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Relationship Between Country Culture, Country Demographics, and Restaurant Electronic Word-of-Mouth Valence Ratings

Cynthia Roberts Maubert
Walden University

Walden University

College of Management and Human Potential

This is to certify that the doctoral dissertation by

Cynthia Roberts Maubert

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Review Committee
Dr. Holly Rick, Committee Chairperson, Management Faculty
Dr. Tom Butkiewicz, Committee Member, Management Faculty
Dr. Raghu Korrapati, University Reviewer, Management Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
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Abstract

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Cynthia R. Maubert

MPhil, Walden University, 2019

MBA, Virginia Tech, 1987

BS, University of Tennessee, Knoxville, 1984

Dissertation Submitted in Partial Fulfillment

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Abstract

Researchers have documented that country culture and country demographics influence electronic word-of-mouth (eWOM) within various industries. Although past research has shown the importance of eWOM to restaurants as a measure of consumer satisfaction, researchers have not established the effect of country culture and country demographics on eWOM within the restaurant industry. Thus, the specific management problem addressed in this quantitative correlational study was the lack of knowledge and understanding regarding the relationship between country culture, country demographics, and restaurant eWOM valence ratings. Grounded in Hofstede's cultural dimensions theory, the research questions addressed six measures of country culture, 12 measures of country demographics, and their relationship with restaurant eWOM valence ratings. With a purposive sample from the Yelp social media platform, eWOM ratings from 3,659 restaurants in 21 countries were analyzed with correlation analyses and multiple linear regression. Results indicated that a model of five variables and eight two-factor interactions statistically and significantly explained 14.4% of the variance in restaurant eWOM valence ratings. This study may promote positive social change by informing restaurant managers about which aspects of country culture and country demographics relate to restaurant eWOM valence ratings. Restaurant leaders may improve their eWOM response strategies by focusing on the most relevant country culture and country demographic constructs when developing eWOM communication.

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Dedication

I dedicate this study to my family, especially my husband, Paul. My love, you have supported me in many ways through this long journey, did not let me give up, and, most importantly, helped me finish my Ph.D. I will always treasure your significant sacrifice and dedication to our family. Words cannot express how much I value and love you! Laurelle, you were a little girl when Mom started her Ph.D., and you have grown into a lovely young lady. Here you are, a Morehead Cain Scholar at the University of North Carolina, Chapel Hill, a member of Deloitte's Leadership, Allyship, & Mentorship Program (DLAMP) with a bright professional future ahead! However, more importantly, you have faced the complex challenges life has given you with grace and grown into a beautiful and insightful woman. Henry, it is hard to believe you barely walked when I started at Walden, and now you are taller than me. Your intelligence, strength as an autodidactic individual, neurodiversity, and kindness toward others will serve you well in life. I am also grateful that you are talented in coding. You were instrumental in writing the code to pull my API data. Laurelle and Henry, you have matured into amazing young adults, and I hope you will look back on this time in your lives and realize how important it is to never give up on your dreams. Emma, you were a joyful addition to our family toward the end of this journey. Your graduation from the Citadel was an incredible accomplishment, and your hard work and dedication to graduate school at Virginia Tech will provide you with excellent opportunities. I know life has fantastic things in store for you. My love to you all!

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Chapter 1: Introduction to the Study

In this study, I analyzed the relationship between country culture, country demographics, and restaurant electronic word-of-mouth (eWOM) ratings. The importance of eWOM ratings to restaurant success is underscored by the previous findings that 94% of diners select a restaurant based on eWOM (Luo et al., 2020), and eWOM valence ratings reflect customer satisfaction (Hong & Pittman, 2020; Wang et al., 2021; Zhao et al., 2019). According to findings by Baer (2016), when consumers post dissatisfaction through negative eWOM valence ratings or reviews, consumer brand advocacy declines by 37%. Additionally, country culture and country demographics account for 70% of the differences in consumers' product usage (de Mooij, 2017), such as restaurant brand choice or dining frequency.

Global restaurant managers' lack of tacit cultural knowledge due to their brands' rapid international expansion may leave the managers ill-prepared to understand and, therefore, respond appropriately to eWOM valence ratings (Kim & Velthuis, 2021; Lee & Moon, 2018; Lichy & Kachour, 2019; Memarzadeh & Chang, 2015; Vaughan & Koh, 2019; Wade et al., 2018). Therefore, understanding the relationship between country culture, country demographics, and restaurant eWOM valence ratings could lead to positive social change by giving restaurant managers greater insights into how consumers express satisfaction on social media platforms.

The following describes the contents of this chapter. The chapter contains the background of the study, problem and purpose statements, research questions (RQs), hypotheses, and the theoretical foundation. The chapter also included the nature of the study, operational definitions, assumptions, scope and delimitations, limitations, and significance.

Background of the Study

With the click of a mouse or the touch of a mobile device screen, consumers can post eWOM valence ratings about their restaurant experiences. Consumers' increased use of eWOM has caught the interest of scholars, prompting studies that have highlighted the growth of eWOM (Kepios, 2022), consumers' use of eWOM (Babić Rosario et al., 2020), and eWOM's effect on restaurant sales (Luca, 2016; Wang et al., 2021). In this section, I preview research related to restaurant eWOM, describe the knowledge gap in the discipline I addressed, and conclude why this study was needed.

The growth of eWOM has been driven by three conditions. First, access to the Internet is vital for consumers to post eWOM ratings, and the global digital infrastructure has expanded during this century. In 2021, Internet usage increased by 4%, outpacing the yearly world population increase of 1% (Kepios, 2022). Second, mobile devices make it easier for consumers to post ratings. Mobile devices have hyper-saturated the global market. There are now 1.54 connections per unique mobile user, and 92.1% of the world's population can access the Internet via a mobile device (Kepios, 2022). Finally, eWOM growth is dependent on social media users. In 2021, 58.4% of the worldwide population (4.62 billion people representing a 10.1% increase over the prior year) considered themselves active social media users (Kepios, 2022). Thus, the conditions causing eWOM's growth have made eWOM easier to access and use.

Increased daily access to eWOM has also affected consumer decision making. For example, studies have emphasized eWOM's increasing role with consumers in supporting risk reduction (Kim & Tanford, 2019), purchase intention (de Lima et al., 2019), information sharing (Shaw, 2021), and increased brand usage (Weisskopff & Masset, 2020). Additionally, eWOM's role continues after purchase because consumer ratings that are posted online directly represent guest satisfaction for a brand (Hong & Pittman, 2020; Zhao et al., 2019). Therefore, eWOM has become a vital tool for consumers, as evidenced by consumers' use of eWOM throughout their restaurant decision process.

In addition to exploring eWOM as part of consumers' decision-making process, researchers have examined eWOM in terms of country demographics. For example, consumers from different countries have different needs and wants (de Mooij, 2015; de Mooij & Hofstede, 2010; Pratesi et al., 2021), which suggests country-level demographic profiles with unique product preferences. Moreover, country demographics can also affect how quickly a consumer adopts or tries a new product. For example, Tellis et al. (2009) studied consumer innovativeness across countries with linkages to country culture and noted distinct antecedents for country demographics. Thus, country-level demographics appear to influence consumer behavior.

For global restaurant managers, the challenge presented by eWOM is twofold. First, their consumers have varied cultural and demographic backgrounds, and these consumers are using eWOM to share brand satisfaction levels. Second, researchers have revealed that restaurant brands' rapid global expansion has led to management teams who lack tacit cultural knowledge (Lee & Moon, 2018; Vaughan & Koh, 2019; Wade et al., 2018) and have little knowledge of how to respond appropriately to eWOM.

Researchers have studied country culture, country demographics, and eWOM for other goods and services. For example, studies have provided insights into eWOM for movie reviews and revenue (Chiu et al., 2019), the helpfulness of Amazon reviews (Barbro et al., 2020), and Amazon product features and their associated opinions (Wang et al., 2019). Researchers have also published studies regarding hospitality eWOM topics such as reviews of cruise lines (Buzova et al., 2019), airline reviews (Stamolampros et al., 2019), hotel ratings (Mariani & Predvoditeleva, 2019), hotel room rates (Hu et al., 2019), and negative eWOM (Sann et al., 2020). Thus, eWOM research within specific niches has breadth and depth.

Still, scholars have called for further research examining country culture, country demographics, and eWOM. Serra Cantallops and Salvi (2014) analyzed studies within the hospitality industry and found a need for future research on cross-cultural differences in eWOM. Two questions emerged from their research: “Do cultural differences influence the generation of comments?” and “What aspects contribute to the generation of comments in different nationalities?” (pp. 49–50). Chen and Law (2016) suggested that one direction for hospitality research is the influence of national culture on consumer decision making and eWOM. Bore et al. (2017) observed that, because of the global reach of the Internet and eWOM, hospitality managers would benefit from a deeper understanding of how eWOM is influenced by the culture or nationality of the reviewer. Further, Babić Rosario et al. (2020) called for a better understanding of how culture influences eWOM. Global restaurant managers will have improved knowledge by addressing the knowledge gap regarding country culture, country demographics, and eWOM.

This study was necessary because the research on the relationship between country culture, country demographics, and restaurant eWOM was limited. Hong et al. (2016) analyzed culture as an antecedent for restaurant review characteristics. Nakayama and Wan (2018, 2019) studied the effect of culture on restaurant review expression and helpfulness. Wang et al. (2021) examined the effect of brand equity, eWOM ratings, eWOM reviews, and local demographics on restaurant financial performance. I found no studies, however, that analyzed the relationship between country culture, country demographics, and restaurant eWOM valence ratings.

The analysis in this study was distinctive for the following reasons. First, I explored the relationship between country culture, country demographics, and eWOM valence ratings within the restaurant sector. Second, I developed a predictive model of restaurant eWOM valence ratings based on a set of predictor variables and assessed the predictability of the predictor variables. Third, I leveraged an extensive digital dataset of restaurant eWOM aggregate valence ratings using a priori data (Han & Anderson, 2021). Fourth, some of the 32 countries included in the study encompassed research settings often neglected in restaurant and hospitality management studies (Buzova et al., 2019).

Problem Statement

The general management problem is that global restaurant managers lack tacit cultural knowledge (Wade et al., 2018), which places them at a deficit when responding to the demands of eWOM in the respective countries they serve (Kim & Velthuis, 2021). Restaurants failing to respond appropriately to eWOM have experienced declines in consumer brand advocacy (Baer, 2016) and increased customer defection (Stauss & Seidel, 2019). Despite eWOM's growth, eWOM's role in reflecting consumer satisfaction, and eWOM's importance to restaurant success, researchers have not examined the relationship between country culture, country demographics, and restaurant eWOM valence ratings. Therefore, the specific management problem was the lack of knowledge and understanding regarding the relationship between country culture, country demographics, and restaurant eWOM valence ratings. As a consequence, this lack of understanding decreases the ability of restaurant managers to respond appropriately to a market's cultural sensitivities when ratings are posted or issues are raised on eWOM platforms (Barbro et al., 2020).

Understanding the relationship between culture, country demographics, and restaurant eWOM valence ratings may lead to positive social change. Global restaurant eWOM managers may have greater knowledge about their consumers, which could inform eWOM response strategies and ultimately increase sales (Khan, 2017) and brand equity (Barbro et al., 2020). Additionally, examining the relationship between country culture and country demographics with restaurant eWOM valence ratings would extend the research of Serra Cantallops and Salvi (2014), Chen and Law (2016), Bore et al. (2017), and Babić Rosario et al. (2020), who called for greater understanding of the relationship between country culture and eWOM.

Purpose of the Study

The purpose of this quantitative correlational study was to examine the relationship between measures of country culture, country demographics (predictor variables), and restaurant eWOM valence ratings (response variable) for all countries on the Yelp platform with eWOM restaurant valence ratings. Valence represents restaurants' past performance based on consumers' perception of brand satisfaction (Wang et al., 2021). The variables were selected after thoroughly reviewing the marketing and cross-cultural research literature and were readily available from publicly accessible data sets.

The research objectives were twofold and addressed the specific management problem. The first objective was to understand the relationship between country culture, country demographics, and restaurant eWOM valence ratings. The second objective was to develop a predictive model of eWOM valence ratings based on a set of predictor variables and then assess those variables' predictability. To accomplish these objectives, I examined the relationship between the response variable and the 18 predictor variables listed in Table 1.

Table 1

Study Variables

Variable Type	Description	Label	Scale
Response	Restaurant valence	*VAL*	Ratio
Predictor (country culture)	Power Distance Index	*PDI*	Ratio
Predictor (country culture)	Individualism/Collectivism	*IDV/CLV*	Ratio
Predictor (country culture)	Uncertainty Avoidance Index	*UAI*	Ratio
Predictor (country culture)	Masculinity/Femininity	*MAS/FEM*	Ratio
Predictor (country culture)	Long/Short-term Orientation	*LTO/STO*	Ratio
Predictor (country culture)	Indulgence versus Restraint	*IVR*	Ratio
Predictor (country demographics)	Population	*POP*	Ratio
Predictor (country demographics)	Gross domestic product per capita	*GDP*	Ratio
Predictor (country demographics)	Mobile Device Penetration	*MDP*	Ratio
Predictor (country demographics)	Internet Penetration	*INP*	Ratio
Predictor (country demographics)	Social Media Use	*SMU*	Ratio
Predictor (country demographics)	Restaurant Units	*RU*	Ratio
Predictor (country demographics)	Restaurant Sales	*FRS*	Ratio
Predictor (country demographics)	Yelp Visits	*VIS*	Ratio
Predictor (country demographics)	Yelp Unique Visitors	*UVI*	Ratio
Predictor (country demographics)	Yelp Pages Per Visit	*PPV*	Ratio
Predictor (country demographics)	Yelp Average Visit Duration	*AVD*	Ratio
Predictor (country demographics)	Yelp Percent Spill-In	*PSI*	Ratio

Research Questions and Hypotheses

I examined the relationship between country culture as measured by Hofstede's (2001, 2021) and the Hofstede et al. (2010) cultural dimension indexes (as measured by power distance, individualism/collectivism, uncertainty avoidance index, masculinity/femininity, long/short-term orientation, and indulgence versus restraint), country demographics (as measured by population, gross domestic product per capita, mobile device penetration, Internet penetration, social media use, restaurant units, restaurant sales, Yelp visits, Yelp unique visitors, Yelp pages per visit, and Yelp average visit duration, Yelp Spill-In), and restaurant eWOM valence ratings (as measured by Yelp valence ratings) for all countries on the Yelp platform with eWOM restaurant valence ratings. The following research questions and corresponding hypotheses guided the study:

RQ1: What is the relationship between country culture and restaurant eWOM valence ratings?

$H_0$1: There is no significant relationship between country culture and restaurant eWOM valence ratings.

H_a1: There is a significant relationship between country culture and restaurant eWOM valence ratings.

RQ2: What is the relationship between country demographics and restaurant eWOM valence ratings?

$H_0$2: There is no significant relationship between country demographics and restaurant eWOM valence ratings.

H_a2: There is a significant relationship between country demographics and restaurant eWOM valence ratings.

RQ3: What is the relationship between country culture and country demographics on restaurant eWOM valence ratings?

$H_0$3: There is no significant relationship between country culture and country demographics on restaurant eWOM valence ratings.

H$_a$3: There is a significant relationship between country culture and country demographics on restaurant eWOM valence ratings.

RQ4: What country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings?

H$_0$4: There are no country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings.

H$_a$4: There are country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings.

Theoretical Foundation

The theoretical foundation for the study was Hofstede's (2001) cultural dimensions theory. Hofstede et al. (2010) defined *culture* as the collective mental programming of people in an environment, further suggesting that culture is not a characteristic of individuals; instead, it encompasses a group of people conditioned by similar life experiences. Hofstede's (2001, 2021) and Hofstede et al. (2010) six unique dimensions for country culture include measures of a power distance index, individualism/collectivism, uncertainty avoidance index, masculinity/femininity, long/short-term orientation, and indulgence versus restraint. I further discuss cultural dimensions theory in Chapter 2.

Hofstede's (2001, 2021) cultural dimensions theory is one of the most accepted and widely used theories in cross-cultural communications research (Cantwell & Verbeke, 2017; Hudson et al., 2016; Leonhardt et al., 2020; Obara et al., 2021; Wang et al., 2019), and it aligned with my study in the following ways. First, my analysis explored the relationship between country culture, country demographics, and restaurant eWOM, and Hofstede's model provides measures of six different cultural constructs. Second, my research questions focused on country-level analysis, and Hofstede's model is based on country-level cultural indexes.

Nature of the Study

I used a quantitative correlational study design to examine the relationship between country culture, country demographics, and restaurant eWOM valence ratings for all countries on the Yelp platform with eWOM restaurant valence ratings. Correlational research design measures the strength and direction of a relationship between two or more quantitative variables (Gogtay & Thatte, 2017). Additionally, correlation studies can test hypotheses when groups cannot be randomly assigned, such as those formed by naturally occurring characteristics (Wrench et al., 2018). As such, in this correlational study, I measured three quantitative constructs (country culture, country demographics, and eWOM valence ratings). I also used a country-level unit of analysis, which is a naturally occurring characteristic.

Country culture is a construct defined by six discrete measures (predictor variables) from Hofstede's (2001, 2021) cultural dimensions model: power distance index (*PDI*); individualism/collectivism (*IDV*/*CLV*); uncertainty avoidance index (*UAI*); masculinity/femininity (*MAS*/*FEM*); long/short-term orientation (*LTO*/*STO*); and indulgence versus restraint (*IVR*). I provide a more detailed definition of Hofstede's cultural dimensions model in the theoretical foundation section and Chapter 2. The cultural dimensions data were publicly available for download from the Hofstede website.

