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# Essays on the Influence of Review and Reviewer Attributes on Online Review Helpfulness: Attribution Theory Perspective

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# ESSAYS ON THE INFLUENCE OF REVIEW AND REVIEWER ATTRIBUTES ON ONLINE REVIEW HELPFULNESS: ATTRIBUTION THEORY PERSPECTIVE

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ABSTRACT

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With the emergence of digital technology and the increasing availability of information on the internet, customers rely heavily on online reviews to inform their purchasing decisions. However, not all online reviews are helpful, and the factors that contribute to their helpfulness are complex and multifaceted. This dissertation addresses this gap in the literature by examining the antecedents that determine online review helpfulness using attribution theory. The dissertation consists of three essays. The first essay examines the impact of authenticity (review attribute) on review helpfulness, showing that the expressive authenticity of a review enhances its helpfulness. The second essay investigates the relationship between the reviewer attributes i.e., motivation, activity, and goals in online reviews. The study employs various machine. learning techniques to investigate the influence of these factors on reviewers' goal attainment. The third essay explores how the reviewer attributes are related to the helpfulness of online reviews. The dissertation offers significant theoretical and practical implications. Theoretically, the dissertation provides new insights into novel review and reviewer attributes. The study proposes a taxonomy of online reviews using means-ends fusion theory offering a framework for understanding the relationships between different components of online reviewer attributes and

their contribution to the attainment of specific goals, such as emotional satisfaction. The study also highlights the importance of understanding the motivations and activities of online reviewers in predicting emotional satisfaction and the conditional effects of complaining behavior on emotional satisfaction. The findings inform review platform owners, business owners, reviewers, and prospective consumers in decision-making through helpful reviews. To review platform owners, the findings help segregate helpful reviews from the humongous number of reviews by determining the authenticity of the review. To business owners, the findings can help in understanding consumer behavior and taking necessary actions to provide better service to their customers. To reviewers, this dissertation can act as a guideline to write helpful reviews and to determine their helpfulness. Finally, to consumers or review readers, this dissertation provides an understanding of helpful reviews, thus allowing them to take product or service purchase decisions.

# DEDICATION

To my loving parents, friends, and well-wishers, in humble acknowledgment and wholehearted appreciation of the unwavering support, patience, and love, I dedicate this dissertation to you. To my dearest parents, for being my rock and my refuge. It is from you that I inherited my unquenchable thirst for knowledge, and you have continuously encouraged me to follow my curiosity, no matter where it led. Without your sacrifices, none of this would have been possible. You taught me that the road to achievement is not always smooth but filled with challenges that shape and grow us. It's your enduring faith in my potential that has fueled my journey to this moment. To my steadfast friends, who have been my second family throughout this journey. Your unyielding belief in me, even in times when I faltered in my own faith, has been invaluable. It is your friendship that has sustained me during the trying periods of this pursuit, and for that, I am forever grateful. To all my well-wishers, mentors, and teachers, whose guidance has been a beacon throughout this journey. The faith you had in my capabilities, even when they were not readily apparent, inspired me to reach beyond the horizon. Your constructive criticisms and advice have been instrumental in making this dissertation, and me, better. I am profoundly grateful for your unwavering support and enduring love. The completion of this work is not just my achievement but also a testament to the village that raised and nurtured me. Thank you.

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# CHAPTER I

## THREE-ESSAY DISSERTATION SYNOPSES

Online reviews have become an integral part of the consumer decision-making process in today's digital age. With the rise of e-commerce and the increasing availability of information on the internet, customers are more reliant on the experiences and opinions of others to inform their purchasing decisions. The importance of online reviews lies in the fact that they provide valuable information to potential customers, such as product or service quality, reliability, and customer satisfaction. They can also help customers make informed decisions by providing insight into the experiences of others, thereby reducing the risk of an adverse purchase. Moreover, online reviews can serve as a source of feedback for businesses, helping them improve their products and services, and increase customer satisfaction (Chevalier & Mayzlin, 2006). The helpfulness of online reviews has been the focus of much research in recent years, as it has a direct impact on the credibility and authenticity of these reviews.

However, not all online reviews are equally helpful or trustworthy. The helpfulness of a review depends on several factors, such as the content of the review, the credibility of the reviewer, the time and context in which the review was written, and the platform on which the review was posted (Dellarocas, 2003). For example, a review that provides detailed and specific information about the product or service, such as its pros and cons, is likely to be more helpful than a review that is vague or simply says "I liked it." without any explanation behind the liking.

Similarly, a review written by an individual who has purchased and experienced the product or service is generally considered to be more authentic and credible than a review written by someone who has not by verifying the purchase (a widely available feature on various digital platforms). A study by Sahoo et al. (2018) found that online reviews have a significant influence on purchase decisions, with as many as 70% of participants reporting that they consult online reviews before making a purchase. Another study by Lu and Rui (2018) found that online reviews have a positive impact on purchase intention, especially when the reviews are perceived to be trustworthy and credible. Overall, as the number of online reviews continues to grow, it is important for both businesses and consumers to understand the factors that contribute to the helpfulness of these reviews and how they can be used to make informed decisions.

This dissertation focuses on the antecedents that can determine online review helpfulness using attribution theory. The research objective is to explore specific review attributes and reviewer attributes and their influence on the helpfulness of an online review. From the review perspective, I explore the impact of the authenticity of the review on helpfulness by developing a theory using the decision tree induction approach. Utilizing Means-Ends Fusion theory (MEF), I examined various motivations (i.e., altruistic, expression of emotions, product/service involvement, vengeance, and self-enhancement), activities (i.e., feedback and complaint), of the reviewer and how they help the reviewer to reach specific goals (i.e., emotional satisfaction, financial gain, damage to business, and other goals). As the reviewer attributes, I explore the various motivations, activities, and goals of the reviewers and how they are related to the review's helpfulness. This dissertation offers significant theoretical and practical implications.

Theoretically, this dissertation offers a taxonomy of online reviews (ORs) using MEF theory, providing a framework for understanding the relationships between different components of ORs and their contribution to the attainment of specific goals. The research highlights the importance of understanding the motivations and activities of online reviewers in predicting goals. The study also finds a moderating relationship between activity and goal in ORs, suggesting that different types of reviewers may require different types of tools and features. Additionally, the study examines the influence of authenticity on online review helpfulness, showing that the expressive authenticity of a review can enhance its helpfulness. The research also explores the differences in sibling rules that foster the recommendation of personalized services, using Decision Tree (DT) induction to derive propositions that are subjected to empirical statistical analysis.

Practically, the findings from the dissertation inform review platform owners, business owners, reviewers, and prospective consumers in decision-making through helpful reviews. To review platform owners, the findings will help segregate helpful reviews among the humongous number of reviews by determining the authenticity of the review. To business owners, the findings can help in understanding consumer behavior thus taking necessary actions to provide better service to their customers. To reviewers, this dissertation can act as a guideline to write helpful reviews. Finally, to consumers or review readers this dissertation provides an understanding of helpful reviews thus allowing them to take product or service purchase decisions.

Essay 1: How Does the Authenticity Attribute of an Online Review Affect Its Helpfulness? A Decision Tree Induction Theory Development Approach

The concept of the helpfulness of online reviews is complex and influenced by several factors. There have been studies on the relationship between review helpfulness and factors such as sentiment, valence, truthfulness, and length of the review. However, the authenticity of a review, i.e., whether it accurately represents the business or simply the reviewer's opinion has not been examined.

In this essay, I examined the influence of two types of authenticity (nominal and expressive) on helpfulness. I argue that the authenticity of a review plays a significant role in its helpfulness. Using qualitative and quantitative analysis (text analysis) I identified the nominal and expressive authenticity of reviews from two different platforms. In the first study, the decision tree induction approach is used to examine the main and interaction effects of the two dimensions of authenticity on review helpfulness. Results show that expressive authenticity's word density is the most significant predictor of online review helpfulness. However, the effect of expressive authenticity sentence density, and nominal authenticity word density on helpfulness, varies depending on the expressive word density. In the second study, I verified the model generated from the decision tree through conventional analysis. This study offers new theoretical perspectives and practical implications for understanding the helpfulness of online reviews.

Essay 2: How do Reviewer Motivation and Activity attributes Help Achieve Goal: Extended Means-Ends-Fusion Theory in Online Review Context

Online reviews have become an increasingly popular way for consumers to share their opinions about products and services and for businesses to market their offerings. While previous research has explored online reviews from various perspectives, including the readers, businesses, and writers, a systematic understanding of the motivations behind online reviews and the outcomes associated with them has not been fully explored. This essay aims to address this gap in the literature by developing a systematic understanding of the motivations and activities associated with online reviews and investigating the relationships between reviewer motivation, activity, and goal.

To achieve these objectives, I use various machine learning techniques to investigate the influence of motivations and activities on reviewers' goal attainment. The findings of this study will contribute to a deeper understanding of online review motivations and activities and their relationship to reviewers' goals.

Essay 3: How Reviewer Attributes are Related to Online Review Helpfulness: An Extended Means-Ends Fusion Theory Perspective

The helpfulness of online reviews is not always clear and may be influenced by reviewers' motivations and activities. This study aims to investigate the relationship between these factors and the helpfulness of a review. In the previous essay, I identified different motivations for writing an online review, such as expressing emotions, self-enhancement, and vengeance, and different activities, such as providing feedback and complaining, and the goal of attaining emotional satisfaction. In this study, I examined how these reviewer attributes are related to the helpfulness of an online review. By exploring these relationships, the study aims to provide insight into how online review platforms and businesses can use this information to improve the helpfulness of reviews for consumers. The results of this study will contribute to the understanding of the role of reviewers' motivations, activities, and goals in determining the helpfulness of an online review.

# CHAPTER II

# INTRODUCTION

## Overview

The helpfulness of online reviews is a decisive factor in the consumer's decision-making process, as it influences the trust consumers have in the product and the business owner. The helpfulness of online reviews is positively related to the credibility of the website, the comprehensiveness of the review, and the overall sentiment expressed in the review. The helpfulness of online reviews can be influenced by various factors including the authenticity of the reviews, and reviewer motivations, activities, and goals. Businesses should strive to provide high-quality, comprehensive, and personalized online reviews to increase consumer trust and ultimately provide better service to consumers.

## Motivation

The growing reliance on online reviews as a source of information has made them a crucial aspect of the purchasing decision-making process. With the increasing popularity of e-commerce, the number of online reviews has increased, and become an essential tool for consumers to evaluate the quality of products and services before making a purchase. Online reviews provide a wealth of information and can influence consumers in a variety of ways, making it essential to understand the impact they have on the purchasing process.

Recent studies have shown that online reviews can significantly impact consumer behavior (Chevalier & Mayzlin, 2006). The finding highlights the importance of online reviews in shaping consumer perceptions and decision-making. A study by Weisstein et al. (2017) found that consumers are more likely to purchase a product if it has a high number of positive reviews and is less likely to purchase it if it has a high number of negative reviews. This demonstrates the significance of online reviews to sway consumers' opinions and ultimately drive sales.

It is important to note that not all online reviews are created equal. It has been shown that the helpfulness of online reviews can vary significantly (Jindal & Liu, 2006). For instance, some reviews may provide detailed and in-depth information about a product or service, while others may only provide a one-line comment. It is important to understand how the helpfulness of online reviews affects consumer behavior, as it can provide valuable insights into how businesses can improve their online reputation and attract more customers. In light of these findings, there is a need for research on online reviews and their helpfulness. Such research can provide a better understanding of the impact online reviews have on consumer behavior, and how businesses can use them to their advantage. By examining the helpfulness of online reviews and their impact on consumer decision-making, businesses can gain valuable insights into how they can improve their online reputation and attract more customers. Further research on online reviews and their helpfulness is necessary to provide valuable insights for various stakeholders in the realm of online reviews.

## Statement of the Problem and Research Questions

Online reviews play a crucial role in the decision-making process of prospective consumers in digital and mobile commerce (Heydari et al., 2015). Digital opinion-sharing platforms, such as Yelp, allow individuals to share their experiences and emotions about products or services in the form of a review (Heydari et al., 2015). In recent years, the volume of online reviews, also known as user-generated consumer content posted on various digital platforms, has increased dramatically (Xu & Jin, 2022). However, this explosion of online reviews often leads to information overload for prospective consumers, reducing the value of the reviews (Jones et al., 2008; Lee et al., 2017; Miller, 1964; Xu & Jin, 2022; Zhang et al., 2022). To overcome this challenge, it is important to differentiate between helpful and unhelpful reviews.

Various factors have been identified in prior studies as influencing the helpfulness of online reviews (Rietsche et al., 2019). These include reviewer-related factors such as reputation (Chua & Banerjee, 2016), experience (Huang et al., 2015), and information disclosure (Ghose & Ipeirotis, 2010); and review-related factors such as rating (Yang et al., 2017), readability (Singh et al., 2017), affect (Willemsen et al., 2011), and the presence of anger versus anxiety in online reviews (Yin et al., 2020a; Yin et al., 2014). However, aspects such as the review's authenticity and reviewers' various motivations and goals, and their influence on helpfulness have not been examined. This dissertation seeks to address significant gaps in literature. First, I seek to explain how to review attributes and reviewer attributes influence online review helpfulness using attribution theory. Second, I study the influence of two types of authenticity (nominal and expressive) on helpfulness. Third, I seek to develop a systematic understanding of the motivations and activities associated with online reviews and investigate their relationship to the reviewers' goals. Finally, I will examine the relationship between reviewers' motivations and activities and the helpfulness of an online review, with the aim of providing insight into how online review platforms and businesses can improve the helpfulness of reviews for consumers.

The studies use various qualitative and quantitative analysis techniques, including text analysis and machine learning techniques, to examine the relationships between the variables.

Overall, the objective of this dissertation is to answer the research question: how does an online review attribute i.e., the authenticity of the review, and the reviewer attributes i.e., the motivation, activity, and goals of the reviewer impact review helpfulness?

The three studies are aimed at answering these questions, specifically.

a) How does the authenticity of an online review influence review helpfulness?
b) How do an online reviewer's motivations and activities influence reviewer goals?
c) How are online reviewer attributes related to online review helpfulness?

## Relevance and Contributions of the Study

The studies offer insights into the factors that contribute to online review helpfulness and reviewers' goal of attaining. This dissertation provides a new taxonomy of online reviews using MEF theory and highlights the importance of understanding reviewer motivations and activities in predicting emotional satisfaction. This research also identifies the conditional effects of complaining behavior on emotional satisfaction and the moderating relationship between activity and goal in online reviews. The study identifies two dimensions of authenticity in online reviews and shows that expressive authenticity can enhance review helpfulness. The study adds a more nuanced understanding of authenticity in the context of online reviews and provides insights for collaborative consumption. Also, the study tests for differences in sibling rules that foster recommending personalized services and demonstrates the importance of inductive theory building and testing. Overall, this dissertation contributes to a better understanding of the factors that drive online reviews and their impact on customer satisfaction and decision-making. The findings suggest that the motivations and activities of reviewers, context, authenticity, and emotions play an important role in shaping the perception and effectiveness of online reviews. The studies also provide implications for the design and evaluation of online review systems, suggesting that different types of reviewers may require different types of tools and features to encourage participation and engagement.

## Organization of the Research

The remainder of the study is organized as follows. Chapter 3 provides the theoretical framework and previous literature in attribution theory and online review helpfulness. Chapter 4 focuses on examining the impact of authenticity on review helpfulness. Chapter 5 examines various online reviewer motivations, activities, and goals. Chapter 6 discusses the role of reviewer motivations, activities, and goals on review helpfulness. Lastly, Chapter 7 summarizes the key findings, implications, identified limitations, and future research directions.

CHAPTER III

# THEORETICAL BACKGROUND

## Attribution Theory

Attribution theory is a psychological framework that seeks to explain how individuals make sense of the causes of events and behaviors. This theory seeks to understand the process of attributing causes to events, behaviors, and outcomes. The theory has its roots in social psychology and has been applied to various fields, including information systems. According to attribution theory, individuals tend to make dispositional attributions for positive outcomes and situational attributions for negative outcomes. This tendency is known as the "fundamental attribution error" (Jones & Davis, 1965). For example, when someone succeeds, people tend to attribute success to their personal qualities, such as intelligence or effort. On the other hand, when someone fails, people tend to attribute the failure to situational factors, such as a lack of resources or external constraints.

In the field of information systems, attribution theory has been used to explain various outcomes and behavior. For example, in a study by Kim and Malhotra (2005), the authors examined the role of causal attributions in the adoption of information technology. They found that users' causal attributions for the success or failure of technology play a significant role in their adoption decisions. When users attribute technology failures to internal factors, such as a lack of user skills, they are less likely to adopt the technology. Conversely, when users attribute technology failures to external factors, such as a lack of support or resources, they are more likely to adopt the technology. Another study by Kalankesh et al. (2020) applied attribution theory to the examination of user satisfaction with information systems. The authors found that users' attributions of causality play a significant role in their satisfaction with information systems. When users attribute the success of an information system to internal factors, such as the quality of the system or the user's skills, they are more likely to be satisfied with the system. On the other hand, when users attribute the failure of an information system to external factors, such as a lack of resources or support, they are less likely to be satisfied with the system.

Attribution theory posits that individuals make causal attributions to explain the behavior of others, as well as their behavior. This theory suggests that individuals are motivated to explain events, behaviors, and outcomes and to identify the causes of these events. In the process of making causal attributions, individuals consider both internal and external factors. Internal factors refer to dispositional characteristics of the actor (such as personality, skills, or abilities), while external factors refer to situational and environmental factors (such as luck or external constraints).

In the current context, the earliest studies on online review helpfulness focused on the content of the reviews, such as their length and the use of specific words (Kekäläinen & Järvelin, 2000). However, more recent studies have shifted their focus to understanding the underlying psychological processes that influence the perceived helpfulness of reviews. Attribution theory provides a framework for understanding these processes by exploring the different types of attributions that consumers make about reviews.

One of the key ways that attribution theory has been applied in online review helpfulness research is through the study of consumer reviews' source credibility. Source credibility refers to the perceived trustworthiness, expertise, and authority of the reviewer (Petty & Cacioppo, 1986). Attribution theory suggests that consumers are more likely to perceive a review as helpful if they believe that the reviewer is credible. For example, a study by Kalyanam and McIntyre (2001) found that the perceived credibility of the reviewer was a significant predictor of the perceived helpfulness of online reviews. Another way that attribution theory has been applied in online review helpfulness research is through the study of consumer reviews' source motivation. Source motivation refers to the reasons why the reviewer wrote the review, such as to provide helpful information or to gain attention (Petty et al., 1986).

Attribution theory suggests that consumers are more likely to perceive a review as helpful if they believe that the reviewer was motivated by a desire to provide helpful information, rather than by a desire to gain attention or to pursue some other goal. For example, a study by Dellarocas et al. (2003) found that consumers were more likely to perceive a review as helpful if they believed that the reviewer was motivated by a desire to help others.

A third way that attribution theory has been applied in online review helpfulness research is through the study of consumer reviews' source similarity. Source similarity refers to the degree to which the reviewer is similar to the consumer in terms of demographics, values, or other characteristics (Petty et al., 1986). Attribution theory suggests that consumers are more likely to perceive a review as helpful if they believe that the reviewer is similar to them in some way. For example, a study by Bakhshi et al. (2014) found that consumers were more likely to perceive a review as helpful if they believed that the reviewer was similar to them in terms of demographics or interests.

Finally, attribution theory has been applied in online review helpfulness research through the study of consumer reviews' source objectivity. Source objectivity refers to the degree to which the reviewer provides a balanced and impartial assessment of the product or service (Petty et al., 1986). Attribution theory suggests that consumers are more likely to perceive a review as helpful if they believe that the reviewer is objective and unbiased. For example, a study by Chevalier & Mayzlin (2006) found that consumers were more likely to perceive a review as helpful if they believed that the reviewer was objective and unbiased.

Overall, some of the key factors that have been identified using attribution theory include:

1) Reviewer expertise: Research has found that users are more likely to perceive a review as helpful when the reviewer is perceived to be an expert in the product or service being reviewed (Cheung & Lee, 2012).

2) Reviewer similarity: Users are more likely to find a review helpful when the reviewer is similar to them in terms of demographics, interests, or preferences (Bakhshi et al., 2014).

3) Reviewer motivation: The motivation behind a review has been shown to influence its perceived helpfulness. For example, reviews written by users who have a personal stake in the product or service (e.g., product users or employees) are typically perceived as more helpful than reviews written by those without a personal connection (Chatterjee, 2020).

4) Review content: The content of a review, including the level of detail and specificity, has also been shown to influence its perceived helpfulness (Chevalier & Mayzlin, 2006).

5) Review format: The format of a review, including the use of images or videos, has also been shown to impact its perceived helpfulness (Huang et al., 2020).

These findings suggest that attribution theory can be a useful framework for understanding the factors that influence online review helpfulness.

## Integrated Framework

Drawing on the extant literature, this dissertation aims to examine the two key factors that can determine the helpfulness of the review. *Review authenticity:* literature suggests that the reviewer's credibility will influence review helpfulness (Chevalier & Mayzlin, 2006; Kalyanam & McIntyre, 2001). However, these studies considered credibility through the lens of source credibility i.e., the reviewer. By examining credibility i.e., authenticity from two different dimensions (Dutton, 2005) I argue that the authenticity i.e., whether the reviewer is interested in providing details about the business or the service (nominal authenticity) or writing the review to express his feelings (expressive authenticity) will also influence online review helpfulness. *Reviewer motivations, activities, and goals:* From the literature, it is evident that reviewer motivations will influence the helpfulness of the review. However, from a reviewer's perspective, a reviewer may be motivated to write a review to achieve a certain goal. In this dissertation, I examine not only the influence of reviewer motivations but also reviewer activity (feedback vs complaint) and goals' overall influence on review helpfulness. To achieve this objective, I first examined how motivations and activities influence reviewer goals using extended MEF theory. Later, I examine how motivations, activities, and goals impact the review's helpfulness. The integrated model of this dissertation is presented in Figure 1.

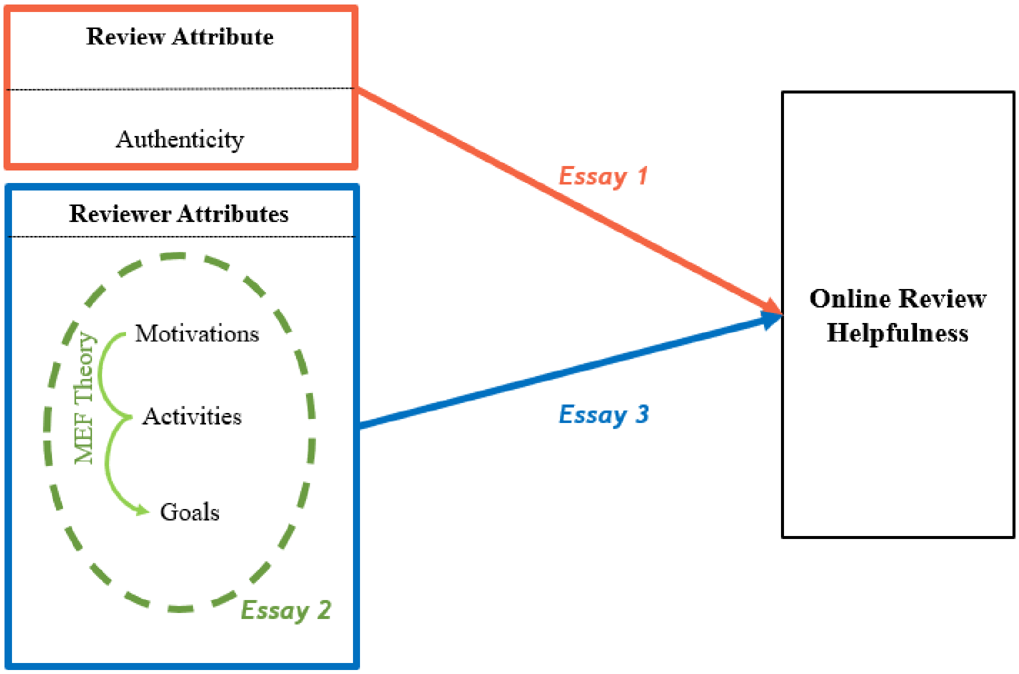


**Figure 1. Integrated Research Framework**

# CHAPTER IV

# HOW DOES THE AUTHENTICITY IN AN ONLINE REVIEW AFFECT ITS HELPFULNESS? A DECISION TREE INDUCTION THEORY DEVELOPMENT APPROACH


## Abstract

Online review helpfulness is a multi-faceted concept that can be driven by several types of factors. Prior literature focused on the relationship between review helpfulness and review sentiment, valence, veracity, and length. However, the authenticity embedded in a review (i.e., whether the review is describing the business or solely the opinions of the reviewer) received little attention. Drawing on the multi-dimensionality of authenticity, this paper explores the association between two distinct authenticities: nominal and expressive and helpfulness. We propose that the authenticity embedded in a review contributes to its helpfulness. In this paper, we use qualitative and quantitative analysis (i.e., text analysis) to identify the nominal and expressive authenticity of a review using the data from two different platforms. Study one examines the effect of two dimensions of authenticity (word density and sentence density of expressive authenticity, nominal word, and sentence density) on the helpfulness of online reviews using decision tree induction. The results show that word density of expressive authenticity is the main predictor of review helpfulness, and the effects of other dimensions vary based on expressive word density. Study two confirms the findings of study one using

conventional analysis and provides new insights into the relationship between authenticity and online review helpfulness.

**Keywords:** nominal authenticity, expressive authenticity, online review helpfulness, decision tree induction

## Introduction

Online reviews play a vital role in prospective consumers' decision-making processes in digital and mobile commerce. Digital opinion-sharing platforms (e.g., Yelp, TripAdvisor) enable individuals to share their product or service experiences and emotions in the form of a review (Heydari et al., 2015). In recent years, online reviews, also referred to as user-generated consumer content, posted on various digital platforms have dramatically increased in volume (Xu & Jin, 2022). Due to the ubiquity of online reviews, prospective consumers often come across numerous reviews about a product or a service, which creates information overload (Jones et al., 2008; Miller, 1964; Zhang et al., 2022), reducing the value of the reviews (Ghose & Ipeirotis, 2010; Lee et al., 2017).

To address this problem, prior studies have identified various factors that influence online review helpfulness (Rietsche et al., 2019). These factors include reviewer-related elements: reputation (Chua & Banerjee, 2016), experience (Huang et al., 2015), and quality of information disclosed (Ghose & Ipeirotis, 2010); as well as review-related elements:  rating (Yang et al., 2017), readability (Singh et al., 2017); affect (Willemsen et al., 2011), and anger /anxiety (Yin et al., 2020a; Yin et al., 2014).

The cognitive ability of the readers to understand the meaning of reviews influences how they consider reviews as helpful in collaborative consumption (Viviani & Pasi, 2017). However, the psychological process of evaluating either a review or reviewer-related factors depends on an appreciation of cues in the review that indicate its authenticity (Agnihotri & Bhattacharya, 2016; Banerjee & Chua, 2014; Le et al., 2021). The term 'authenticity' as a unidimensional concept refers to "owning one's personal experiences, be they thoughts, emotions, needs, wants, preferences or beliefs" (Harter, 2002, p. 382). Although some forms of authentic qualities such as trust, reputation, or originality (fake vs real) have been investigated in prior research, we argue that the increasing number of reviews classified as unhelpful on platforms such as Yelp.com is due to the treatment of authenticity as a homogenous concept (Kokkodis et al., 2022). Consider the following two reviews from Yelp.com.

*Review A:* "Very new store. Lots of options in the form of *bakery items*. The *cakes* are *4 levels* and they have at least *5 different types* of *cake* (*red velvet, carrot*, etc...). I had the *cupcakes*. **Not bad**. I noticed that you can *order online* and *pick up in-store*. They, also, have a *coffee bar* with many options. I wouldn't go out of my way to make it here, but if you are shopping in *La Cantera*, I would **definitely stop in for a treat**."

*Review B:* "Ordered *Valentine's Day cookies* for loved ones and these *cookies* were **horrible**. **Hard**, **tasteless**. And **dried out**. **Like cardboard**. I should've just baked some homemade *cookies* myself. Even I can bake **way better** *cookies* than these. Not quality at all. Paid 40$ What a **horrible waste of money**."

Upon close examination, one may notice that review "A" consists of more factual information (italicized) on the location, the interior and exterior setting, menu items offered by the business, and a few expressive words (bold) disseminated by the reviewer. Review "B" however, consists of more expressive words related to the business, products, or service when compared to review A. Each cue provides different pointers of distinct authenticities that aid a reader in assessing the helpfulness of a review.

