that allows customers to take advantage of the price discount, the larger price differences may attract more customers to book directly than lower price differences. Future work might consider how large the price difference between the two channels is for a specific hotel in the customers booking periods. Second, our model does not consider how the customers browsing behavior for a given visit might influence their final purchase decision on a given channel. It might have been possible that an OTA sent the customers a commercial email asking them to visit their website, which may have had a greater impact on the customers purchase decisions than reduced loyalty. The opposite situation may occur as well. For example, prior research has reported evidence that a customer who finds a hotel from an OTA may be more likely to visit the hotels official website, which is called the billboard effect [1]. It would be fruitful to integrate each customers website history up until the customer makes a final purchase decision.

CHAPTER 5

# SUMMARY

Conducting CSS has become so prevalent that many firms have started to outsource to market research companies that develop a customer interaction system and design questionnaires for the firm. This practice is perceived as more important in the service industry, due to the ability to track the inconsistent quality of the service. Considering its popularity, however, our understanding of this practice is limited.

The first chapter provides an overview of the typical CSS process. In Chapter 2, regular self-motivated online hotel ratings collected from TripAdvisor were compared with the ratings that went through the CSS before being posted online. Using a random-intercept logistic regression, I demonstrated that customer intention to post an online hotel review varies, depending on the level of customer satisfaction. Online reviewers are more motivated to post extreme and negative ratings. However, this underreporting bias is mitigated when ratings are generated by reviewers who are familiar with the online review posting process. This study implies that without firms' intervention with CSS, customer eWOM behavior is more likely to be negatively biased, due to customers' intrinsic motivation to post negative reviews.

While Chapter 2 discusses the effect of conducting CSS itself, Chapters 3 and 4 focus on the effects of the interactive nature of CSS. In Chapter 3, I investigated how managerial email responses to the CSS affect future customer satisfaction, and, in turn, customer online review posting. I conducted a natural experiment in which hotel managers were given the opportunity to respond to customer comments through written communication. I then analyzed the impact of specific characteristics in managerial responses to customer feedback. First, I found that personalized apologies to dissatisfied customers increase future customer satisfaction. Second, I found that fast responses directly increase online review posting. Lastly, I found that personalized apologies indirectly decrease customers' motivation to post negative online reviews. These findings suggest that facilitating effective communication with customers at the post-purchase stage can change customers' future attitudes and behavior with respect to the firm.

As a natural extension of the research in Chapter 3, Chapter 4 studies how customer participation in CSS and the managerial email responses to these customers affect customer future loyalty. In this study, I found that the complaining behavior of customers who have a lower loyalty state is positively associated with higher future loyalty. I also found that sending an email apology to the complainants increases customers' future brand loyalty, but only for those who are already at the higher loyalty state. This finding implies that customers evaluate service recovery and update their loyalty to the hotel. Therefore, complaints from low loyalty customers are a rather good signal for managers to invest more effort into writing apologies to loyal customers.

This research is limited by the endogeneity problem, where any changes in customer outcomes (e.g., satisfaction, eWOM, or loyalty) can be due to unobserved firm-level or customer-level changes during the data collection period. For example, hotels may change the way they respond to customers' feedback. Thus, in future research, I should measure the complex quality of managerial responses from different dimensions, using the recent text analytic techniques. Another example where a potential endogeneity issue arises is when customers' browsing history affects their hotel booking behavior. Prior research shows that the sequence of visited web-pages and the content of each page can influence customers' purchase behavior [34, 65]. In order to account for prior browsing behavior, I could use customers' website tracking data to investigate whether a specific website visit affects a customers purchase behavior, which is something I could not observe from the CSS data.

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