Country demographics is also a construct defined by 12 discrete measures (predictor variables): population (*POP*); gross domestic product per capita (*GDP*); mobile device penetration (*MDP*); Internet penetration (*INP*); and social media use (*SMU*); the number of restaurant units (*RU*); restaurant sales (*RS*); Yelp platform visits (*VIS*); Yelp platform unique visitors (*UVI*); Yelp pages per visit (*PPV*); Yelp average visit duration (*AVD*); and Yelp percent spill in (PSI). The country demographic variables will be further explained in Chapter 2. The country demographic variables were also publicly available data (see Table 2). I accessed *POP* data online from The United Nations World Population Review (2021) and *GDP* data from The World Bank (2021) websites. The World Bank describes itself as an independent organization without political affiliations whose mission is to provide up-to-date and transparent demographic data. I accessed *MDP*, *INP*, and *SMU* data from reports produced by Kepios (2022), a global consultancy that tracks and analyzes evolving digital behaviors; *RU* and *RS* were accessed from the Barnes Reports (2020), which publishes U.S. and global industry studies. Finally, *VIS*, *UVI*, *PPV*, *AVD*, and *PSI* were accessed from Semrush (2022), which tracks and publishes key performance indicators (KPIs) about social media platforms.

Table 2

Country Demographic Data Sources

Variable	Source
Population (*POP*)	The United Nations, Department of Economic and Social Affairs, Population Division
Gross domestic product per capita (*GDP*)	The World Bank
Mobile device penetration (*MDP*)	Kepios, Local Insights
Internet penetration (*INP*)	Kepios, Local Insights
Social media use (*SMU*)	Kepios, Local Insights
Restaurant units (*RU*)	Barnes Reports, Restaurants: Worldwide Industry Market Report
Restaurant sales (*RS*)	Barnes Reports, Restaurants: Worldwide Industry Market Report
Yelp visits (*VIS*)	Semrush, Yelp Traffic Analytics Overview Report
Yelp unique visitors (*UVI*)	Semrush, Yelp Traffic Analytics Overview Report
Yelp pages per visit (*PPV*)	Semrush, Yelp Traffic Analytics Overview Report
Yelp average visit duration (*AVD*)	Semrush, Yelp Traffic Analytics Overview Report
Yelp percent spill-in (*PSI*)	Semrush, Yelp Traffic Analytics Overview Report

Restaurant eWOM valence ratings (*VAL*) (response variable) represent consumer satisfaction. It was measured by the average of all cumulative prior Yelp ratings from a purposive sample of a country's restaurants. Yelp ratings are numerical scores of 1 to 5 stars, rounded to the nearest .5 star (Yelp, 2022b). Yelp was the social media platform that best addressed my research questions. I accessed publicly available *VAL* data from Yelp's application programming interface (API) for each of the 32 countries in which Yelp currently operates.

The correlational design uses quantitative statistical analyses, such as correlation coefficient tests and regression models (Gogtay & Thatte, 2017). I calculated the correlation coefficient to understand the strength and direction of the linear relationship between the variables. I also used multiple linear regression (MLR) to develop a predictive model of the response variable based on the predictor variables and to assess the significance of the relationship between the predictor and response variables.

Definitions

Application programming interface (API): A set of definitions and protocols necessary when building and integrating application software (Lomborg & Bechmann, 2014).

Average visit duration (AVD): A demographic representing the average time in minutes, per visitor, per month, spent on a social media platform (Semrush, 2021).

Brand: A combination of marketing elements such as name, symbols, and offerings differentiating a seller's product or service from the competition (Lamb et al., 2017).

Brand advocate: A person who supports and promotes a brand through social media word-of-mouth. Brand advocates are relevant because they expand an organization's reach to new markets and customers with minimal internal expense and add credibility to messaging (Geyser, 2021).

Country culture: The beliefs, norms, practices, and values that members of a country's culture follow, even given individual differences in the population (Gannon & Rajnandini, 2015).

Electronic word-of-mouth (eWOM): The positive or negative reviews and ratings about brands made by potential, current, or past consumers and conducted via Internet-based platforms (Mariani & Visani, 2019).

Global restaurants: Restaurant brands with locations outside their home country (Wade et al., 2018).

Gross domestic product per capita (GDP): A demographic representing a country's measure of economic prosperity. Gross domestic product per capita divides the annual gross domestic product by population. This measure presents an economic indicator of the total economic well-being of a country (The World Bank, 2021).

Individualism/Collectivism (IDV/CLV): A cultural dimension describing how well a society is integrated into groups. Cultures below 50 are collectivist, and cultures above 50 are individualistic (Hofstede, 2001, 2011, 2021).

Indulgence versus restraint (IVR): A cultural dimension measuring a society's strength in allowing or controlling happiness and gratification. Cultures below 50 are considered low indulgence versus restraint cultures, and cultures above 50 are considered high indulgence versus restraint cultures (Hofstede, 2001, 2011, 2021).

Internet penetration (INP): A demographic representing the percentage of a country's total population with access to the Internet (The Central Intelligence Agency, n.d.).

Long-term orientation/Short-term orientation (LTO/STO): A cultural dimension describing how society views its past and present versus the future. Cultures below 50 have a long-term orientation, and those above 50 have a short-term orientation (Hofstede, 2001, 2011, 2021).

Masculine/Feminine (MAS/FEM): A cultural dimension reflecting the level of a society's assertiveness or caring, which can be considered proxies for competitiveness. Cultures below 50 are feminine, and cultures above 50 are masculine (Hofstede, 2001, 2011, 2021).

Mobile device penetration (MDP): A demographic representing the percentage of a country's total population that owns a mobile device (Kepios, 2022).

Pages per visit (PPV): A demographic measure of the average number of pages a person visits on a social media platform each visit (Semrush, 2021).

Percent spill in (PSI): A demographic measure of the percentage of visits that flows to a social media platform from a foreign country (Semrush, 2021).

Population (POP): A demographic measure of all inhabitants 18 years or older for a defined country (World Population Review, 2021).

Power distance index (PDI): A cultural dimension representing how the less powerful members of organizations or institutions expect and accept that social power is distributed unequally. The significance of power distance is that it reflects social inequality. Cultures below 50 have a low power distance index, and those above 50 have a high power distance index (Hofstede, 2001, 2011, 2021).

Ratings: Average ratings, often designated as star ratings from 1 to 5 stars, that social media users assign as a proxy for their experience with a brand (Tuten & Solomon, 2017).

Recommended review: To combat fake ratings and reviews, Yelp will not include posts from users who are new and have not posted anything else. Additionally, the platform excludes ratings and reviews from people who are the business owner or are somehow related to the business owner (Yelp, 2022a).

Restaurant sales (RS): A demographic measure of customer revenue for food and services rendered. Restaurant sales do not include carrying or credit charges, sales or other taxes collected, or gross sales or commissions collected for third-party operators (Barnes Reports, 2020).

Restaurant unit (RU): A demographic measure of the count of single physical locations at which business is conducted, and services are provided (Barnes Reports, 2020).

Reviews: Written assessments posted by social media users about their experience with a brand (Tuten & Solomon, 2017).

Social media use (SMU): A demographic measure of the percentage of a country's total population accessing social media (Kepios, 2022).

Spill-in: Spill-in represents the traffic a social media platform receives outside the host country (Semrush, 2021).

Tacit cultural knowledge: Cultural knowledge that cannot be taught but must be learned through experience (Wade et al., 2018).

Uncertainty avoidance index (UAI): A cultural dimension representing comfort with ambiguity or unstructured situations. Cultures below 50 have a low uncertainty avoidance index, and cultures above 50 have a high uncertainty avoidance index (Hofstede, 2001, 2011, 2021).

Unique visitors (UVI): A country demographic measure of the count of unique visitors to a social media platform in a month (Semrush, 2021).

User-generated content: Content disseminated by social media users through social media platforms, excluding content created and shared by brands, organizations, or professionals hosting social media sites (Zainal et al., 2017).

Valence (VAL): The average of all cumulative prior ratings for a brand, such as star ratings, on a score from 1 to 5 stars, rounded to the nearest .5 star (Yelp, 2022b). One star represents a low rating, and five stars represent a high rating (Y. Yang et al., 2018). Valence reflects consumer satisfaction regarding a product and measures future purchase decisions and brand sales (Barbro et al., 2020).

Visits (VIS): A demographic measure of the total count of visits in a month to a social media platform (Semrush, 2021).

Yelp: A social media platform that connects people with local businesses. Using the various services offered through the Yelp platform, consumers can search and communicate about local companies of all sizes, request quotes or join waitlists, and make reservations, appointments, or purchases. Yelp was founded in San Francisco in July 2004 (Yelp, 2021b).

Yelper: An individual who uses the social media platform Yelp.com by reading reviews, writing reviews, or otherwise participating in the Yelp.com community (Yelp, 2021c).

Assumptions

This research was based on the following two assumptions. First, people posting to Yelp had brand exposure, permitting them to rate and post about their restaurant experiences accurately. Additionally, the Yelp platform accurately captured consumer ratings and then accurately transmitted the data. These assumptions were necessary for this study because I could not validate or verify the ratings posted on or transmitted from the Yelp platform.

Scope and Delimitations

This correlational, quantitative study examined the relationship between measures of country culture, country demographics, and restaurant eWOM valence ratings for all countries on the Yelp platform with eWOM restaurant valence ratings. Furthermore, I addressed a knowledge gap for restaurant managers about the effect of country culture and country demographics on restaurant eWOM valence ratings, which warranted further study. The analysis included restaurant eWOM valence ratings as the response variable, six predictor variables for country culture, and an additional 12 predictor variables for country demographics. The response variable was selected because it represented consumer satisfaction with brands (Wang et al., 2021). The six predictor variables representing culture were selected because they represented measures of country culture that have been widely used in cross-cultural communications research (Cantwell & Verbeke, 2017; Hudson et al., 2016; Leonhardt et al., 2020; Obara et al., 2021; Wang et al., 2019). I selected the country demographic variables because prior research indicated their influence on eWOM within other domains (de Mooij, 2015, 2017). Additionally, my decision to include the country demographic variables was influenced by Hofstede (2001), who advocated for the use of "economic, geographic, and/or demographic indicators when assessing culture against alternative explanations so as to avoid a myopic focus on culture alone" (p. 465).

The population relevant to this study included all countries with restaurants with eWOM valence ratings for all time. The target population consisted of 32 countries with restaurants with eWOM valence ratings, for which Yelp has eWOM data. My sampling frame consisted of all 32 countries with restaurant eWOM valence ratings provided via the Yelp Fusion API on October 3, 2021. The target and sampling frame was dictated by selecting Yelp as the social media platform and then using the Yelp Fusion API to access the eWOM valence data (response variable). Also, because of the nature of Yelp, the data I accessed represent a single point in time (Quan-Haase & Sloan, 2016). By delimiting the research scope to a single social media platform (Yelp), I ensured my data came from a consistent source and time frame, thus reducing collection bias (Mayr & Weller, 2016). Mayr and Weller (2016) advocated that social media research results can be generalized to users of the platform under study, which means the results of my study may provide insights into the influence of country culture on eWOM valence for restaurant managers who use the Yelp platform, as well as other establishments using the Yelp platform.

Although I reviewed culture theories such as the GLOBE study (House et al., 2004) and Schwartz's theory of basic values (2011, 2012), the relationship between these theories is not as well established as the cultural dimensions theory (de Mooij, 2017). Moreover, the cultural dimensions theory is one of the most widely used theories for evaluating country culture (Obara et al., 2021; Stamolampros et al., 2019; Wang et al., 2019). I used cultural dimensions as my theoretical foundation because it helped address external validity issues. According to Trochim (2001), the proximal similarity model holds that my study benefitted from other studies that have used cultural dimensions theory to evaluate country culture because of an implicit gradient of similarity.

Limitations

Limitations are weaknesses in the research design or an issue in the research process (Wrench et al., 2018). A potential shortcoming of this correlation study was that the action had already occurred, and it was not possible for random assignment to groups. This limitation makes it difficult to confidently state a definitive cause-and-effect result (Wrench et al., 2018). Additionally, I monitored historical events, such as geopolitical events or natural disasters, which might have influenced the data, to reduce threats to internal validity (Choi, 2020; Le et al., 2021). A review of major news media in the 32 countries included in the study found no reference to significant historical events that might influence the study.

Another limitation was that no complete list of the population existed (i.e., all countries and all establishments with an eWOM presence), nor was it practical to create one. Therefore, conducting a random sample of the entire population was impossible. Also, I accessed data for the response variable, eWOM *VAL*, from the Yelp API. Yelp controls the data; based on the keywords used for the API calls (*country*, *restaurants*), the API limits the number of records returned to a maximum of 200 restaurants in which each of the 32 countries Yelp operates.

The lack of a random sample of the entire population and using a Yelp-controlled data set may have resulted in bias. However, to address this limitation, I conducted a purposive sample of a well-defined target population that included the 32 countries with restaurants with eWOM valence ratings, for which Yelp had eWOM valence ratings data. My sampling frame included 6,108 restaurant eWOM valence ratings from all 32 countries provided via the Yelp Fusion API on October 3, 2021. My final sample after screening and cleaning was $N = 3{,}659$ and included 21 countries. I performed a priori and post hoc power analyses to calculate the probability of a Type II error or false negative (β) and statistical power ($1 - \beta$), representing the likelihood of detecting a true effect. The results from the a priori and post hoc power analyses did not raise concern regarding Type II errors.

Paschek (2015) and Wijnhoven and Bloemen (2014) advocated that researchers may address limitations and bias by ensuring a match between the population and research target, ensuring alignment between the data and research questions, using the same social media platform for all markets, and being as transparent as possible in reporting the results. I used a purposive sample of my target population, and my eWOM data directly aligned with my research question. I used one platform, Yelp, to access my eWOM data in all markets. Finally, I was as transparent as possible when reporting my research.

Threats to internal validity included the interaction of effects with units, treatments, settings, and outcomes (Schenker & Rumrill, 2004). Interactions between predictor variables create complexity and challenges to explaining the main effects: the influence of any one predictor variable on the response variable. To address this issue, I investigated, as part of MLR, the two-factor interactions (2FIs) between pairs of predictor variables.

Significance of the Study

I sought to address a gap in the literature and advance theory by examining the relationship between country culture, country demographics, and restaurant eWOM valence ratings. With a better understanding of country culture and country demographic influences on eWOM valence ratings, the results can help restaurants develop and implement differentiated eWOM strategies. Positive social change may occur because of this research through better eWOM response strategies, customer relationships, sales, and brand equity.

Significance to Theory

The results of this quantitative correlational design study provided an original contribution to knowledge in the restaurant sector and the emerging field of eWOM research by analyzing the effect of country culture and country demographics on restaurant eWOM valence ratings. Specifically, I addressed the eWOM question posed by Serra Cantallops and Salvi (2014), “Do cultural differences influence the generation of comments?” (pp. 49-50). Serra Cantallops and Salvi (2014) and Lui et al. (2018) also noted a need to understand the differences between American and European eWOM content. Buzova et al. (2019) also established a need to examine American and European cross-cultural eWOM and stated that most previous cross-cultural eWOM studies lacked an analysis of multiple cultures. Chen and Law (2016) emphasized the importance of culture on consumer behavior. Therefore, my research addressed how different cultural backgrounds influence eWOM. Chen and Law also suggested that research include geographic areas such as North America (other than the United States), Oceania and sectors such as airlines or restaurants. Finally, Sann et al. (2021) called for future restaurant eWOM research analyzing cultural differences, along with data mining social media sites, not only because of its power as an analytics tool but also because the use of big data analytics has seldom been used in prior studies.

Significance to Practice

This study contributed to professional practice by providing managers with a better understanding of country culture and country demographic influences on restaurant eWOM valence ratings. Knowledge of country cultural and country demographic influences helps provide restaurant eWOM managers with consumer insights. These insights could foster greater online engagement between restaurant brands and consumers. Additionally, contextual understanding could foster more powerful and targeted responses to issues or complaints raised on eWOM, thus preventing problems from growing and damaging the brand’s reputation and image.

Significance to Social Change

This study may promote positive social change by encouraging better eWOM communication practices for restaurant eWOM managers. When restaurant eWOM managers have stronger eWOM communication with their target audiences, they can enjoy stronger consumer relationships, which have been shown to positively influence brand equity (Kotler & Keller, 2016). Additionally, some have argued that strong consumer relationships and positive brand equity positively correlate with the firm's shareholder or market value (Interbrand, 2020).

Summary and Transition

In Chapter 1, I addressed the lack of knowledge and understanding of the relationship between country culture, country demographics, and restaurant eWOM valence ratings. Hofstede's cultural dimensions theory served as the theoretical foundation for the research. I used a quantitative correlational research design to explore the relationship between the predictor variables (country culture, country demographics) and the response variable (restaurant eWOM valence ratings). A purposive sample was used to access the data in each of the 32 countries included in the study. Correlation coefficients were calculated to determine the relationship between the variables (strength and direction). MLR was used to develop a predictive model of the response variable based on the predictor variables and to assess the significance of the relationship between the predictor and response variables. In Chapter 2, I analyze and detail current and relevant research relating to country culture, country demographics, eWOM, and restaurants. I also describe the search strategy and theoretical foundation used to guide my study. Chapter 3 describes the research methodology I used to analyze the data. Chapter 4 contains details regarding the data collection and the results of the correlation or regression analyses related to each research question. Chapter 5 contains interpretations of the findings, limitations of the study, recommendations for future research, and implications for positive social change.