Drawing upon the concept of multidimensional authenticity from psychology literature (Dutton, 2005; Newman, 2019), which encompasses nominal and expressive authenticities, we propose that the differences in helpful and unhelpful online reviews should be understood along the variance between the two dimensions. *Nominal authenticity* refers to origin, authorship, or provenance (Dutton, 2003), while expressive authenticity refers to subjective evaluations (Newman & Smith, 2016). Individuals may determine the usefulness of a review contingent on the information they seek. For instance, the reader may be interested in whether the review provides a detailed account of a business, or conveys emotions experienced by the reviewer who made use of the business's products or services. We, therefore, contend that the disparate salient features identified in reviews A and B embody different facets of authenticity. These distinct aspects could influence the review's helpfulness in unique ways. However, such a perspective has been largely overlooked in the existing literature on online reviews (Kokkodis et al., 2022). We answer the following research question:

How do the different dimensions of authenticity relate to online review helpfulness?

Given that the multidimensionality of authenticity has not been explored in prior information systems research, this paper adopts a hybrid methodology for empirically based theory development (Kositanurit et al., 2011). We conduct the theory development process using two studies. In study one, we conduct a content analysis (Sidorova et al., 2008) of 300 reviews from a popular review platform, Tripadvisor.com, to identify the two (word and sentence) forms of nominal authenticity and expressive authenticity; this step was further supported by machine-assisted text analysis. Decision tree (DT) induction is useful to explore the conditional relationships between the various forms of distinct authenticities and online review helpfulness (Osei-Bryson & Ngwenyama, 2011). We use DT induction to uncover interconnections between the dimensions of authenticity and online review helpfulness. This approach reveals implicit connections between multiple decision attributes without any preexisting biases about how these attributes are expected to be linked with the decisions (Karhade et al., 2015). In study two, we empirically examine the conditional relationships derived from the inductive data-driven analysis from study one, using data from Yelp.com.

Our findings demonstrate that the word density of expressive authenticity is a strong predictor of online review helpfulness and constitutes the most important out of the four dimensions of authenticity. We also found a significant relationship between online review helpfulness and both the sentence density of expressive authenticity and the word density of nominal authenticity, which are further moderated by the word density of expressive authenticity. The findings' theoretical contribution is centered on developing a theory and initial evidence for understanding how multidimensional authenticities influence review helpfulness. We formulated and tested a multidimensional authenticity model specific to online reviews, thereby contributing to the online review and user-generated content literature in general. Our findings also have practical implications for platform administrators who currently depend on voting to classify a review as helpful. Although voting methods are useful, it may take time for a review to be voted as helpful (Zhang & Tran, 2010). Using other techniques to classify helpful reviews proactively helps the readers (Yin et al., 2014). Additionally, the findings provide insights for online review platforms when deploying filtering algorithms to differentiate helpful from unhelpful reviews by suggesting the inclusion of multidimensionality of authenticity in the algorithm design.

The rest of this chapter is organized as follows. In the next section, we present an overview of the literature on online review helpfulness, and authenticity. In the subsequent section, we describe the methodology, i.e., the conceptualization of authenticity dimensions in the context of online reviews and the data used. We then present results and relevant discussion. We conclude by presenting the implications of our findings.

## Literature Review

### Online Review Helpfulness

In the current research context, ‘online review’ refers to the user-generated evaluation of a business that is posted on a website of the company or third party (Mudambi & Schuff, 2010). As our study involves authenticity embedded in a review, we summarize the studies that have examined the content of reviews in Table 1. Online review helpfulness is the extent to which consumers rate a user-generated review of a service as useful in facilitating consumers’ decision-making processes (Yin et al., 2014). Online reviews and their helpfulness have received wide attention since the inception of various e-commerce and review-based platforms. We examine the literature on online reviews, along with papers on trust, helpfulness, and authenticity that inform the current study. The results of the systematic literature review presented in Appendix A demonstrate the need to investigate other important factors such as authenticity regarding online reviews.

Scholars have identified multiple review, reviewer, and platform-based factors that impact a review’s helpfulness (Malik, 2020). One study found varying effects of reviewer characteristics and review characteristics on review helpfulness, in which the word count was found to be a good predictor of review helpfulness (Huang et al., 2015). A study examined the influence of the consistency of a reviewer's pattern of rating on review helpfulness and found that reviewers that exhibit highly biased ratings in the past receive more helpful votes in the future (Gao et al., 2017). From a social influence perspective, a study found that the display order of review – where a specific review falls within a series of multiple reviews on a specific product or service - negatively relates to helpfulness, and the negative effect is inversely proportional to the reviewer's expertise (Zhou & Guo, 2017).

**Table 1. Literature on Online Review Helpfulness**

| **Author (s)** | **Research Objective (s)** | **Methodology** | **Conclusions** |
|---|---|---|---|
| (Chua & Banerjee, 2016) | Effect of review sentiment and product type on review helpfulness | Factorial Analysis of Variance (ANOVA) and Multiple Regression Analysis | The Helpfulness of a review varies across review sentiment regardless of product type (i.e., search vs experience). |
| (Yin et al., 2014) | Effect of anxiety and anger embedded in reviews on review helpfulness | Experimental and text analysis using Linguistic Inquiry and Word Count (LIWC) | Anxiety-embedded reviews are considered more helpful than anger-embedded reviews. |
| (Qazi et al., 2016) | The impact of number of concepts per sentence, sentence length, and concepts per review, on review helpfulness, and moderation of the relationship by review type | Tobit Regression | The number of concepts within a review, the average number of concepts per sentence, and the classification of the review have a significant relationship with the perceived helpfulness of online reviews. This implies that the impact of review types and concepts on review helpfulness varies considerably. |

Table 1, cont.

| | | | |
|---|---|---|---|
| (Malik & Hussain, 2017) | Identifying the importance of discrete emotions and their impact on review helpfulness | Sentiment analysis, LIWC | Trust, Joy, and Anticipation (positive emotions), and Anxiety and Sadness (negative emotions) are the most influential emotional dimensions and have a greater impact on perceived helpfulness compared to other emotions such as Trust, Anger, and Disgust. |
| (Eslami et al., 2018) | How review length, argument framing, and score impact review helpfulness | Sentiment analysis, ANOVA | A review with medium length, lower review score, and negative or neutral argument framing is perceived to be more helpful. |
| (Yin et al., 2020b) | How anger in a review affects its helpfulness | Survey Method, Analysis of Covariance (ANCOVA) | Anger in a negative review reduces the perceived review helpfulness. |
| (Yin et al., 2022) | How and when cross-review incoherence influences helpfulness and credibility | Experimental, Path Analysis | Cross-review incoherence i.e., disagreement between multiple reviewers' opinions negatively impacts consumers' perceived helpfulness and credibility of the review set. |
| (Majumder et al., 2022) | The impact of review content, length, and rating on perceived helpfulness | Text mining and analysis | Review length and rating are predominant predictors of review helpfulness. |

Prior research has examined the sentiment, length, and valence of review content to determine the helpfulness of reviews. While previous research recognizes that the extent of authenticity present in a review may influence review helpfulness (Eslami et al. (2018), empirical analysis of this relationship mains unexplored. A theoretical understanding of various dimensions of authenticity would aid in explaining the disparate findings on online review helpfulness in prior research.

**Theoretical Background- Authenticity and Online Reviews**

Prior research has examined the veracity of reviews through such lenses as honesty, truthfulness, bias, and authenticity (Rietsche et al., 2019). Authenticity allows for distinguishing what is real from what may be imaginary. Extensive research in various disciplines such as management and the tourism industry has underlined the importance of authenticity in online reviews. For example, Safaaa et al. (2017) examined how the term ‘authenticity’ is used in commercial and tourism brochures and its relevance to the actual travel experience. The findings suggest that the term ‘authenticity’ should reflect the appropriate meaning to the objects and experiences present in the promotional brochures. Banerjee et al. (2017) examined the potential of linguistic analysis to distinguish between authentic and fictitious reviews. Kovács et al. (2014) found that consumers assign higher value ratings to organizations regarded as authentic (i.e., consumers perceive mom-and-pop and specialist restaurants as authentic compared to chain-operated or non-family-owned restaurants). All the preceding studies consider authenticity as important but have regarded it as a single construct. Additionally, the relationship between multi-dimensional authenticity and online review helpfulness has not been studied. In the following section we briefly describe authenticity and its dimensions which are explored in the current study.

**Multi dimensionality of Authenticity**

Dutton (2005) considers authenticity as a multi-dimensional entity and argues that if an individual is not particular about the dimension of authenticity that is being judged, the word 'authenticity' makes no sense. Therefore, at the broadest level, the concept of authenticity can be judged differently based on the application and/or the context. Several researchers have sought to identify various dimensions of authenticity by categorizing the judgments based on structural similarities. Newman and Smith (2016) proposed two general dimensions that describe the type of entity that is being judged or evaluated and the source of information that is consulted for the evaluation.   The first dimension of our conceptualization of authenticity in the online review context captures the entity (location, artwork, product, service) that is being judged by the evaluators, and the second dimension captures the criteria the judges use to evaluate the entity. These two dimensions measure the objective beliefs and subjective beliefs which present different aspects of what makes an object or action authentic, which are the nominal authenticity and expressive authenticity respectively (Newman & Smith, 2016). In this study we explore how nominal and expressive authenticities are related to online review helpfulness.

**Nominal Authenticity versus Expressive Authenticity**

Nominal authenticity (NA) has been defined as 'the correct identification of the origin, authorship or provenance of an object" (Dutton, 2003, p. 259). Information relevant to nominal authenticity thus presents statements of purported facts which are in principle verifiable. These facts serve to ground the review in reality, as opposed to statements of opinion. Insofar as a review incorporates factual statements which entail a legitimate possibility of either confirmation or disconfirmation, it provides a foundation for a reader's reliance on the review as a helpful source. We define NA as the extent to which the information in a review describes a business or a product or service that allows the reader to verify the information.

For example, consider a review ‘ABC place is located at XYZ road.’ Through this review the reviewer - is establishing NA by explicitly locating the place or object or service they are evaluating. Upon reading this review a reader, through various informational sources, could verify the information in the review.

Expressive authenticity (EA) is defined as the “true expression of an individual’s or a society’s values and beliefs” (Dutton, 2003, p. 259). In the current context, we define EA as the extent to which a reviewer effectively expresses their feelings about a business or a product, or service that aids in the evaluation of a review. For example, consider a review ‘The ambience of ABC is so good. I love the décor and the staff are very friendly’. The review consists of subjective expressions such as ‘so good’, ‘love’ and ‘very friendly’. A review with extensive EA tends to be more subjective, influencing the process of establishing authenticity of the review and subsequent perception of online review helpfulness. Thus, the NA and EA dimensions of authenticity may influence online review helpfulness differently. However, the effect of NA and EA on a reader’s perception of helpfulness of a review is not established in prior IS literature.

## Methodology

Given that little prior research has examined the dimensions of authenticity and understood their effects particularly in the online review context, a hybrid process for empirical theory development is used ( Kositanurit et al., 2011). This process involves two studies. In study one we use decision tree induction to generate a testable hypothesis by examining the interactions between the covariates and the outcome variable. In study two, we use conventional regression analysis to test the hypothesis generated from the previous study and establish the validity of the findings from study one using a dataset from a different context. Figure 2 provides a graphical representation of the methodological process.

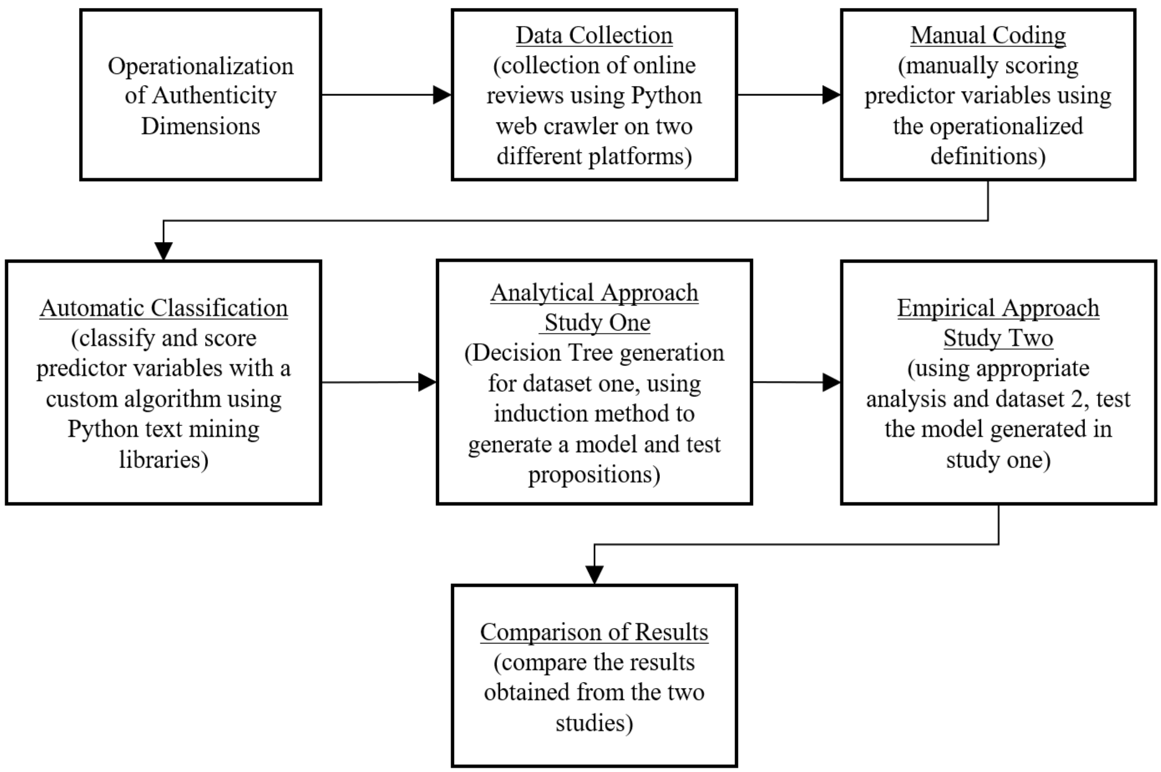


**Figure 2. Methodological Process**

## Study One

A dataset of 1443 online reviews was extracted from *Tripadvisor.com*, a popular online review platform (Scott & Orlikowski, 2014). To minimize the effect of confounds, we collected online reviews from 23 restaurants located in and around two major cities in southern United States. Also, to account for the time gap between the reviews on a particular business, an average of twenty reviews spanning from 2019 to 2022 were collected from each restaurant. The collected reviews were coded for further analysis. The challenge of identifying NA and EA is that they can be expressed using different terms; therefore, we initially identified terms that describe NA and EA authenticity.

Content analysis revealed informative (nominal) words that describe the business and demonstrated that the expressions of reviewers can be flamboyant but contain little unique information. Therefore, to examine the interaction effect of NA and EA dimensions across word level occurrence and sentence level occurrence, we categorized each dimension into word density and sentence density subgroups based on the word level and sentence level occurrence respectively (Kumar et al., 2022) . Following Kumar et al. (2022), we computed the variables as in Table 2.

As this research involves two distinct dimensions of authenticity that have not been explored empirically in prior literature, tools such as Linguistic Inquiry and Word Count (LIWC) which treat authenticity as a single dimension will not be useful or appropriate. Therefore, we manually measured NA and EA of 300 reviews through content analysis, guided by definitions of the proposed concepts. This classification technique can be considered as manual content analysis as it involves human knowledge and interpretation to identify key themes emerging from the data (Moore & Zuev, 2005). A panel of 3 researchers with interest and expertise in text analytics and online review individually tagged the reviews based on the descriptions in Table 2. After several iterations, interrater reliability of 95% was achieved.

**Table 2. Variable Operationalization**

| Variable | Operationalization | Definition |
|---|---|---|
| NA Word Density (NAWD) | (Number of nominal words) / (Total number of words) *100 | Proportion of informational words present in a review |
| NA Sentence Density (NASD) | (Number of nominal sentences) / (Total number of sentences) *100 | Proportion of informational sentences present in a review |
| EA Word Density (EAWD) | (Number of expressive words) / (Total number of words in review) *100 | Proportion of expressive words present in a review |
| EA Sentence Density (EASD) | (Number of expressive sentences) / (Total number of sentences) *100 | Proportion of expressive sentences present in a review |
| Helpfulness | Total number of votes of helpfulness received by the review | Consumer's value assessment of a review |

Due to the tedious procedure involved in manual classification we developed a custom Python algorithm that can produce a score for each predictor variable (See Figure 3).

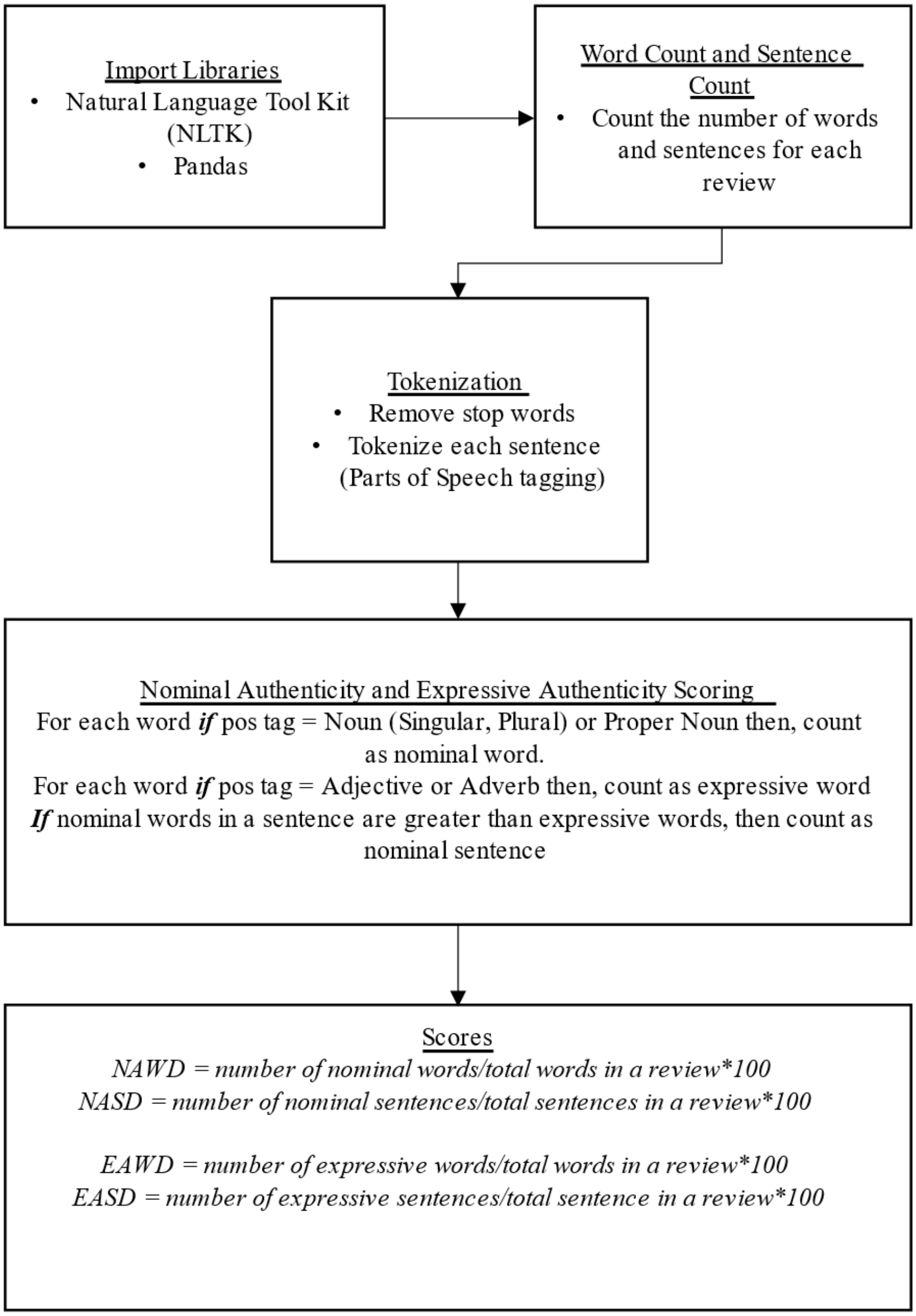


**Figure 3. Nominal Authenticity and Expressive Authenticity Scoring Mechanism**

Using the classification algorithm procedure, scores were obtained by deploying various parts-of-speech (POS) tagging libraries available in Python (Hussain et al., 2008). The libraries include, NLTK tokenizer, VADER sentiment tokenizer and SpaCy. The scores derived from VADER sentiment library provided the best interrater reliability when compared with the manually coded reviews. The interrater reliability of the manually coded reviews and the algorithm classified reviews is 72% which is considered to be very good (Regier et al., 2013). Thus, the automatic approach was used to classify a total of 1443 reviews for further analysis.

### Decision Tree Induction Technique

The decision tree (DT) induction method utilizes a tree structure to illustrate a specific decision issue. In this structure, every non-leaf node correlates with a decision variable, each branch stemming from a non-leaf node associates with a subset of that decision variable's values, and each leaf node corresponds to a value of the target (or dependent) variable. Essentially, the process of decision tree induction involves creating a DT from a provided dataset. Researchers have noted that the DT induction approach provides new insights on conditional relationships between independent variables and a target variable that may not be possible with traditional statistical inference methods (Karhade et al., 2015; Osei-Bryson & Ngwenyama, 2011). DT also facilitates abduction, deduction, and induction processes which allow researchers to postulate hypotheses (abduction) based on empirical observations, and statistically test them (induction) to generate a theoretical model (Karhade et al., 2015; Osei-Bryson & Ngwenyama, 2011).

Generally, a decision tree is generated in two phases: growth phase and a pruning phase (Kim and Koehler 1995). The growth phase involves inducting a DT from the training data (initial set used to generate tree structure and therefore the rules) in such a way that either each leaf node is associated with a single class or further partitioning of the given leaf would result in the number of cases in one or both child nodes being below some specified threshold. The pruning phase seeks the generalization of the DT generated from the training set to avoid overfitting the DT. Hence, in the pruning phase, the DT is evaluated against the validation dataset to generate a subtree of the DT generated in the growth phase with the lowest error rate against the validation dataset.

In the growth phase, DTs are built using greedy algorithms in a top-down manner. The algorithm involves a recursive class dependent partitioning (i.e. splitting) of the relevant training data. The splitting method is the component of the DT induction algorithm that determines both the attribute (variable) that is selected for a given node of the DT and the partitioning of the values of the selected attribute into mutually exclusive subsets such that each subset uniquely applies to one of the branches that emanate from the given node. Various splitting methods have been proposed including those based on information theory (e.g. entropy) and those based on distance between probability distributions (e.g. Gini) (Breiman et al. 1984; Quinlan 1993). It is established in the literature that there is no single splitting method that will give the best performance for datasets, and that some datasets are sensitive to the choice of splitting methods while other datasets are insensitive to the choice of splitting methods (Osei-Bryson & Giles 2002).

In this research, a DT is generated using IBM's statistical package for the social sciences (SPSS) version 28.0.1.1 application. SPSS offers various growing algorithms such as quick unbiased efficient statistical tree (QUEST), classification and regression tree (CRT), and chi-squared automatic interaction detection (CHAID) to split and classify the variables forming a tree structure. It is possible that the generated DT may differ from one algorithm to the other. To address this issue, we generated several trees using various algorithms with 10-fold cross validation. All trees are pruned to avoid overfitting. A common pattern, i.e., EA word density and EA sentence density forming as root node and subsequent node respectively is observed in the sixteen of the twenty generated decision trees. The DT that best explains the interaction effect of independent variables (different dimensions of authenticity of the review) on the outcome variable (online review helpfulness) is retained (Andoh-Baidoo et al., 2012) and is presented in Figure 4.

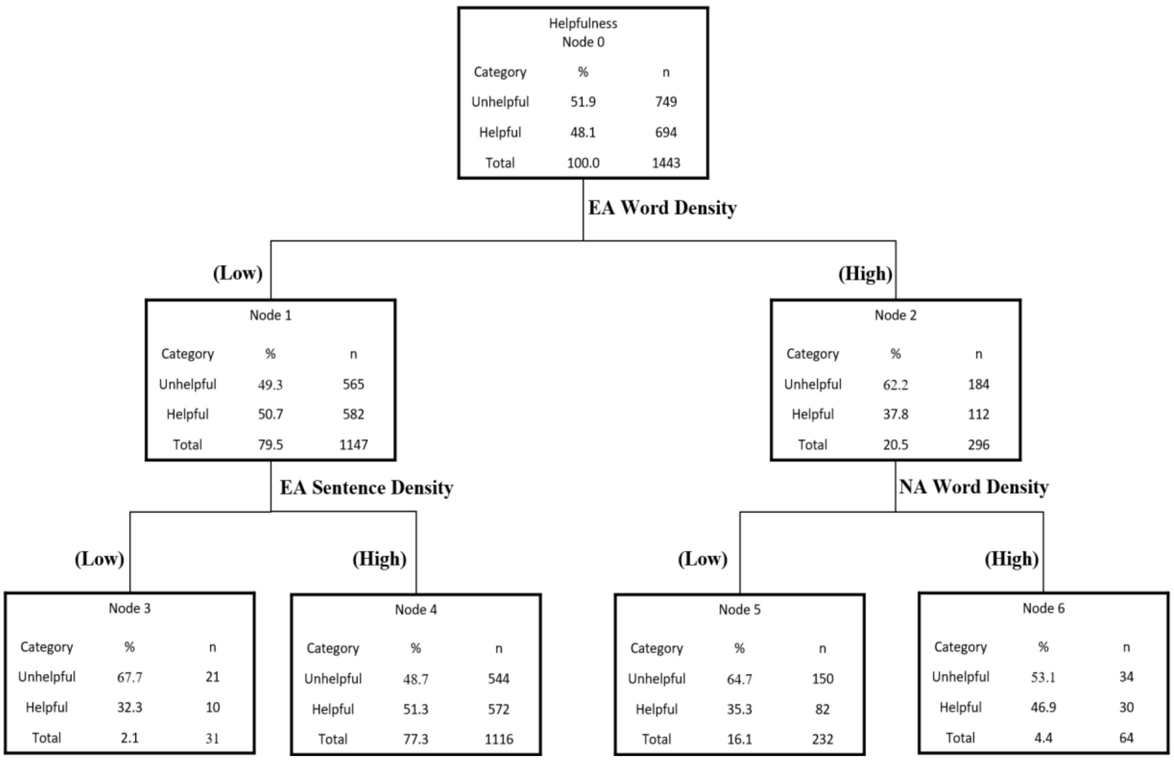


**Figure 4. Decision Tree**

### Study One Results

Figure 4 depicts the retained DT subjected to 10-fold cross validation. In the DT, each variable is discretized into two classes, Yes and No, where these are based on the helpfulness percentage, and an integer N is the number of cases associated with the condition component of the rule. These rules are also used to generate a set of propositions which we discuss in detail in the next section.

Decision tree (DT) induction is used to partition the dataset into subsets based on input variables selected by the relevant splitting method. In a DT, Nodes that have the same non-root parent node (i.e. input variable) are referred to as sibling nodes, where each sibling is associated with a mutually exclusive subset of the values of the relevant input variable, and the relevant value of any higher ancestor node. Figure 4 displays several pairs of sibling rules where all conditions are the same except for the one involving the given subject variable (Node 1 and 2, Node 3 and 4, and Node 5 and 6).

**Propositions**

From the set of sibling rules as shown in Table 3, we generated sibling rule hypotheses (propositions) (Osei-Bryson & Ngwenyama, 2011). A sibling rule hypothesis could be directional or non-directional. For example, Nodes 1 and 2 constitute a set of sibling rules.

**Table 3. Rule set of Decision Tree**

| **Rule ID** | **Condition** | **Helpfulness (%)** | **N** |
|---|---|---|---|
| 1 | EAWD (Low) | Yes: 50.7; No: 49.3 | 1147 |
| 2 | EAWD (High) | Yes: 37.8; No: 62.2 | 296 |
| 3 | EAWD (Low) & EASD (Low) | Yes: 32.3; No: 67.7 | 31 |
| 4 | EAWD (Low) & EASD (High) | Yes: 51.3; No: 48.7 | 1116 |
| 5 | EAWD (High) & NAWD (Low) | Yes: 35.3; No: 64.7 | 232 |
| 6 | EAWD (High) & NAWD (High) | Yes: 46.9; No: 53.1 | 64 |

Having this pair of rules, one could generate and indirectly test the directional hypothesis: given that EA word density is low, EA sentence density has a positive impact on online review helpfulness. We could indirectly explore the validity of the above sibling rule hypothesis by testing the surrogate hypothesis given that EA word density is low then, a review is helpful if EA sentence density is high. Acceptance of this surrogate hypothesis would suggest that the given sibling rule hypothesis might be valid and should be accepted (see Table 4).