Chapter 2: Literature Review

The general management problem I addressed in this study is that global restaurant managers lack tacit cultural knowledge (Wade et al., 2018), which places them at a deficit when responding to the demands of eWOM in the respective countries they serve (Kim & Velthuis, 2021). The specific management problem was the lack of knowledge and understanding regarding the relationship between country culture, country demographics, and restaurant eWOM valence ratings. The purpose of this quantitative correlation study was to examine the relationship between measures of country culture, country demographics (predictor variables), and restaurant eWOM valence ratings (response variable) for all countries on the Yelp platform with eWOM restaurant valence ratings.

Numerous authors have analyzed the growing impact of eWOM on both organizations (Chen & Law, 2016; Kepios, 2022; Park & Jeon, 2018; Zhang et al., 2016) and consumers (Gellerstedt & Arvemo, 2019; Lui et al., 2018; Mariani & Predvoditeleva, 2019; Mariani & Visani, 2019). Researchers have found that restaurant managers lack tacit cultural knowledge (Jung et al., 2018; Lee & Moon, 2018; Vaughan & Koh, 2019; Wade et al., 2018). Other studies have suggested that restaurant managers lack the knowledge and skills to manage or respond to consumer eWOM posts (Kim & Velthuis, 2021; Lichy & Kachour, 2019). For restaurant brands, the eWOM challenges are twofold: consumers with a variety of cultural backgrounds using and sharing eWOM valence ratings about their dining experiences and restaurants located across foreign markets managed by restauranteurs who lack tacit cultural knowledge and eWOM management skills.

In Chapter 2, I explain my literature search strategy, describe my theoretical foundation, and present my literature review. First, I describe the theoretical foundation, Hofstede’s cultural dimensions theory, used in this study. Specifically, I review the historical influences on the theory, significant components, applications in prior research, and rationale for why cultural dimensions theory was appropriate for my research. Second, I present a literature review that addresses eWOM, the restaurant sector, consumer decision making, and country demographics. I explain how country culture, eWOM, the restaurant sector, consumer decision making, and country demographics provided a structure for my research questions. I conclude by summarizing the key points in the chapter relevant to the gap in the research, knowledge, and understanding regarding the specific management problem.

Literature Search Strategy

For this literature review, I searched multiple sources. I selected articles and books relating to the influence of country culture on eWOM content from Walden University, Mount St. Mary’s University, and Western Governors University library websites. I augmented the literature review with books and articles from other sources. The databases I used included Academic Search Complete, Business Source Complete, Communication & Mass Media Complete, EBSCO e-books, Google Scholar, Emerald Insight, Hospitality & Tourism Complete, ProQuest Central, Sage Premier, Science Direct, Springer eBooks, and Thoreau. My search criteria included peer-reviewed articles from scholarly journals primarily published within the past five years; however, if an article or book was published outside the date parameters or was found to be published as a professional resource instead of an academic journal and held significant merit for the literature review, I included the resource in the literature review. My search focused on the following keywords: *big data, country culture, cross-cultural differences*, *culture of origin*, *electronic word-of-mouth*, *eWOM*, *hospitality*, *hotel*, *qualitative*, *quantitative*, *online reviews*, *online word-of-mouth*, *research*, *restaurant*, *social media*, *volume*, *valence*, *Yelp*, *Yelp.com*, *WWW*, *World Wide Web,* and *Web*.

Theoretical Foundation

I used Hofstede’s cultural dimensions theory as the theoretical foundation for my research. Cultural dimensions theory resulted from Hofstede’s more than 40 years of IBM survey research conducted in more than 70 countries (Hofstede, 2001; Hofstede et al., 2010). In the following sections, I provide an overview and seminal influences on cultural dimensions theory. I also discuss components of the theory and explain how the use of cultural dimensions theory supported my study.

Cultural Dimensions Theory

Hofstede’s original four dimensions categorizing the effects of personal values on social culture were measured using multi-item constructs scored on a 5-point Likert scale (Hofstede, 2001). Hofstede’s original cultural dimensions included power distance, individualism versus collectivism, uncertainty avoidance, and masculinity versus femininity (Hofstede, 2001). Using research from the Far East, Hofstede constructed a fifth dimension titled long-term versus short-term orientation (Hofstede, 2001; Hofstede

& Bond, 1988). Analysis from Bulgarian scholar M. Minkov led Hofstede to add a sixth and final dimension termed indulgence versus restraint (Hofstede, 2011; Hofstede et al., 2010).

Hofstede et al. (2010) created the cultural dimensions theory based on the concept that culture is the "collective programming of the mind that distinguishes the members of one group or category of people from others" (p. 6). What Hofstede meant is signified by his use of the word *collective*. Culture does not reflect individual differences such as personality, occupation, education, or income (Hofstede, 2001; Hofstede et al., 2010). Nor does culture reflect universal qualities, which Hofstede described as human physical and psychological functions, such as feelings of fear, anger, sadness, or happiness (Hofstede et al., 2010). Instead, Hofstede's theory is that culture reflects a group's collective symbols, heroes, rituals, and values. Thus, Hofstede's collective programming of the mind can be considered a country's shared social structures and norms.

Seminal Influences on Cultural Dimensions Theory

When he developed the cultural dimension theory, Hofstede (2001) was influenced by other theorists. These influences can primarily be traced to the research of Inkeles and Levinson (1969), and Kluckhohn (1951).

Inkeles and Levinson

Inkeles and Levinson (1969) believed previous efforts to characterize culture had a subjective bias. To prevent this deficiency in their metanalysis of sociological and anthropological literature, Inkeles and Levinson proposed analyzing culture at a national level. In their resulting research, they discovered and described countries by national social personality types. Hofstede (2001) followed Inkeles and Levison by also categorizing cultural groups within his research at the national level. While Inkeles and Levinson used *standard analytic issues* to describe group norms, Hofstede (2011) labeled them *dimensions*; however, Hofstede used three of the same criteria as Inkeles and Levinson when evaluating and grouping national-level cultural values:

- Relation to authority
- The conception of self, including views on masculinity and femininity
- Conflicts and how they are resolved, including aggression and inhibition

These criteria help demonstrate how country culture is a national-level construct. For example, while an individual member of society may have personal views on authority, masculinity, or conflict, the ongoing interaction with other social group members defines the culture.

Kluckhohn

Kluckhohn also influenced Hofstede (2001). Kluckhohn (1951) discovered that members of culture would feel a sense of comfort and normalcy from the beliefs and practices of their society. In contrast, the structure of another culture would feel abnormal and, at times, even inferior. The idea of cultural comfort led Kluckhohn to the understanding that cultures could be differentiated, which is evident in Kluckhohn's definition of culture:

> Culture consists in patterned ways of thinking, feeling and reacting, acquired and transmitted mainly by symbols, constituting the distinctive achievements of human groups, including their embodiments in artifacts; the essential core of

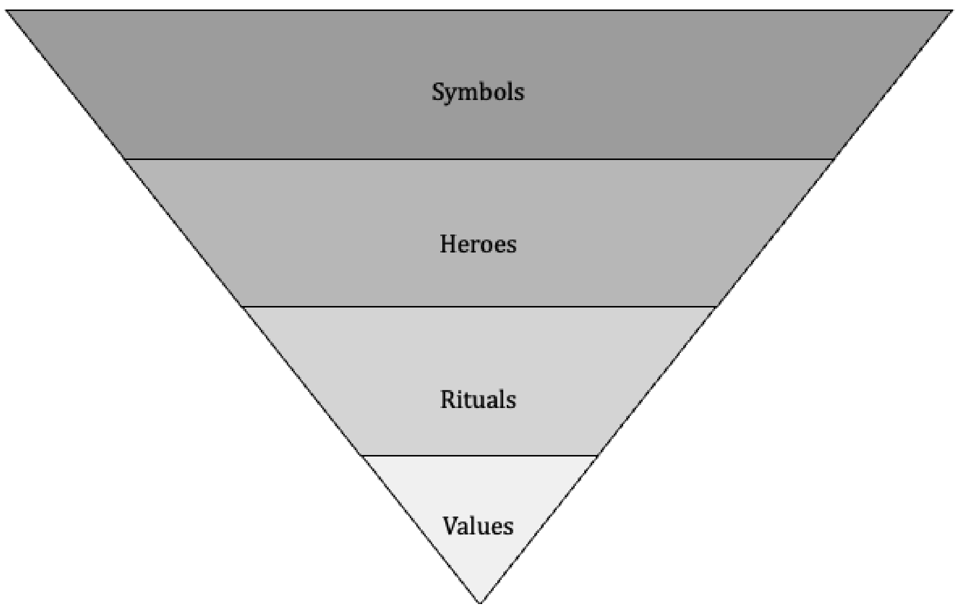
> culture consists of traditional (i.e., historically derived and selected) ideas and especially their attached values. (p. 86)

Like Kluckhohn (1951), Hofstede (2001) also noted that cultures could be differentiated; however, Hofstede extended Kluckhohn's definition by theorizing culture as having different manifestations of social structures and norms with visible and invisible components. Both Hofstede and Kluckhohn believed that shared values are a critical cultural foundation. Kluckhohn defined values as a human process that included "conception, explicit or implicit, distinctive of an individual or characteristic of a group, of the desirable, which influences the selection from available modes, means, and ends of action" (p. 395).

For Hofstede (2001), values were the key feature differentiating one culture from another. He asserted, however, that values are only visible once they become evident through social behaviors. For Hofstede, these visual social behaviors are explained by three cultural strata (see Figure 1). The outermost visual representation of culture is symbols. Symbols are recognized by cultural members and characterized by monuments, food, dress, colors, or logos. Next, Hofstede defined heroes as public figures or athletes. Heroes can be alive, dead, or even make-believe. Hofstede asserted that heroes play an important role because they demonstrate characteristics of culturally desired behaviors. After heroes, Hofstede defined rituals, which he described as representing recurring activities such as greetings or tipping in a restaurant. Hofstede also asserted that rituals, such as social and religious ceremonies, could be events. Rituals are characterized by the fact that while they are not necessary, they are still considered socially essential. Finally, Hofstede argued that its values are at a culture's core. Values represent a general preference for a social hierarchy. Furthermore, Hofstede asserted that culture does not appear unless there is a conflict, hence, the need to delineate between visible and invisible levels of culture.

Figure 1

Cultural Dimensions



Note. Hofstede asserted that there are levels of culture progressing from outwardly visible to intrinsic. The shading represents this progression from darker to lighter shading. At the base are a nation's values, which help to define a unique national culture (Author's figure).

Components of Cultural Dimensions Theory

Hofstede's (2001) cultural dimensions theory has six composite dimensions reflecting a country's shared and defining cultural values: measures of individualism and collectivism, power distance, uncertainty avoidance, masculinity and femininity, long-term and short-term orientation, and indulgence versus restraint (Hofstede, 2001, 2011, 2021). Individualism and collectivism are cultural dimensions that reflect how well a society is integrated into groups (Hofstede, 2001, 2011, 2021). Individualistic cultures have loose social ties, and members of society are expected to take care of their own needs. Conversely, collectivistic cultures have strong groups and extended families. Additionally, collectivistic cultures value group loyalty and oppose sub-groups.

Power distance represents how much the less powerful members of organizations or institutions expect and accept that social power is distributed unequally in groups (Hofstede, 2001, 2011, 2021). To create the power distance dimension, Hofstede (2001) considered followers just as much as he considered social leaders. Thus, the significance of power distance is that it reflects a holistic view of social inequality.

Uncertainty avoidance is the cultural dimension representing comfort with ambiguity or unstructured situations groups (Hofstede, 2001, 2011, 2021). Countries with high uncertainty avoidance have high stress and anxiety (Hofstede, 2001). Members of these societies seek to reduce unpleasant feelings and minimize ambiguity by imposing strict codes, rules, or laws to make life more predictable. Low uncertainty avoidance cultures experience low stress and anxiety; therefore, there is no sense of urgency for rules or laws. Additionally, low uncertainty avoidance cultures are more accepting of diversity in people or ideas.

Masculinity and femininity are cultural dimensions reflecting how assertive or caring social groups are (Hofstede, 2001, 2011, 2021), which can be considered proxies for a society’s competitiveness. Hofstede (2001) based the masculinity and femininity dimensions on differences he found between male and female goals. In countries with high masculinity scores, boys and girls were brought up differently from each other and therefore had a higher level of gender role differentiation. Conversely, the two genders were raised with similar values in countries with high femininity scores. Thus, there was a more negligible difference between roles and social norms for men and women.

Long-term and short-term orientation describes how society views past and present versus future groups (Hofstede, 2001, 2011, 2021). Societies with a long-term orientation look forward to the future, value thrift, and have high regard for perseverance. Those with a short-term orientation will hold on to traditions, avoid change, and value personal stability and service.

Indulgence versus restraint reflects a society's strength in allowing or controlling happiness and gratification groups (Hofstede, 2001, 2011, 2021). Societies with high indulgence versus restraint scores believe they control their destiny. Societies with low indulgence versus restraint scores believe external societal components dictate life and emotions.

Application of Cultural Dimensions Theory in Prior Research

Cultural dimensions theory has been applied in previous research similar to mine. Moreover, Hofstede's (2001) theory has been cited as one of the most widely used metrics for measuring culture on a national level (Obara et al., 2021; Stamolampros et al., 2019; Wang et al., 2019). Bendahou and Berbou (2020) used Hofstede's cultural dimensions to propose a theoretical model for the effect of culture on social media use within travel destination search. The three components of the researchers' theoretical model included set theory to address the destination choice process, the Curran and Lennon (2011) model to address social networking behavior, and three of Hofstede's cultural dimensions (masculinity and femininity, individualism and collectivism, and uncertainty avoidance) to address cultural differences.

Tang (2017) used the cultural dimensions theory to examine the moderating effect of eWOM on Amazon reviews for cell phones. Tang's research indicated that the influence of online reviews varies based on the cultural orientation of the buyer. For example, review valence was less influential in individualistic cultures and more appreciated in uncertainty avoidance cultures.

Stamolampros et al. (2019) used Hofstede's theory to research consumers' online reviews of airline rankings and services. The researchers found variations in air passenger valence ratings based on differences in inherent cultural values. Additionally, the researchers found that passenger satisfaction was higher for airlines when there was a higher alignment between the passengers and the airline's cultural values.

Mariani and Predvoditeleva (2019) used each of Hofstede's six cultural dimensions to research the influence of culture and perceived experience of online ratings data from Bookings.com for Moscow hotels. Mariani and Predvoditeleva found that online hotel ratings negatively affected individualism, masculinity, uncertainty avoidance, and power distance. Moreover, the researchers discovered that the higher the score on the cultural dimension, the lower the hotel's rating. The researchers also found that a reviewer's perceived experience is negatively related to online hotel ratings.

Chatterjee and Mandal (2020) combined user-generated content from an online database, Skytrax's airlinequality.com, with three of Hofstede's cultural dimensions to understand how country culture, economic background, and travel goals influenced consumers' formation of air travel preferences and online evaluations. Specifically, Chatterjee and Mandal discovered that air travelers from countries with lower levels of individualism were more likely to award positive ratings than travelers from highly individualistic cultures. Additionally, the researchers found that air travelers with higher uncertainty avoidance are more likely to award lower ratings. Finally, the researchers discovered that air travelers with a long-term orientation would offer higher positive ratings.

Shapoval et al. (2021) used the cultural dimensions theory to assess the opinions and viewpoints of hospitality leaders regarding the effects of the COVID-19 pandemic. The researchers found that cultural differences were reflected in perceptions of the pandemic. Additionally, the research revealed cultural differences regarding the personal feelings of the hospitality leaders' regarding their home country.

Rationale for Cultural Dimensions Theory in the Study

Cultural dimensions theory relates to my study. First, my research questions examined the relationship between the predictor variables (country culture and country demographics) and eWOM (an aggregate country-level measure). Additionally, my research extended the application of cultural dimensions theory into the emerging realm of eWOM research by developing a model to predict the response variables.

Several scholars have argued that globalization has caused a loss of national cultural identity (Arnett, 2002; O'Hara & Biesecker, 2003); consequently, they claimed that country culture is no longer a viable construct. However, Wang (2016) studied data from 50 countries to understand globalization's effect on country culture and discovered no wholesale loss of national identity despite increasing globalization. While Wang did note an increase in individual identity, 95% of respondents also remained attached to their culture of origin.

Additionally, Minkov and Hofstede (2012) analyzed World Values Survey data from 28 countries and 299 in-country regions and determined that cultural values were the only defining factor for nation units. Furthermore, Reisinger and Crotts (2010) analyzed Hofstede's five dimensions of national culture using hospitality survey data and found that the dimensions had validity and reliability as a marketing segmentation tool. Thus, Reisinger and Crotts advocated using Hofstede's cultural dimensions to measure the central tendency for hospitality-related products and services. Prior research has demonstrated country culture's continuing importance in the globalized world; therefore, cultural dimensions theory is an appropriate model for my research.

Literature Review

In my literature review, I found research related to the constructs of interest for my study. In the following sections, I define and explain eWOM, the restaurant sector, consumer decision making, country culture, and country demographics. I also analyzed and synthesized the literature to understand research methods consistent with my research questions.

Electronic Word-of-Mouth (eWOM)

Consumers use eWOM to communicate a variety of messages. The definition of eWOM is positive or negative communication made by potential, actual, or former customers about a product or company. The eWOM is transmitted electronically to many people or institutions via the Internet (Mariani & Predvoditeleva, 2019). Consumer reviews and ratings posted to company-owned websites such as Amazon or BestBuy and social media platforms such as Yelp or TripAdvisor are examples of eWOM communication (Tuten & Solomon, 2017).

The driving forces behind eWOM have been Internet penetration, mobile devices, and social media use. Internet penetration has been supported through the improving global digital infrastructure. The number of Internet users outpaced population growth in 2021 as the world population increased by 1%, whereas the number of Internet users grew by 4% (Kepios, 2022). Additionally, mobile devices have hyper-saturated the global market. There are now 1.54 connections per unique mobile user, and 92.1% of the world's population accesses the Internet via a mobile device (Kepios, 2022). Finally, eWOM continues to benefit from the growth in social media users. In 2021, 4.62 billion people (58.4% worldwide population) considered themselves active social media users, a 10.1% increase over the prior year (Kepios, 2022).

In the following sections, I provide context for eWOM by reviewing the current research on eWOM and its predecessor, word-of-mouth (WOM). Next, I review the research related to the technology that enables eWOM. Finally, I review the literature that explores and analyzes the characteristics and significance of eWOM and then transition to the other topics related to my study of restaurants and consumer decision making.

Word-of-Mouth (WOM)

WOM has been defined as direct interpersonal brand-focused communication (Khan, 2017; Ring et al., 2016). WOM is the offline predecessor to eWOM, the technological evolution of face-to-face WOM. While WOM communication is more personal than eWOM, it is considered less influential because eWOM has immediate, significant, credible, and public reach (Park & Jeon, 2018; Zhang et al., 2016). Furthermore, message reach and breadth are much more significant for eWOM due to the connectivity of social media (Chen & Law, 2016).

WOM was initially discovered as a construct in the early 1970s by Silverman (2011) during pharmaceutical research with doctors. Silverman noted during teleconferenced peer groups that doctors who had a good experience with a particular drug would change the opinions of nonprescribers and ex-prescribers simply by talking about the efficacy and safety of the prescription. The importance was the ability to sway physicians' opinions, given that this drug had been directly linked to several deaths. Moreover, Silverman reported that the drug's sales had a remarkable 700% increase after positive word-of-mouth was communicated during research sessions.

The effects of WOM have long been known, with researchers documenting its organizational importance. Ring et al. (2016) found that WOM communication effectively delivered messages to target audiences. Pauwels et al. (2016) discovered that WOM communication was more successful in achieving organizational goals than paid marketing efforts. East et al. (2017) established that positive WOM has twice the effect on recruiting customers versus retaining customers; however, negative WOM has over four times the impact on recruiting versus retaining customers. Thus, the significance of negative WOM can be detrimental to a brand's growth efforts.

In addition to documenting the organizational importance of WOM, researchers have also studied WOM's significance for consumers. Chen and Law (2016) found that consumers considered WOM more reliable than advertising communication. Similarly, Yingying (2017) asserted that WOM is essential in consumer decision making due to consumers' eroding trust in advertising messages. Yingying discovered that consumers rely on WOM because the communication is independent of brand influence; thus, consumers trust the content more. Dolnicar et al. (2016) analyzed WOM to find drivers of WOM communication. Berger (2016) discovered six WOM communication components, including social currency, triggers, emotion, public, practical value, and stories, which he synthesized into the STEPPS model. Berger's research identified consumer motivations for sharing WOM communication. Berger also found that these WOM components ultimately influenced consumer behavior (see Table 3).

Electronic-Word-of-Mouth Technology

In this section, I review the literature on the technology necessary to support eWOM and social media platforms. A common misconception is that the Internet and the Web are synonymous (Ackland, 2013). However, the Internet was created in the 1960s with funding from the Defense Advanced Research Projects Agency (DARPA) as an efficient communications network to be used in the event of war (Ackland, 2013). The World Wide Web, or Web as it is called, was invented in 1991 by Berners-Lee while he was based at the Conseil Européen pour la Recherche Nucléaire (CERN) (Ackland, 2013; van Dijck, 2013). The Web is built on top of the Internet and uses the Internet's infrastructure in order to operate (Kaplan & Haenlein, 2010).

Table 3

Motivations for Sharing WOM: The STEPPS Model

Component	Why Consumers Share
Social Currency	Consumers share what makes them look good
Triggers	Context and top-of-mind increased sharing
Emotion	Things we care about we will share
Public	Consumers are influenced by seeing others' behavior
Practical value	We share the news that can be used
Stories	Consumers pay attention to stories

Note. The STEPPS model's six WOM communication components help to explain why consumers share information with others. Adapted from *Contagious* (p. 207), by J. Berger, 2016, Simon and Schuster (https://jonahberger.com/books/contagious/). Copyright 2013 by Social Dynamics Group, LLC. Used with permission.

Historically, the three phases of the Web are differentiated by the level of engagement or interactivity within each phase (see Table 4). Web 1.0, or the static Web, was a simple one-way communication medium of websites or web pages that published content (Ackland, 2013; Tuten & Solomon, 2017; van Dijck, 2013). Web 2.0, first used in 2004, offered software developers and end-users a forum for dynamic collaboration because all users could continuously modify web content (Ackland, 2013; Kaplan & Haenlein, 2010; Tuten & Solomon, 2017). The significance of Web 2.0 was that it spawned social media and user-generated content, which led to eWOM ratings and reviews. Finally, Web 3.0, known as the semantic Web, can "make the Web more machine-readable, leading to a web of data, which is an evolution of the Web 1.0 web of documents" (Ackland, 2013, p. 5). While the technology for Web 3.0 is currently available, Web 3.0 still needs to be fully implemented due to the costs of retrofitting current technology and disagreements as to its actual worth (Rudman & Bruwer, 2016). Some authors have argued that, with Web 3.0, computers can analyze data using processes similar to deduction and inference, ultimately creating knowledge (Ackland, 2013; van Dijck, 2013). However, other authors cautioned that relying on human-like behavior from web-based computers creates a situation where bad actors could intentionally place inaccurate information, which can then spread virally (Rudman & Bruwer, 2016).

Table 4

Phases of Evolution of the Web

Phase	Name	Applications
Web 1.0	Static Web	Websites, Web browsers
Web 2.0	Collaborative Web	Blogs, SNS, User-generated content
Web 3.0	Semantic Web	Semantic databases, Intelligent personal agents

Note. As the Web has evolved, usage has increased due to the ease of consumer access. Based on text material in *Web Social Science* (p. 4), by R. Ackland, 2013, Sage (https://sk.sagepub.com/books/web-social-science). Copyright 2013 by Robert Ackland.

Characteristics of Electronic-Word-of-Mouth

In the following, I synthesized prior research regarding the characteristics of eWOM. A literature review found several key eWOM characteristics relevant to this study. These characteristics included communication, data produced, and valence.

Communication. There are three primary characteristics of eWOM: communication, collaboration, and sharing of ideas or information. First, eWOM fosters communication through online user-generated, written, visual, or audio media regarding a brand (Babić Rosario et al., 2020; McCay-Peet & Quan-Haase, 2016). Second, eWOM supports collaboration by removing geographic barriers, thus increasing access to information (McCay-Peet & Quan-Haase, 2016). Finally, eWOM facilitates sharing because users can easily comment, copy, or send media without high costs (i.e., the click of a mouse or the touch of a screen; (McCay-Peet & Quan-Haase, 2016).

Data Produced. Due to eWOM's communication and collaboration, consumers produce digital data. Latzko-Toth et al. (2016) stated that a critical characteristic of eWOM is the tremendous amount of trace data produced. The researchers maintained that while a large amount of trace data presents a challenge for qualitative researchers, the size of the data sets is well-suited for quantitative research studies.

Valence. One element of the eWOM data produced is valence. Valence represents consumers' positive or negative emotions or sentiments regarding a brand (Babić Rosario et al., 2020; Zhang et al., 2016). Valence is measured by collecting individual consumer scores (for example, from one star, signifying very negative, to five stars, signifying very positive) to compute an average valence rating for each business or product (Hong & Pittman, 2020). Li et al. (2019) revealed that valence provides a general proxy for consumers' satisfaction level, including a brand's quality or value. Lin and Kalwani (2018) linked valence to consumers' perception of satisfaction: "Strong positive reviews are likely to convey approval, the potential for exceeded expectations, or high levels of enjoyment. Strong negative reviews may signal the potential for a highly negative, and thus risky purchase experience" (p. 82). Moreover, Lee and Kim (2020) found that because valence ratings reflect average evaluations from past guests, potential guests are more likely to select restaurants with high ratings to reduce uncertainty. Within an international context, low valence decreases purchase intention, particularly for consumers from conservative cultures (Barbro et al., 2020).

Significance of Valence. Studies have demonstrated the ability of valence to influence consumer decision making, satisfaction, and sales. C. Yang et al. (2018) found that eWOM valence from online reviews influences consumer decision making by serving as a consumer shortcut for understanding quality, thus helping to reduce consumer risk. Zhao et al. (2019) discovered that eWOM valence indicates guest satisfaction. Finally, Hong and Pittman (2020) and Li et al. (2019) identified a direct influence of eWOM valence on sales volume.

Significance of Electronic-Word-of-Mouth

Researchers have found that eWOM is essential to brands because of its role in consumer decision making (Jiang & Erdem, 2017; Lepkowska-White & Parsons, 2019). This significance is magnified in the restaurant sector. Kotler et al. (2017) asserted that due to the intangible nature of restaurants, consumers must rely on experience attributes or qualities to make purchase decisions. Lamb et al. (2017) explained and clarified the context of consumer restaurant decision making when the researchers stated, “an experience quality is one which can only be assessed after use, such as the quality of a meal in a restaurant” (p. 205). Thus, eWOM valence ratings are used as a proxy to understand inexperienced attributes and reduce risk in the consumer decision process (Lui et al., 2018; Mariani & Visani, 2019).

Moreover, Lui et al. (2018) revealed that cumulative online review scores, or valence, are positively related to a firm's competitive performance. Additionally, the significance of consumer reliance on eWOM is demonstrated by consumers' outsourcing their choices to a social media network which gives them a range of perspectives and specific recommendations, over the use of search engines, which only provide a list of possibilities (Gellerstedt & Arvemo, 2019; Wan Zulkiffli & Kamaluddin, 2017). Finally, consumers view higher ratings, or valence, as a proxy for product quality (Lui et al., 2018).

Restaurant Sector

Definition and Scale

The literature defined the restaurant sector by venue type and meal occasions. The restaurant sector includes full-service restaurants, quick-service restaurants, fast-food establishments, coffee and snack shops, bars and taverns, and other establishments providing food and beverages for guests (Arienti & Puddu, 2021; Hiner, 2020). Manzo (2020) found that consumers patronize restaurants for a variety of reasons, including vacation, work-related travel, family celebrations, or away-from-home dining; however, the researcher also found that revenue for 2019 was primarily driven by consumer leisure occasions, 78.6%, and business travel comprised 21.4%. When considering the types of venues consumers visited, Nastasi and Nobili (2020) found that the global restaurant mix for 2019 included street food 5%, cafes and bars 17%, quick-service 29%, and full-service 49%.

The literature categorized the restaurant sector's scale using sales and growth rates. Restaurants contribute significantly to the global economy through sales and the volume of induced value generated by store operations (Arienti & Puddu, 2021). Henkes (2020) revealed that restaurants contributed $2.105 trillion to the world's economy in 2019. Manzo (2020) stated that the restaurant sector's growth outpaced the global economic growth in 2019 for the 9th straight year, with a 5.6% growth rate compared to the worldwide market's 2.5% growth rate. Within the U.S., restaurants contributed $863 billion to the domestic economy in 2019, representing 4% of the gross domestic product (GDP; (NRA, 2019). Ruggles (2019) revealed that while U.S. restaurant sales reached a record high in 2019, up 3.6% over the prior year; however, industry growth has moderated due to declines over the past decade.

Restaurant Brand Offering

Due to several features, the restaurant brand offering is complex. This complexity must be considered from both the consumer and restaurant perspectives. Regarding the consumer perspective, Kotler et al. (2017) asserted that restaurant brands contend with consumer consumption of tangible elements, such as menu selections, and intangible elements, such as ambiance or service delivery. Horner and Swarbrooke (2016) underscored that due to the intangible nature of their offerings, restaurant brands are experience goods. Consumers cannot touch, see, taste, hear, or feel experience goods like physical goods (Huang et al., 2009; Lamb et al., 2017). Akerlof (1970) found that experience goods cause asymmetry because consumers need brand knowledge or experience before purchasing.

Regarding the restaurant perspective, Marshall and Johnston (2019) revealed that experience goods are produced at the same time as they are consumed; therefore, they are highly perishable. Once the opportunity for production and consumption passes, there is no opportunity to regain a sale. For example, once a day has passed, a restaurant can no longer sell food or make a reservation for a table. Finally, Sundbo and Dixit (2020) emphasized that experience goods are produced simultaneously with consumption which creates production variations; this results in various consumer experiences: positive, neutral, or negative, and adds to the difficulty in maintaining a consistent brand image. Asymmetry and the potential for variability in consumer experience result in a complex restaurant brand offering.

COVID-19 Effects on Restaurant Sector

Restaurants place customers and employees in direct contact with each other, dramatically increasing the potential for exposure to and spreading of infections (Leung & Lam, 2004). Therefore, the COVID-19 pandemic left restaurant consumers and employees vulnerable. The first cases of the COVID-19 pandemic started in China in December 2019, with the virus quickly spreading to Europe, the U.S., and the rest of the world (Burrow, 2020).

Researchers have studied the effects of COVID-19 on the restaurant industry. Shapoval et al. (2021) argued that the adverse effects of the pandemic have been profound and challenging to political systems and subsequent responses worldwide. Moreover, restaurants were one of the most severely affected business sectors by COVID-19 (Burrow, 2020; Yang et al., 2020). Shapoval et al. (2021) found that mixed political responses across countries added hardship to the restaurant sector, adversely affecting communities and individuals. Consumer demand and sales fell because of stay-at-home orders, travel and mobility restrictions, social distancing requirements, and limited stores only to take-out (Gursoy & Chi, 2020; Kostromitina et al., 2021). A reduction in consumer spending resulted in 79% of U.S. restaurants reporting an average 29% decrease in 2020 sales (NRA, 2020a). Moreover, it is estimated that COVID-19 caused 17% of U.S. restaurants to close permanently or for the long term, with an additional 500,000 units in economic distress (NRA, 2020b).

The restaurant sector has been adversely affected by the COVID-19 global pandemic. However, it will play a vital role in driving recovery in a post-pandemic global economy when consumers can more fully dine out or use accommodations again. Restaurants will support economic recovery by generating employment opportunities and increasing store sales, positively affecting the supply chain (Manzo, 2020; Shapoval et al., 2021).

Restaurant Brand Challenges

A literature review found several unique restaurant brand challenges related to this study. These challenges included global expansion, the liability of foreignness, negative eWOM, and managing eWOM. I will explain and synthesize research relating to each challenge in the following paragraphs.

Global Expansion. One challenge faced by restaurant brands is global expansion. Hiner (2021) found that the U.S. restaurant sector is in a mature life cycle due to high domestic geographic saturation and price-based menu competition, reducing operating margins. Additionally, while the sector posted record sales of $863 billion in 2019 (NRA, 2019), growth over the previous ten years was moderate (Ruggles, 2019). These challenges have forced U.S. restaurant brands to grow revenue through rapid global expansion (Hiner, 2021; Jung et al., 2018; Lee & Moon, 2018). Highlighting the speed of the U.S. restaurant brand's global growth, Lee and Moon (2018) found that Starbucks increased its international presence by 171 stores in the European market and 742 stores in the Asian Pacific market in a single year. In comparison, Vaughan and Koh (2019) found that McDonald's opened a new restaurant in a foreign market every 4 hours, 365 days a year.

Rapid global expansion has exposed a variety of issues for restaurant brands. One of the first steps in an expansion plan is to evaluate and select markets based on strategic analysis. However, Lee and Moon (2018) found that instead of strategic analysis, senior management's tenure and stock options were leading indicators for global expansion decisions by U.S. restaurant brands. Jung et al. (2018) discovered that global expansion led to a need for risk mitigation compounded by the restaurant sector's sensitivity to economic conditions. This threat was confirmed by Sun and Lee (2013), who discovered that restaurant internationalization was risky due to food preferences, religion, and economic and political conditions. Finally, cost and regulatory issues were challenges in global restaurant expansion (Sun & Lee, 2013; Wade et al., 2018).

Liability of Foreignness. Another challenge faced by restaurants was the liability of foreignness. The most significant issue faced by restaurants because of rapid global expansion was a lack of cultural knowledge (Lee & Moon, 2018; Sun & Lee, 2013; Wade et al., 2018). Wade et al. (2018) found that careful research can overcome specific challenges, such as regulatory differences, before opening a new market. Other challenges result from tacit-related market knowledge. Wade et al. confirmed the challenge of gaining tacit market knowledge when they stated, “this type of knowledge is not taught, but experienced. For service-based industries that sell customer experiences, like restaurants, the more tacit-related knowledge is crucial to the success of the business” (p. 150). Thus, rapid growth does not allow restaurant brands the time to gain tacit-related knowledge or cultural experience in new markets. Vaughan and Koh (2019) described this condition as the “liability of foreignness” and argued that in addition to presenting local market challenges, it also hurts overall firm value.

Vaughan and Koh (2019) found that to alleviate the liability of foreignness, restaurant brands needed to have excess capacity or “slack resources.” Slack resources put brands in a better position for successful global expansion because brands could gain local cultural knowledge, thus accommodating differences in environments more efficiently. Similarly, Wade et al. (2018) found that restaurant brands that experienced successful cross-border expansion understood the importance of tacit knowledge and “used this unwritten knowledge to adapt to the local environments by adjusting menus, food delivery, and marketing strategies” (p. 143).