Where,

P1: EA word density is related to online review helpfulness.

P1a: If EA word density is low, then EA sentence density is related to online review helpfulness.

P1b: If EA word density is high, then NA word density is related to online review helpfulness.

P2*: EA sentence density is related to online review helpfulness.

P3*: NA word density is related to online review helpfulness.

*Based on conditional interaction

To test the propositions, we perform a difference of proportion test to confirm that the difference of posterior probabilities for the sibling nodes is statistically significant. Our test statistics are given by,

$$Z = \frac{\hat{P}_1 - \hat{P}_2}{\sqrt{\frac{\hat{P}_1(1-\hat{P}_1)}{n_1} + \frac{\hat{P}_2(1-\hat{P}_2)}{n_2}}}$$

Where $p_1$ and $p_2$ are the sample proportions of two independent samples of size $n_1$ and $n_2$ respectively.

**Table 4. Sibling rule propositions for DT**

| | **Conditional event** | | | | |
|---|---|---|---|---|---|
| | Node(s) | Rule | N | Frequency (f) | Proposition (P) |
| | 1 | EAWD (Low) | 1147 | 0.507 | P1 |
| | 2 | EAWD (High) | 296 | 0.378 | |
| | 3 | EASD (Low) | 31 | 0.323 | P2 |
| | 4 | EASD (High) | 1116 | 0.513 | |
| | 5 | NAWD (Low) | 232 | 0.353 | P3 |
| | 6 | NAWD (High) | 64 | 0.469 | |
| **Backend Rule** | | **Frontend Rule** | | | |
| EAWD (Low) | 1,3 | EASD (Low) | 31 | 0.323 | P1a |
| | 1,4 | EASD (High) | 1116 | 0.513 | |
| EAWD (High) | 1,5 | NAWD (Low) | 232 | 0.353 | P1b |
| | 1,6 | NAWD (High) | 64 | 0.469 | |

This approach has been used in prior IS research in internet security breaches announcement (Andoh-Baidoo & Osei-Bryson, 2007), user performance (Osei-Bryson and

Ngwenyama 2011), and ecommerce initiatives announcements (Andoh-Baidoo et al., 2012). Table 5 presents the results of the empirical validation of the propositions developed from the DT induction. The results reveal that all the three propositions are statistically significant suggesting that they can be subjected to empirical validation using other data from the similar or different contexts.

**Table 5. Propositions test results**

| Proposition | Z Score | P(Z) | Supported/Not Supported |
|---|---|---|---|
| P1 | 4.0546 | 0.00002 | Supported |
| **Surrogate Hypothesis** | | | |
| P1a | 2.2271 | 0.01297 | Supported |
| P1b | 1.6612 | 0.04833 | Supported |
| P2 | 2.2217 | 0.01315 | Supported |
| P3 | 1.6612 | 0.04833 | Supported |

### Generation of Model and Hypothesis from Study One

Using the propositions derived from the decision tree approach, we construct a model with the abducted hypothesis (propositions are represented as hypotheses) presented in Figure 5.

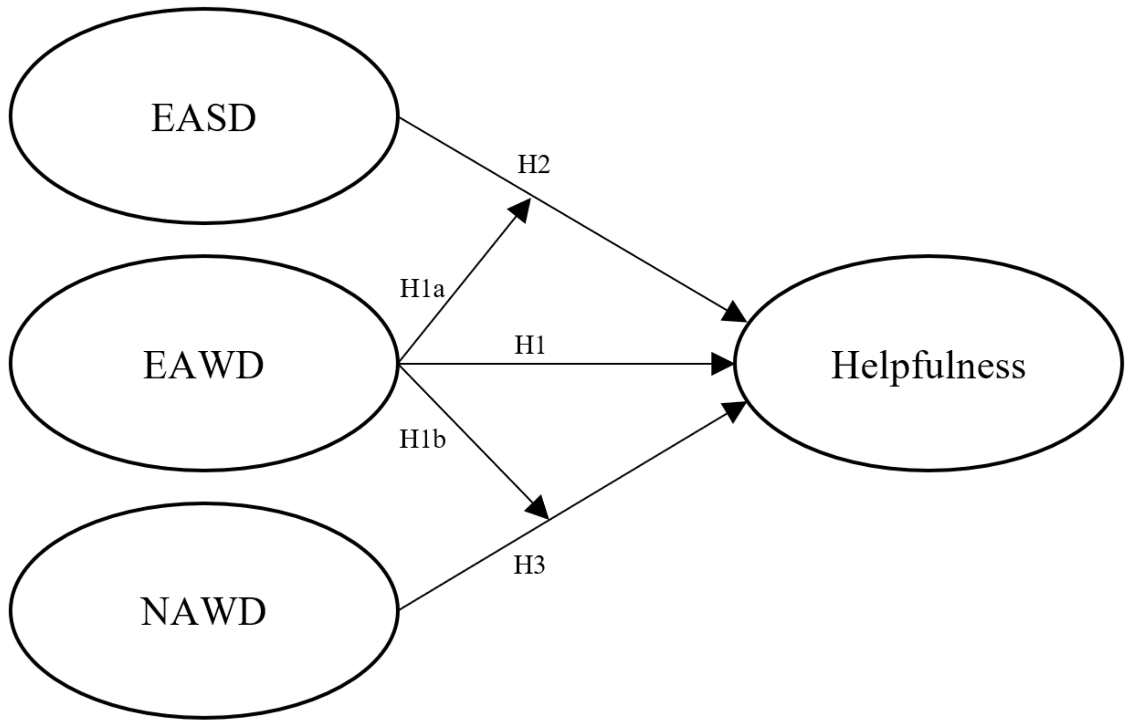


**Figure 5. Derived Model with Abducted Hypotheses**

## Study Two

### Hypotheses Development

Word density refers to the ratio of the number of informational words to the total number of words in each text (Johansson, 2008). Reviews with high word density may provide in-depth information about a product or a service, thus making them more helpful to the review readers. A meta-analytic study found elements such as review specificity, relevance, and credibility to be key determinants of review helpfulness (Hong et al., 2017). These elements suggest that word density could indeed play a role in review helpfulness, as a higher density of meaningful words may lead to greater specificity and relevance in the review content. Moreover, reviews containing detailed information and a well-structured argument were perceived as helpful, further supporting the notion that word density is a significant factor in the perceived value of online reviews (Salehan & Kim, 2016). Additionally, the impact of word density on review helpfulness can be assessed through the lens of information processing theory. The theory suggests that individuals have a limited capacity for processing information, and are thus more likely to pay attention to and retain information that is presented concisely and efficiently (Tybout et al., 1981). Therefore, we posit that word density of expressive authenticity and nominal authenticity are related to online review helpfulness.

H1: Word density of expressive authenticity is related to online review helpfulness.

H2: Word density of nominal authenticity is related to online review helpfulness.

Word density of expressive authenticity can moderate the relationship between sentence density and online review helpfulness. For example, a review with high sentence density and word density is more difficult to comprehend, making it less helpful regardless of the useful information. On the other hand, a review with high sentence density but low word density, is easier to comprehend, making it more likely to be perceived as helpful. Word density may also moderate the relationship by influencing the persuasiveness of the review. If a review has high sentence density and high word density, it may include much information and many arguments, but it may also appear dense and overwhelming, reducing the reviewer's persuasiveness and thereby making the review less helpful. On the other hand, if a review has high sentence density but low word density, it may be more concise and straightforward, thereby making it more persuasive and helpful. Therefore, we propose that,

H1a: Word density of expressive authenticity moderates the relationship between the sentence density of expressive authenticity and online review helpfulness.

The EA word density will also moderate the relationship between nominal authenticity and online review helpfulness. For example, a review with a high density of NA i.e., nominal, or informative words are perceived as more helpful. However, a high density of EA i.e., extensive use of metaphors and emotional words, may decrease the perceived helpfulness of the review. In contrast, reviews with a high density of nominal authenticity and low density of expressive authenticity make a review less engaging, also making the review perceived as less helpful. Therefore, we posit that,

H1b: Word density of expressive authenticity moderates the relationship between the word density of nominal authenticity and online review helpfulness.

Sentence density refers to the ratio of the number of target sentences (sentences containing information of interest) to the total number of sentences in each text. In the context of online reviews, a sentence with high density may contain more information than a sentence with a low density. Ghose and Ipeirotis (2010) found that perceived helpfulness of product reviews, specifically for search items, is significantly affected by the level of subjectivity in the review. Reviews with highly subjective sentences tend to be considered less useful. Reviews with a broad range of subjectivity/objectivity across sentences were deemed more beneficial, suggesting that a mix of objective and highly subjective sentences is preferred by users. Thus, from the literature and the support from the theoretical model in study one, we posit that sentence density of expressive authenticity will influence online review helpfulness.

H3: Sentence density of expressive authenticity is related to online review helpfulness.

We provide the summary of the hypotheses in Table 6.

**Table 6. Summary of Hypotheses**

| **Hypothesis** | **Description** |
|---|---|
| H1 | Word density of expressive authenticity is related to online review helpfulness. |
| H1a | Word density of expressive authenticity moderates the relationship between the sentence density of expressive authenticity and the online review helpfulness. |
| H1b | Word density of expressive authenticity moderates the relationship between the word density of nominal authenticity and the online review helpfulness. |
| H2 | Word density of nominal authenticity is related to online review helpfulness. |
| H3 | Sentence density of expressive authenticity is related to online review helpfulness. |

In study two, the goal is to test the abducted model for helpfulness using data collected from a different platform. The classification algorithm that was used in the prior study is deployed to extract the scores for the predictor variables. The data sample includes 1506 restaurant reviews that are collected from *Yelp.com*. Table 7 represents the descriptive statistics of the Yelp data.

**Table 7. Descriptive Statistics**

| Variables | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| NAWD | 0.05 | 0.70 | 0.23 | 0.06 |
| NASD | 0.25 | 1.00 | 0.93 | 0.11 |
| EAWD | 0.00 | 0.42 | 0.07 | 0.04 |
| EASD | 0.00 | 1.00 | 0.67 | 0.22 |
| Helpfulness | 0.00 | 10.0 | 1.35 | 3.50 |

## Measurement Validity

The correlation matrix presented in the Table 8 demonstrate that the variance inflation factor (VIF) is above 1 and less than 3.33 indicating that the included variables do not pose collinearity problems (Burns et al., 2022).

**Table 8. Correlation Matrix and VIFs**

| Variables | EASD | NAWD | NASD | EAWD | VIF |
|---|---|---|---|---|---|
| EASD | 1.00 | 0.18 | -0.25 | -0.59 | 1.57 |
| NAWD | 0.18 | 1.00 | -0.22 | -0.19 | 1.07 |
| NASD | -0.25 | -0.22 | 1.00 | 0.24 | 1.11 |
| EAWD | -0.59 | -0.19 | 0.24 | 1.00 | 1.56 |

**Hypotheses Testing**

The purpose of study two is to test the model derived from the decision tree induction results. In the current study, the outcome variable is online review helpfulness, which is indicated by the number of helpful votes that a review has received from review readers as at the point of data collection. It is possible that a review might not receive a helpful vote (i.e., unhelpful) in which case the helpfulness of the review is zero. On the other hand, a review might receive more votes compared to its neighboring review. The data collected for this study contains a total of 1506 reviews of which 783 are unhelpful and 723 are helpful with minimum helpful score 1 and maximum 10. We considered only reviews that have been online for a minimum of 60 days to ensure that all reviews had sufficient time to generate helpfulness. To check the dispersion of the reviews that are helpful we calculated the mean (2. 598) and variance (3.086) and found that there is no over-dispersion in the helpfulness score of the outcome variable (see Figure 6).

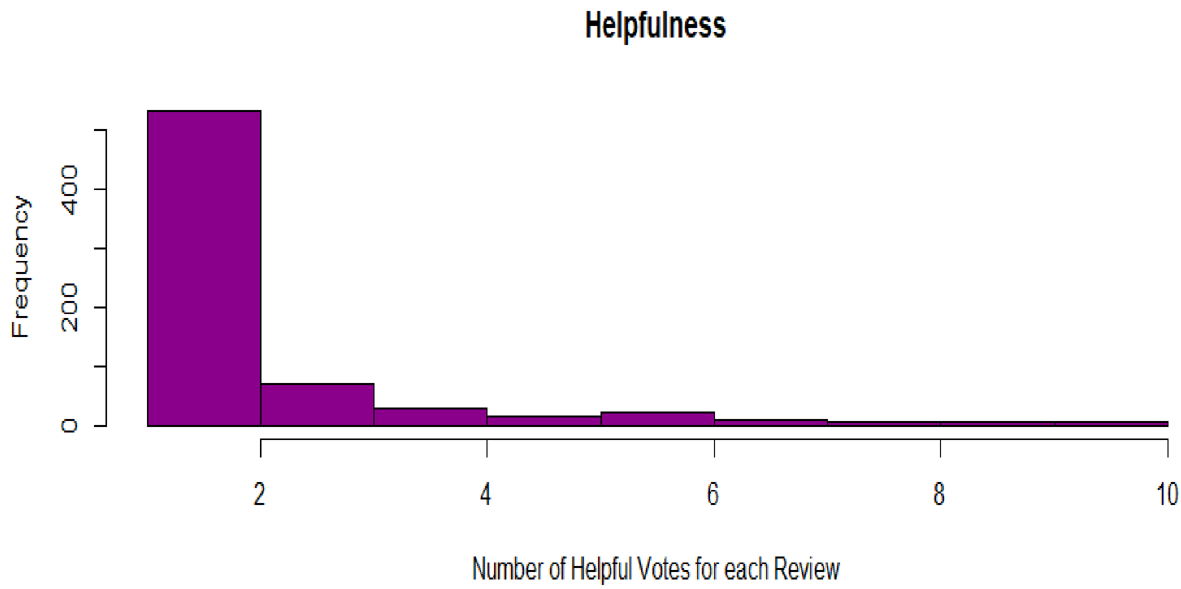


**Figure 6. Helpfulness score distribution**

As fifty percent (approximately) of the outcome variable consists of 0 as helpfulness score, we use zero-inflated Poisson (ZIP) regression model. ZIP model assumes that for the observation where only 0 is possible the probability is $p$ and with probability (1- $p$) a random variable is assigned a Poisson($\lambda$). Thus, we present results for (1- $p$) (helpful) in table 9.

The abducted model from study one with significance derived from study two is presented in Figure 7.

**Table 9. Results for Helpfulness**

| Outcome = Helpfulness | Estimate | Z Value | Significance |
|---|---|---|---|
| EAWD | -9.21 | -8.10 | <= 0.001**** |
| EASD | 0.72 | 4.01 | <= 0.001**** |
| NAWD | 1.09 | 2.79 | 0.0052*** |
| NASD | 0.06 | 0.21 | 0.8270 |
| EAWD * EASD | 3.82 | 1.21 | 0.2261 |
| EAWD * NAWD | 18.25 | 1.89 | 0.0578 * |
| Note: **** $p < 0.001$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; EAWD = Expressive Authenticity Word Density; EASD = Expressive Authenticity Sentence Density; NAWD = Nominal Authenticity Word Density ; NASD = Nominal Authenticity Sentence Density | | | |

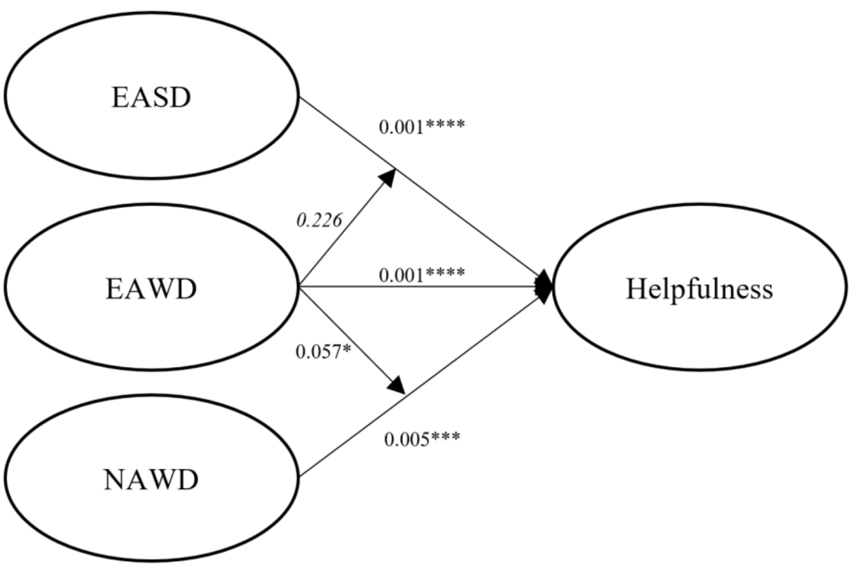


**Figure 7. Model with Significance Levels**

The hypothesized relationships for helpfulness are summarized in Table 10.

**Table 10. Summary of Hypothesis for Helpfulness**

| Label | Relationship | Direction | Supported/Unsupported |
|---|---|---|---|
| H1 | EAWD has a significant impact on Helpfulness | Negative | Supported |
| H1a | EAWD moderates the relationship between EASD and Helpfulness | Positive | Unsupported |
| H1b | EAWD moderates the relationship between NAWD and Helpfulness | Positive | Marginal Supported |
| H2 | NAWD has a significant impact on Helpfulness | Positive | Supported |
| H3 | EASD has a significant impact on Helpfulness | Positive | Supported |

**Post-hoc Analysis**

In this section we further extend our analysis by examining the DT split with helpfulness as a categorical variable. Following the steps mentioned in study one, we present the DT that represents the similar splits as in figure 4 with a different data source. The results of the DT performed on the Yelp dataset are presented in figure 8.

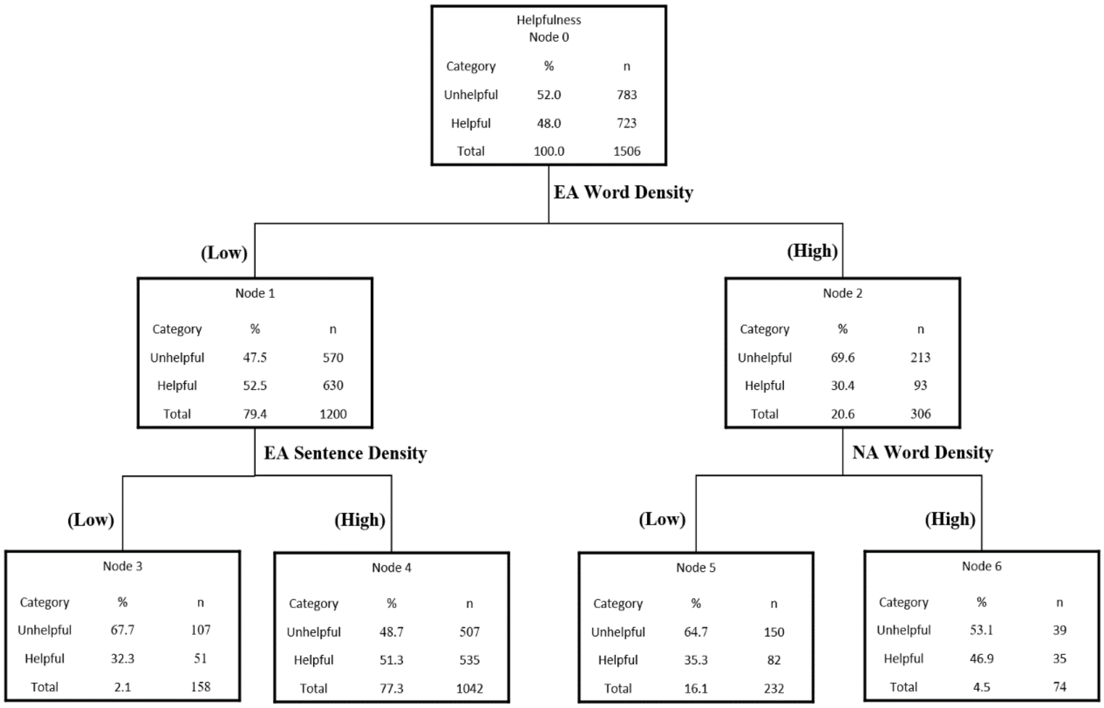


**Figure 8. Ad-hoc DT Results**

The results for figure 7 reveal that the EA word density, EA sentence density, and NA word density have similar relationship with helpfulness when compared to the DT in the study one (see. Figure 3). This indicates that the influence of expressive authenticity and nominal authenticity on review helpfulness is similar across the two different online platforms used in the current research.

## Discussion

This study inductively identified interaction of two dimensions of authenticity and empirically tested their role in online review helpfulness. Our results (Table 7) confirm that the expressive authenticity breadth and depth, and nominal authenticity breadth are effective in predicting helpfulness which are statistically significant in study two.

Finally, we compare the results for study one and two to ascertain the generalizability of our theoretical model. In study one, we identified abducted sibling rule hypotheses that were significant. And in study two, the hypotheses are tested using a dataset from a different platform which supports the findings derived from study one. Table 11 summarizes the comparison of the results of two studies.

**Table 11. Validation by comparison of results from the two studies**

| | Observed Relationship | Study One | Study Two | Similarity between Studies 1 & 2 (Yes/No) |
|---|---|---|---|---|
| H1 | EAWD has a significant impact on Helpfulness. | Supported | Supported | Yes |
| H1a | EAWD moderates the relationship between EASD and Helpfulness. | Supported | Partial Support | Yes |
| H1b | EAWD moderates the relationship between NASD and Helpfulness. | Supported | Not Supported | No |
| H2 | NAWD has a significant impact on Helpfulness. | Supported | Supported | Yes |
| H3 | EASD has a significant impact on Helpfulness. | Supported | Supported | Yes |

In study one, the statistical significance of the three propositions in Table 3 convey various insights on authenticity and its multidimensional impact on online review helpfulness. First, EA word density, at the root of the tree, is the most significant predictor of online review helpfulness. The rest of the variables vary based on EA word density levels. A review with low

EA word density makes a review more likely to be helpful and can be classified as helpful, whereas those with high EA word density can be classified as unhelpful. Thus, reviews that possess minimal expressive elements will be perceived as helpful to the readers. When EA word density is high, then EA sentence density can be used to determine a review's helpfulness. Where EA sentence density is high i.e., for reviews with higher EA word density, low NA word density is necessary for a review to be classified as helpful. The results suggest that the readers tend to perceive a high EA word density review as helpful only when the reviewers provide sufficient explanation behind the expressive content. These results are consistent with prior studies in which extremely positive or negative valence reviews tend to be more narrative (Jurafsky et al., 2014) and negative reviews tend to be more helpful (Yin et al., 2014).

In study two, the results from Poisson regression analysis indicate that the EA word density is significant in predicting helpfulness with an inverse relationship, i.e., the lower the EA word density, the higher the helpfulness. This result is consistent with the results derived from study one. Other predictor variables such as EA sentence density and NA breath are also found to be significant with a positive relationship towards helpfulness. To test the significance of the variable NA sentence density, which was not able to explain helpfulness in study one, we introduced that variable in Poisson regression analysis and found that the NA sentence density is not significant ($z = 0.218$, $p = 0.82$). This means that a sentence in a review that provides extensive nominal information does not contribute to the helpfulness of the review. The moderation of the relationship between EA sentence density and helpfulness by EA word density is partially supported, indicating that EA breath does influence how EA sentence density affects helpfulness. We did find support for our argument that EA moderates the relationship between NA word density and helpfulness relationship by. However, we found marginal support for the moderating role of EA such that higher levels of EA word density and NA word density may lead to lower helpfulness. This is consistent with results obtained from the study one.

Overall, our results extend our understanding of the role of authenticity in evaluation of online reviews. Additionally, our results illustrate that the different dimensions of authenticity influence perceptions of helpfulness in different ways.

## Implications

### Theory

Although prior research has examined the impact of review characteristics such as honesty, trust, and appeal on online review helpfulness (Banerjee & Chua, 2017; Bigne et al., 2019; Chatterjee, 2020; Evans et al., 2021; Fresneda & Gefen, 2019; Kim et al., 2019; Teeny et al., 2021; Wang et al., 2022; Xia Liu et al., 2021; Zhang & Patrick, 2021), few studies have examined the influence of authenticity on online review helpfulness (Banerjee & Chua, 2017; Kovács et al., 2014). Additionally, prior studies conceptualized authenticity of reviews as a unidimensional construct (Banerjee et al., 2017). The exploration and confirmation of the two authenticity dimensions emerging from online reviews highlight the nuanced roles which these two authenticity dimensions can play in influencing reader inference and attitude formation about online reviews. The current research plays an important role in reshaping the reader's interpretation and value assessment of reviews significantly, where authenticity is usually perceived from the perspective of the customer rather than in terms of ‘verified facts’ of objects. The study also provides valuable insights into the conditional effects of expressive authenticity in online reviews.  The research shows that the helpfulness of a review can be enhanced by the expressive authenticity of the review. This implies that the emotions and feelings expressed in a review can have a significant impact on its usefulness and impact and should be taken into consideration when evaluating the authenticity of an online review.

**Practice**

The proposed model has several implications for different stakeholders in the online review ecosystem. For platform owners, the model can be used to identify potentially helpful reviews early. This means that the platform owners can use the scores generated by the model to identify which reviews are likely to be the most informative, well-written, and useful to the readers. This can help the platform owners to promote these reviews and ensure that they are seen by the right audience. Specifically, online review platforms can identify and highlight reviews based on their authenticity, to reduce information overload to the readers. Also, businesses could identify and segment their customers based on their assessments and expectations of authenticity. By doing this, they can target and cater to specific expectations of authenticity for each customer segment, which in turn increases their customers' satisfaction and loyalty. The results can aid service providers with appropriate digital and mobile technologies to enhance verification of various dimensions of authenticity of online reviews.

For review readers, online review platforms can be designed to help readers identify helpful reviews. This means that the platforms can be designed to prominently display the scores generated by the model for each review. This can help the readers to quickly identify the most informative and well-written reviews, and to avoid reviews that are overly expressive or otherwise unhelpful. By making it easier for readers to identify high-quality reviews, the online review platforms can improve the overall user experience and make it easier for people to make informed decisions based on the information they find on the platform.

For review writers, platform managers can educate the reviewers to write reviews that are not overly expressive. This means that the platform managers can provide guidance to the reviewers on how to write reviews that are more focused, informative, and well-structured. This can help the reviewers to write better quality reviews, which in turn can improve their scores and increase their visibility on the platform. By educating the reviewers on how to write better reviews, the platform managers can help to improve the overall quality of the reviews on the platform and ensure that the platform is a valuable resource for both readers and reviewers.

# CHAPTER V

# HOW DO REVIEWER MOTIVATION AND ACTIVITY ATTRIBUTE HELP ACHIEVE GOAL: EXTENDED MEANS-ENDS-FUSION THEORY IN ONLINE REVIEW CONTEXT


## Abstract

Online reviews (ORs) are crucial for both consumers and businesses, significantly influencing purchase decisions and business strategies. This study aims to systematically understand the complex interplay of motivations, activities, and goals of online reviewers using the Means-Ends Fusion (MEF) theory. A two-phased mixed-method approach was employed, involving a qualitative examination to develop a taxonomy of reviewer behaviors, followed by a quantitative examination using machine learning techniques. The taxonomy developed includes motivations like altruism, expression of emotions, product/service involvement, vengeance, and self-enhancement; activities like feedback and complaint; and goals like emotional satisfaction, financial gain, business damage, and others. The machine learning model, an ensemble of Decision Trees and Artificial Neural Networks, achieved high accuracy in predicting the goals of reviewers. The findings reveal diverse motivations and activities driving online reviews, offering valuable insights to review platforms and businesses. The findings of this research can provide valuable insights for businesses and researchers seeking to better understand OR motivations and improve the effectiveness of their marketing strategies.

## Introduction

Online Review (OR) refers to an individual's evaluation of a product or a service present in the form of a text addressing prospective consumers or a business (Hennig-Thurau et al., 2004). Various platforms including electronic commerce (e.g., Amazon.com, Bestbuy.com) and opinion sharing (e.g., Yelp.com) enable consumers to create, receive, and forward their opinions or feelings on products or services. Online reviews, also referred to as electronic Word of mouth (eWOM), can assist prospective consumers to evaluate and select the best product or service (Tunc et al., 2021). From the merchant's perspective, ORs serve as marketing mechanisms to increase sales (Li et al., 2021).

Online reviews have received great interest among researchers and practitioners (Dellarocas et al., 2005; Tunc et al., 2021; Yin et al., 2020b; Yin et al., 2014). Much prior research has examined ORs from the reader/business and/or writers' perspectives (Davis & Agrawal, 2018; Hennig-Thurau et al., 2004; Zheng, 2021). Studies that focus on the review readers' perspective examined the helpfulness or usefulness of a review by investigating the characteristics of the review and the reviewer (e.g., Zheng, 2021). Those with a business perspective have proposed frameworks to enhance product/service development to maintain customer satisfaction and loyalty (Davis & Agrawal 2018). Research on review writers' perspectives has highlighted that motivations for ORs are many (Dellarocas et al., 2005; Hennig-Thurau et al., 2015).

The reviewers behind the ORs constitute a diverse group, each with unique motivations, activities, and goals. Some could be genuinely interested in sharing their experiences to help others make informed decisions. Others may be influenced by incentives provided by the platforms or businesses. On the other hand, some engage in malicious activities, providing misleading or false reviews for personal gain or to harm competitors. Understanding these various elements is critical in maintaining the integrity of online reviews and platforms.

Despite the insights from prior research, systematic study of the different motivations and the associated outcomes have not been fully explored. This is important because systematic association between motivation and outcomes would allow managers to appropriately respond to consumers which is critical for most business survival or recovery (Ravichandran & Deng, 2023).

Thus, this study has two research objectives. The first is to develop a systematic understanding of a variety of OR motivations and activities. Our second objective is to investigate the relationships between reviewer motivation, activity, and goal. We investigate the underlying relationships of the key tenets of online reviews by employing machine learning techniques. By leveraging seven predictors across motivations and activities, we aim to develop a framework to detect and categorize the reviewers' goals, contributing to the literature on online consumer behavior and providing valuable insights for review platforms.

The potential benefits of this research are manifold. Firstly, it will help platforms enhance their credibility by identifying and managing reviewers' intentions, which will, in turn, foster trust among consumers. Secondly, understanding the motivations of reviewers can help platforms tailor their interfaces and features to encourage high-quality reviews thereby improving user engagement and satisfaction. Finally, the knowledge gained from this research can assist businesses in leveraging online reviews for their benefit, guiding their customer service and product development strategies.

The ever-evolving digital landscape has positioned online reviews as a pivotal factor in shaping market dynamics. The key to maximizing their value lies in understanding the behaviors of the reviewers themselves. Our study is poised to unlock these insights, advancing the frontier of knowledge in the realm of ORs and shaping the future of online review platforms.

## Theoretical Background - Means-Ends Fusion (MEF) Theory

Online reviews have been studied in various disciplines such as marketing, management, information systems, computer science, and hospitality and tourism (Bafna & Toshniwal, 2013; Chen et al., 2011; Clemons et al., 2006; Yin et al., 2014). These studies examined implications of OR features on outcomes such as credibility, helpfulness, adoption, purchase intention and impact on sales. However, the understanding of how reviewers reach goals is underexplored. We use MEF theory to explore how reviewers can reach their goals.

MEF theory proposed by Kruglanski et al. (2018) posits that the fusion between an activity and a goal is caused by the major antecedent i.e., means. The theory describes how motivations as means, or the antecedents determine the activities that lead to a definite goal. Aligning with the theory we contend that the motivation of the reviewer would determine the activity i.e., disseminating feedback or a complaint which would lead to the goal.

### Motivations

Positive ORs help consumers express gratification, whereas negative ORs express emotions such as anger and anxiety about their experience (Yin et al., 2020). Prior studies suggest that the psychological motivation of participation in traditional word of mouth (WOM) may extend to eWOM (Dellarocas 2003; Ren et al., 2013). Traditional WOM motivations include product/self/other involvement, altruism, self-enhancement, and vengeance (Dichter, 1966;

Sundaram et al., 1998), and eWOM motivations include economic incentives, expression of emotions, need for social interaction, and care for others (Hennig-Thurau et al., 2004; Ho & Dempsey 2010; Tong et al., 2007; Yan et al., 2011). We review these motivations in the context of ORs.

**Altruistic.** Individuals participate in altruistic behavior to express concern for the welfare of others by overcoming their self-interest. Prior studies have considered altruism as a motivation to participate in traditional WOM (Sundaram et al., 1998), and in eWOM (Cheung & Lee 2012; Ho & Dempsey 2010; Tong et al., 2007). Ho and Dempsey (2010) suggest that the need to belong is an important factor in altruistic motivation. In addition, a study by Chen et al., (2019) found that consumers who wrote reviews had a greater sense of community and were more likely to be motivated by the desire to help others. They also found that consumers who wrote reviews had a greater sense of trust in the online community, which is an important factor in the formation of social capital. Studies also indicate that reviewers attain self-satisfaction by helping others (Tong et al., 2007). We define altruistic motivation as a motive of the reviewer to aid/warn other consumers by posting an OR that portrays their positive/negative experience.

**Product or Service Involvement.** Experiencing a new product or a service creates excitement among consumers (Sundaram et al., 1998). Prior literature describes product involvement as a key determinant of WOM (Dichter, 1966). Norman and Russell (2006) argue that involvement in a product or service creates an urge to disseminate information about the product to influence other consumers. If a product or a service meets or exceeds one's expectation it may lead to positive eWOM and if not, negative eWOM (Dellarocas, 2003). Positive product involvement reviews explicitly boast, whereas negative reviews describe defects of the product or quality of the service. Therefore, we define product or service involvement as the motive of the reviewer to boast about or deprecate a product or service.

**Expression of Emotions.** Hennig-Thurau et al., (2004) suggest that reviewers disseminate information to express positive or negative emotions. High satisfaction elicited by a product experience may lead to a positive OR describing the reviewer's happiness (Hennig-Thurau et al., 2004). On the other hand, dissatisfaction may lead to a negative OR to vent negative emotions such as anger, sadness, and regret (Yin et al., 2020). We define expression of emotions as the display of happiness, sadness, anxiousness, fear, anger, regret, etc., aroused by the experience with a product or service.

**Self-Enhancement.** Online platforms such as Amazon and Yelp have introduced mechanisms to enhance repeat engagement. One such mechanism is reputation, awarding compliments and 'useful' votes from other consumers (Ma et al., 2013). Also, review readers can see previous ratings and reviews of a particular reviewer to evaluate the reviewer's credibility. Prior literature suggests that participants share experiences to project themselves as knowledgeable consumers, expecting positive recognition (Engel et al., 1969; Sundaram et al., 1998). For ORs, self-enhancement is described as disseminating information about a product or service to project oneself as highly knowledgeable. Therefore, we define self-enhancement as the motive of the reviewer to portray oneself as knowledgeable to enhance image or reputation.

**Vengeance .** Some reviewers post of a negative eWOM is motivated by vengeance (Sundaram et al., 1998). Through ORs, reviewers' express discontent with a product or service, serving as cautionary advice to other consumers. From the reviewer's perspective, venting negative feelings can reduce emotional distress caused by the consumption experience (Pennebaker and King 1999). Furthermore, emotional dissatisfaction arouses users to express vengeance in writing of reviews (Berger 2014). Therefore, vengeance is defined as the motive of the reviewer to explicitly express retribution about consumption experiences.

**Advice Seeking .** Advice seeking motivation refers to the act of seeking information or guidance from others in order to make a decision or solve a problem. In the context of online reviews, advice seeking motivation refers to the act of writing a review to seek information or guidance from others about a product or service. Research has shown that advice seeking motivation is a key factor in the decision to write an online review. A study by Cheung and Lee (2012) found that consumers who wrote reviews were more likely to be motivated by the desire to seek advice and information from others about a product or service. The study also found that consumers who wrote reviews were more likely to engage in other forms of advice seeking behavior, such as asking friends and family for recommendations. In the current research we define advice seeking as the motive to seek information or guidance about a product or service from the online review platforms.

**Desire for social interaction.** In the context of online reviews, the desire for social interaction refers to the need to connect and communicate with others by writing reviews. Wang et al., (2016) suggests that reviewers post online reviews motived by the desire to interact socially with peer community members. The study also suggests that consumers who wrote reviews were more likely to engage in other forms of social interaction, such as commenting on and sharing reviews with others. We define desire for social interaction as a motive to write an online review expressing intent to interact with others.

**Activity**

Two types of OR dissemination activities have been identified in prior literature – feedback and complaint (Ravichandran & Deng 2022). Feedback is online written communication to present reactions to a product or a service. Feedback as an activity not only aids consumers but also helps a business evaluate customer satisfaction. A second OR activity is complaint. Complaints as an activity allow customers to express dissatisfaction while enabling businesses to improve. Customers may expect an apology or other compensation. We define complaint as communication expressing a negative view of a product or service.

## Goals

The goal of an OR might differ when the users are motivated by different factors and engage in different activities to express opinions. We summarize various goals or objectives of the reviewers in the following sections.

**Emotional satisfaction.** Emotional satisfaction is the gratification attained by expressing feelings through an OR. Consider a scenario where a reviewer writes to vent anger or frustration rather than highlight defects of a product or service; the reviewer may be trying to achieve emotional satisfaction. Prior IS studies have examined the role of emotions in measuring consumer satisfaction (e.g., Willemsen et al., 2011; Yin et al., 2014), but these have not examined the role of goal in users' expressions. To capture the emotional satisfaction goal, we define the construct as when the reviewer disseminates an OR to attain enjoyment by explicitly divulging in expressing feelings and emotions through the dispersed information.

**Financial Gain.** Hennig-Thurac et al., (2004) suggest that individuals participate in eWOM for economic reasons. Prior research has highlighted individual propensity to post manipulative reviews seeking compensations or restitutions (Choi et al., 2017). Individuals often participate in OR to seek financial rewards due to a sense of entitlement. This can arise when the product/service experience does not meet the consumer's expectations, leading to dissatisfaction.

We define financial gain as the expression of opinion seeking economic compensation for the negative experience caused by a product or service.

**Business Damage.** Although disseminating negative feedback or a complaint is highly correlated with financial gain and damaging a business, the distinction between them is important. An individual whose experience with a product or service is negative may either continue patronage, or switch from the business. Prior research suggests that the intention to post negative eWOM reduces the chances of patronage or re-patronage intentions (Verhagen et al., 2013). However, the reviewer may purchase from the same business again. In the case of complete dissatisfaction, individuals may stick to switching behavior by posting an OR against the business, thereby damaging its reputation. To capture this behavior, damage to the business is defined as the objective attained by undermining the business/product reputation.

## Methodology

In the first phase of our investigation, we use the MEF theory to identify and develop a taxonomy of motivation, activity, and goals through a qualitative examination of ORs from a review platform. The second phase of the preliminary study involves a quantitative examination of the relationship between motivation, activity, and goal which were identified in Phase 1.

### Phase 1: Qualitative Taxonomy Development

Two datasets of 313 ORs each were extracted from online review platforms of *BestBuy* and *Yelp*. In the first round, two researchers individually coded the collected data according to definitions presented in the theory section. Initial intercoder reliability was 0.812 (Cohen's Kappa). The two coders resolved the discrepancies by revisiting the definitions; one reviewer coded the rest of the reviews. In the second round, the coding team was expanded to four members. We classified the review dataset based on our proposed definitions. Reviews that did not fit our proposed definitions based on MEF theory were treated as "other" category. Closely following the literature and maintaining mutual exclusivity, we identified and classified motivation into five categories: Altruistic, Product or Service Involvement, Expression of Emotions, Self-Enhancement, and Vengeance. Activity is classified into two categories: Feedback and Complaint. Figure 9 presents the initial taxonomy developed through the qualitative assessment of the ORs. It is to be noted that the proposed taxonomy represents a sequential process of various reviewer attributes but not a casual model.

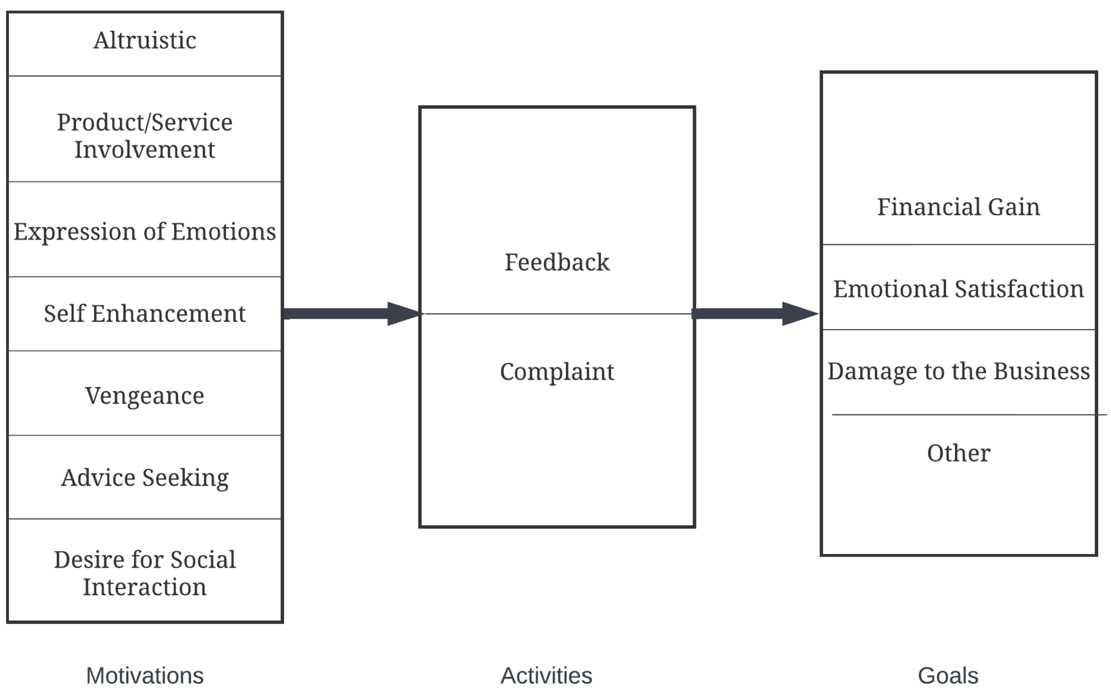


**Figure 9. Proposed Taxonomy of Online Reviews**

We present the descriptive statistics of the classification in Table 12.

**Table 12. Classification of Online Reviews**

| Category | Dimension | Number of Reviews |
|---|---|---|
| Motivations | Altruistic | 105 |
| | Expression of Emotions | 386 |
| | Product/Service Involvement | 104 |
| | Vengeance | 3 |
| | Self-Enhancement | 28 |
| | Advice Seeking | 0 |
| | Desire for Social Interaction | 0 |
| Activity | Feedback | 447 |
| | Complaint | 179 |
| Goals | Financial Gain | 0 |
| | Emotional Satisfaction | 394 |
| | Damage to the Business | 24 |
| | Other | 208 |

Out of 626 reviews, 394 are categorized as emotional satisfaction and 228 categorized into “other” category including the 24 reviews that are classified as business damage due to the less number of reviews. A comprehensive literature on the reviewer's goals is presented in the following section.

**Emotional Satisfaction and ORs**

In the context of OR's reviewers may attain emotional satisfaction by reviewing a product or a service is a topic that has been extensively researched in recent years. Studies have shown that reviewers jot down opinions and experiences with others, which can also have a positive impact on their emotional status. Kozinets (1999) argue that it is important to capture the emotions and textural qualities in virtual interactions to understand the consumer's view of the business and the products which can provide consumers with a sense of empowerment. This sense of empowerment can lead to emotional satisfaction.

Cheung et al. (2008) highlight the emotional catharsis that can be derived from the review-writing process. Their study reveals that writing reviews, particularly those expressing negative experiences, allows consumers to express and work through their negative emotions related to the product or service. This ability to publicly voice their frustrations can provide a sense of closure, enabling them to let go of residual negative feelings.

In a subsequent study, Djafarova and Trofimenko (2019)found that review writing can also facilitate an increased understanding of consumers' own preferences. The process of articulating their experiences and evaluating products or services often leads consumers to a heightened sense of self-awareness and subsequently, emotional satisfaction. Overall, the literature suggests that writing reviews can be an emotionally fulfilling experience for the reviewers. Furthermore, it can provide them with a means of self-reflection and self-discovery, as well as a sense of control over their consumption experiences.

In the current study, we aim to explain an individual's intention to participate in ORs, as reviewers participate in OR writing activity to attain a goal motivated by experiencing a product or service.

**Financial Gain and ORs**

The act of writing a review for financial gain has been a focal point of many scholarly works. It's often recognized as a double-edged sword that can either be leveraged to enhance the quality of reviews or lead to deceitful behavior. One of the earliest studies discussing financial motivation was conducted by Dellarocas et al. (2005), who explored the potential of economic incentives to encourage reviewers to provide more thoughtful and detailed reviews. Dellarocas argued that offering financial rewards could prompt more people to contribute, improving the overall quantity and quality of the information available on online platforms.

Despite the potential benefits of incentivizing reviewers, this practice can also encourage biased reviews. Chevalier and Mayzlin (2006) found that financially motivated reviews were generally more positive than those written by non-incentivized reviewers. The researchers suggested that the prospect of gaining financial can sway reviewers into providing overly positive feedback, skewing the overall sentiment of reviews and potentially misleading consumers.

This problematic aspect of financial incentives was further explored by Luca and Zervas (2016). Their study suggested that a significant number of businesses were offering financial rewards to reviewers in exchange for positive reviews, indicating a rise in unethical practices. They stressed the need for improved algorithms to detect these financially motivated but biased reviews to maintain the integrity of online review platforms. Furthermore, Mayzlin et al. (2014)

underscored the prevalence of strategic review manipulation for financial gain. Their findings highlighted that some firms may orchestrate negative reviews against competitors, demonstrating how financial motives can foster a harmful competitive landscape in the online review ecosystem.

In summary, while financial incentives can stimulate more engagement and detailed reviews, they also come with potential pitfalls, such as promoting biased feedback and unethical practices. A thorough understanding of these dynamics is vital for the fair operation of online review platforms.

**Business Damage and ORs**

The objective of writing reviews to damage a business's image is an area of interest with significant implications for companies, consumers, and review platforms. Whether these reviews are an outcome of genuine dissatisfaction or malicious intent, their impact on businesses can be substantial. A comprehensive study by Anderson, (2011) confirmed that negative reviews, often written with the intention of harming a business's image, could significantly influence consumers' purchasing decisions. However, the study also found that these negative reviews were not always grounded in authentic customer dissatisfaction but could be strategically orchestrated.

Exploring this further, Mayzlin et al. (2014) detailed how firms might orchestrate negative reviews against competitors, demonstrating the harmful competitive landscape created by these actions. The goal of these reviews was not to provide constructive criticism but to deliberately damage the image of competing businesses for relative advantage. Similarly, Luca and Zervas (2016) revealed the phenomenon of review fraud, where businesses incentivized individuals to write negative reviews for competitors. They emphasized the need for robust fraud detection mechanisms to maintain the credibility of review platforms and to protect businesses from these damaging practices. However, not all damaging reviews are results of dishonest tactics. In some cases, they are genuine responses to negative experiences. A study by Hennig-Thurau et al. (2004) found that consumers who have experienced a service failure were more likely to write reviews with the intention of damaging a business's image, viewing it as a form of retribution for the harm they perceived to have experienced.

Overall, the goal of writing reviews to damage a business's image is multifaceted, stemming from both genuine dissatisfaction and strategic manipulation. The recognition and management of these reviews are vital to maintaining the integrity of online reviewers, platforms, and businesses.

**Phase 2: Quantitative Analysis**

Leveraging the proposed taxonomy, we further carry out quantitative analysis to examine the influence of motivations and activity on goals. To increase the sample size and to identify the proposed variables in the sample, we utilized Yelp Academic Dataset which contains over 6 million reviews, pertaining to 150,346 businesses around 11 metropolitan areas in the United States (Li et al., 2021; Ning & Karypis, 2012; Rabinovich & Blei, 2014). For computational efficiency and accuracy reviews with less than 50 words were dropped resulting in over 4 million reviews of which 1 million reviews were randomly selected for further analysis.

To identify the motivations, activities, and goals custom keywords (see, Table 13) were fed into an algorithm that scores and classifies a review into each category of motivations (Figure 10), activities (Figure 11), and goals (Figure 12). First, we introduced the 626 reviews classified in Phase 1 into the algorithm, and the resulting classification is 82% present accurate in comparison with the human-classified reviews. Second, with the necessary changes we classified the 1 million reviews. The descriptives for the classification are presented in Figures 13,14 and,15.

**Table 13. Sample keywords and key phrases**

| **Category Name** | **Example Keywords** |
|---|---|
| Altruistic | "helpful", "supportive", "caring", "thoughtful", "generous", "go early", "park on", "avoid", etc. |
| Product or Service Involvement | "user-friendly", "convenient", "beneficial", "functional", "versatile", "dependable", "durable", "sturdy", "luxurious", "stylish", "trendy", etc. |
| Expression of Emotions | "happy", "joyful", "excited", "thrilled", "delighted", "ecstatic", "enthusiastic", "pleased", etc. |
| Self-Enhancement | "knowledgeable", "skilled", "experienced", "competent", "goal-oriented", "self-motivate" "high-achieving", etc. |
| Vengeance | "never recommend", "scam", "fraud", "bad experience", "terrible service", "awful quality", "poor customer service", "disappointing experience", etc. |
| Advice Seeking | "recommend?", "recommendation needed", "seeking advice", "looking for suggestions", "need help", "any recommendations", "any suggestions", "advice required", etc. |
| Desire of Social Interaction | "meet", "connect", "network", "interact", "get together", etc. |
| Activity | Example Keywords |
| Feedback | "not bad", "do better", "good", "impressed", "need work", "lacking", etc. |
| Complaint | "Unfriendly"," rude", "bad service", "unprofessional", "Horrible", etc. |
| Emotional Satisfaction | "loved", "liked", "enjoyed", "happy", "satisfied", "pleased", "fun", "exciting", "excited", etc. |
| Financial Gain | "refund", "compensation", "discount", "compensate", "money", "pay", "cost", "expensive", etc. |
| Business Damage | "awful", "disappointed", "unsatisfied", "displeased", "avoid", "scam", "fraud", "cheat", "fake", etc. |