Restaurants and eWOM. Positive interactions with restaurant venues and complaints or negative brand experiences are conveyed through eWOM posts. Lepkowska-White and Parsons (2019) argued that eWOM offers restaurants the opportunity to “learn about what their customers like and dislike without conducting extensive market research studies and can alter their operations based on their findings" (p. 353). Murphy (2020) found that restaurants will likely have more online reviews than other sectors.

Researchers have demonstrated that restaurant sales, brand equity, and bookings benefit from positive eWOM. Kim et al. (2016) found that online reviews significantly impact net sales, guest counts, and average check. Luca (2016) found that a one-star increase in a Yelp.com rating can raise revenues by 5-9%. Barger et al. (2016) discovered that consumers with positive brand engagement are more likely to endorse or share information regarding the brand via eWOM. Anderson and Magruder (2012) found that a half-star rating increases restaurant reservations by 19%.

However, negative eWOM can harm restaurant brands. Rating and review websites such as Travelocity or Yelp host 55% of all eWOM complaints posted online versus 29% posted to social media sites (Baer, 2016) and 16% posted to forums (Y. Yang et al., 2018). Moreover, Yu et al. (2021) found that because negative eWOM can remain on a website for a long time, it can have a lasting effect on a restaurant brand's sales, consumer brand perceptions, and brand equity. Furthermore, Guo et al. (2017) revealed that the risk to a brand is significant because brands have no control over what consumers post.

One area of extremely negative eWOM is brand sabotage. Kähr et al. (2016) described brand sabotage as deliberate actions often caused by consumer frustration, anger, or outrage with a brand. What was significant in the researcher's findings was the ease with which consumers use social media to cause substantial harm to brands.

Management of eWOM. While negative eWOM can hurt restaurant brands, poor management of negative eWOM can have disastrous results. In a seminal study of online restaurant comments, Pantelidis (2010) highlighted the case of the Australian restaurant Casa Flamenco. In response to a negative guest review, Casa Flamenco management replied by telling the guest they were an idiot and that the restaurant did not need the guest's feedback. The guest then forwarded the restaurant's response to a few friends; it quickly went viral, with over 20,000 copies reposted online. The restaurant also received negative news coverage, and given the extent of the bad publicity, Casa Flamenco went out of business. While the Casa Flamenco case is extreme, it is not an isolated example of restauranteurs' challenges when managing eWOM. Similar results were also identified by Memarzadeh and Chang (2015), who revealed that management and operations suffer when dissatisfied guests spread negative eWOM.

Other research focused on restaurant management's perception and understanding of eWOM. While some restaurant eWOM managers saw value in eWOM as a business tool, overall, there was a lack of enthusiasm for incorporating eWOM into a restaurant's business strategy. Lichy and Kachour (2019) stated that restaurant eWOM managers were uncertain of eWOM's usefulness for improving a restaurant brand's value. The eWOM managers were concerned about the cost of implementing eWOM monitoring and response systems. Lepkowska-White and Parsons (2019) found that restaurant eWOM managers struggled with negative reviews; there was difficulty not taking comments personally and remaining objective when reading negative posts. Furthermore, the researchers revealed that creating posts was challenging for eWOM managers because of a lack of expertise, training, and time.

Kim and Velthuis (2021) analyzed how restaurant eWOM managers perceive and respond to eWOM. The researchers identified that eWOM managers are skeptical of eWOM and viewed it as a subjective portrayal of a guest experience instead of an objective reflection of the restaurant’s performance. Therefore, eWOM managers are selective when using eWOM to make staff, goals, or operations decisions. Conversely, Kim and Velthuis (2021) found that restaurant eWOM managers felt a sense of urgency to respond to eWOM, especially negative reviews, to engage in reputation management. However, these responses were often symbolic and designed to portray the restaurant in a good light rather than address substantive issues.

The research presented in the literature review showed that negative eWOM could hurt brands, restaurant managers lack tacit cultural knowledge in foreign markets, and restaurant eWOM managers lack the skills to manage eWOM. However, Pantelidis (2010) found that restaurant eWOM managers who successfully address concerns can improve consumer satisfaction. Pantelidis also discovered that addressing negative eWOM also led to improved guest loyalty.

Consumer Decision Making

Consumer decision making describes the process consumers use to recognize a need, evaluate options, and then make a purchase decision. Hofstede (2021) argued that cultural values could define countries, providing a framework for consumer decision-making differentiation and segmentation. de Mooij (2017) wrote that cultural values help to define "consumer motives and behavior, product ownership and usage, success of a product or brand and appeals in advertising for global brands" (p. 444). Furthermore, de Mooij argued that approximately 70% of the differences in product usage could be attributed to different cultures. Lamb et al. (2017) amplified the vital effect of culture on consumer behavior by stating, "of all the factors that affect consumer decision making, cultural factors exert the broadest and deepest influence" (p. 101).

Engel et al. (1968) discovered that consumers go through a five-step process when making a purchase decision, the Engel, Kollat, and Blackwell (EKB) model. Schiffman and Wisenblit (2019) argued that consumers have various external or internal influences as they go through the decision-making process, while Gabriele (2018) argued that the steps in the EKB model could be viewed as a consumer journey. Two areas of influence relevant to my study are cultural values and eWOM. Therefore, I will synthesize the five consumer decision-making steps with cultural values and eWOM considerations in the following paragraphs.

Need Recognition

The first step in the consumer decision process is need recognition. During need recognition, a consumer recognizes a gap between their actual and desired state (Kotler & Keller, 2016; Schiffman & Wisenblit, 2019). Schiffman and Wisenblit (2019) found that consumers have internal or external motivations for needs. Internal triggers are generally psychological and demonstrate the need for status or belonging, whereas external triggers are physiological.

Consumers’ internal and external motivations manifest differently depending upon the culture. While de Mooij (2015) found that high collectivist and power distance cultures will be motivated by internal psychological triggers, uncertainty avoidance cultures will be motivated by an external physiological trigger. One example would be being motivated by purity when purchasing bottled water.

Information Search

The second step in the consumer decision-making process is information search. During the second step, consumers pursue information to help address unmet needs (Kotler & Keller, 2016; Schiffman & Wisenblit, 2019). The amount and type of information will vary by culture, with collectivist cultures seeking less information than individualistic cultures (de Mooij, 2015). In collectivistic cultures, information gathering is considered an unconscious process. There is a tremendous amount of social communication; therefore, members of the culture are unaware of where they are getting information. Additionally, de Mooij found that, within high power distance cultures, fellow consumers are viewed as credible sources of information, while low power distance cultures prefer company marketing messages. Finally, de Mooij discovered that expert groups, opinion leaders, and detailed product information are preferred in high uncertainty avoidance cultures.

With information search and restaurant eWOM, Kotler et al. (2017) found that consumers seek information from several sources, including restaurant reviews and social media. Personal responses and eWOM held far more credibility than traditional marketing activities because the information came from other consumers and not commercial sources (Kotler et al., 2017). Specifically, within social media communications, Zainal et al. (2017) discovered that eWOM provides content that consumers consider highly credible. Mackiewicz et al. (2016) found that 68% of millennials trust eWOM peer reviews more than professionally written reviews for products or services.

Also, regarding information search, Gellerstedt and Arvemo (2019) measured the effect of eWOM reviews on the booking intention of hospitality guests. The researchers found an overall valence score was critical to booking intention, as was the most recent pair of reviews, although the reviews had a lower effect. The last two reviews had no effect if the overall valence was negative. The booking intention could be suppressed if the valence were positive and the previous two reviews were negative. Additionally, the researchers identified that a good friend's word-of-mouth held higher importance than an online majority. Gellerstedt and Arvemo concluded that the research results emphasize the management "importance of being active in social media, analyzing and using online reviews systematically as guidance for improvements" (p. 307). Therefore, eWOM valence is a tool that can be used by restaurant managers when evaluating consumer satisfaction.

Evaluate Alternatives

The third step in consumer decision making is the evaluation of alternatives. Consumers process gathered information while evaluating alternatives (Kotler & Keller, 2016; Schiffman & Wisenblit, 2019). Kotler and Keller (2016) stated that consumers analyze a brand as a group of attributes by directly ranking brands' attributes to see which brand best addresses their needs. When evaluating brand decision making and the number of choices available, de Mooij (2015) identified that individualistic cultures believe a better choice can be made by having a larger decision set. In contrast, collectivistic cultures believe a smaller selection is preferable.

Kim and Tanford (2019) evaluated the influence of eWOM valence on alternative evaluation. The researchers found that while consumers are evaluating, they use reviews to support reward-seeking behavior, and at this point in the decision process, the risk was not a consideration. Conversely, Christodoulides et al. (2012) explored eWOM exposure and its effect on consumers' pre-purchase intentions. The researchers found that Chinese consumers were influenced by recent eWOM comments regardless of their valence; however, U.K. consumers focused on negative information regardless of the order in which it was acquired. Finally, these results held strong significance for experience goods.

Purchase Decision

Consumers form their purchase intentions during the fourth step. Consumers use information and analysis gathered in previous steps in the decision-making process (Kotler et al., 2017; Schiffman & Wisenblit, 2019). Kotler and Keller (2016) stated that consumers generally select the brand they prefer; however, unexpected or external stimuli can influence purchase decisions. Schiffman and Wisenblit (2019) identified external stimuli that influence the consumer decision process as including social, personal, and cultural characteristics.

The degree to which consumers rely on others when making a purchase decision varies by culture and is influenced by eWOM. In a study by de Mooij (2015), collectivist cultures and high power distance cultures were found to rely more on the group and conformity for decision making than individualistic cultures or low power distance cultures. A global consumer study found that eWOM influenced 69% of purchase decisions (Nielsen, 2016). Researchers have argued that this may result from eWOM's consumer-to-consumer communication structure, which increases trust in the message and reduces the tendency of consumers to hold negative brand biases (Ring et al., 2016; Serra Cantallops & Salvi, 2014). Kim and Tanford (2019) found that, like the evaluation stage, eWOM reviews influence restaurant decisions; consumers continue using eWOM to support reward-seeking behavior, and the risk continues not being a consideration.

Post-Purchase Behavior

The final step in the consumer decision-making process is post-purchase behavior. During post-purchase behavior, consumers go through a post-evaluation phase to determine their purchase satisfaction (Schiffman & Wisenblit, 2019). Satisfaction is based on a restaurant brand meeting the consumer's expectations. Conversely, dissatisfaction is the gap between the consumer's expectations and the brand's performance. According to the expectation-confirmation theory, customer satisfaction is determined by comparing pre-consumption expectations and a perceived brand experience; a perceived experience lower than expectations will result in dissatisfaction (Oliver, 1980). Zhao et al. (2019) found that consumers mention their perceived quality and pre-consumption expectation, or both, to communicate satisfaction or dissatisfaction.

Boo and Kim (2013) found that negative eWOM is one of the most powerful methods of communication that consumers have to express their dissatisfaction.

Because of the need for harmony, collectivist cultures are considered loyal and less likely to complain (de Mooij, 2015). However, when they do complain, it is negative WOM to members within their group. Additionally, de Mooij (2015) found that cultures with high individualism and high masculinity will exhibit complaint behavior that can be taken to the extreme. For example, an aspect of U.S. culture is litigation for settling consumer complaints, such as suing fast-food chains because of a consumer’s weight gain (de Mooij, 2017). In research comparing U.S. and U.K. restaurant consumers, Shaw (2021) revealed that Brits are more likely to complain directly about poor service, while Americans are likelier to complain on social media. Kim and Tanford (2019) discovered that during the post-purchase stage, consumers’ behavior is influenced by eWOM. However, the behavior varies between risk avoidance and reward-seeking depending upon market conditions such as distance, review valence, and price.

Research Regarding Cultural Differences

Scholars have explored cultural differences within eWOM valence ratings and reviews for various goods and services. I will detail eWOM research within the general market in the following paragraphs. I then provide insights regarding eWOM research in the hospitality market. Finally, I will highlight eWOM research targeted at restaurants.

General Market eWOM Research

Several studies have focused on eWOM in industries such as movies or retail. Chiu et al. (2019) explored cultural differences in movie rating reviews for the Chinese and U.S. markets. The researchers utilized a web scraper to download eWOM data from two social media movie rating and review websites and accessed supplemental data, including box office revenue and movie characteristics from other public websites. Chiu et al. (2019) used an independent sample *t*-test for consumer behavioral differences and log-linear regression to determine which factors influence cultural differences. The researchers found that American reviewers are more engaged, while Chinese reviewers are more moderate. Additionally, the research suggested that the average rating significantly affects box office sales in China, whereas there was no effect in the United States.

Authors have also studied cultural differences in ratings and reviews for Amazon products. Wang et al. (2019) reviewed cultural differences in Amazon product features and opinions. The researchers collected feature-opinion pairs from Amazon reviews for U.S. and Chinese consumers for experience and search goods. Experience goods are products, such as food or wine, which need consumer experience to determine product quality. Search goods are products such as clothing that consumers can collect information to determine quality prior to purchasing. While the exact data collection method is not straightforward, Wang et al. alluded to using a web crawler. Independent two-sample *t*-tests were used to examine cultural differences in the review content. Using Hofstede's cultural dimensions as the theoretical foundation, the researchers found that U.S. consumers focused more on usability and product features and were more inclined to share negative opinions. Alternatively, Chinese consumers focused more on aesthetics and were less likely to share negative options. These results also held for search goods but not experience goods. Wang et al. (2019) asserted that it is essential for managers to understand unique preferences for products and features within different cultures.

Barbro et al. (2020) researched the volume, valence, and helpfulness of Amazon reviews within different cultural contexts. The researchers collected a census of reviews across a diverse and representative sample of categories and products from Amazon sites in five countries; however, the authors failed to disclose their data collection method. The countries were selected based on the high review volume during data collection. Barbro et al. measured volume by the number of characters in a review, adjusted by structural differences in language. The Amazon star rating captured valence, and helpfulness was measured by "yes" votes for the question: "Was this review helpful to you?" Using MLR for their statistical analysis, the researchers found cultural influences across all three dependent variables: volume, valence, and helpfulness.

Moreover, the study indicated there were significant country differences in valence. The researchers argued that managers should be cautioned not to take a lower star rating in one country versus another as a sign of lower satisfaction. Instead, the difference in ratings may be attributable to differences in culture.

Hospitality Market eWOM Research

Additional research has been conducted on cultural differences within eWOM for hospitality services. Buzova et al. (2019) examined the cultural differences between North American and European cruise tour eWOM sentiments. The study used a web crawler to retrieve 1,127 reviews from TripAdvisor. The research discovered that reviews authored by North Americans are more emotional, personalized, and expressive than the reviews posted by Europeans. Buzova et al. advocated that cruise managers must be cognizant of cross-cultural differences in reviews and should consider how to guard against cultural biases when responding and engaging online.

Stamolampros et al. (2019) researched the effect of country culture on eWOM within the airline industry. The researchers accessed their data, airline travel reviews, and ratings, from 203 countries using the API for a travel booking and review aggregator. Hofstede's (2001) six cultural dimensions were the theoretical foundation for the study. Stamolampros et al. used logistic regression analysis to review ratings as the dependent variable, country scores from Hofstede's cultural dimensions theory as independent variables, and additional demographic variables that could influence the overall rating, such as cabin class or flight distance. The researchers found variations in passengers' service expectations and satisfaction based on country culture. Additionally, the research identified that airline passengers have higher satisfaction with airlines that more closely align with their cultural values. Finally, Stamolampros et al. argued that airline management should consider cultural values as part of their target psychographics when developing marketing and promotional strategies.

Within the hotel domain, Mariani and Predvoditeleva (2019) analyzed the role culture plays in eWOM valence ratings for Moscow hotels. The researchers collected 74,284 ratings representing 602 hotels and 93 different countries. The data were collected from Booking.com using a web scraper; the researchers also accessed country scores for four cultural dimensions from the Hofstede Center. The overall rating was regressed against the country scores using ordinary least squares (OLS) and Tobit regression. The findings suggested that culture was negatively related to hotel ratings. Therefore, the researchers concluded that cultural differences significantly affect hotel eWOM. Finally, the researchers advocated that hotel management pay attention to eWOM valence ratings better understand raters' cultural differences so that management could craft effective intra-organizational communication and eWOM engagement strategies.

Hu et al. (2019) evaluated the interplay of eWOM with culture and hotel room rates. Specifically, the researchers examined if consumers' behavioral intentions are more likely to be swayed by eWOM in individualistic versus collectivistic cultures. Data were analyzed from a meta-analysis of 22 papers using a hierarchical linear model for meta-regression. Hu et al. found that online ratings are more influential in countries or regions exhibiting collectivist cultures. Finally, the researchers recommended that hotel managers consider a target market's culture when establishing pricing strategies, as hotels appear to be able to charge higher prices in collectivist cultures for premium brands with strong ratings.

Sann et al. (2020) investigated how Asian and non-Asian cultures influenced negative eWOM for hotels. The researchers manually extracted reviews for randomly selected hotels on the TripAdvisor United Kingdom website. To ensure the credibility of the source and sample, the researchers only included hotels with more than 200 reviews, only the most recent 20 negative reviews, and hotels with 1- or 2-star overall ratings. Additionally, reviews that did not include the reviewers' country of origin were excluded. This sample resulted in 2,020 negative eWOM reviews representing 63 countries. The data were analyzed using independent sample *t*-tests and one-way analysis of variance

(ANOVA) to determine significance. Scheffe's post hoc test was used to help explain differences between groups, and Cronbach's alpha was used to evaluate the reliability of the variables. The research team identified that negative eWOM is influenced by country culture. Asian guests were likelier to complain about service, whereas non-Asian guests would complain about cleanliness, room, sleep quality, and location. Finally, the researchers underscored the role of culture in consumer hotel perceptions when they stated, "the nuanced perceptions held by travelers coming from different parts of the world is going to be a factor determining success, failure or something somewhere in between" (p. 89). Thus, the antecedent characteristics of negative eWOM can differ based on country culture.