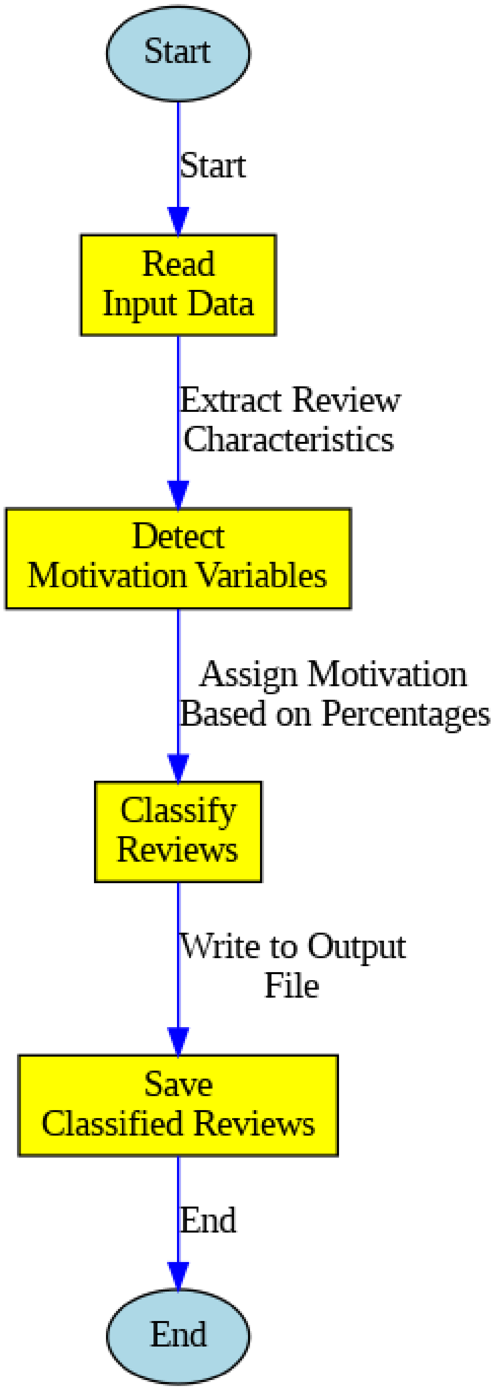


**Figure 10. Classification Process for Reviewers' Motivations**

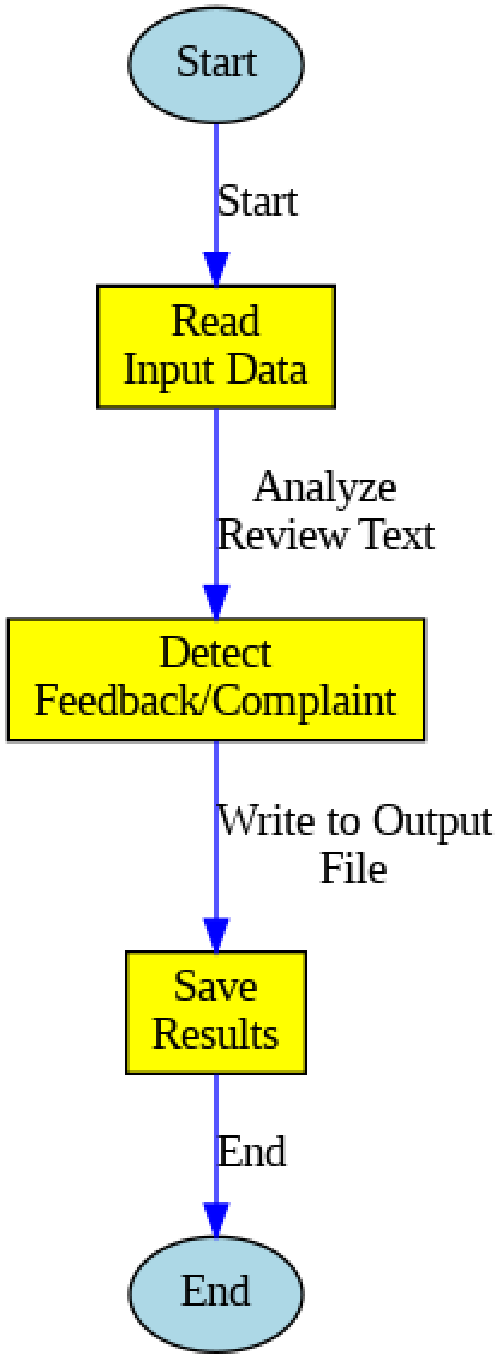


**Figure 11. Classification Process for Reviewers' Activites**

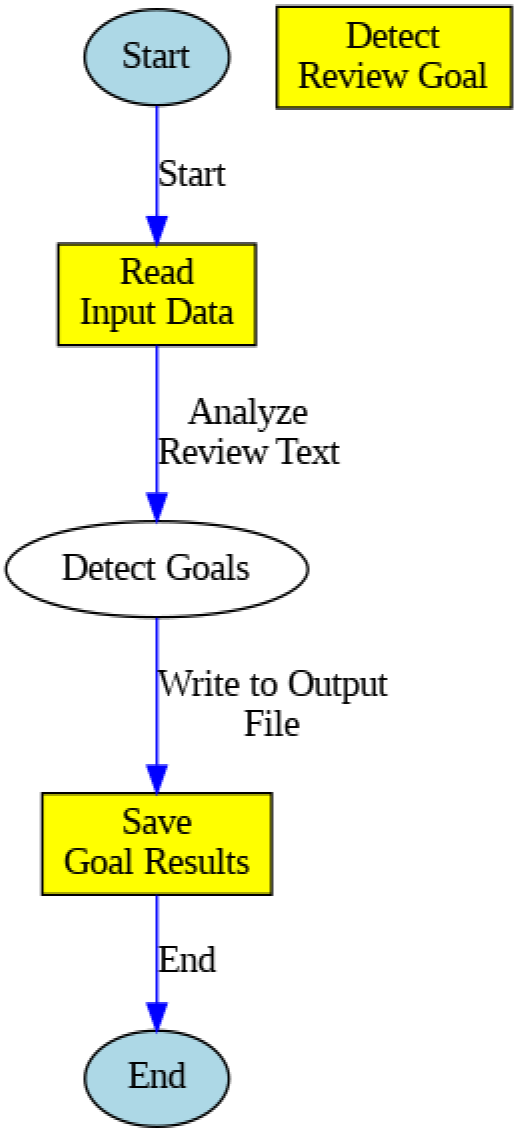


**Figure 12. Classification Process for Reviewers' Goals**

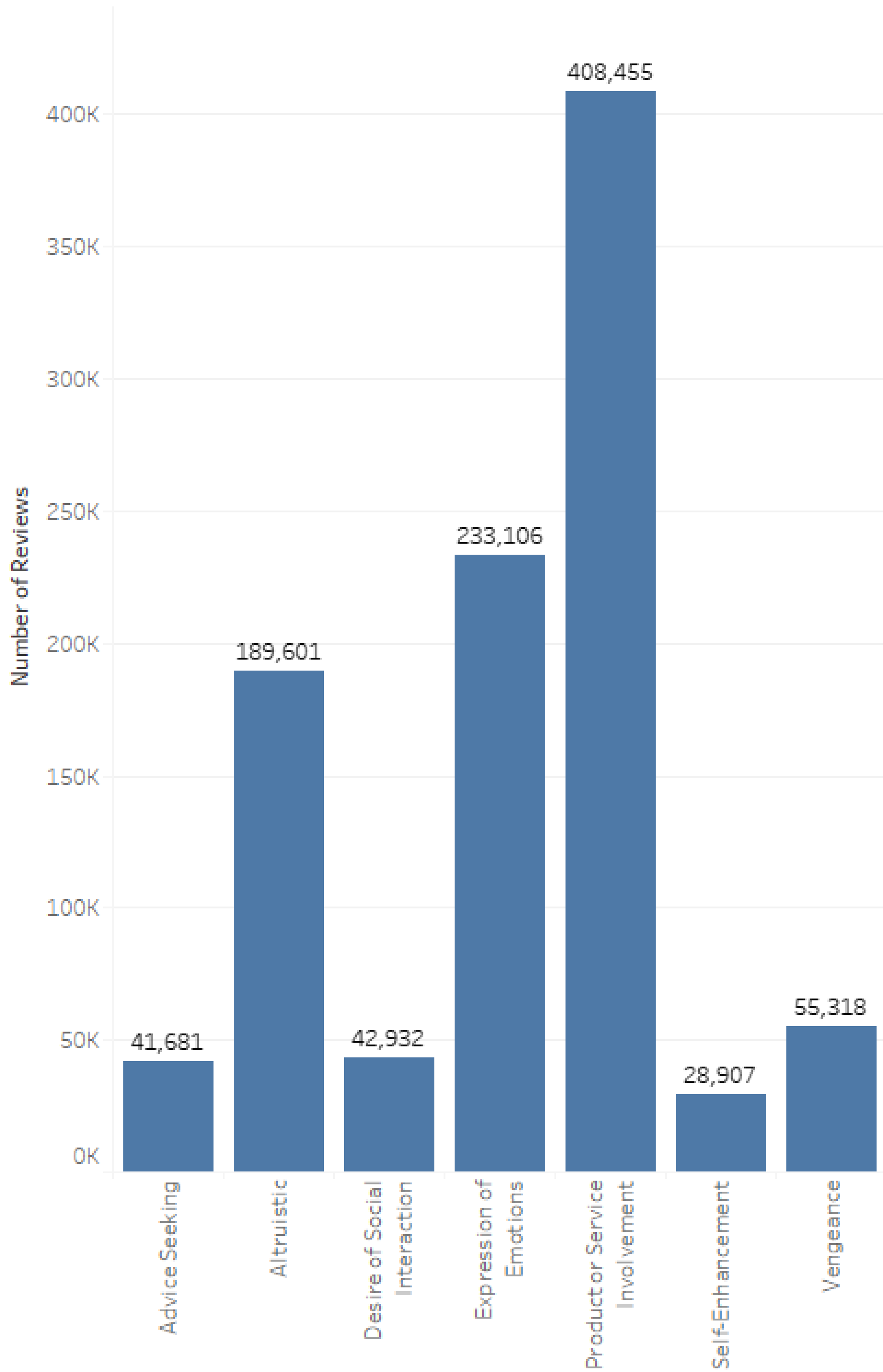


**Figure 13. Number of Reviews Classified According to the Motivations**

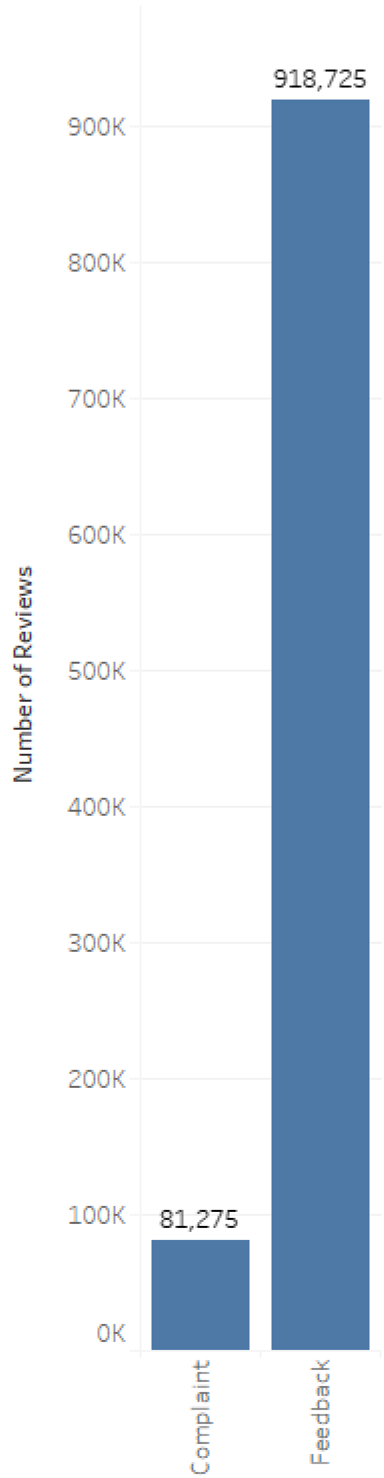


**Figure 14. Number of Reviews Classified According to the Activities**

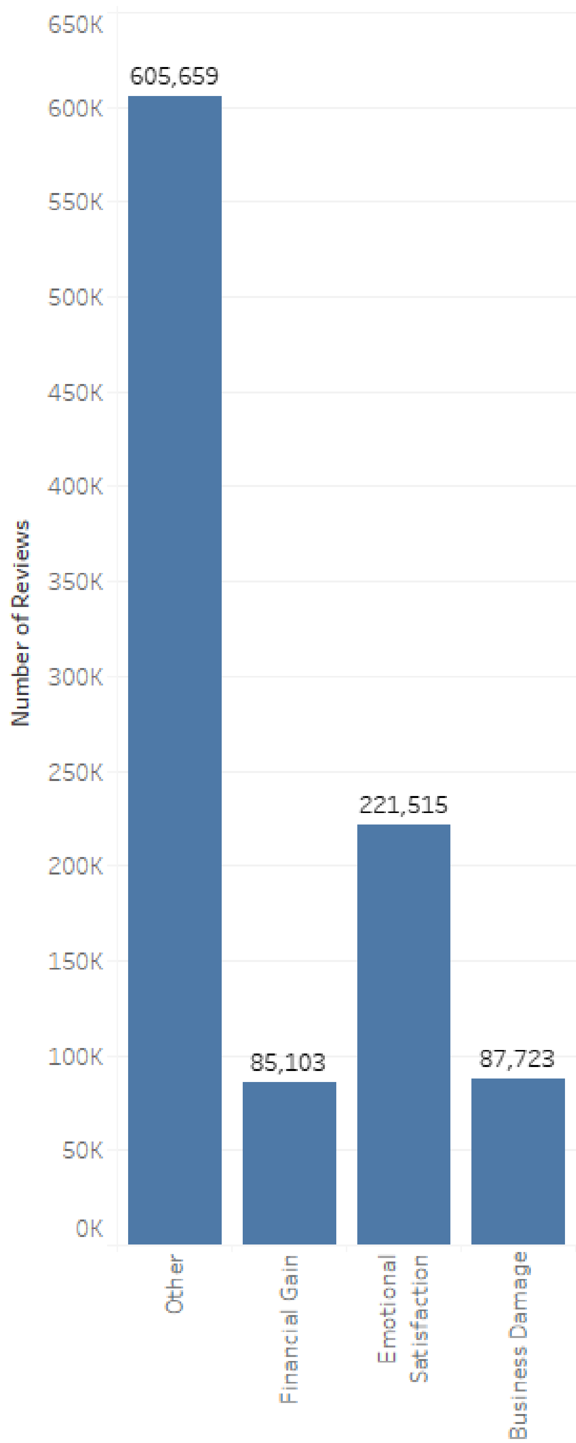


**Figure 15. Number of Reviews Classified According to the Goals**

**Table 14. Classified Yelp Reviews**

| Category | Dimension | Number of Reviews |
|---|---|---|
| Motivations | Altruistic | 189,601 |
| | Expression of Emotions | 233,106 |
| | Product/Service Involvement | 408,455 |
| | Vengeance | 55,318 |
| | Self-Enhancement | 28,907 |
| | Advice Seeking | 41,681 |
| | Desire for Social Interaction | 42,932 |
| Activity | Feedback | 918,725 |
| | Complaint | 81,275 |
| Goals | Financial Gain | 85,103 |
| | Emotional Satisfaction | 221,515 |
| | Damage to the Business | 87,723 |
| | Other | 605,659 |

## Supervised Learning Models

Our approach is evaluated using several supervised-learning classification models. To address potential issues from feature correlation affecting performance, we compute the correlation coefficients between features (after transformation). The correlation matrix (Figure

17) shows that the magnitude of correlation coefficients is small, indicating no serious correlation issues. Multiple machine-learning methods are used for this classifier, each inducing a unique mixture of underlying probability distributions, ranging from simple linear combinations to complex nonlinear ones. The classifiers used in our experiments are briefly described below.

| | Altruistic | Product or Service Involvement | Expression of Emotions | Self-Enhancement | Vengeance | Advice Seeking | Desire for Social Interaction | Emotional Satisfaction | Financial Gain | Damage to the Business | Other | feedback | complaint |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Altruistic | 1.0000 | -0.4019 | -0.2667 | -0.0835 | -0.1170 | -0.1009 | -0.1024 | 0.0002 | 0.0012 | 0.0010 | -0.0014 | -0.0400 | 0.0400 |
| Product or Service Involvement | -0.4019 | 1.0000 | -0.4581 | -0.1434 | -0.2011 | -0.1733 | -0.1760 | -0.0001 | -0.0034 | -0.0010 | 0.0026 | 0.0455 | -0.0455 |
| Expression of Emotions | -0.2667 | -0.4581 | 1.0000 | -0.0951 | -0.1334 | -0.1150 | -0.1168 | 0.0008 | 0.0001 | 0.0004 | -0.0010 | -0.0037 | 0.0037 |
| Self-Enhancement | -0.0835 | -0.1434 | -0.0951 | 1.0000 | -0.0418 | -0.0360 | -0.0365 | 0.0004 | -0.0003 | 0.0003 | -0.0004 | -0.0005 | 0.0005 |
| Vengeance | -0.1170 | -0.2011 | -0.1334 | -0.0418 | 1.0000 | -0.0505 | -0.0513 | -0.0021 | 0.0049 | 0.0001 | -0.0010 | -0.0190 | 0.0190 |
| Advice Seeking | -0.1009 | -0.1733 | -0.1150 | -0.0360 | -0.0505 | 1.0000 | -0.0442 | 0.0002 | -0.0003 | -0.0007 | 0.0004 | -0.0048 | 0.0048 |
| Desire for Social Interaction | -0.1024 | -0.1760 | -0.1168 | -0.0365 | -0.0513 | -0.0442 | 1.0000 | 0.0000 | 0.0005 | 0.0001 | -0.0003 | 0.0011 | -0.0011 |
| Emotional Satisfaction | 0.0002 | -0.0001 | 0.0008 | 0.0004 | -0.0021 | 0.0002 | 0.0000 | 1.0000 | -0.1627 | -0.1654 | -0.6611 | 0.0012 | -0.0012 |
| Financial Gain | 0.0012 | -0.0034 | 0.0001 | -0.0003 | 0.0049 | -0.0003 | 0.0005 | -0.1627 | 1.0000 | -0.0946 | -0.3780 | -0.0019 | 0.0019 |
| Damage to the Business | 0.0010 | -0.0010 | 0.0004 | 0.0003 | 0.0001 | -0.0007 | 0.0001 | -0.1654 | -0.0946 | 1.0000 | -0.3843 | -0.0017 | 0.0017 |
| Other | -0.0014 | 0.0026 | -0.0010 | -0.0004 | -0.0010 | 0.0004 | -0.0003 | -0.6611 | -0.3780 | -0.3843 | 1.0000 | 0.0011 | -0.0011 |
| feedback | -0.0400 | 0.0455 | -0.0037 | -0.0005 | -0.0190 | -0.0048 | 0.0011 | 0.0012 | -0.0019 | -0.0017 | 0.0011 | 1.0000 | -1.0000 |
| complaint | 0.0400 | -0.0455 | 0.0037 | 0.0005 | 0.0190 | 0.0048 | -0.0011 | -0.0012 | 0.0019 | 0.0017 | -0.0011 | -1.0000 | 1.0000 |

**Figure 16. Correlation Matrix**

**Support Vector Machines.** Support Vector Machines (SVMs) are a powerful and widely used type of supervised machine learning algorithm for solving both linear and non-linear classification and regression problems. They were first introduced by Vladimir Vapnik and Alexey Chervonenkis in the mid-1960s and have since become a popular choice for a variety of real-world applications, including image classification, text classification, and bioinformatics.

The goal of an SVM is to find the hyperplane that best separates the data into classes, while maximizing the margin, which is the distance between the hyperplane and the closest data points. These closest data points, called support vectors. In the case of a linear classification problem, the hyperplane is simply a line that separates the classes. For non-linear classification problems, the input data can be transformed into a higher-dimensional space using a technique called the kernel trick, which enables the algorithm to create a non-linear decision boundary that separates the data into classes. SVMs are effective because they are able to handle high-dimensional data, as well as provide good generalization performance, meaning that they are able to make accurate predictions on new, unseen data.

In addition, SVMs are efficient in terms of both training time and memory usage, making them a good choice for large-scale problems. One of the strengths of SVMs is their ability to handle data with a lot of noise, or data that is not linearly separable. By using a kernel function to transform the data into a higher-dimensional space, the SVM algorithm can create a non-linear decision boundary that effectively separates the classes. This is particularly useful in real-world applications where the data is often noisy or complex. For example, in Figure 17, you can see points scattered across the 2D plane, which represent individual data samples. Each point is positioned according to its values for the two features: "Altruistic" and "Expression of Emotions". The color of each point (blue or red) indicates its label or category - whether

"Emotional Satisfaction" was achieved (1) or not (0). The colored background represents the prediction space of the SVM classifier - blue for "Emotional Satisfaction" not achieved and red for achieved. The decision boundary, which separates these spaces, is the line where the SVM model changes its prediction from one class to another. Lastly, the points circled in black are called the support vectors. These are the data points that are closest to the decision boundary and that the SVM uses to determine the optimal position and orientation of the decision boundary. The SVM algorithm aims to maximize the margin, which is the distance between the decision boundary and the nearest points of each class (the support vectors).

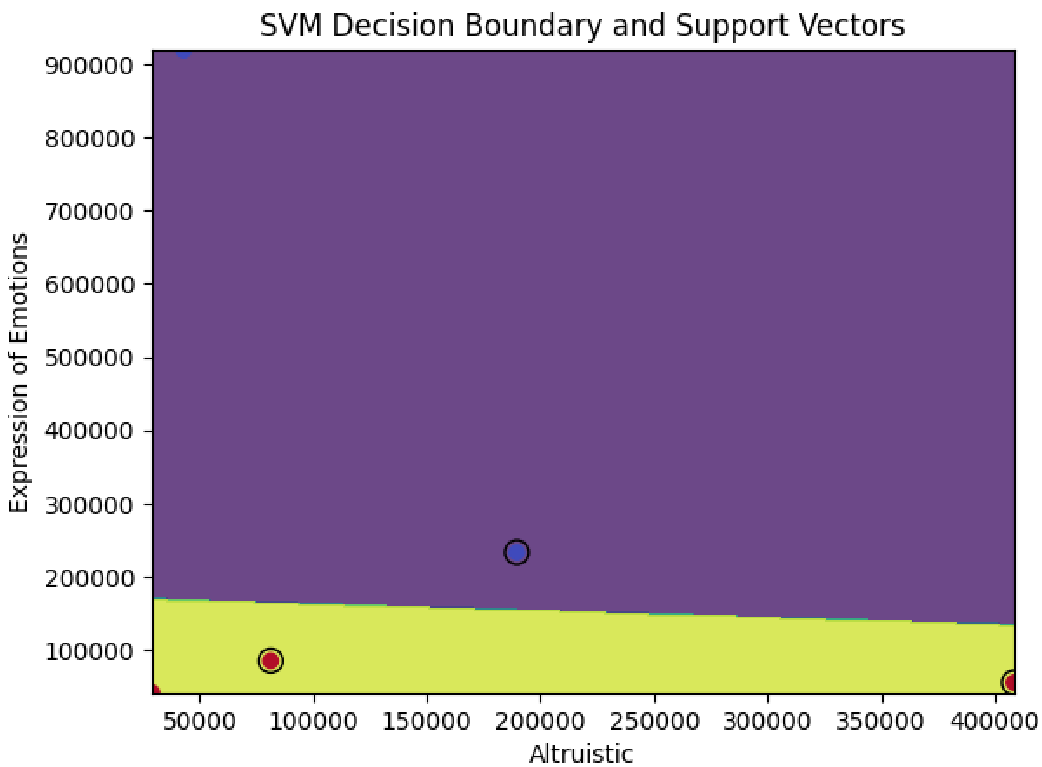


**Figure 17. SVM Example with Decision Boundary**

Another important aspect of SVMs is their ability to handle imbalanced datasets. This is a common problem in real-world applications, where one class may have significantly more instances than another. SVMs can handle this imbalance by assigning higher weights to the minority class, which helps ensure that the decision boundary accurately reflects the relationship between the classes.

**Binary Logistic Regression.** Binary logistic regression is a statistical technique used for predictive modeling, in which a binary outcome is predicted based on one or more independent variables. The outcome in binary logistic regression is a binary variable, meaning it can take only two possible values, such as yes/no, pass/fail, or present/absent. In binary logistic regression, the independent variables are used to predict the likelihood of the binary outcome occurring. This is done by estimating the probability of the outcome being either "0" or "1". The probability estimate is transformed into a binary decision using a threshold value, such as 0.5. If the probability estimate is greater than or equal to 0.5, the binary outcome is predicted as "1", and if the probability estimate is less than 0.5, the outcome is predicted as "0" see figure 18.

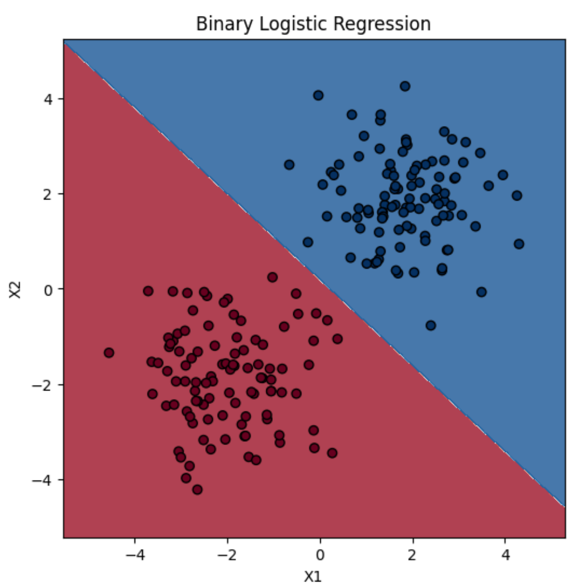


**Figure 18. Binary Logistic Regression Example**

The binary logistic regression model is estimated using maximum likelihood estimation. The maximum likelihood method is used to find the parameters of the model that best fit the data, given the assumptions of the model. The model parameters can be used to make predictions about future observations based on the independent variables. One of the key assumptions of binary logistic regression is that the relationship between the independent variables and the binary outcome is linear. If the relationship is non-linear, the model may not fit the data well, and alternative techniques, such as non-linear logistic regression, may need to be used. Another important aspect of binary logistic regression is interpreting the coefficients of the independent variables. The coefficients represent the change in the log-odds of the binary outcome occurring for a one-unit change in the independent variable, while holding all other variables constant. The log-odds can be transformed into odds ratios, which represent the change in the odds of the binary outcome occurring for a one-unit change in the independent variable. In Python, the scikit-learn library provides an implementation of logistic regression through the Logistic Regression class. This class makes it easy to train and evaluate a logistic regression model on a given dataset.

**Naive Bayes.** Naive Bayes is a simple yet powerful machine learning algorithm based on Bayes' Theorem. The theorem states that the probability of an event occurring is equal to the prior probability of the event multiplied by the likelihood of the event given some evidence. In the case of Naive Bayes, the event is the class label, and the evidence is the feature set. The algorithm is called "Naive" because it assumes that all the features in the feature set are independent of each other, which is often not the case in real-world problems. Naive Bayes has three main variants: Gaussian Naive Bayes, Multinomial Naive Bayes, and Bernoulli Naive Bayes. Gaussian Naive Bayes assumes that the features follow a Gaussian distribution, Multinomial Naive Bayes is used for discrete count-based distributions, and Bernoulli Naive Bayes is used for binary features. Figure 19 illustrates an example for prediction classes 0 (emotional satisfaction : goal) and 1 (not emotional satisfaction : goal).

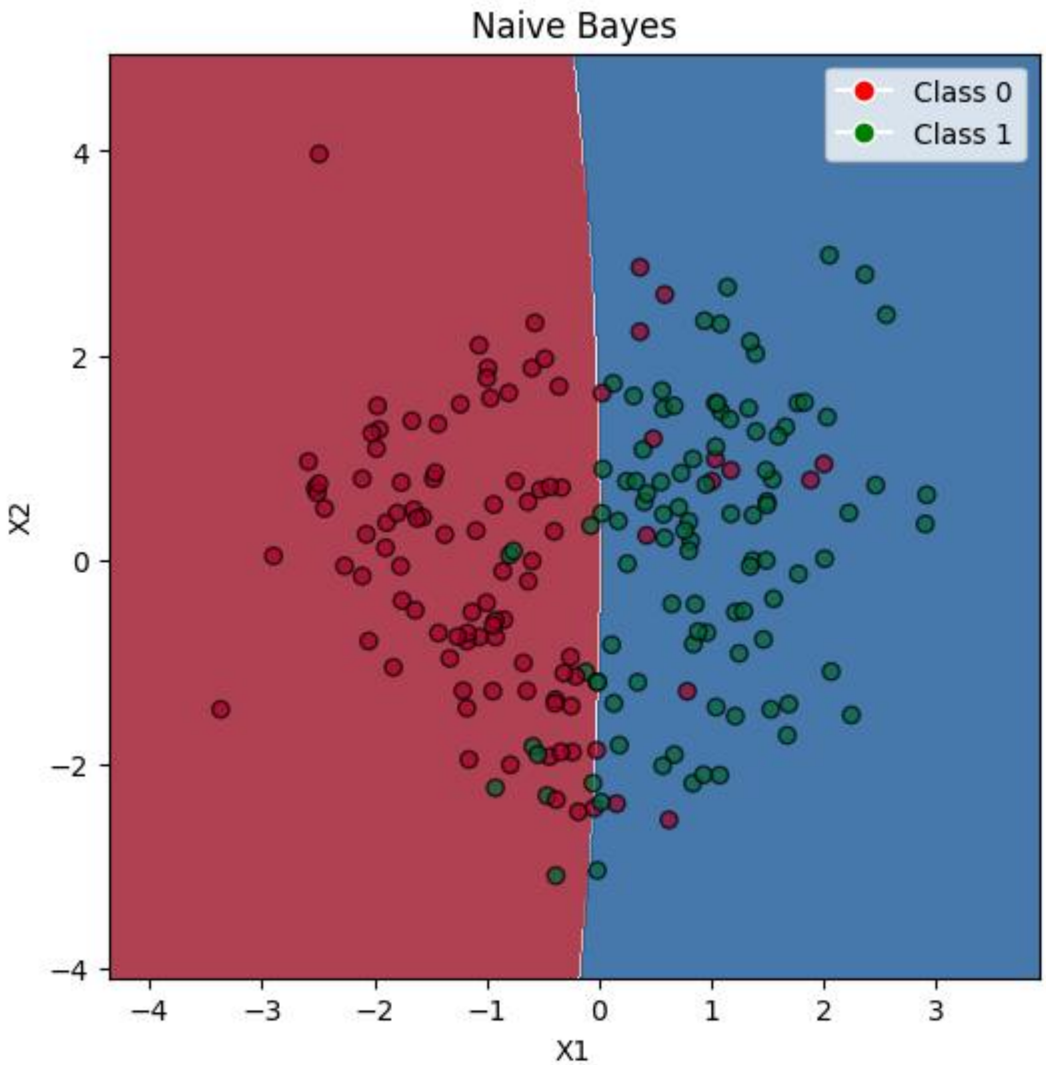


**Figure 19. Naive Bayes Scatter Plot (Example)**

The algorithm starts by calculating the prior probability of each class, which is the number of instances of each class divided by the total number of instances. Given a new instance and its feature set, the algorithm calculates the likelihood of each feature given each class and multiplies them with the prior probability to get the posterior probability of each class. The class with the highest posterior probability is then chosen as the predicted class.

**K-Nearest Neighbor.** The K-Nearest Neighbor (K-NN) algorithm is a simple and effective machine learning algorithm used for classification and regression problems. The algorithm is based on the idea that similar instances are likely to have similar class labels. The algorithm classifies a new instance based on the majority class label of its k nearest neighbors in the training dataset. In k-NN, the distance between instances is calculated using a distance metric, such as Euclidean distance which is represented as cool map in Figure 20.

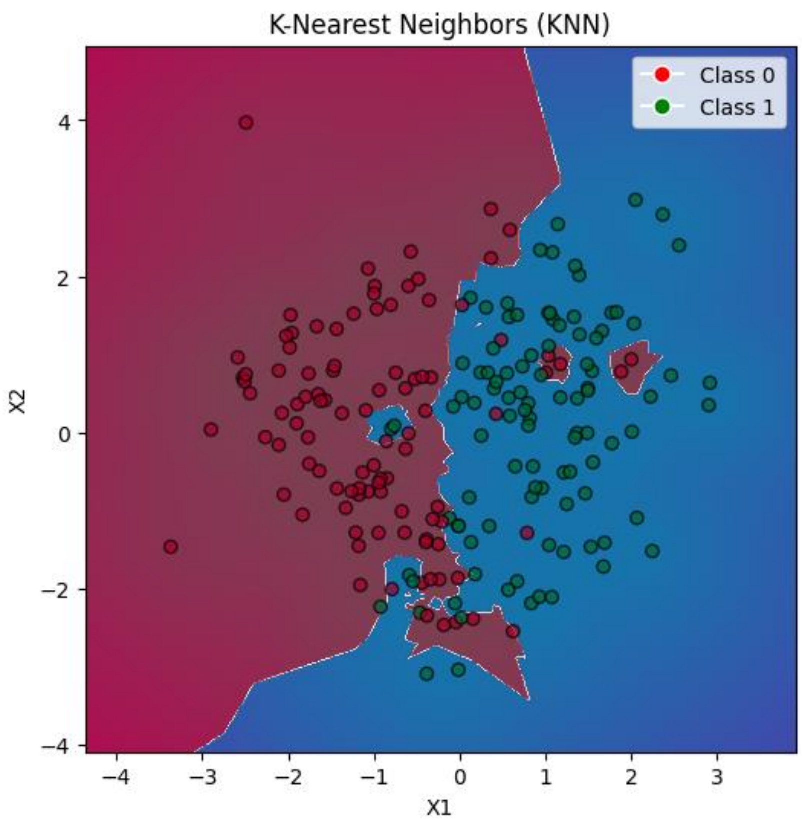


**Figure 20. KNN Example with Euclidean Distance**

The algorithm first finds the k nearest neighbors to a new instance and then assigns the class label based on the majority class label of the neighbors. The value of k is a hyperparameter that can be tuned for the best performance on the specific problem. A common approach is to use an odd number for k to break ties between two classes. K-NN has several advantages, including its simplicity and versatility. The algorithm does not make any assumptions about the distribution of the data, and it can handle non-linear relationships between features. Additionally, K-NN can handle missing data and noisy data, making it a useful algorithm for real-world problems.