Restaurant eWOM Research

Research on the effect of country culture on restaurant eWOM is limited. Hong et al. (2016) analyzed culture as an antecedent for restaurant review characteristics. Specifically, the researchers were interested in the effect of individualism versus collectivism on reviewers' tendency to conform to prior reviewers' opinions and emotionality. Data for 3,750 restaurants in six major U.S. cities were collected from TripAdvisor using a web crawler, and cultural value scores were obtained from the World Values Survey. The research team revealed that consumers from individualistic cultures are more likely to deviate from prior opinions and more likely to express emotions in their reviews versus those from collectivist cultures. Additionally, Hong et al. underscored the importance for individuals who manage online review platforms to understand cultural biases because review conformity and emotion contribute to lower review helpfulness.

Nakayama and Wan (2018, 2019) studied the effect of culture on restaurant review expression and helpfulness. In both studies, the researchers explored cultural differences in eWOM expression for Japanese restaurants in Japan versus four Western markets. Data were collected from the Yelp API, and the researchers' unit of analysis was business entities classified within the Japanese restaurant category. Text phrases from reviews were analyzed using Watson Explorer Content Analysis (WCA), which allows for deep analysis of Japanese and English reviews, including correlation analysis. Nakayama and Wan (2018) found that Western reviews significantly varied in emotional expression. The authors emphasized the importance for ethnic restaurant managers to understand key cross-cultural differences. Western consumers expressed more interest in service than their Japanese counterparts. However, Japanese and Western consumers were equally expressive about poor food quality. Nakayama and Wan (2019) found that Western consumers prefer to consume reviews that contain information regarding service quality, focusing more on negative service quality than positive service quality. Alternatively, Japanese consumers find reviews that contain positive expressions more helpful. The authors stated that the results align well with Hofstede's cultural dimensions theory, particularly long and short-term orientation, which explains the Japanese preference for positive expressions. Additionally, Nakayama and Wan (2019) highlighted the need for restaurant management to "optimize the mix of service delivery for customers' predominant cultural preferences" (p. 1160) to maximize success.

Country Demographics

When analyzing a market, researchers use two primary tools to understand and categorize the consumer base and then define a target audience. Psychographics reflect consumers' values, whereas country demographics are the statistical measures of the population of interest (Meiselman et al., 2021). Psychographics offers insights into a country's unique perspective on its sociocultural environment. For example, Hofstede's (2001) cultural values model offers a complete picture of country psychographics based on six unique and bimodal aspects of country values. Country demographics are considered consumer facts and include details such as population, gross domestic product per capita, industry competition, and technological penetration. In the following paragraphs, I explain the country demographic measures relevant to this study and how country demographics related to my research.

Country demographic variables that address economic issues include population, gross domestic product per capita, and industry competition. A primary demographic that is considered is the population age mix (Kotler et al., 2017). Population and age are important because a critical mass of consumers must match the desired target audience for an organization to succeed. Gross domestic product per capita is also a key economic consideration because it helps to illustrate the level of prosperity within a country (de Mooij, 2003). Consumers must have disposable income when considering restaurants because dining out is not a necessary purchase (Kotler et al., 2017). Finally, when evaluating industry competition, researchers consider data such as industry sales or the number of units. While sales are one of the most critical indicators of success for any business, within the restaurant domain, sales substantially affect other key metrics, such as the break-even point (Biel, 2022). The number of units reflects the concentration within an industry (Organisation for Economic Co-operation and Development, 2021). A highly concentrated industry offers more choices to consumers and thus is more competitive.

Technological penetration helps researchers understand the extent to which consumers can access or use technology. A primary technology metric is the Internet penetration rate, which represents the country's population with Internet access divided by the total population (The World Bank, 2021). Internet penetration is an important metric because research has found that countries with high Internet penetration also have high levels of education and economic development (Singh, 2022). Mobile device penetration is of great interest to researchers. Today's mobile devices can process nearly the same information as desktop or laptop computers. Thus, mobile devices have helped increase digital access because of their portability and lower costs (Mariani et al., 2019). Social media use tells researchers the strength of digital connections in a country because social media facilitates sharing of ideas and information through digital communities and communication channels.

When conducting eWOM research, it is also essential to understand the demographics of a specific social media platform. Platform demographics can include metrics such as traffic (number of visitors to the site) and how sticky a site is (time spent, pages visited (Tuten & Solomon, 2017). Both traffic and stickiness are important metrics because they can help determine the likelihood that a consumer is interested in a brand or will make a purchase.

Finally, when researching eWOM ratings in a cross-cultural study, country eWOM ratings should be matched with other variables from the same country. Therefore, a researcher needs some way of protecting data from being contaminated by out-of-country posts spilling in. The metric percent spill-in tracks a rating based on the poster's home country Internet protocol address (Semrush, 2021). Therefore, percent spill-in is a tool researchers can use to prescreen their data.

Summary and Conclusions

The information in my literature review focused on the restaurant sector, consumer decision making, and eWOM. Additionally, I presented my rationale for using Hofstede's cultural dimensions as the theoretical foundation. The following summarizes the key points from Chapter 2.

Consumers' use of eWOM to seek and share information has seen significant global growth. Moreover, eWOM ratings are considered a proxy for consumer satisfaction. The importance of eWOM for restaurants is amplified because restaurant consumers do not have the opportunity to fully experience a brand before purchasing it. Therefore, consumers increasingly turn to eWOM to help inform purchase decisions, share their experiences, and express their opinions.

The rapid global expansion of restaurants has created challenges for restaurant managers because they lack the tacit cultural knowledge of the markets served. Thus, restaurant managers are ill-prepared to deal with the demands of eWOM. Restaurant management must understand the relationship between country culture, country demographics, and eWOM valence ratings, representing consumer satisfaction with brands. While there has been research regarding restaurant eWOM and the effect of culture and demographics on eWOM for other products and services, there is a gap in the literature on the interplay between country culture, country demographics, and eWOM valence ratings. I examined the relationship between country culture, country demographics, and eWOM valence ratings within the restaurant sector in this quantitative correlation study. Understanding the interplay between country culture, country demographics, and restaurant eWOM valence ratings could provide restaurant managers with insights to guide strategic decision making regarding eWOM strategy, responses, and communication.

In Chapter 3, I discuss the methodology used in my study. This discussion includes the research design and rationale, and methodology. I also explain my data analysis plan and threats to validity. I conclude Chapter 3 with a summary and transition to Chapter 4.

Chapter 3: Research Method

The purpose of this quantitative correlation study was to examine the relationship between measures of country culture, country demographics (predictor variables), and restaurant eWOM valence ratings (response variable) for all countries on the Yelp platform with eWOM restaurant valence ratings. Chapter 3 includes a detailed overview of the study's research methods. This overview includes sections on research design and rationale, methodology, data analysis, and threats to validity. Chapter 3 concludes with a summary and transitions to Chapter 4.

Research Design and Rationale

The study variables include measures of country culture, country demographics, and restaurant eWOM valence ratings. Country culture (predictor variables) data were measured by Hofstede et al. (2010) and Hofstede's (2021) cultural dimension indexes, including power distance, individualism/collectivism, uncertainty avoidance, masculinity/femininity, long/short-term orientation, and indulgence-restraint. Country demographics (predictor variables) data are measured by population, gross domestic product per capita, mobile device penetration, Internet penetration, social media use, restaurant units, restaurant sales, Yelp visits, Yelp unique visitors, Yelp pages per visit, Yelp average visit duration, and Yelp percent spill-in. Finally, restaurant eWOM valence ratings (response variable) were measured by Yelp restaurant valence ratings.

The nature of my research questions supported using a quantitative correlational research design. Correlation studies analyze the strength and the direction of the relationship between two or more quantitative variables (Gogtay & Thatte, 2017). The research questions examined the relationship between measures of country culture, country demographics, and restaurant eWOM valence ratings, all ratio-level variables. Additionally, correlation studies are helpful when the research analyzes naturally occurring characteristics (Wrench et al., 2018). My study's variables (country culture, country demographics, and eWOM valence ratings) represent naturally occurring constructs that cannot be manipulated.

In this correlational research design, I used archival data from foreign markets to avoid the expense of time and travel. Moreover, eWOM data, hosted on social media platforms, can best inform researchers about various consumer behaviors and perceptions within the context of an online world. This correlation study advanced knowledge in the eWOM discipline by extending the work of Babić Rosario et al. (2020), Bore et al. (2017), Chen and Law (2016), and Serra Cantallops and Salvi (2014), who have called for research analyzing the effect of culture on eWOM. Additionally, Bore et al. and Chen and Law called for research that analyzed country demographics as an antecedent to eWOM ratings.

Methodology

The growth of eWOM in size and social influence has attracted researchers' interest in various disciplines such as epidemiology, economics, statistics, demographics, and sociology. The increase in the breadth of disciplines and the growth in eWOM research has also fostered various eWOM research methods (Acker & Kreisberg, 2020; Freelon, 2018; Quan-Haase & Sloan, 2016; Zagheni & Weber, 2015; Zeller, 2016). While the increase in eWOM research studies has offered researchers multiple research methods, published articles have lacked clarity regarding methods used in social media research (Quan-Haase & Sloan, 2016). This lack of clarity has resulted in no definitive methodology for eWOM research (Acker & Kreisberg, 2020; Freelon, 2018; Quan-Haase & Sloan, 2016; Zeller, 2016). Therefore, because of the lack of consistency in the published literature regarding eWOM research methods, as well as my desire to follow ethical research principles, I developed my research methodology based on the work of Mayr and Weller (2016), Brown et al. (2016), and Janetzko (2016).

Population

When developing an eWOM research methodology, Mayr and Weller (2016) recommended using the research questions as a first step to guide the selection of the social media platform. By focusing on the platform that provides the best answers, researchers avoid being data-driven at the expense of theory. Instead, researchers develop knowledge by “blending aspects of abduction, induction, and deduction” (Kitchin, 2014, p. 10). Thus, my choice of platform informed the definition of my research population.

The research questions for my study were designed to examine the relationship between measures of country culture, country demographics, and restaurant eWOM valence ratings. My research questions defined the theoretical research population as all countries with restaurants with eWOM for all time, which is theoretically an infinite population (see Frankfort-Nachmias & Nachmias, 2014). Therefore, my selected social media platform needed a global presence within the restaurant sector and the ability to collect eWOM valence data.

Four platforms fit the criteria for global restaurant eWOM presence: Google, Facebook, Travelocity, and Yelp (Kim, 2019; Yang et al., 2017); however, Facebook replaced its rating function in 2018 with a simple yes or no question asking if customers recommend an establishment (Penflorida, 2021a). Therefore, Facebook was eliminated from consideration because it did not meet the valence rating criteria. Google was eliminated because of cost considerations; data access starts with a $200 deposit (Google, 2021). Thus, Travelocity and Yelp remained as two potential platforms for my study.

An important focus in research is collecting data that accurately represent the target population. Within social media research, fraudulent posts can skew results. Therefore, it is essential to use a platform that proactively manages false posts. Researchers have found that 17% to 20% of all posts are fraudulent (Domenico et al., 2021). Travelocity and Yelp have active filtering algorithms to flag and remove suspicious reviews or ratings (Expedia, 2020; Yelp, 2021c). However, Yelp's algorithm uses several criteria, such as looking for multiple reviews from the same computer, seeing if a review shows text bias, and finding and removing suspicious posts from the aggregate total (Luca & Zervas, 2016; Penflorida, 2021b). As an additional step to prevent fraudulent posts, Yelp does not include a rating in a business's overall star rating unless the reviewer has had multiple Yelp posts and is not directly connected to the business (Schur, 2022). Moreover, to ensure transparency, Yelp visitors can still see the flagged reviews in a special area on Yelp's platform (Yelp, 2021c). Yelp's transparency, proactive stance in flagging and removing suspicious reviews, and ability to deliver restaurant eWOM from its global user base of adults 18 and older (Yelp, 2021c) led me to select Yelp as the platform for my research.

During platform selection, the research questions must be addressed using a single platform or, if needed, a multiplatform approach (Mayr & Weller, 2016). A single platform answered my research questions. Yelp can provide eWOM valence ratings data for restaurants from 32 countries; thus, the Yelp restaurant eWOM valence data aligned with my research questions. While restricting data to one platform may limit a study's generalizability, my decision was based on the importance of platform consistency during data analysis (Janetzko, 2016; Mayr & Weller, 2016).

The target population for my study consisted of 32 countries with restaurants with eWOM valence ratings for which Yelp has eWOM data. Because Yelp controls the data, the target population size is unknown. I delimited the research scope to a single social media platform, Yelp, to ensure my data had a consistent source and a consistent time frame, thus reducing collection bias (Mayr & Weller, 2016). Additionally, Mayr and Weller (2016) advocated that social media research results can be generalized to users of the platform under study, which means the results of my study may provide insights into the relationship between country culture, country demographics, and restaurant eWOM valence ratings for restaurant managers who use the Yelp platform.

Data Selection Criteria and Strategy

Mayr and Weller (2016) stated that the second step in developing a social media research methodology is determining the data selection criteria. The authors assert that four criteria can be employed when selecting digital data: time frame, user accounts, topics or keywords, and metadata. Time frame reflects when data are captured and can influence results; so, it is essential to maintain consistency across geographies or, at a minimum, to reflect special events that may affect results. When matched against a complete list of users, user accounts offer the advantage of getting as close as possible to a census. Topics and keywords can capture data related to events, topics, or business categories. Finally, metadata captures specific information unrelated to a person or an account. Examples include aggregate status updates for a particular geographic area or time frame. The data selection criteria to answer my research questions include metadata, keywords, and time frame considerations. Aggregate ratings from the Yelp social media platform represent metadata. The keywords *restaurants* and *country name* (which align with my research questions) were used to filter the data access. Finally, the time for data access was consistent across all countries, and any major geopolitical events during data access were monitored and noted.

Sampling and Sampling Procedures

The third step in social media research methodology is how much data are necessary to answer the research questions (Mayr & Weller, 2016). Because there is no list of all restaurants with an eWOM presence available, nor is it practical to create one, random sampling was not a viable option. Therefore, I used a purposive sample of the Yelp data. Purposive sampling is the nonrandom selection of cases to fulfill a specific research purpose (Wrench et al., 2018). Purposive sampling is considered an appropriate alternative when random sampling is not an option (Singleton & Straits, 2017).

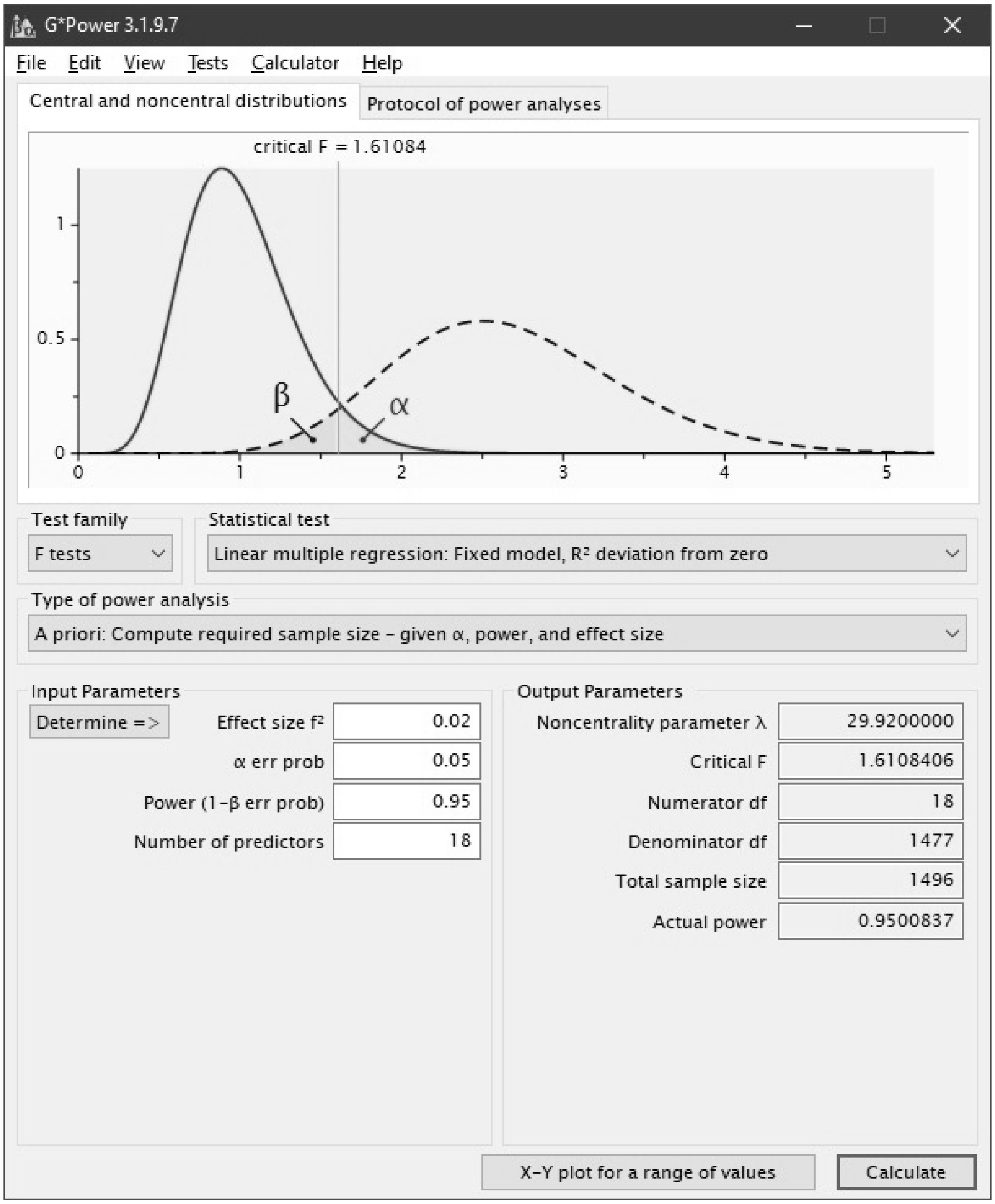
In purposive sampling, cases are selected based on specific, predetermined criteria (Wrench et al., 2018). My sampling unit was a country. My sampling frame consisted of all 32 countries with restaurant eWOM valence ratings provided via the Yelp Fusion API on October 3, 2021. Yelp's Fusion API limits data retrieval to 200 records per country; the Yelp Fusion API algorithm selects records to return based on the search parameters given (*restaurants*, *country name*, *data requested on a specific date*), presence of at least one review, and recency of activity on the Yelp platform (Elfsight, 2020). I used all of the data I accessed from Yelp, which provided me with $N = 6{,}018$ and helped mitigate the chance that a sampling unit and the data collected were not representative of the population. Additionally, the large sample size allowed me to gain extra power and precision in my testing.