**Decision Tree.** The Decision Tree algorithm is a widely used machine learning algorithm for both classification and regression problems. The algorithm works by recursively dividing the data into smaller subsets based on the most significant feature, known as the root node. The process continues until the leaves of the tree are pure, meaning they contain instances belonging to only one class or having similar values for the target variable in regression problems. A key advantage of decision trees is their interpretability. The tree structure can be easily visualized, and the decision-making process of the algorithm can be understood. Additionally, decision trees can handle both categorical and numerical data, and can handle missing values in the data.

The accuracy of a decision tree can be improved by controlling its growth through techniques such as pruning. Pruning involves removing the branches of the tree that do not contribute much to the overall accuracy of the model. This helps in avoiding overfitting, which occurs when the model becomes too complex and fits the training data too closely. Another important aspect of decision trees is the choice of the splitting criteria, such as Gini impurity or information gain. The splitting criteria determine the feature that is used to split the data at each node of the tree. For example, in figure 21, the decision at each node is based on either 'Category' or 'Number of Reviews'. The value of 'Category' goes from 1 (representing 'Motivations') to 3 (representing 'Goals'), and the value of 'Number of Reviews' is the count of reviews for each category. The 'class' at each node represents whether the emotional satisfaction was achieved or not, based on the provided labels.

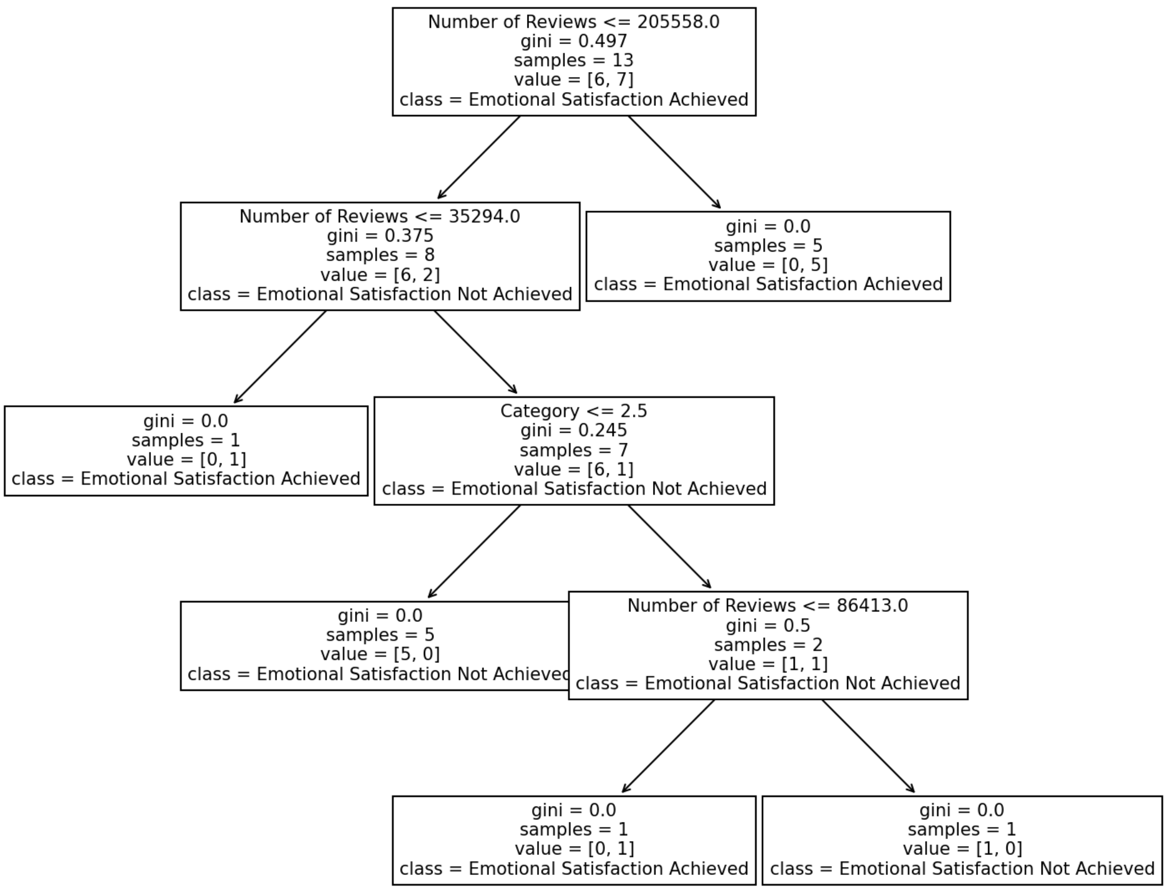


**Figure 21. DT Example**

**Artificial Neural Networks.** Neural networks, also known as artificial neural networks (ANNs), are a class of machine-learning models designed to mimic the functioning of human brains. Likewise, neural networks consist of interconnected nodes called neurons representing brain cells. Neurons consist of three components, the input layer, one or multiple hidden layers, and the output layer. Figure 22 depicts the architecture of a simple artificial neural network model with one input layer, one hidden layer, and one output layer. The input layer receives two features, "Category" and "Number of Reviews", while the output layer produces a binary prediction indicating the achievement of "Emotional Satisfaction". The hidden layer performs complex computations using weights and biases, which are adjusted during the training process to improve the model's predictive accuracy. The connections between neurons are represented by weights, which determine the strength and impact of the input on the neuron's output. During training, the network adjusts these weights based on the provided input data and the desired output, using a process called backpropagation. This iterative process aims to minimize the difference between the network's predicted output and the true output.

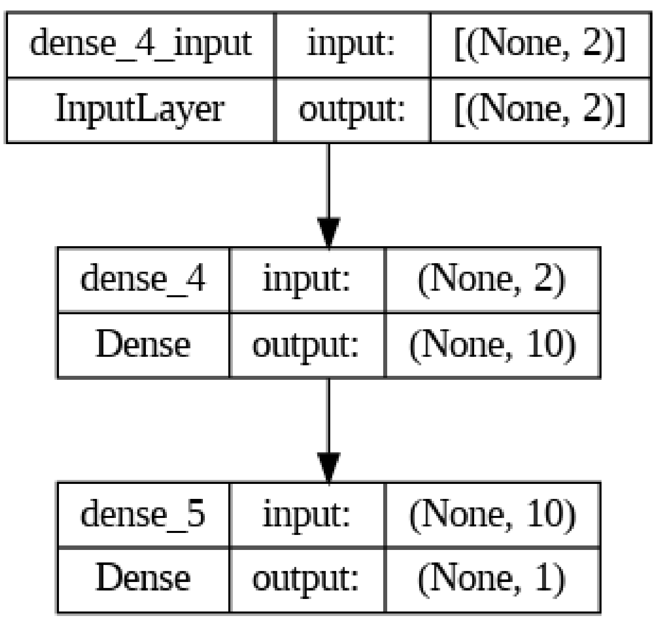


**Figure 22. ANN example**

Some popular types of neural networks include feedforward neural networks (FNNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks. Each type is designed to handle specific types of data and address different learning problems. This ability makes them particularly well-suited for tasks such as image and speech recognition, natural language processing, and predictive modeling.

We evaluate the above machine learning models using the metrics: accuracy, precision, recall, specificity, and area under the curve (AUC) which are briefly described below.

Accuracy: Accuracy is a widely used metric that measures the overall correctness of a classification model's predictions. It calculates the ratio of the correctly predicted instances (both positive and negative) to the total number of instances. A higher accuracy score indicates a more accurate model. The formula for accuracy is (TP + TN) / (TP + TN + FP + FN), where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

Precision: Precision is a metric that focuses on the positive predictions made by the model. It measures the proportion of correctly predicted positive instances out of the total instances predicted as positive. Precision helps evaluate the model's ability to avoid false positive predictions. The formula for precision is TP / (TP + FP).

Recall: Recall, also known as sensitivity or true positive rate, evaluates the model's ability to correctly identify positive instances out of the total actual positive instances. It measures the proportion of correctly predicted positive instances. A high recall indicates that the model is effective at capturing positive instances. The formula for recall is TP / (TP + FN).

Specificity: Specificity is a metric that complements recall by evaluating the model's ability to correctly identify negative instances out of the total actual negative instances. It measures the proportion of correctly predicted negative instances. Higher specificity indicates that the model is effective at avoiding false positive predictions. The formula for specificity is

TN / (TN + FP). The implementation of the classifiers discussed above is represented by the following Figure 23.

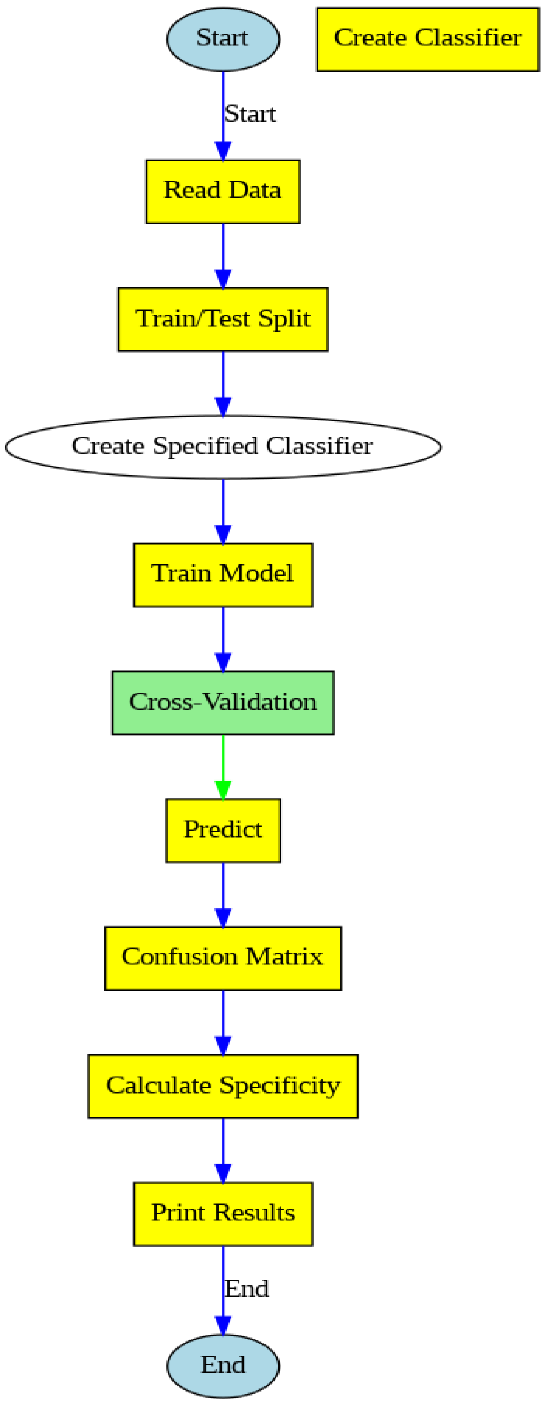


**Figure 23. Classifiers' Implementation Procedure**

## Results and Discussion

We performed the above models using python sklearn module. As one may notice that, in order to evaluate the model, one should specify the true positive (TP) outcome for each model. Therefore, we performed the model several times for each category of the goal. The highest accuracy, precision and recall values for each category are presented below.

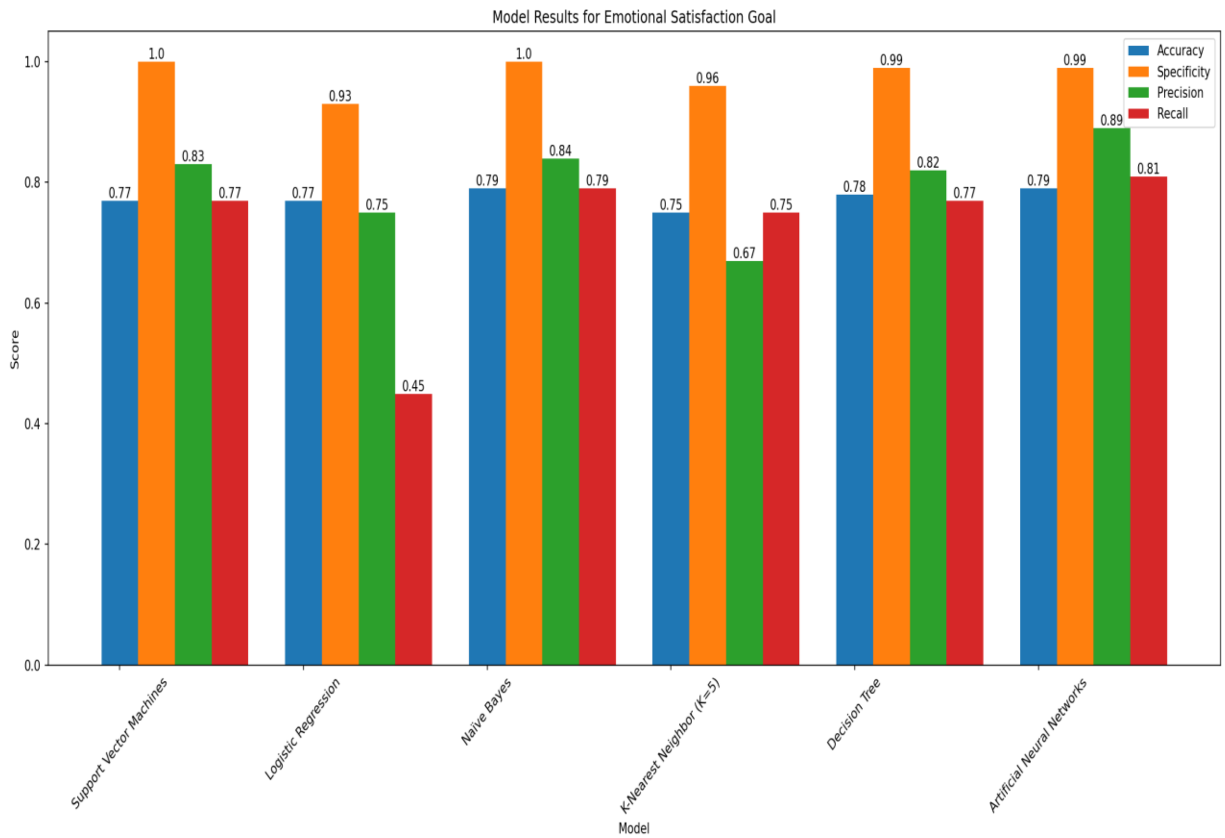


**Figure 24. Model Results for Emotional Satisfaction Goal**

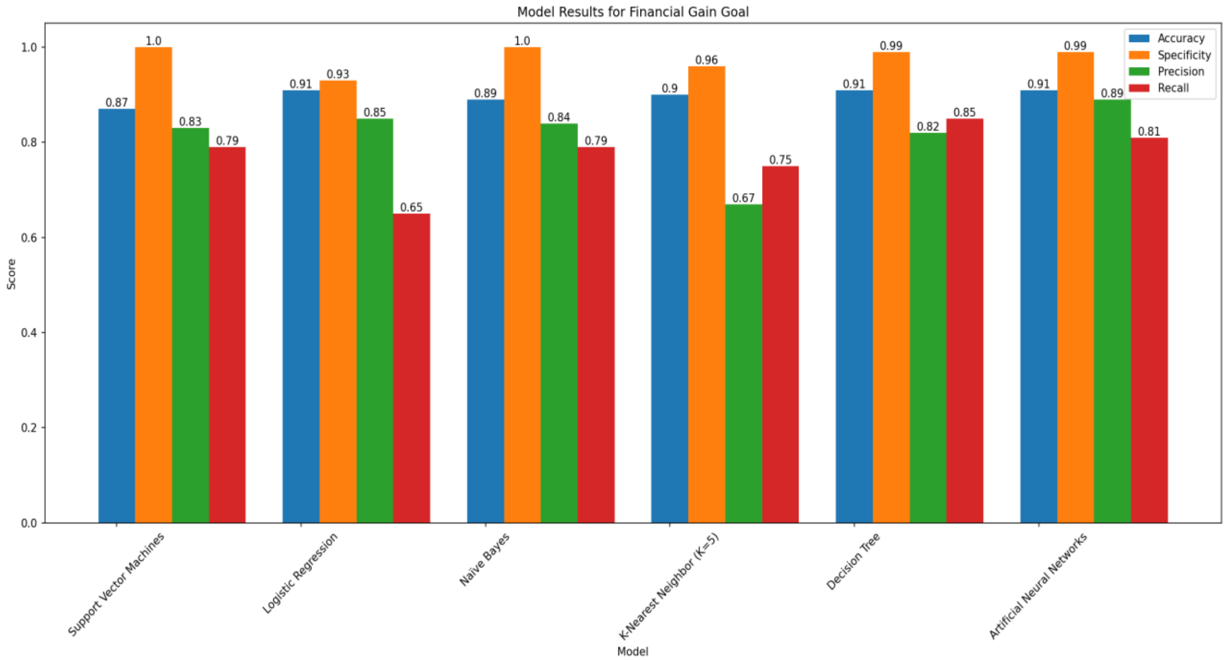


**Figure 25. Model Results for Financial Gain Goal**

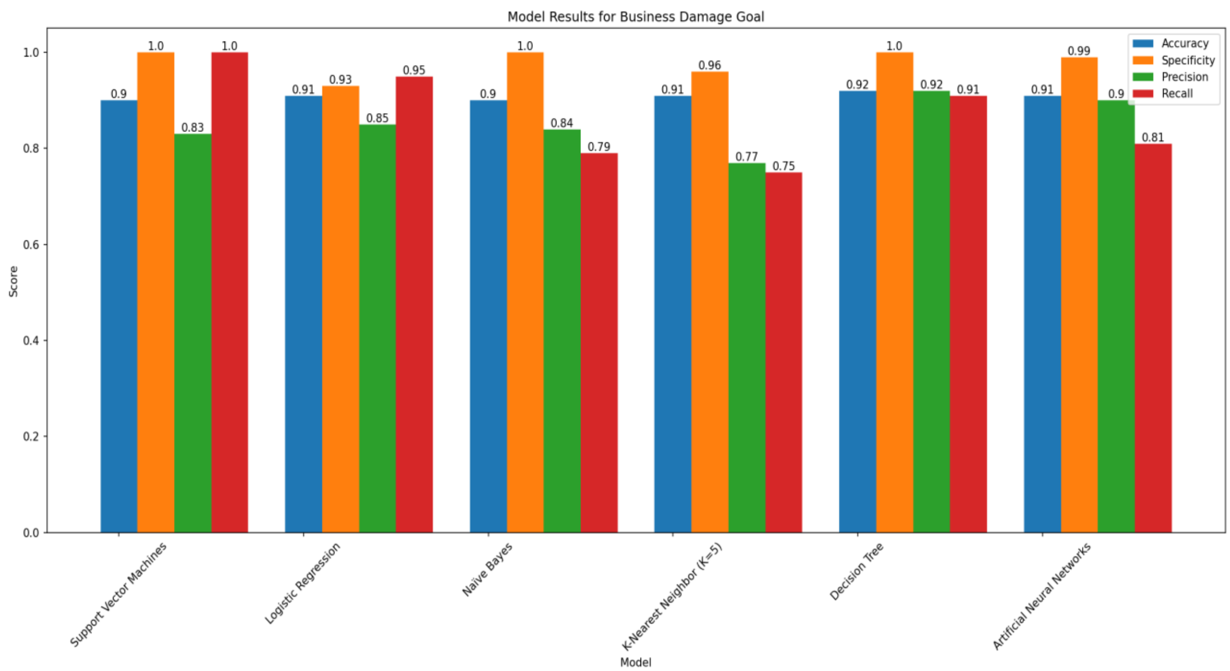


**Figure 26. Model Results for Business Damage Goal**

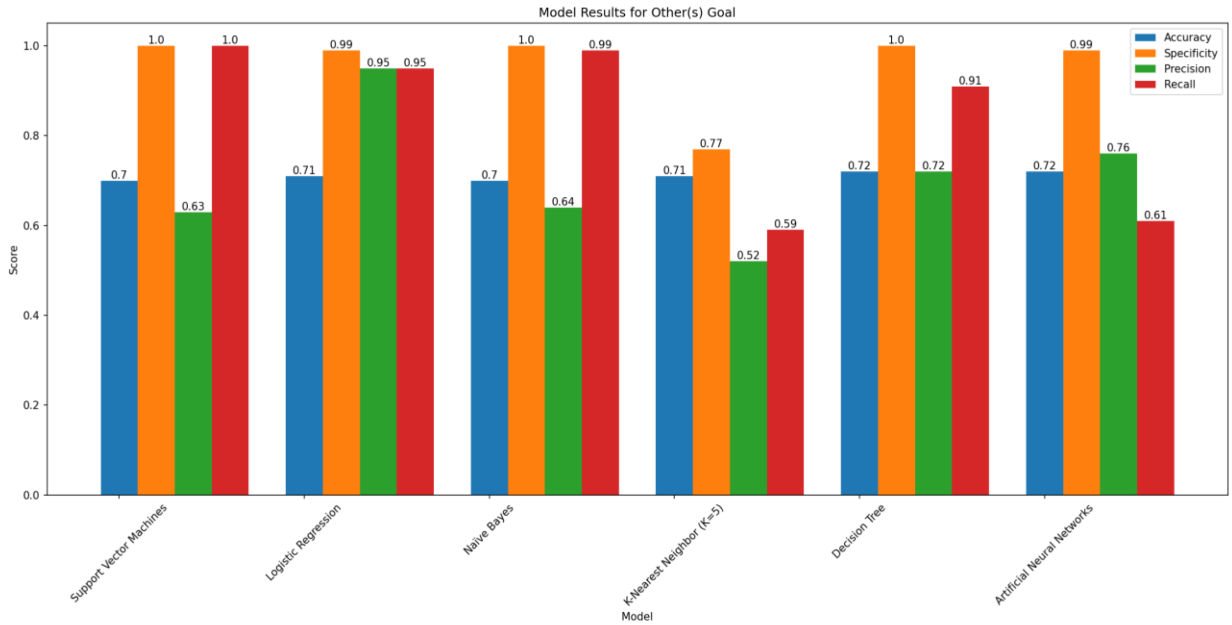


**Figure 27. Model Results for Other Goals**

From the above tables, DT and ANN are closely outperforming other models. Therefore, we use the ensemble model which performs the classification based on majority voting to increase the robustness and reduce any overfitting in the model.

**Ensembling Method**

Ensembling, alternatively known as model combination or model aggregation, is a strategic method employed to enhance the efficiency and dependability of machine learning models. This enhancement is achieved by amalgamating the predictions yielded by various independent models. In the current research, ensembling is performed by integrating the results generated by Decision Tree (DT) and Artificial Neural Networks (ANN) models. This integration aims to augment accuracy, specificity, precision, and recall for each distinct goal i.e., Emotional Satisfaction, Financial Gain, Business Damage, and Other. Ensembling's method has several advantages. First, ensembling can significantly increase accuracy. This increase is achieved by combining the predictions of multiple models, thus capitalizing on the collective wisdom of different models to offer more precise predictions. Second, ensembling can considerably reduce overfitting. Overfitting transpires when a model performs exceedingly well on the training data but struggles to generalize this performance to new, unseen data. By amalgamating multiple models, each with its biases and learning patterns, the risk of overfitting is mitigated. Third, ensembling enhances model robustness. This enhancement results from a reduction in the influence of outliers or noisy data, which, if affecting a single model, can be offset by other models in the ensemble, thereby yielding more dependable predictions. Similarly, the model's stability is increased through ensembling, as it curtails the variance associated with individual models. Variations in a single model's performance can be balanced out when pooled with other models, leading to more consistent and dependable predictions.

The generalization ability of models is also enhanced through ensembling. This enhancement is achieved by collating models that have learned different facets of the data, facilitating a more comprehensive understanding of the underlying patterns, and consequently, better generalization to unseen data. Lastly, ensembling can bolster the resilience of the model to alterations in the dataset or feature space. This robustness is a result of ensembling reducing the risk of a single model being overly reliant on specific features or data distributions, ultimately leading to a more adaptable and robust model. The implementation procedure for the ensemble model is represented in the Figure 28. The results for the ensembling of DT and ANN for each goal are presented in Table 15.

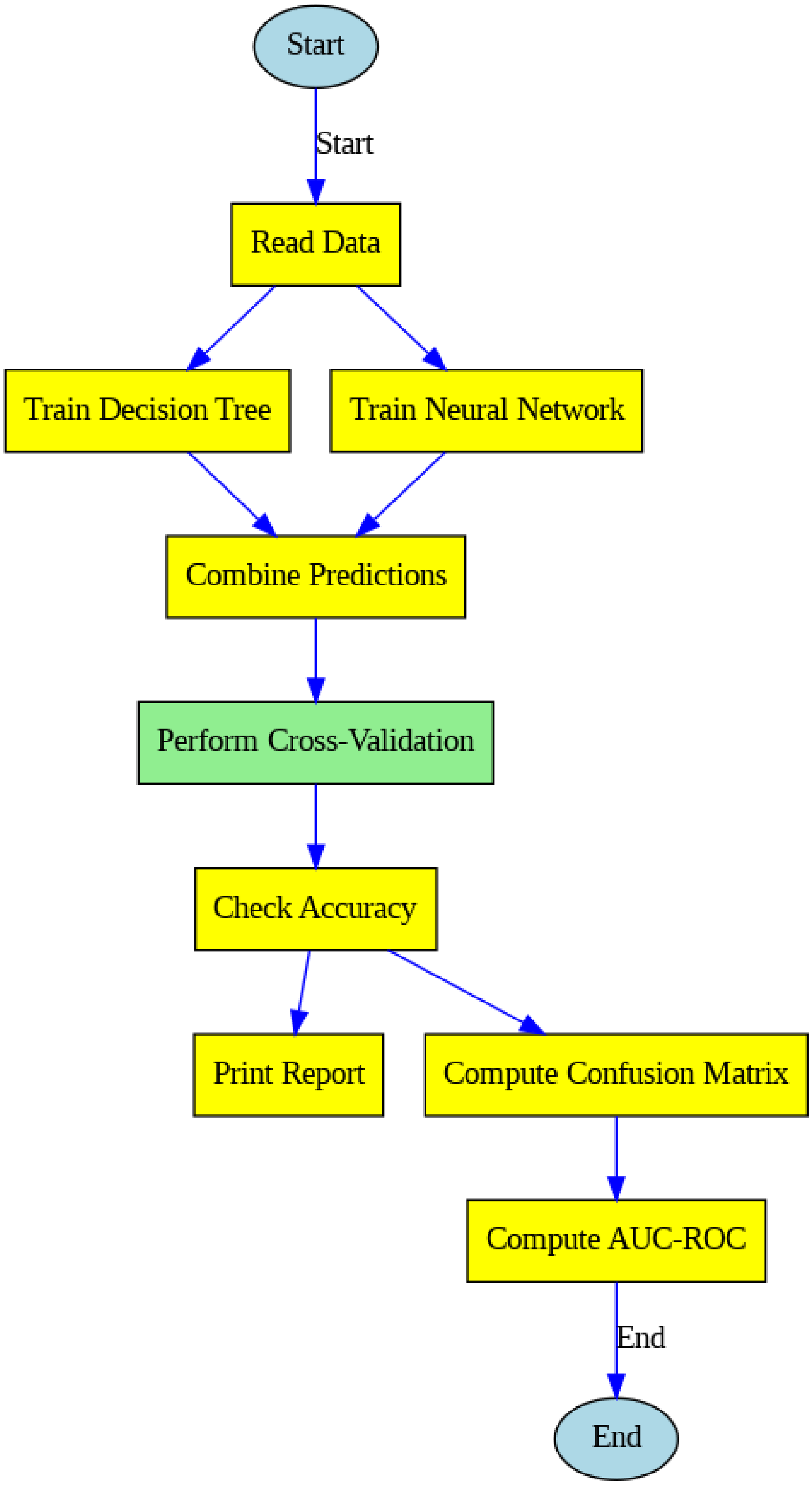


**Figure 28. Ensemble of DT and ANN**

**Table 15. Ensembling (DT&ANN) Results**

| | **Emotional Satisfaction** | **Financial Gain** | **Business Damage** | **Other** |
|---|---|---|---|---|
| Accuracy | 0.83 | 0.94 | 0.94 | 0.75 |
| Specificity | 1.00 | 0.99 | 1.00 | 1.00 |
| Precision | 0.87 | 0.95 | 0.89 | 0.79 |
| Recall | 1.00 | 0.99 | 0.99 | 0.99 |

Overall, the ensembling results, shown in Table 15, revealed significant improvements across all categories. The ensemble method demonstrates the advantages of combining multiple models, including increased accuracy, decreased overfitting, and enhanced robustness. Particularly, ensembling bolsters resilience to alterations in the dataset and augments the model's generalization ability. In conclusion, our study illustrates the effectiveness of the ensemble method, combining Decision Tree and Artificial Neural Networks, in predicting the reviewer goals given their motivations and activities.