Power Analysis

Researchers use power analysis to determine the sample size necessary for the study. Using G*Power, version 3.1 (Faul et al., 2009), I conducted an a priori power analysis to compute a sample size using the *F*-test, multiple linear regression: fixed model. Based on Cohen (1988), I used a small effect size of $f^2 = 0.02$, $\alpha = .05$, and 18 predictors. The minimum required sample size was $N = 1{,}496$ (see Figure 2). Given that my analysis reflected 32 countries (cases) replicated by a maximum of 200 restaurants in each country, for potentially $N = 6{,}400$, and I planned to use all the valence data provided by Yelp, my expected target population exceeded the minimum required sample size.

Figure 2

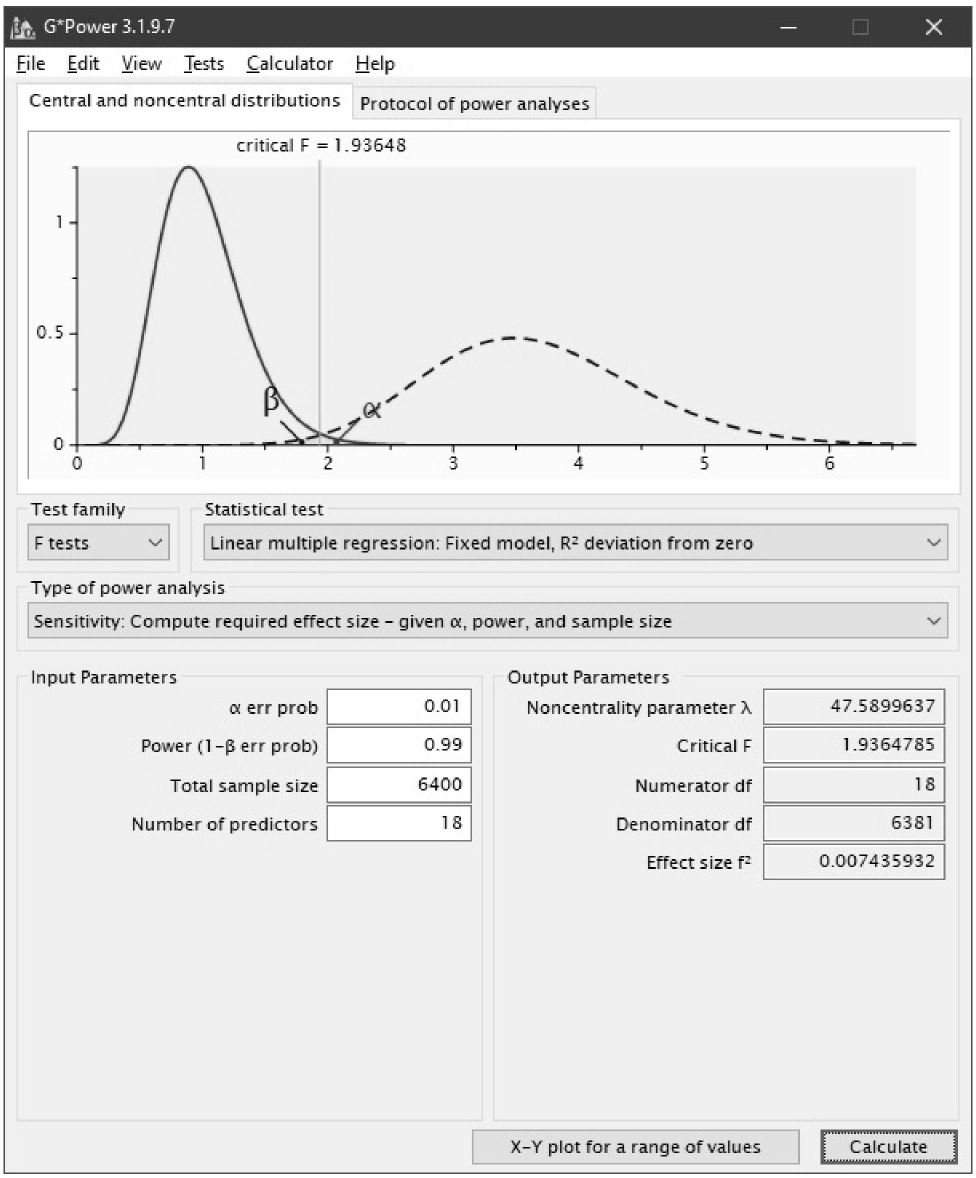
*A Priori G*Power Sample Size*



I also conducted an a priori G*Power sensitivity analysis to determine the effect size, which can be detected given $\alpha = \beta = .01$. With the probability of Type I and Type II error at .01, I could detect a true effect size of $f^2 = 0.0074$ (see Figure 3), which is significantly more precise than Cohen's (1988) small effect size.

Figure 3

*A Priori G*Power Sensitivity Analysis*



Archival Data

Archival data can take the form of public records, such as a government census, economic indicators, or even private records, such as an individual's purchases or industry sales trends (Frankfort-Nachmias & Nachmias, 2014). While archival data could limit a researcher because the data might not perfectly align with the research questions, archival data can still be an asset for researchers. For example, archival data can save time and resources within a research study (Dooley, 2001). Additionally, researchers can use archival data to access information about a population that otherwise would have been inaccessible (Frankfort-Nachmias & Nachmias, 2014). I used archival data accessed from several sources in my study. In the following sections, I will briefly describe the methodology or research purpose used by the original data source and how I accessed the data.

Archival Data Predictor Variables Access

The first predictor variable consists of Hofstede's (2021) cultural dimension indexes, which measure country culture (see Table 5). Hofstede's (2001) original data were collected during IBM employee research between 1967 and 1973 and covered more than 70 countries. The four cultural dimensions (power distance, individualism vs. collectivism, uncertainty avoidance, and masculinity vs. femininity) were developed from Hofstede's original IBM employee research, which collected approximately 116,000 questionnaires in 72 countries (Hofstede, 2001). The data for long/short-term orientation were developed from research in the Far East (Hofstede & Bond, 1988). Data for indulgence versus restraint were developed from Minkov's research in 2007 (Minkov &

Hofstede, 2012). Hofstede used an ANOVA, correlation, and factor analysis to answer questions about the differences in country values (Hofstede, 2001). From this analysis, Hofstede developed six dimensions that reflect societal values' effect on its members (see Table 5). Hofstede's research since 2001 is based on replications and extensions of his original work. Country culture data were accessed from the Hofstede website and reflected the most recent publication of Hofstede's (2021) model (see Table 5). The six cultural dimension scores for each of the 32 countries included in the study were downloaded into a Microsoft Excel spreadsheet. The Hofstede website has posted a statement granting permission to use the data for non-commercial research studies.

Table 5

Archival Data Country Demographic Sources

Description and label	Access source
Power Distance Index (*PDI*)	https://geerthofstede.com/research-and-vsm/dimension-data-matrix/
Individualism/Collectivism (*IDV/CLV*)	https://geerthofstede.com/research-and-vsm/dimension-data-matrix/
Uncertainty Avoidance Index (*UAI*)	https://geerthofstede.com/research-and-vsm/dimension-data-matrix/
Masculinity/Femininity (*MAS/FEM)*	https://geerthofstede.com/research-and-vsm/dimension-data-matrix/
Long/Short-term Orientation (*LTO/STO)*	https://geerthofstede.com/research-and-vsm/dimension-data-matrix/
Indulgence versus Restraint *(IVR*)	https://geerthofstede.com/research-and-vsm/dimension-data-matrix/

The second predictor, country demographics, consists of 12 variables (see Table 6). Country population represented national census data of the number of individuals over 18 years of age from each country included in my study. The country population data were accessed from the United Nations website, which is publicly available. I downloaded the data into a Microsoft Excel spreadsheet. Gross domestic product per capita is a measure of average living standards. I accessed and downloaded these data into a Microsoft Excel spreadsheet from the publicly available World Bank website. Mobile device penetration, Internet penetration, and social media reflect how a country's digital and Internet technology is leveraged. Mobile device penetration, Internet penetration, and social media use were accessed from Kepios, a publicly available website, and the data were downloaded into a Microsoft Excel spreadsheet.

Restaurant units and sales are measurements available from Barnes Reports (2020). Barnes Reports track key industry indicators and are publicly available through research libraries. The aggregate country-level restaurant units and sales data were downloaded into a Microsoft Excel spreadsheet for each country in my study. Yelp data represent the breadth and depth of visitor traffic on the platform. Specifically, the Yelp percent spill-in data represents the platform traffic that originates outside the host country. By monitoring spill-in data, I screened for and addressed any issues of collection bias. Yelp data were accessed from Semrush (2021), a company that researches and publishes data about social media trends. The Yelp data were downloaded to a Microsoft Excel spreadsheet.

Table 6

Archival Data Country Demographic Sources

Description and label	Access source
Population (*POP*)	https://population.un.org/wpp/DataQuery/
Gross domestic product per capita (GDP*)*	https://data.worldbank.org/indicator/NY.GDP.PCAP.CD
Mobile Device Penetration (*MDP)*	https://kepios.com/
Internet Penetration (*INP*)	https://kepios.com/
Social Media Use (*SMU*)	https://kepios.com/
Restaurant Units (*RU*)	https://www.barnesreports.com/retail-product-reports-page
Restaurant Sales (*RU*)	https://www.barnesreports.com/retail-product-reports-page
Yelp Visits (*VIS*)	https://www.Semrush.com/kb/26-traffic-analytics
Yelp Unique Visitors (*UVI*)	https://www.Semrush.com/kb/26-traffic-analytics
Yelp Pages Per Visit (*PPV*)	https://www.Semrush.com/kb/26-traffic-analytics
Yelp Average Visit Duration (*AVD*)	https://www.Semrush.com/kb/26-traffic-analytics
Yelp Percent Spill-In (*PSI*)	https://www.Semrush.com/kb/26-traffic-analytics

Archival Data Response Variable Access

The response variable was measured by restaurant eWOM valence ratings and was accessed from Yelp. Yelp is a social media platform established in 2004 that allows people to view and post content for over 1,200 different categories of businesses; the platform currently has over 224 cumulative million reviews of businesses in 32 different countries (Yelp, 2021c). Yelp has consistently had the largest hospitality listings and millions more users than rivals like CitySearch, TripAdvisor, and Restaurant.com (Racherla et al., 2013). Moreover, 18% of Yelp's reviews are from restaurants, which is one of Yelp's largest categories (Yelp, 2021c). Yang et al. (2017), who stated that Yelp has consistently held the largest number of posted online restaurant reviews across major global markets, used it to collect representative sample data of online reviews.

Yelp is a public platform because anyone with Internet connectivity can access content simply by going to the Yelp.com website. There is no registration required to view Yelp's content. A user visits the website or downloads the mobile app to post reviews or ratings. For posting, the public website and mobile app require users to agree to Yelp's terms of service (see Appendix A). Section 5B of the terms of service includes granting irrevocable and worldwide rights to Yelp and its users to use, copy, and analyze all content. Section 5B was necessary for my study because it demonstrated that Yelp data are available beyond platform display.

Researchers have accessed eWOM data, such as Yelp, using various methods. Each method has its advantages and disadvantages. In the following paragraphs, I explain and evaluate the access methods used by researchers. I also explain how social media platforms' terms of service affect data access. I conclude by explaining how I accessed eWOM data for my research study.

Some researchers advocated web scraping (Hong et al., 2016; Kusawat & Teerakapibal, 2021; Xia et al., 2020). Web scraping is the automated capture of information from web pages or social media platforms. Web scrapers use custom code, commonly written in Python or R, to select specific and relevant data. The apparent advantage for researchers is that web scraping allows data to be captured quickly and efficiently; the negative for social media platforms is that web scrapers can potentially send hundreds of thousands of requests for data each minute, which can slow or even shut down a server (DeVito et al., 2020). Web scrapers are one of the reasons social media platforms changed their terms of service and limited access to eWOM data (Acker & Kreisberg, 2020; Freelon, 2018; Perriam et al., 2020; Walker et al., 2019).

Terms of service define how a platform should be accessed and used, acceptable and unacceptable methods of collecting or using platform content, and standards for online behavior (Stringam et al., 2023). Web scrapers violate the terms of service on most social media platforms (Freelon, 2018; Han & Anderson, 2021). Therefore, researchers must consider a platform's terms of service to maintain ethical research principles. Using a web scraper for data collection could be considered an unethical research procedure.

Researchers have also supported using APIs for eWOM research (Acker & Kreisberg, 2020; Dewi et al., 2019; Gerber & Lynch, 2017; Janetzko, 2016; Lomborg & Bechmann, 2014). APIs allow third parties, which in the eWOM world are called *developers*, to gain access to and query a social media platform's data (Acker & Kreisberg, 2020). APIs offer researchers the ability to automate the collection of eWOM data. At the same time, the platform acts as a gatekeeper establishing rules and granting access to content, use, and frequency through the platform's API terms of service (Gerber & Lynch, 2017; Janetzko, 2016; Walker et al., 2019).

Other eWOM research methods used surveys or interviews to gain knowledge of online behavior (Han & Anderson, 2021). Surveys and interviews are independent of a social media platform; therefore, researchers' access is not limited to a social media platform's terms of service. However, this method presents a disconnect between consumer behavior and the subjects in the experiments, who are often undergraduate university students or Amazon Mechanical Turk participants (Han & Anderson, 2021). Additionally, the use of survey data has been criticized for quality issues, including sampling error, delinquent respondents, respondent fatigue and response style, and problems with construct measurement and scale development when used in marketing studies (Dolnicar et al., 2016).

Given the three methods of eWOM data access—scraping, APIs, and surveys or interviews—I decided the most efficient and ethical way to address my research questions was to access the restaurant eWOM valence ratings data through an API. Specifically, I used the following process to access the Yelp Fusion API. First, I created an online application through the Yelp developers' portal. The app automatically generated a private API key, which granted access to the Yelp Fusion API data. Second, with assistance from a computer programmer, I wrote the Yelp Fusion API request parameters in Python 3.0. Third, I placed the Yelp Fusion API calls using the endpoints *business search* and the filters *category, location, offset,* and *limit*. I also used the keywords *country* and *restaurant* to filter my data. Fourth, I downloaded the JavaScript Object Notation (JSON) Yelp data files.

While Yelp data are publicly accessible, permission for access through the Yelp Fusion API is granted through Section 5 of the Yelp Fusion API Terms of Use (see Appendix B). Two key criteria must be met when using the API. First, data analysis must be at the aggregate level. Second, the user must receive no promotional or monetary benefit from the data. My study met both criteria by analyzing aggregate country-level restaurant eWOM valence ratings. Also, there was no profit motive for this research.

Operationalization of Constructs

When working with abstract concepts, researchers have used the term *theoretical construct* to define their measurements (Dooley, 2001). This quantitative correlation study examined the relationship between country culture, country demographics, and restaurant eWOM valence ratings. Additionally, researchers must carefully define the constructs relevant to a study to maintain criterion validity. Dooley (2001) defined criterion validity as articulating the measure for a value based on another measure that most closely resembles what the researcher is trying to capture and argued that criterion validity is the best indicator of a construct's meaning. Singleton and Straits (2017) helped further clarify the operationalization of constructs when they asserted that researchers define the values of a variable. I followed previous cross-cultural, demographic, and eWOM research when developing my study's operational definitions. In the following narrative, I provide the operational definition (what it represents) and explain the measurement for each variable.

Hofstede's (2001, 2011) cultural dimensions indexes were used to measure country culture. There has been strong support within the literature for using Hofstede's model in studies like mine. For example, Graafland and Noorderhaven (2018) stated, "Hofstede's cultural dimensions have become the de-facto standard in cross-cultural studies in management" (p. 959). Moreover, Hofstede's framework has been used in more than 60% of the cross-cultural research published within the management domain (Mariani & Predvoditeleva, 2019). Hofstede's index comprises six measures reflecting a country's cultural values (see Table 7). Each cultural dimension has a score (ratio measurement) ranging from 0 to 100 points. A cultural dimension score of less than 50 is considered low, and a score greater than 50 is considered high for the index. Therefore, for my study, each country had six discrete measures of culture, with one score for each dimension from the index.