## Implications

### Theory

This study has considerable theoretical significance and contributes substantially to the existing body of knowledge surrounding online reviews (OR). Despite the profusion of research examining online reviews from the reader, business, and writer's experience perspectives, there is a paucity of systematic studies exploring the association between different motivations and the resulting outcomes. This research addresses this gap and contributes to theoretical understanding in several ways.

Firstly, the study adopts the Means-Ends Fusion (MEF) theory to provide a fresh theoretical lens through which to explore and understand the world of online reviews. The MEF theory, which posits that motivations (means) determine the activities leading to a specific goal, is a novel approach in the context of online reviews. This novel application of MEF theory serves to expand its scope and utility in new research contexts, thereby enriching theoretical discourse.

Secondly, the study offers a systematic exploration of a diverse range of OR motivations and activities. It presents a framework for detecting and categorizing the goals of reviewers. This not only advances understanding in the literature of online consumer behavior but also provides useful insights for review platforms. Finally, the research employs machine learning techniques to investigate the underlying relationships of the key tenets of online reviews. The use of such techniques in the current context adds to the growing body of literature employing advanced computational techniques to explore complex phenomena, further cementing the role of such techniques in modern research.

In summary, the study makes significant theoretical contributions by providing a systematic understanding of OR motivations and activities, applying MEF theory in a novel context, and using machine learning techniques to explore complex relationships. It provides a solid foundation for further research in the field and can serve as a catalyst for novel theoretical and practical insights into online consumer behavior and the dynamics of online reviews.

### Practice

The proposed taxonomy for online reviews can be a valuable tool for both platform owners and business owners. Platform owners can use this taxonomy to differentiate between general feedback and complaints, which can help them provide a better experience for both reviewers and business owners. By understanding the motivations behind online reviews, platform owners can design features that cater to the needs of their users, improve the overall quality of reviews, and increase the usefulness of the platform.

For online review platforms, by identifying and managing reviewers' intentions, the research can help enhance the credibility of platforms. For instance, the models might identify certain characteristics of a review that suggest the reviewer is motivated by emotional satisfaction, financial gain, or even malicious intent to damage a business. These predictions can then be used to categorize reviews, aiding in more effective management of online review platforms. Additionally, understanding the motivations of reviewers can allow platforms to fine-tune their interfaces and features. By catering to these motivations, platforms can encourage the production of high-quality reviews, enhancing user engagement and satisfaction. This can improve the user experience, increase user retention, and ultimately contribute to the platform's success.

Furthermore, taxonomy can help business owners understand the root causes of customer complaints. Additionally, businesses can leverage the understanding of reviewers' motivations and goals to guide customer service strategies and product development. For instance, reviews motivated by emotional satisfaction might provide insights into what consumers value most in a product or service. In addition to improving the overall customer experience, the taxonomy can also help business owners identify areas where they can improve their online presence. For example, if a business owner notices that most complaints are related to their website or social media presence, they can invest in improving their online presence and make it more user-friendly. This can help increase the visibility of their business, attract new customers, and improve their overall brand reputation.

# CHAPTER VI

## HOW REVIEWER ATTRIBUTES ARE RELATED TO ONLINE REVIEW HELPFULNESS: AN EXTENDED MEANS-ENDS FUSION THEORY PERSPECTIVE

### Abstract

Online reviews have become an important source of information for consumers and understanding the factors that influence their helpfulness is critical for businesses and online review platforms. Previous research has suggested that reviewers have different motivations and engage in different types of activities, but their impact on review helpfulness is not fully understood. We adopt the Means-Ends Fusion theory as the underpinning framework to examine how the fusion of reviewer activities and goals gives rise to various motivations, and in turn, influences the helpfulness of their reviews. Utilizing a sample from the Yelp Academic Dataset comprising over a million reviews, we employ data mining techniques, namely cluster analysis and association rule mining, to investigate the relationships between the variables. Our findings reveal distinct patterns of motivations, activities, and goals that contribute to the helpfulness of a review. Notably, reviews driven by the expression of balanced emotions, product/service involvement, or altruistic motives, and which provide constructive feedback, are generally perceived as more helpful. Conversely, reviews based solely on product/service involvement or those seeking financial gain tend to be viewed as less helpful, suggesting a demand for more balanced and objective evaluations from consumers

## Introduction

In the era of digital commerce, online reviews (ORs) have become an important source of information for consumers to facilitate purchase decisions. The proliferation of online reviews on crowd-sourced review platforms such as Yelp and TripAdvisor has made them an important tool for prospective consumers to assess a product or a service before consumption. However, an increase in the availability of reviews may overwhelm consumers and demands additional cognitive effort from the consumers due to the information overload. The ranking system of online platforms provides mechanisms to identify helpful reviews to aid consumers in their decision-making process. Consequently, prior research has suggested various factors that contribute to the helpfulness of an OR. For example, reviewer-related factors such as reviewer reputation on the platform, experience, and identity disclosure were found to be significant in determining helpfulness (Chua & Banerjee, 2016; Huang et al., 2015).

Our research focuses on understanding the interaction between reviewer-related factors such as reviewer motivation, type of activity, goals, and OR helpfulness. Literature suggests that online reviewers have different motivations for writing an OR, such as expressing emotions, seeking self-enhancement, or vengeance (Baumeister et al., 2001; Ye et al., 2009). In alignment with the literature, we examine five motivations of online reviewers, including product/service (P/S) involvement, expression of emotions, altruistic, self-enhancement, and vengeance. P/S involvement refers to reviewers who provide information about a product or service to assist consumers make better purchasing decisions. Expression of emotions refers to reviewers who post online reviews to express their feelings and emotions about the product or service. Altruistic motivation refers to reviewers who write ORs to aid others without seeking any personal gain. Self-enhancement motivation refers to reviewers who write ORs to enhance their own image or reputation i.e., to portray themselves as knowledgeable. Finally, vengeance motivation refers to reviewers who write ORs to seek revenge against a business or product.

Furthermore, reviewers may engage in different types of activities such as providing feedback or complaining, which can also influence the helpfulness of an online review (Chen & Xie, 2008). Feedback activities refer to reviewers who provide constructive feedback to businesses about their products or services. Complaint activities refer to reviewers who express negative feedback about a business or product.

Although, previous research has suggested that reviewers have different motivations for writing an OR and may engage in different types of activities, such as providing feedback or complaining to achieve various goals, the influence of these on review helpfulness is not known. According to Means-Ends Fusion (MEF) theory "motivation is the outcome of fusion between the activity and goal" (Kruglanski et al., 2018, p. 271) i.e., motivation arises when activity is fused with a goal. In this research context we examine the reviewers' goal of attaining emotional satisfaction. The current study aims to understand the relationship between reviewers' motivations, activities, goals, and the helpfulness of an online review.

To examine the research objective, we use data mining techniques such as cluster analysis and association rule mining technique. Cluster analysis and association rule mining are powerful data mining techniques that have been used extensively in research to identify patterns and relationships in labeled datasets. Cluster analysis is a technique used to group similar objects or cases together based on a set of variables or features, while association rule mining is a technique used to identify associations or relationships between different items in a dataset.

The current study used cluster analysis to group reviewers based on their motivations, activities, and goals. Identifying distinct groups of reviewers with similar characteristics can provide valuable insights into the factors that influence online review helpfulness. Association rule mining is used to identify the relationships between reviewer motivations, activities, goals, and online review helpfulness. The use of cluster analysis and association rule mining in this study has several advantages. Cluster analysis will allow us to identify groups of reviewers with similar characteristics, which can provide insights into the different motivations, activities, and goals that influence online review helpfulness. Association rule mining allowed us to identify the most significant relationships between these variables, which can provide a more detailed understanding of how these factors interact.

By investigating the relationship between reviewers' motivations, activities, goals and the helpfulness of an online review, this study provide insights into how consumers, businesses, and online review platforms construe OR helpfulness from reviewers' perspective. The findings from this study have significant implications for online review platforms and businesses. Online review platforms can use the information obtained from this study to design algorithms that can better identify and prioritize helpful ORs. By prioritizing helpful ORs, online review platforms can provide more accurate and reliable information to consumers. Furthermore, businesses can identify various motivations, and activities of the reviewers allowing them to address the needs and expectations of their customers.

## Literature Review

### Reviewer Motivations and Helpfulness

A considerable body of research has been dedicated to exploring the underlying motivations that prompt individuals to pen online reviews, an activity that has become a cornerstone of e-commerce and digital consumer culture. Numerous scholars have developed a deep understanding of these motivating factors and have traced their consequential impact on the perceived utility of reviews (Chen et al., 2016). Delving deeper into the motivations that propel individuals to write online reviews, several more nuanced factors have been identified and examined.

Altruistic behavior, driven by a regard for others' welfare, has been noted as a prime motivator in both traditional Word-of-Mouth (WOM) communication (Sundaram et al., 1998), and its electronic equivalent (e-WOM) (Cheung & Lee, 2012; Ho & Dempsey, 2010). The need for social belonging plays an influential role in altruistic motivation (Ho & Dempsey, 2010). Moreover, scholars have found that individuals often achieve a sense of self-satisfaction by aiding others through their reviews (Yi et al., 2018).

Product or Service Involvement is another critical determinant of online reviewing. The excitement that arises from experiencing a new product or service may encourage customers to share their experiences (Sundaram et al., 1998). This notion aligns with Dichter's (1966) argument that product involvement is a fundamental driver of WOM. Norman and Russell (2006) contended that engagement with a product or service stimulates the urge to spread information about it, thereby influencing other consumers. Additionally, if a product or service meets or surpasses consumers' expectations, it may generate positive e-WOM. Conversely, unmet expectations can lead to negative e-WOM (Dellarocas, 2003).

Expression of Emotions is yet another motivation behind online reviews. Reviewers disseminate information to express their emotions, both positive and negative (Hennig-Thurau et al., 2015). A satisfactory product experience may lead to positive reviews that echo the reviewer's happiness, while dissatisfaction can lead to negative reviews to vent emotions such as anger, sadness, and regret (Yin et al., 2020).

Self-Enhancement motivations arise in environments where online platforms reward repeated engagement. Platforms such as Amazon and Yelp incorporate reputation mechanisms, including awarding 'useful' votes and compliments from other consumers. In this regard, review readers can assess a reviewer's credibility by evaluating their past ratings and reviews. Literature suggests that sharing experiences can help reviewers present themselves as knowledgeable consumers, anticipating positive feedback (Engel et al., 1969; Sundaram et al., 1998). In online reviewing, self-enhancement is seen when information about a product or service is shared to portray oneself as highly knowledgeable.

Individuals with a motivation of seeking vengeance tend to write negative e-WOM. These reviews allow customers to express their discontent with a product or service, serving as cautionary advice to other consumers (Sundaram et al., 1998). From a psychological perspective, expressing negative feelings can mitigate the emotional distress caused by the consumption experience (Pennebaker & King, 1999). Furthermore, emotional dissatisfaction can motivate users to express vengeance when writing reviews (Berger, 2014).

Advice Seeking is an integral motivator that often inspires individuals to post online reviews. According to Senecal and Nantel (2004), online reviewers may often seek advice or suggestions from other consumers about their experiences with a specific product or service. This type of interaction may drive reviewers to participate more actively in online communities, further fostering a symbiotic environment where advice is both sought and given. It also motivates reviewers to share their experiences to facilitate others in making informed decisions.

On the other hand, the Desire for Social Interaction is a unique motivation distinct to the online realm. The advent of digital platforms has transformed the way individuals interact, turning online review spaces into social forums. Consumers do not merely use these platforms to share their experiences but also to connect and interact with other users (Ridings & Gefen, 2004). Posting reviews offers an opportunity to engage in social discourse, fostering a sense of community and belonging. Reviews become a medium for interaction, making the experience more engaging and rewarding for the reviewer (Zhang et al., 2014).

In conclusion, understanding these diverse motivations for online reviews can provide businesses with valuable insights to enhance their customer engagement strategies and refine their products or services.

**Reviewer Activity and Helpfulness**

Prior studies have shown that reviewer activity, such as providing feedback or complaints, can influence the helpfulness of online reviews. One study found that providing feedback on a product or service can have a positive impact on the helpfulness of subsequent reviews. Specifically, reviewers who had previously provided feedback on a product were viewed as more trustworthy and credible by other consumers, leading to an increase in the helpfulness of their subsequent reviews (Godes & Mayzlin, 2004). In contrast, complaints by reviewers have been found to have a negative impact on review helpfulness. One study found that negative reviews that contained complaints were viewed as less helpful by other consumers, as they were seen as less objective and more emotional (Liu et al., 2016). Similarly, another study found that the presence of complaints in a review led to a decrease in the helpfulness of the review, as consumers perceived the complaints as detracting from the overall credibility of the review (Bolton et al., 2013).

The tone of the review can also influence the impact of feedback and complaints on review helpfulness. Reviews that are written in a positive or neutral tone and contain feedback are more likely to be viewed as helpful, as consumers perceive them as providing constructive criticism and suggestions for improvement (Clemons et al., 2006). On the other hand, reviews that are written in a negative or aggressive tone and contain complaints are less likely to be viewed as helpful, as consumers perceive them as being more emotional and less objective (Liu et al., 2016).

**Reviewer Goals and Helpfulness**

Research has shown that the goals of reviewers, such as attaining emotional satisfaction, damaging a business, or financial gain, can have a significant impact on the perceived helpfulness of the review. Emotional satisfaction is a frequently observed objective for writing online reviews. Reviews penned to vent emotions like anger or frustration are often deemed less helpful by readers, as they are perceived to be more emotionally driven and less impartial (Liu et al., 2016). Conversely, reviews articulating positive emotions like excitement or gratitude may also be viewed as less beneficial due to their perceived lack of informative content and objective analysis (Kang et al., 2018).

In some instances, the intent to damage a business or its products becomes a motivator for negative reviews. Such reviews, aimed at harming a business, are often considered less helpful as they appear less unbiased and more subjective (Dellarocas et al., 2007). Consumers may deem these reviews less credible and trustworthy, suspecting motivations beyond an honest assessment of the product or service (Zhang et al., 2011).

Financial gain also serves as a significant motivator, particularly in the context of incentivized reviews. When consumers perceive reviews as driven by financial gain, they may view them as less trustworthy and biased due to potential influence by the offered rewards (Wang et al., 2012). Likewise, reviews created to promote a business or product may also be seen as less objective and trustworthy, as consumers may perceive them as biased towards the business or product being reviewed (Clemons et al., 2006).

Conversely, other motivations such as the desire to provide information or advice have demonstrated a positive impact on review helpfulness. Reviews penned with the objective of delivering useful information or advice are frequently deemed more helpful by consumers due to their informative nature and perceived objectivity (Godes & Mayzlin, 2004).

Overall, the interplay of reviewers' motivations, activities, and goals can significantly influence the perceived value of online reviews. Therefore, examining the interaction between these factors can provide critical insights into online review utility. These insights can equip businesses and organizations with the necessary knowledge to develop effective strategies for managing online reviews and leveraging this potent source of consumer feedback.

## Data Collection and Methodology

In the following analysis, I use the dataset that has been coded in the phase 1 analysis of chapter 4. Accordingly, Motivations are identified and classified into five categories: Altruistic, Product or Service Involvement, Expression of Emotions, Self-Enhancement, and Vengeance. Activity is classified into two categories: Feedback and Complaint. Goals are classified into emotional satisfaction, business damage, financial gain and others. The helpfulness will be measured using the helpfulness score of the review. A review with helpful votes is classified as helpful and the reviews with no helpful votes are identified as unhelpful. To amplify the sample size and to discern the proposed variables within the sample, we employed the Yelp Academic Dataset. This dataset encompasses more than 6 million reviews corresponding to 150,346 businesses across 11 metropolitan regions in the United States (Ning & Karypis, 2012; Rabinovich & Blei, 2014; Xia Liu et al., 2021).

In consideration of computational efficiency and accuracy, reviews comprising fewer than 50 words were excluded from the dataset. This exclusion resulted in a revised dataset of over 4 million reviews. From this refined set, a random sample of 1 million reviews was chosen for subsequent analysis.

To detect the underlying motivations, activities, and goals, we designed an algorithm. This algorithm utilized custom keywords to score and categorize a review into each corresponding category of motivations, activities, and goals. Initially, we fed 626 reviews classified in Chapter 5, Phase 1 into the algorithm. The subsequent classification yielded an 82% accuracy rate when compared with reviews manually classified. Following the necessary refinements based on this initial run, we proceeded to classify the 1 million reviews. The descriptive statistics for this classification are delineated in Table 16. Upon categorizing the reviewer motivations, activity and goals, the coded variables are analyzed for their influence on online review helpfulness using the following datamining techniques i.e., association rule mining technique and cluster analysis. In the literature, numerous studies have used association rule mining and k-means cluster analysis to analyze similar types of data. For example, a study by Alshamaila et al. (2013) used association rule mining to identify patterns in customer complaints in the telecommunications industry. Similarly, a study by Liao and Ho (2021) used k-means cluster analysis to segment customers based on their attitudes towards mobile banking.

Overall, association rule mining and k-means cluster analysis are both valuable techniques that can be used to analyze the variables of interest in this dataset. By using these techniques, it is possible to identify patterns and relationships between the variables of interest, which can be useful for making predictions and informing business decisions.

**Association Rule Mining.** Association rule mining is a technique used in data mining to identify relationships between variables in large datasets. The goal of association rule mining is to find patterns in the data that can be used to make predictions or inform business decisions. This technique is commonly used in market basket analysis, where it is used to identify which items are frequently purchased together in a retail setting.

The basic process of association rule mining involves identifying frequent item sets in a dataset and then using these sets to generate association rules. The frequent item sets are identified by specifying a minimum support threshold, which is the minimum number of times an item set must appear in the dataset to be considered frequent. Once the frequent item sets have been identified, association rules are generated by specifying a minimum confidence threshold, which is the minimum probability that the rule will hold true in the dataset. For example, in Figure 29, each node represents an item (in this case, "Motivations = Altruistic", "Goals =

Financial Gain", and "Activity = Feedback") and each edge or link between nodes represents an association rule. The labels on the edges represent the confidence and support of the corresponding association rule, which indicate the reliability of the rule and the relative frequency of the itemset in the dataset, respectively.

**Table 16. Classified Online Reviews**

| Category | Dimension | Number of Reviews |
|---|---|---|
| Motivations | Altruistic | 189,601 |
| | Expression of Emotions | 233,106 |
| | Product/Service Involvement | 408,455 |
| | Vengeance | 55,318 |
| | Self-Enhancement | 28,907 |
| | Advice Seeking | 41,681 |
| | Desire for Social Interaction | 42,932 |
| Activity | Feedback | 918,725 |
| | Complaint | 81,275 |
| Goals | Financial Gain | 85,103 |
| | Emotional Satisfaction | 221,515 |
| | Damage to the Business | 87,723 |
| | Other | 605,659 |
| Usefulness | Useful Reviews | 500,000 |
| | Not Useful Reviews | 500,000 |

One of the most well-known algorithms for association rule mining is the Apriori algorithm, which was first proposed by Agrawal and Srikant (1994). The Apriori algorithm uses a bottom-up approach to identify frequent item sets by first identifying frequent individual items and then progressively building larger item sets. The algorithm has a time complexity of O(2^n*m), where n is the number of items in the dataset and m is the number of transactions.

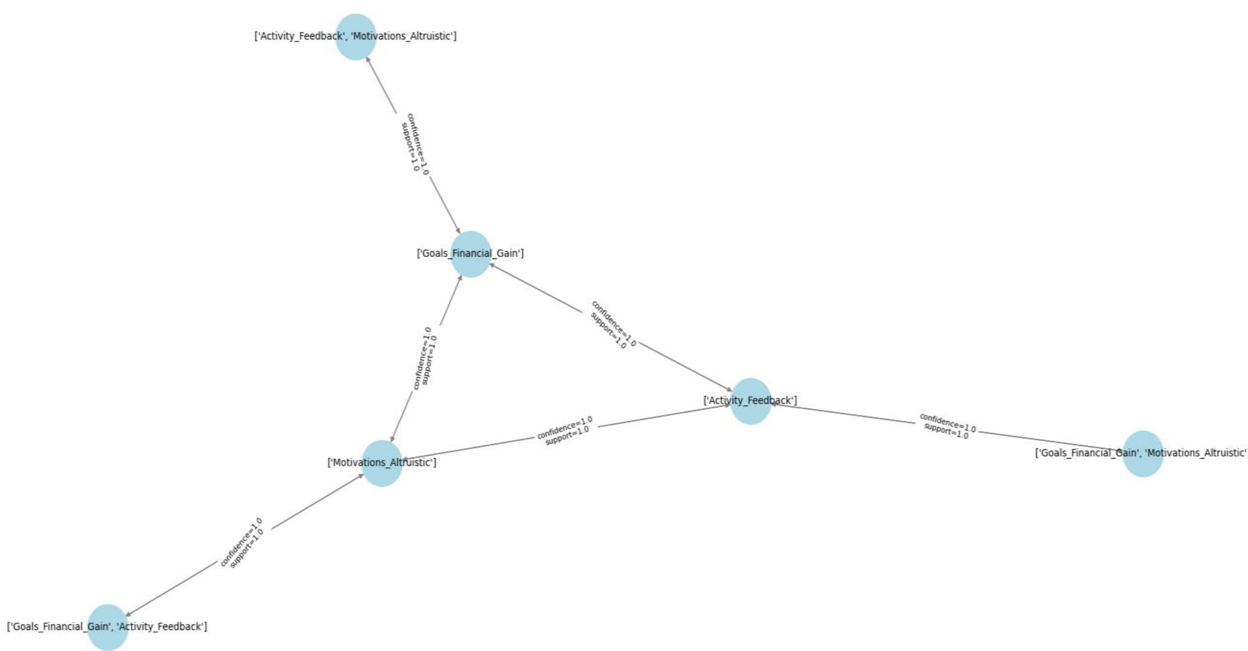


**Figure 29. Association Rule Mining Decision Pattern**

Another popular algorithm for association rule mining is the FP-Growth algorithm, which was first proposed by Han et al. (2000). The FP-Growth algorithm uses a top-down approach to identify frequent item sets by building a compact data structure called an FP-tree. The algorithm has a time complexity of O(n*m) and is faster than the Apriori algorithm for large datasets. Due to the current size of the dataset, I use Apriori algorithm to generate the rules.

**K – Means Cluster Analysis.** K-means clustering is a method of clustering objects based on their attributes. The goal of K-means is to partition a set of objects into K clusters, where each cluster is defined by a centroid (also called a prototype or center), which is the arithmetic mean of all the points in the cluster. The algorithm proceeds by iteratively assigning each object to the cluster with the nearest centroid, and then adjusting the centroid of each cluster to be the mean of the points in the cluster. The K-means algorithm begins with an initial set of K centroids, which can be randomly generated, or selected from the data set. The objects are then assigned to the cluster with the nearest centroid. The centroids are then recalculated as the mean of all the points in the cluster. This process is repeated until no further change in the assignment of objects to clusters or the location of the centroids occurs.

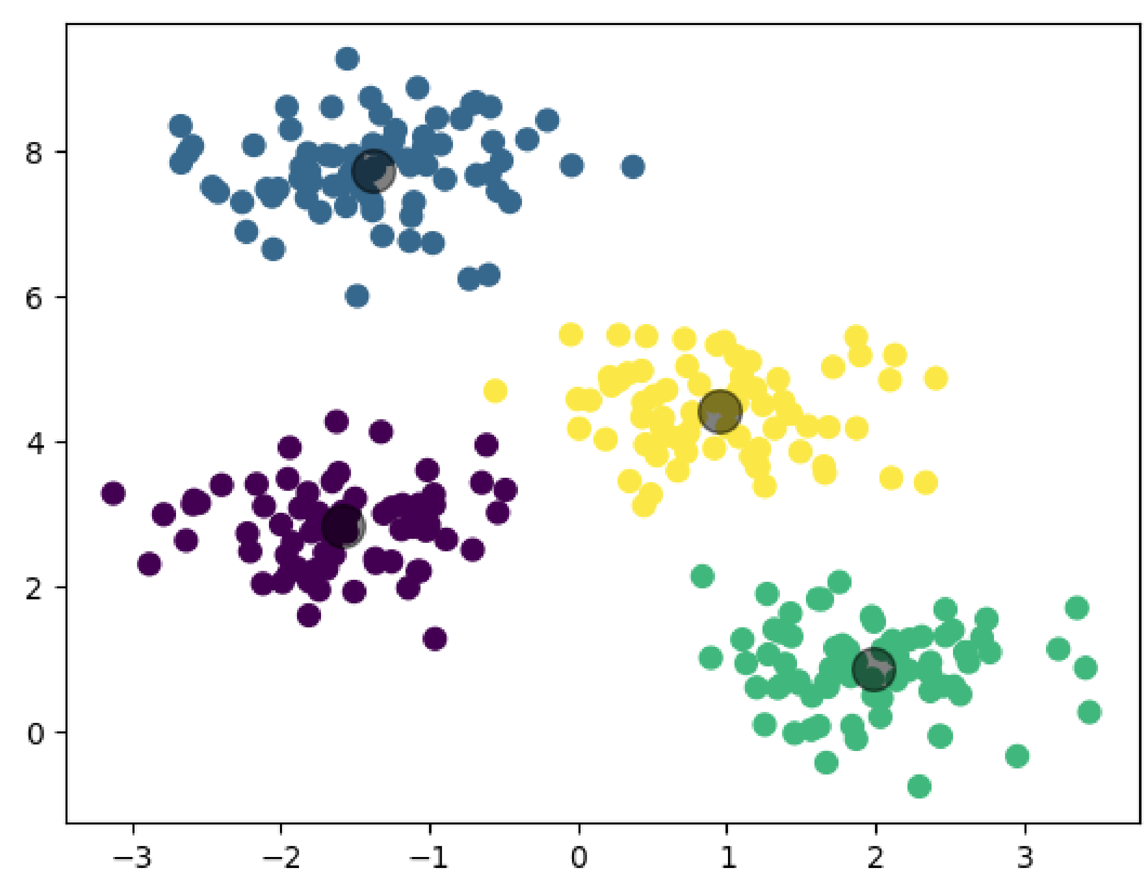


**Figure 30. Cluster analysis working model**

For example, in Figure 30, each point could represent a single review. The colors differentiate the clusters, where each cluster could represent a group of reviews that are similar to each other in terms of the categories (Motivations, Activities, and Goals). The black dots represent the calculated 'centers' of each cluster, a kind of average review for each group.

For instance, one cluster might represent reviews that are motivated by altruism, involve feedback activity, and aim towards emotional satisfaction. Another cluster might represent reviews motivated by vengeance, involving complaints, and aiming towards damage to the business. Each cluster would capture a different 'type' of review, based on the categories in the dataset.

One of the main advantages of K-means clustering is its simplicity and ease of implementation. Furthermore, the algorithm is very versatile, and it can be applied to a wide range of data types, such as continuous, categorical, and binary data. However, one of the main limitations of K-means clustering is that the number of clusters, K, needs to be specified in advance. For the current dataset the optimal k value is found to be 3 by elbow method. Thus, I performed K-means cluster analysis with k = 3.

## Results

### Association Rule Mining Results

The results from the apriori association rules (i.e., top 6 rules sorted by lift) are presented in Table 17. From Table 17, in each rule, the left-hand side (LHS) represents the antecedent, or the set of variables that precede the consequent (RHS), which is the right-hand side of the rule.

**Table 17. Association rule mining results**

| Antecedents | Consequents | Support | Confidence | Lift |
|---|---|---|---|---|
| 'Product or Service Involvement', 'Other', 'notuseful ' | 'feedback' | 0.12 | 0.940 | 10.277 |
| 'Product or Service Involvement', 'notuseful ' | 'feedback' | 0.20 | 0.939 | 9.743 |
| 'Product or Service Involvement', 'Emotional Satisfaction' | 'feedback' | 0.18 | 0.934 | 6.993 |
| 'Altruistic' | 'useful' | 0.20 | 0.917 | 5.776 |
| 'Expression of Emotions' | 'useful' | 0.12 | 0.813 | 6.176 |
| 'Expression of Emotions', 'Other' | 'useful' | 0.17 | 0.812 | 6.141 |
| 'feedback', 'Altruistic' | 'useful' | 0.09 | 0.812 | 3.961 |
| 'Expression of Emotions', 'feedback' | 'useful' | 0.11 | 0.809 | 3.885 |
| 'Emotional Satisfaction' | 'useful' | 0.11 | 0.803 | 3.763 |
| 'Product or Service Involvement', 'Other', 'feedback' | 'notuseful ' | 0.12 | 0.800 | 3.75 |
| 'Product or Service Involvement', 'feedback' | 'notuseful ' | 0.20 | 0.758 | 2.533 |
| 'Product or Service Involvement', 'Other' | 'notuseful ' | 0.13 | 0.746 | 4.112 |
| 'Product or Service Involvement' | 'notuseful ' | 0.21 | 0.715 | 2.634 |
| 'Other', 'feedback' | 'notuseful ' | 0.28 | 0.705 | 2.174 |
| 'feedback' | 'notuseful ' | 0.46 | 0.650 | 2.25 |

The support refers to the proportion of transactions in the dataset that contain both the antecedent and consequent of the rule. It is a measure of the frequency of the rule in the dataset. Confidence, on the other hand, is the probability that the consequent will occur given that the antecedent is present. It measures the strength of the association between the antecedent and consequent. Coverage is the proportion of transactions that contain the antecedent, and lift measures the strength of the association between the antecedent and the consequent, relative to the frequency of the consequent.

Examining the rules obtained, we can see that several of them have high confidence values, indicating a strong association between the antecedent and consequent. For example, the first rule implies that when 'Product or Service Involvement' and 'Other' are the motivations, and the review is 'not useful', there is a 94% confidence that the review will receive 'feedback'. This rule is supported by 12% of the transactions (support = 0.12), and the lift value of 10.277 indicates that 'feedback' is more than ten times as likely to occur in this scenario than it would in random transactions.

The second and third rules follow a similar pattern, involving 'Product or Service Involvement' and resulting in 'feedback'. These associations are significant and indicate that when reviewers are highly involved with a product or service, they are likely to receive feedback, especially if the reviews are deemed 'not useful'. This could reflect a demand for more balanced, objective reviews.

The rules involving 'Altruistic' and 'Expression of Emotions' motivations have 'useful' as a consequent. This indicates that these types of motivations are generally linked to reviews perceived as useful by consumers. These findings align with prior research which found altruistic behavior and the expression of balanced emotions to be positively associated with perceived usefulness (Cheung & Lee, 2012; Hennig-Thurau et al., 2015). The final set of rules, mainly involving 'Product or Service Involvement' and resulting in 'not useful' reviews, suggests that these reviews often generate 'feedback'. This might be due to perceived bias or over-enthusiasm about a product or service, which readers may interpret as less objective or informative (Dichter, 1966).

Overall, these rules provide useful insights into the motivations behind online reviews and their perceived usefulness. These findings could have important implications for businesses looking to understand consumer feedback and improve their services accordingly (Li et al., 2021; Dellarocas, 2003).

**Cluster Analysis Results**

Table 18 represents the results from the k-means cluster analysis with k=3.

**Table 18. Cluster analysis in terms of review helpfulness**

| | **Motivation** | **Activity** | **Goal** | **Helpfulness (Yes/No)** |
|---|---|---|---|---|
| 1 | Expression of Emotions, | Feedback | Other | Yes |
| 2 | Product or Service Involvement | Feedback | Other | No |
| 3 | Altruistic | Feedback | Other | Yes |

Each cluster is characterized by a unique combination of motivation behind the review, activity of giving feedback, the goal involved, and the perceived helpfulness of the review.

In Cluster 1, the motivating factor behind writing reviews is 'Expression of Emotions'. Reviews in this cluster encompass feedback as the main activity, with the goal categorized as 'Other', which could include a variety of miscellaneous or less common objectives. Significantly, these reviews are perceived as helpful, indicating that consumers value reviews that express emotions when they are coupled with constructive feedback.

Cluster 2 is characterized by 'Product or Service Involvement' as the dominant motivation. The reviews in this cluster involve giving feedback about the product or service, with the goal again categorized as 'Other'. However, in contrast to Cluster 1, these reviews are not perceived as helpful by the consumers. This could suggest that reviews based solely on 'Product or Service Involvement' may lack other elements that consumers find useful, such as balanced evaluation or personal experience (Dichter, 1966).

Finally, Cluster 3 comprises reviews motivated by 'Altruistic' reasons. These reviews involve the provision of feedback, with the goal falling into the 'Other' category. Notably, like Cluster 1, these reviews are perceived as helpful, reflecting the value consumers place on reviews driven by altruistic motives (Cheung & Lee, 2012).

In conclusion, the results of this study will provide valuable insights into the factors that influence online review helpfulness. These insights will help businesses and organizations better understand how to manage online reviews and leverage them as a source of consumer feedback. The results will also help consumers better evaluate the credibility and usefulness of online reviews. Overall, the study is expected to make a significant contribution to the field of online review research and to help advance our understanding of the impact of reviewer motivations, activity, and goals on online review helpfulness.

## Other Goals

Understanding the goals that drive customers to post online reviews is critical, as it provides businesses with valuable insights into customers' needs, expectations, and experiences. In the data analyzed, while financial gain, emotional satisfaction, and damaging the business were identified as explicit goals, the category of 'Other' contained a high number of reviews. This suggested a multitude of underlying goals not captured by the current framework, prompting further exploration through topic modeling.

Topic modeling is a type of statistical modeling for discovering the abstract topics that occur in a collection of documents (Blei et al., 2003). It allows us to understand large volumes of unstructured text, making it a useful tool in this context, given the rich and diverse content in online reviews. The technique proved instrumental in identifying two additional, less explicit, but significant goals: influencing businesses and social influence.

The goal of 'Influencing Businesses' emerged from topics indicating both positive and negative experiences or specific areas of improvement. For example, a customer might post a review praising the restaurant's ambiance but suggesting that the menu could offer more vegan options. This finding is consistent with the notion that consumers utilize online reviews to voice their opinions, hoping to influence business practices (Mudambi & Schuff, 2010). In doing so, customers become active participants in business value creation, making their feedback instrumental in shaping product and service offerings (Grönroos, 2011).

The second additional goal identified, 'Social Influence,' stemmed from reviews discussing diverse topics ranging from specific food items, drinks, to the overall atmosphere of a place. For instance, a reviewer might provide a detailed account of different wine types they tried at a bar and their expert opinion on each. This mirrors the concept that online reviews not only provide feedback to businesses but also serve as a platform for consumers to establish their expertise and build their reputation (Chevalier & Mayzlin, 2006). In the realm of online reviews, exerting social influence can enhance a reviewer's self-perception and increase their perceived social capital, contributing to a sense of satisfaction and accomplishment (Book & Tanford, 2020).

Overall, the incorporation of topic modeling in analyzing online reviews offers a nuanced understanding of the less overt but equally impactful customer goals. Recognizing and addressing these goals can provide businesses with a competitive advantage in this era of customer-centricity and digital interactivity.

## Contributions

### Theory

This research makes several significant theoretical contributions to our understanding of online review (OR) behavior and its implications on perceived helpfulness.

First, this study provides a comprehensive model of reviewer motivations, activities, goals, and their effects on the perceived helpfulness of reviews. Previous studies have separately examined these variables in relation to OR helpfulness. This research, however, has integrated these dimensions into a single model, advancing our understanding of the complex interplay of these factors. Through a detailed analysis of motivations, activities, and goals of online reviewers, this study brings in a new dimension to the theory of online consumer behavior. By demonstrating that a reviewer's motivation, activities and goals can significantly affect the perceived helpfulness of their reviews, it enriches our understanding of how online reviews are construed and utilized by consumers.

Second, by adopting the Means-Ends Fusion (MEF) theory in the context of online reviews, this research provides an innovative theoretical lens to understand reviewer motivations. According to MEF theory, motivation arises when an activity is fused with a goal. By applying this theoretical perspective, this study suggests that the goal of a reviewer, be it emotional satisfaction or otherwise, might be a critical determinant of the review's perceived helpfulness. This new theoretical perspective can spur further research in the domain of online reviews.

Third, this research extends the application of data mining techniques in studying online reviews. By employing cluster analysis and association rule mining, this study has not only identified distinct groups of reviewers with similar characteristics but has also unearthed the relationships between various reviewer factors and OR helpfulness. This methodological contribution provides a powerful new approach to analyze and interpret complex datasets in the digital commerce research.

Fourth, the study contributes to the literature on online consumer behavior by exploring the role of emotions in online review helpfulness. While previous studies have predominantly focused on the informative aspects of reviews, this study emphasizes the importance of emotional expression in determining review helpfulness. This finding underscores the need to consider the emotional aspects of online consumer behavior in addition to the more utilitarian facets.

Finally, by examining reviewer factors in determining review helpfulness, this study underscores the importance of understanding the reviewer's perspective in managing online reviews. Much of the existing literature has focused on the consumer's perspective in interpreting and utilizing online reviews. This study, however, emphasizes the role of the reviewer in influencing the perceived helpfulness of reviews, suggesting that the management of online reviews needs to consider both the consumer's and reviewer's perspectives.

**Practice**

This research carries significant implications for practitioners, particularly for businesses, consumers, and online review platforms navigating the landscape of digital commerce. The practical contributions are multi-fold, offering strategies to optimize the utility of online reviews and improve the effectiveness of their usage.

For Review Platform Owners: For online review platforms like Yelp, TripAdvisor, and others, the findings of this study provide insights that can aid in improving the design of algorithms that sort and prioritize reviews. Platforms can leverage the understanding of how reviewer motivations, activities, and goals affect perceived helpfulness to enhance their ranking algorithms. Consequently, they can offer an enhanced user experience by spotlighting reviews that are deemed most useful based on these critical factors.

Moreover, platforms can utilize these insights to offer reviewer guidance. By understanding the traits of helpful reviews, platforms can provide tips or suggestions to reviewers, encouraging them to draft their reviews in a way that amplifies their helpfulness to other users. Such an initiative can significantly improve the overall quality of reviews on the platform, making the platform more reliable and useful for consumers.

For Business Owners: Businesses operating in the digital realm stand to gain substantially from these findings. By identifying the motivations and activities that characterize helpful reviews, businesses can refine their review solicitation strategies. For instance, firms might motivate their customers to provide feedback by fostering an environment that encourages emotional expression, product/service involvement, or altruism - factors found to enhance the perceived helpfulness of reviews in this study.

Furthermore, the findings can guide businesses in effectively responding to reviews, especially those deemed unhelpful. Understanding that certain motivations or activities can lead to less useful reviews enables businesses to address specific issues in their responses, improving customer relations and potentially rectifying any reputational damage. The insights derived from this study can also be instrumental in businesses' product development or service improvement efforts. By focusing on reviews that are regarded as most helpful - which typically offer rich, balanced, and constructive feedback - businesses can gain a nuanced understanding of consumer needs and preferences, ultimately driving better business decisions.

For Consumers: From a consumer perspective, these findings can help in enhancing digital literacy and the ability to navigate online reviews more effectively. By understanding the factors that contribute to a review's helpfulness, consumers can become more adept at discerning which reviews to trust and base their purchasing decisions on. This understanding can aid in mitigating the issues of information overload often experienced by consumers in the face of abundant reviews.

# CHAPTER VII

# CONCLUSION

## Recap of the Research Objectives

To provide insight on how review attributes and reviewer attributes influence online review helpfulness the essays discussed in this dissertation answer the following research questions

a) How does the authenticity of an online review influence review helpfulness?
b) How do an online reviewer's motivations and activities influence reviewer goals?
c) How do an online reviewer's motivations, activities, and goals influence review helpfulness?

To address the above research question, I adapted attribution theory as an overarching theory that demonstrates that review helpfulness can be influenced by various review attributes and reviewer attributes. This dissertation examines the attributes that received less attention in the literature.

In the first essay, I examined the influence of two types of authenticity (nominal and expressive) on the helpfulness of online reviews. Using a decision tree induction approach, the study found that the lexical breadth of expressive authenticity was the most significant predictor of online review helpfulness. The second essay is aimed to develop a systematic understanding of the motivations and activities associated with online reviews, using various machine learning techniques to investigate the influence of motivations and activities on reviewers' goal attainment. The findings of this study will contribute to a deeper understanding of online review motivations and activities and their relationship to reviewers' goals. In the third essay, I aim to explore the relationship between reviewers' motivations and activities and the helpfulness of online reviews. By examining how these motivations and activities interact, the study aimed to provide insight into how online review platforms and businesses can use this information to improve the helpfulness of reviews for consumers. Overall, the three essays aimed to advance our understanding of the factors that influence online review helpfulness, including authenticity, motivations, and activities, and to provide practical insights for businesses and consumers.

## Contributions

The dissertation makes significant contributions to the online review literature and practice in various ways. In the following section, I will summarize and briefly discuss the key contributions of the three essays presented in this dissertation.

### Implications for Literature

The first essay emphasizes the importance of authenticity, particularly the two dimensions of authenticity, in influencing online review helpfulness. The study provides insights into the granular level of authenticity dimensions that play a significant role in influencing reader inference and attitude formation about online reviews. Additionally, the study offers valuable insights into the conditional effects of expressive authenticity, indicating that emotions and feelings expressed in a review can have a significant impact on its usefulness and impact. The study also contributes to the literature on personalized services by testing for the differences in sibling rules that foster recommendation. The ability to derive propositions through the use of decision tree induction for empirical statistical analysis highlights the importance of the approach used in this study, which leads to inductive theory building and testing of authenticity and online review helpfulness.

The second essay contributes to understanding the motivations and activities of online reviewers by developing a new taxonomy of online reviews using MEF theory. The study highlights the relative effects of reviewer motivations and activities in explaining the goal attainment of emotional satisfaction. This finding suggests that understanding the motivations and activities of online reviewers is crucial in predicting the goal of emotional satisfaction. The conditional effects of complaining behavior on emotional satisfaction are also important to consider. The study finds a moderating relationship between activity and goal in online reviews, which suggests that different types of reviewers may require different types of tools and features to encourage participation. The research emphasizes the importance of considering the context in which complaining behavior occurs, as it may have different outcomes depending on the situation.

The third essay identifies specific combinations of reviewer motivations, activity, and goals that are most strongly associated with helpful online reviews, which sheds light on the underlying psychological and behavioral processes that drive review writing. The findings of the study help to advance our understanding of the role that personal motivations and goals play in shaping the helpfulness of online reviews. The study also refines and extends existing theoretical frameworks of online review writing, such as the MEF theory, which focuses on the role of motivation, emotion, and feedback in shaping online review behavior.

### Implications for Practice

The research conducted in the three studies has several practical implications for various stakeholders in the online review ecosystem. First, platform owners can use the findings to identify potentially helpful reviews early, reduce information overload, and segment reviews based on authenticity. This can help the platform owners to promote informative and useful reviews and ensure that they are seen by the right audience. Secondly, businesses can identify and segment their customers based on their assessments and expectations of authenticity, target and cater to specific expectations, and increase customer satisfaction and loyalty. Service providers can also use appropriate digital and mobile technologies to enhance the verification of various dimensions of the authenticity of online reviews.

For review readers, online review platforms can be designed to help readers and reviewers identify effective reviews by prominently displaying the scores generated by the model for each review. This can help the readers quickly identify the most informative and well-written reviews and to avoid reviews that are overly expressive or otherwise unhelpful.

For review writers, platform managers can educate the reviewers to write reviews that are not over-expressive, and provide guidance to the reviewers on how to write reviews that are more focused, informative, and well-structured. This can help the reviewers to write better quality reviews, improve their scores and increase their visibility on the platform.

The proposed taxonomy for online reviews can be a valuable tool for both platform owners and business owners. Platform owners can use this taxonomy to differentiate between general feedback and complaints, understand the motivations behind online reviews, design features that cater to the needs of their users, improve the overall quality of reviews, and increase the usefulness of the platform. Business owners can use the taxonomy to identify complaints among customer reviews, understand the root causes of customer complaints, take necessary action, and improve their products or services. This can lead to increased customer satisfaction, better brand reputation, and a boost in sales.

The practical contributions of the expected results of the studies are significant for businesses and organizations that rely on online reviews as a source of consumer feedback. The findings provide practical guidance on how businesses can manage and leverage online reviews, encourage reviewers to write helpful reviews, monitor and address issues raised in unhelpful reviews, and help consumers better evaluate the credibility and usefulness of online reviews. Overall, the research contributes to a deeper understanding of the complex and multifaceted nature of online reviews and provides practical insights for various stakeholders.

## Future Research Direction

The components of this research, along with their limitations and future research directions, are worth addressing in detail. One such component is the data used in this dissertation. While one of the strengths of this study lies in the extraction of proposed variables from online reviews, the primary limitation was its reliance on secondary data. To address this limitation and further strengthen the findings, future research could focus on collecting data directly from the actual reviewers using survey methods. This approach would allow for a more nuanced understanding of the reviewers' perspectives and motivations. Another key component of the study is the establishment of causation between the constructs. Some results in the current study did not establish clear causal links. To mitigate this limitation, future research could employ experimental studies. Specifically, these studies could examine the influence of review authenticity, reviewer motivations, activities, and goals on the perceived helpfulness of online reviews. Such an approach would not only help in establishing causality but also enhance our understanding of the proposed constructs, providing a more holistic view of online review systems.

## Conclusion

In summary, the three essays contribute to a deeper understanding of the factors that influence online review helpfulness and the motivations and activities of online reviewers. The first essay highlights the importance of authenticity in online reviews, emphasizing the impact of expressive authenticity on review helpfulness. The second essay offers a new taxonomy of online reviews using MEF theory, providing insights into the relative effects of reviewer motivations and activities on the attainment of emotional satisfaction. The third essay identifies specific combinations of reviewer motivations, activity, and goals that drive review helpfulness extending the existing theoretical frameworks. Together, these essays provide valuable insights for review platform owners, business owners, reviewers, and consumers, helping them to make informed decisions and improve the quality and usefulness of online reviews. The findings of the three essays offer new theoretical perspectives and practical implications that can inform future research and advance our understanding of online review helpfulness.

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APPENDIX

APPENDIX

SYSTEMATIC LITERATURE ON ONLINE REVIEWS FOR RESEARCH DATABASE

**Table 19. Systematic Literature**

| Authors | Online Reviews | Trust | Helpfulness | Nominal Emotions | Expressive Emotions | References |
|---|---|---|---|---|---|---|
| Sit, KJ; Pino, G; Pichierri, M | X | X | | | | http://dx.doi.org/10.1108/IJRDM-10-2020-0412 |
| Kovacs, B; Horwitz, S | X | X | | | | http://dx.doi.org/10.1177/1476127020922482 |
| Fritz, K; Schoenmueller, V; Bruhn, M | X | X | | | | http://dx.doi.org/10.1108/EJM-10-2014-0633 |
| Zhang, Z; Patrick, VM | X | X | | | | http://dx.doi.org/10.1177/0022242921996277 |
| Vita, B; Deitiana, T; Ruswidiono, W | X | X | | | | http://dx.doi.org/10.1080/23311975.2021.1996215 |

Table 19, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| Banerjee, S; Chua, AYK | | X | | | | http://dx.doi.org/10.1108/IntR-11-2015-0309 |
| Ferreira, C; Robertson, J; Chohan, R; Pitt, L; Foster, T | X | X | | | | http://dx.doi.org/10.1108/JSTP-04-2022-0100 |
| Hancock, T; Breazeale, M; Adams, FG; Hardman, H | | X | | | | http://dx.doi.org/10.1108/JPBM-12-2021-3756 |
| Gannon, V; Prothero, A | | X | | | | http://dx.doi.org/10.1108/EJM-07-2015-0510 |
| Hoskins, J; Verhaal, JC; Griffin, A | X | X | | | | http://dx.doi.org/10.1108/EJM-11-2018-0787 |
| Yim, D; Malefyt, T; Khuntia, J | X | | | | | http://dx.doi.org/10.1007/s12525-021-00472-5 |
| Lee, SS; Johnson, BK | | X | | | | http://dx.doi.org/10.1080/02650487.2021.1986257 |
| Armstrong, CMJ; Kang, JY; Lang, CM | | X | | | | http://dx.doi.org/10.1002/cb.1739 |
| Shi, ZJ; Liu, X; Srinivasan, K | X | X | | | | http://dx.doi.org/10.1177/00222437211044472 |
| Hollebeek, LD; Macky, K | | X | | | | http://dx.doi.org/10.1016/j.intmar.2018.07.003 |

Table 19, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| Hoskins, JD; Watts, JK | X | | | | | http://dx.doi.org/10.1177/10949968221118333 |
| Mostafa, MM | | X | | | | http://dx.doi.org/10.1177/1470785318771451 |
| Barlow, MA; Verhaal, JC; Hoskins, JD | X | | | | | http://dx.doi.org/10.1177/0149206316657593 |
| Bialkova, S; Te Paske, S | | | | | | http://dx.doi.org/10.1108/EJMBE-08-2020-0244 |
| Lee, H; Chang, DR; Einwiller, S | | | | | | http://dx.doi.org/10.1108/JPBM-02-2019-2259 |
| Liu, HF; Jayawardhena, C; Osburg, VS; Yoganathan, V; Cartwright, S | | | | | X | http://dx.doi.org/10.1016/j.jbusres.2021.04.030 |
| Ivanova, S; Treffers, T; Langerak, F; Groth, M | | X | | | | http://dx.doi.org/10.1177/10422587221093295 |
| Singh, JP; Irani, S; Rana, NP; Dwivedi, YK; Saumya, S; Roy, PK | | | X | | | http://dx.doi.org/10.1016/j.jbusres.2016.08.008 |
| Akbarabadi, M; Hosseini, M | X | | X | | | http://dx.doi.org/10.1177/1470785318819979 |

Table 19, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| Zhang, Y; Lin, ZJ | | | X | | | http://dx.doi.org/10.1016/j.elerap.2017.10.008 |
| Risselada, H; de Vries, L; Verstappen, M | | | X | | | http://dx.doi.org/10.1108/EJM-09-2016-0522 |
| Guo, B; Zhou, SS | X | | X | | | http://dx.doi.org/10.1007/s10660-016-9234-7 |
| Ismagilova, E; Dwivedi, YK; Slade, E | X | | X | | | http://dx.doi.org/10.1016/j.jretconser.2019.02.002 |
| Lu, SY; Wu, JN; Tseng, SL | X | | X | | | http://dx.doi.org/10.1016/j.intmar.2018.05.005 |
| Biswas, B; Sengupta, P; Ganguly, B | X | | X | | | http://dx.doi.org/10.1007/s12525-020-00452-1 |
| Hu, XB; Yang, Y | X | | X | | | http://dx.doi.org/10.1080/19368623.2020.1780178 |
| Wu, RJ; Wu, HH; Wang, CL | X | | X | | | http://dx.doi.org/10.1111/ijcs.12627 |
| Meek, S; Wilk, V; Lambert, C | X | | | | | http://dx.doi.org/10.1016/j.jbusres.2020.12.001 |
| Fu, N | X | | X | | | http://dx.doi.org/10.1177/14707853211023033 |
| Yi, J; Oh, YK | X | | X | | | http://dx.doi.org/10.1016/j.jretconser.2021.102519 |
| Changchit, C; Klaus, T | X | | X | | | http://dx.doi.org/10.1080/15332861.2019.1672135 |
| Zhang, LY; Guo, DM; Wen, X; Li, YR | | | X | | | http://dx.doi.org/10.1007/s10660-020-09419-y |

Table 19, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| Zhou, SS; Tu, L | | | X | | | http://dx.doi.org/10.1016/j.jretconser.2022.103120 |
| Shin, SH; Du, QZ; Ma, YF; Fan, WG; Xiang, Z | X | | | | | http://dx.doi.org/10.1080/19368623.2020.1778596 |
| Cui, G; Chung, YH; Peng, L; Zheng, WY | X | | X | | | http://dx.doi.org/10.1016/j.jbusres.2021.11.068 |
| Bilal, M; Almazroi, AA | X | | X | | | http://dx.doi.org/10.1007/s10660-022-09560-w |
| Rohde, C; Kupfer, A; Zimmermann, S | X | | X | | | http://dx.doi.org/10.1007/s12525-022-00595-3 |
| Lee, Y; Lin, CA | X | | X | | | http://dx.doi.org/10.1080/15332861.2021.1966722 |
| Maslowska, E; Malthouse, EC; Bernritter, SF | X | | X | | | http://dx.doi.org/10.1080/02650487.2016.1195622 |
| Ghasemaghaei, M; Eslami, SP; Deal, K; Hassanein, K | X | | | | | http://dx.doi.org/10.1108/IntR-12-2016-0394 |
| Costa, A; Guerreiro, J; Moro, S; Henriques, R | | | X | | | http://dx.doi.org/10.1016/j.jretconser.2018.12.006 |

Table 19, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| Barbro, PA; Mudambi, SM; Schuff, D | X | | X | | | http://dx.doi.org/10.1080/08961530.2019.1635552 |
| Dash, A; Zhang, DS; Zhou, LN | X | | X | | | http://dx.doi.org/10.1080/10864415.2021.1846852 |
| Cheong, JW; Muthaly, S; Kuppusamy, M; Han, C | X | | | | | http://dx.doi.org/10.1108/APJML-03-2019-0192 |
| Liu, AX; Xie, Y; Zhang, JR | X | | | | | http://dx.doi.org/10.1016/j.intmar.2018.11.001 |
| Hong, W; Yu, ZM; Wu, LH; Pu, XJ | X | | | | | http://dx.doi.org/10.1016/j.elerap.2019.100912 |
| Garnefeld, I; Krah, T; Bohm, E; Gremler, DD | X | | | | | http://dx.doi.org/10.1007/s11747-021-00770-6 |
| Kim, SJ; Maslowska, E; Malthouse, EC | X | | X | | | http://dx.doi.org/10.1080/02650487.2017.1340928 |
| Kawaf, F; Istanbulluoglu, D | | | | | | http://dx.doi.org/10.1016/j.jretconser.2019.02.017 |

Table 19, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| Maslowska, E; Segijn, CM; Vakeel, KA; Viswanathan, V | X | | X | | | http://dx.doi.org/10.1080/02650487.2019.1617651 |
| Abdul-Ghani, E; Kim, J; Kwon, J; Hyde, KF; Cui, YY | X | | | | | http://dx.doi.org/10.1108/EJM-01-2021-0064 |
| Han, J; Jun, M | X | | | | | http://dx.doi.org/10.1108/EJMBE-07-2020-0185 |
| Li, XF; Ma, BL; Bai, RB | X | | | | | http://dx.doi.org/10.1186/s11782-020-00086-2 |
| Guo, JP; Gou, SY; Li, WH | X | | X | | | http://dx.doi.org/10.1057/s41270-022-00194-3 |
| Brand, BM; Kopplin, CS; Rausch, TM | X | | | | | http://dx.doi.org/10.1007/s12525-022-00543-1 |
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## BIOGRAPHICAL SKETCH

Rakesh Guduru is a scholar and expert in Information Systems with a focus on the digital interface of consumer behavior and decision analytics. Born and raised in India, Rakesh discovered his passion for engineering early in life, ultimately earning a bachelor's degree in electrical engineering from Jawaharlal Nehru Technological University, Kakinada (JNTUK), AP, India. Rakesh moved to the United States to further his education and enhance his research skills. At the University of Texas Rio Grande Valley (UTRGV), he completed a master's in electrical engineering, and his thesis centered around a multi-functional system for biomedical applications using AC Electrokinetics. Rakesh continued his studies at UTRGV, earning a Ph.D. in Information Systems in August 2023. His dissertation explored the influence of review and reviewer attributes on the helpfulness of online reviews, using an Attribution Theory perspective. This intensive study solidified his interest in online platforms, consumer behavior, and decision analytics, among other research areas. Currently, Rakesh is engaged in examining various aspects of digital technology, including predictive analytics, the impacts of social media, blockchain technology, and healthcare information systems. His interdisciplinary research approach allows him to navigate these domains successfully and make valuable contributions to the field.

Outside academia, Rakesh enjoys playing chess. He also likes to spend time in parks, which provides him with an opportunity to unwind and rekindle his connection with nature. Rakesh ensures that he maintains a balance between his professional commitments and personal interests. He can be reached at email@rakeshguduru.com.