To measure country demographics (see Table 8), ratio measurements of country economic measures (population, gross domestic product per capita, mobile device penetration, Internet penetration, and social media use), restaurant operating measures (restaurant sales and restaurant units), and Yelp platform measures (Yelp visits, Yelp unique visitors, Yelp pages per visit, Yelp average visit duration, and Yelp percent spill-in) were used. The use of country demographic variables has been documented in cross-cultural research by Hofstede (2001), de Mooij (2011), and Leonhardt et al. (2020).

Table 7

Predictor Variables Country Culture Operational Definitions

Variable and label	Operational definition
Power Distance Index (*PDI*)	How people accept and give authority specifically reflects an unequal balance of power and social inequality
Individualism/Collectivism (*IDV/CLV*)	Focus on self and immediate family vs. loyalty to the group, which looks after its members in exchange for loyalty
Uncertainty Avoidance Index (*UAI*)	Comfort with uncertainty or ambiguity and the extent to which people will try and avoid it
Masculine/ Feminine (*MAS/FEM*)	Societal assertiveness or an achievement orientation vs. focus on the quality of life or caring for others
Long-term/Short-term Orientation (*LTO/STO*)	A social focus on persistence, pragmatism, thrift vs. tradition, national ride, self-enhancement, and social obligations
Indulgence versus Restraint (*IVR*)	The degree of happiness, control over life, the importance of leisure vs. the importance of hard work and thrift

Note: Operational definitions and data are from "Hofstede Insights," by G. Hofstede, 2021, https://www.hofstede-insights.com/country-comparison/. In the public domain.

Table 8

Predictor Variables Country Demographics Operational Definitions

Variable and label	Support for use from prior research	Operational definition and reference	Data measurement dates
Gross domestic product per capita (*GDP*)	Wang et al. (2021) Leonhardt et al. (2020)	Country gross domestic product divided by mid-year population ($US current) (The World Bank, 2021)	December 2021
Internet Penetration (*INP*)	Busca and Bertrandias (2020)	Percentage of country's population with Internet access (Kepios, 2022)	Year-end 2021
Population (*POP*)	Rahimi et al. (2018)	Count of total country's population 18+ (World Population Review, 2021)	Year-end 2019
Social Media Use (*SMU*)	Goyette et al. (2010)	Percentage of country's population using social media (Kepios, 2022)	Year-end 2021
Mobile Device Penetration (*MDP*)	Mariani et al. (2019)	Percentage of country population that owns a mobile device (Kepios, 2022)	Year-end 2021
Restaurant Units (*RU*)	Wang et al. (2021)	Count of all restaurants located in a country (Barnes Reports, 2020)	Year-end 2020
Restaurant Sales (*RS*)	Wang et al. (2021)	Annual sales revenue of food and beverage for all restaurants located in a country ($US) (Barnes Reports, 2020)	Year-end 2020
Yelp Visits (*VI*)	Messner, 2020	Count of total platform visits in a 30-day period in a country (Semrush, 2021)	June 2021
Yelp Unique Page Visitors (*UVI*)	Messner, 2020	Count of unique platform visitors in a 30-day period in a country (Semrush, 2021)	June 2021
Yelp Pages Per Visit (*PPV*)	Messner, 2020	Average platform pages per visitor session in a 30-day period in a country (Semrush, 2021)	June 2021
Yelp Average Visit Duration (*AVD*)	Messner, 2020	Average time spent on the platform per visitor in a 30-day period in a country (min: sec; Semrush, 2021)	June 2021

Yelp Percent Spill-In (*PSI*)	Messner, 2020	Percentage of platform visits from outside the home country in a 30-day period in a country (Semrush, 2021)	June 2021

The response variable restaurant eWOM valence ratings represent consumers' satisfaction with a brand. Yelp is distinctive because it allows consumers to post (uncompensated) ratings reflecting their experience; businesses can learn what they are doing well and what needs to change (Y. Yang et al., 2018). Thus, the platform is a de facto representation of consumer satisfaction. Restaurant eWOM valence ratings data are measured by the average of all cumulative prior Yelp ratings for a restaurant and then publicly posted using a score of 1 to 5 stars (Yelp, 2022b). Yelp rounds the average star rating posted to the nearest .5 star; a restaurant with a 3.24 rating will be rounded to 3 stars, while a restaurant with a 3.25 rating will be rounded to 3.5 stars (Luca, 2016). The ratings that were pulled from the Fusion API reflected the posted restaurant star ratings. To combat fake ratings, Yelp only includes a rating in the overall star total if the rating is associated with a *recommended review* (Yelp, 2022a). The Yelp restaurant eWOM valence ratings were accessed on the same day, October 3, 2021, for all countries included in the study.

Data Analysis Plan

In this quantitative correlation study, I analyzed the relationship between country culture, country demographics, and restaurant eWOM valence ratings for all countries on the Yelp platform with eWOM restaurant valence ratings. The following research questions and corresponding hypotheses guided the study:

RQ1: What is the relationship between country culture and restaurant eWOM valence ratings?

$H_0$1: There is no significant relationship between country culture and restaurant eWOM valence ratings.

H_a1: There is a significant relationship between country culture and restaurant eWOM valence ratings.

RQ2: What is the relationship between country demographics and restaurant eWOM valence ratings?

$H_0$2: There is no significant relationship between country demographics and restaurant eWOM valence ratings.

H_a2: There is a significant relationship between country demographics and restaurant eWOM valence ratings.

RQ3: What is the relationship between country culture and country demographics on restaurant eWOM valence ratings?

$H_0$3: There is no significant relationship between country culture and country demographics on restaurant eWOM valence ratings.

H_a3: There is a significant relationship between country culture and country demographics on restaurant eWOM valence ratings.

RQ4: What country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings?

$H_0$4: There are no country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings.

H$_a$4: There are country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings.

After accessing and assembling the data, my first step was to clean and screen my dataset using Microsoft Excel, version 16.65. Then, to address my research questions and hypotheses, I analyzed the data using descriptive statistics, correlation analysis, and MLR. I used IBM SPSS Statistics (SPSS) version 28.0.1.0 software for my data analysis. In the following sections, I overview my data preparation and analysis, describe the statistical tests used to test my hypotheses, and present the statistical results.

Data Preparation

Once the JSON data file containing the response variable data was downloaded from the Yelp Fusion API, the original master copy was reserved for safekeeping. I also made a duplicate file for analysis. I converted the JSON analysis file into a Microsoft Excel spreadsheet and prepared the data using a matrix with rows for each country. I replicated each restaurant reported by Yelp in each country (as many as 200 replications for each country). There were columns for record reference numbers and country (not variables) and a column for the response variable (*VAL*). The predictor variables I downloaded from their respective secondary sources were loaded into additional a Microsoft Excel spreadsheet columns, with values for each country. A prototype of the Microsoft Excel spreadsheet is included for reference (see Table 9).

Table 9

Prototype of Excel Data Sheet

Country	PV1	PV2	PV3	Restaurant	REF	RV1
AAA	46	14432	0.00	AAA1	1001	4.0
AAA	46	14432	0.00	AAA2	1002	3.0
AAA	46	14432	0.00	AAA3	1003	2.0
AAA	46	14432	0.00	AAA4	1004	1.5
BBB	90	46473	0.18	BBB1	2001	5.0
BBB	90	46473	0.18	BBB2	2002	4.0
BBB	90	46473	0.18	BBB3	2003	3.5
BBB	90	46473	0.18	BBB4	2004	1.5
CCC	56	11722	0.01	CCC1	3001	3.0
CCC	56	11722	0.01	CCC2	3002	4.0
CCC	56	11722	0.01	CCC3	3003	2.5
CCC	56	11722	0.01	CCC4	3004	4.0
DDD	77	23721	0.06	DDD1	4001	2.5
DDD	77	23721	0.06	DDD2	4002	5.0
DDD	77	23721	0.06	DDD3	4003	3.0
DDD	77	23721	0.06	DDD4	4004	4.5

Note. The PV values are the same for every case (country) and, thus, for every restaurant in each country. There were 18 total PVs; this example only shows three. Each case (country) was replicated multiple times using restaurants; each replication is a separate restaurant, data point, and record. The RVs are different for each record/replication/data point.

I reviewed the Microsoft Excel spreadsheet to ensure I obtained the correct data, cleaned and transformed inconsistent data formats, and identified outliers, missing data, and otherwise corrupted data (Foreman, 2014). I analyzed the data in a Microsoft Excel spreadsheet to find outliers, and I considered any value outside the range of mean $\pm$ 3 standard deviations to be an outlier (see Badiou et al., 1988). Any outliers were examined to determine if it was a true value, error, or corrupted; after evaluation, I accepted the outlier as a valid record or eliminated it and reported the outlier anecdotally in my narrative. My dataset had 925 total outliers. All outliers were accepted as valid records because of the relatively small number of outliers, the large sample size, and because the data were realistic, country data and not spurious unexpected values.

I also reviewed the data for missing or corrupted data. I planned to correct for missing numeric data points by using a mean of the existing records for that variable (see Foreman, 2014) and then noting the imputation anecdotally in my narrative. However, the data included 2,449 cases with missing or corrupted records. Imputation was not an appropriate correction given the nature of the data; therefore, I deleted the 2,449 cases from the dataset. Finally, I reviewed the data for spill-in. Spill-in measures the percentage of platform traffic originating outside the host country (Semrush, 2021). Spill-in analysis ensured that the Yelp data reflected ratings posted by consumers living in the host country. I followed the recommendation of Marucci (2009) and maintained spill-in at or lower than 15%. Finally, I loaded the data from my Microsoft Excel spreadsheet into SPSS for the data analysis.

Data Analysis

Descriptive Statistics

I used descriptive statistics to present a quantitative description of my data. Descriptive statistics provide a simple summary of the purposive sample, and there are two fundamental categories of descriptive statistics measures of central tendency and measures of variability (Aczel & Sounderpandian, 2006). To capture measures of central tendency, I included the measures of the mean (*M*), median (*Mdn*), and number (*n*). To capture measures of variability, I included the range, maximum, minimum, variance (s^2), and standard deviation(s).

Correlation Analyses

To test the hypotheses associated with RQ1–3, I used correlation analyses to evaluate the relationship between the predictor variables (measurements of country culture and country demographic variables) and the response variable (restaurant eWOM valence ratings). Using correlation analysis was supported by prior research similar to my study. For example, Messner (2020) used a correlation analysis to explore the interplay between national culture, demographics, and eWOM data. Mariani and Predvoditeleva (2019) used a correlation analysis to explore the influence of culture on hotel ratings.

Correlation analysis results in a correlation coefficient, which defines the strength and direction of the correlation. A correlation analysis does not establish a causal relationship; it can only assess the strength and direction of the relationship between variables as given by the correlation coefficient (Warner, 2013). I calculated Pearson's correlation coefficient (*r*) for my correlation analysis. Pearson's correlation coefficient requires the following assumptions (Warner, 2013):

- both predictor and response variables are quantitative and normally distributed
- a linear relationship between the predictor and response variables
- predictor variables are independent, and the response variables are independent
- predictor and response variables should have no extreme outliers

First, the predictor and response variables were evaluated to ensure they were quantitative during my data analysis's screening and cleaning stage. Q-Q plots were used to assess normality because I could visually compare the observed quantiles of data (represented by dots) with what would be the expected normal distribution for data quantiles (represented by a solid line) (see Ghasemi & Zahediasl, 2012). Given my large data set, Q-Q plots were more appropriate to assess normality (see Varshney, 2020). A visual review of the scatterplots assessed linearity. Linearity was established if the plots showed a linear band or pattern (see Warner, 2013). Independence was assessed using a Durbin-Watson test. Durbin-Watson scores range from 0 to 4, with test statistic values of 1.5 to 2.5 considered relatively normal (Field, 2009). The data screening and transformation process had previously evaluated and managed outliers.

Once my data met the appropriate assumptions, I used the Pearson correlation coefficient (*r*) test in SPSS to assess the nature of the relationship between the stated variables. Pearson's (*r*) values range from -1 to +1 and measure the direction and strength of the relationship. A correlation coefficient of -1 demonstrates the variables are perfectly related in a negative linear manner, a correlation of +1 demonstrates the variables are perfectly related in a positive linear manner, and a correlation of 0 indicates no relationship between the variables (Gogtay & Thatte, 2017). Statistical significance was also assessed as part of the Pearson correlation coefficient (*r*) test in SPSS. If the *p*-value was less than .05, there was evidence of a statistically significant association between the variables. If the *p*-value was more than .05, there was no evidence of a statistically significant association between the variables.

Multiple Linear Regression (MLR)

To test the hypotheses RQ4, I used MLR and regression model-building to construct a predictive model for the response variable. I used the predictive model building to select the predictor variables and 2FIs comprising the model that best predicts the response variable. The predictive model was also used to assess the sensitivity of my response variable to changes in the predictor variables. The use of regression analysis was supported for this study based on the work of Hofstede (2001) and Stamolampros et al. (2019). Stamolampros et al. used regression analysis to evaluate the relationship between reviewers' cultural values and online ratings for air travel while controlling for flight and passenger characteristics. Hofstede used stepwise multiple regression to "eliminate spurious correlations and show which indexes contributed independently to the outside variable" (p. 465).

The regression model is depicted mathematically as follows (Hatcher, 2013):

$$Y = a + b^*_1X_1 + b^*_2X_2 + \ldots + b^*_pX_p + \varepsilon.$$

where the predictor variables (X_1 to X_p) predict Y

Y = the response variable

a = the Y-intercept, or the value of Y if the value of all $Xs = 0$

b^*_1 = standardized regression coefficient for the first predictor variable X_1

X_1 = the actual score on the first predictor variable

ε = random error in Y.

The null hypothesis and alternate hypothesis for the regression model are written (Hatcher, 2013):

H_0: $b^*_1 = b^*_2 = \ldots = b^*_p = 0$.

(all coefficients = 0; there is no significant relationship between any of the predictor variables and the response variable)

H_a: at least one $b^*_p \neq 0$.

(at least one coefficient ≠ 0, there is a linear relationship between at least one of the predictor variables and the response variable)

I tested my hypotheses regarding the overall regression model. I used the *F*-test (and its associated *p*-value) to explain the significance of the relationship between my set of predictor variables and the response variable. I also used the *t*-test (and its associated *p*-value) to assess the relationship between each of my predictor variables and the response variable. The *t*-test was also used as part of and throughout the regression modeling process to evaluate the influence of each prospective predictor variable and its contribution to the predictability of the regression model. Adjusted R^2, the coefficient of determination, was used to assess the extent of variation in my response variables due to the predictor variables. The model summary from SPSS was used to highlight the portion of the variation in the response variables.

Assumptions. My data had to meet the following MLR criteria, which were evaluated as part of the analysis (see Aczel & Sounderpandian, 2006; Warner, 2013):

- Measurement: The predictor and response variables had quantitative measurement.
- Linearity: The predictor and response variable pairs provided a best-fitting straight-line relationship through the scatterplot.
- Homoscedasticity: The variance of the Y scores remained constant at all values of X.
- Normality: The residuals were normally distributed.
- Absence of multicollinearity: No relationship found among predictor variables.
- Independent errors: The residual terms for any pair of observations were uncorrelated.
- No influential cases: There were no significant outliers.

Both my predictor and response variables were quantitative; therefore, there was no need to convert categorical predictor variables into dummy variables. I inspected the Q-Q plots to assess normality during the initial model-building assessment. I tested the normality of the final model with a visual inspection of the Q-Q plot and a Kolomogoroz Smirnov test (Gogtay & Thatte, 2017). If the Kolomogoroz Smirnov test value was small ($< .05$ with. $\alpha = .05$), then I rejected the null hypothesis that the data were normally distributed (Stephens, 1992). Linearity and homoscedasticity were assessed using a visual inspection of the scatterplots. The data were determined to likely be linear if the plots formed a linear band (Warner, 2013). The data were determined to likely be homoscedastic if there was an absence of funneling in the plots (Warner, 2013).

Multicollinearity was assessed with variance inflation factors (VIFs) during model building. A VIF of one indicated no correlation, and if multicollinearity was present, I eliminated predictor variables sequentially, starting with the variable with the highest VIF. When evaluating the final model, I used VIFs and the collinearity diagnostics table produced in SPSS. First, I reviewed the VIFs in the final model. A VIF of one indicated no correlation among the predictor variables; if there were only two predictors with a VIF above 10, then I assumed the collinearity was between these two predictors, and there was no need to conduct further analysis (Regorz, 2020). However, I reviewed the collinearity diagnostics if there were more than two predictors with a VIF greater than 10. Using the SPSS collinearity diagnostics table, I identified cases with a condition index greater than 15. Then I looked to see if there was more than one predictor (column) with a variance proportion value greater than .90, which signified a collinearity issue (Regorz, 2020). Also, I included a Durbin-Watson test to assess for independence. Durbin-Watson scores range from 0 to 4; test statistic values of 1.5 to 2.5 were considered relatively normal (Field, 2009). The data screening and transformation process had previously evaluated and managed outliers.

Stage 1. Prior analyses from RQs 1–3 satisfactorily addressed the MLR assumptions for two quantitative variables, linearity, normality, independence, and outliers. Therefore, the remaining MLR assumptions for homoscedasticity and multicollinearity were assessed in Stage 1. After all assumptions for MLR were met, a final screening of the predictor variables was done by conducting a regression analysis in SPSS using the enter method.

Stage 2. In Stage 2, the remaining candidate predictor variables and their 2FIs were analyzed using best-subsets regression in SPSS. The result of the best-subsets regression was a group of models with summary statistics. It was then up to me to select the best-fitting model. Three criteria were used: Mallows's *Cp*, adjusted R^2, and a combination of parsimony (fewest terms) and satisfaction of model assumptions (residual analysis) to determine an interim combination of predictor variables (James et al., 2021). During Stage 2, I noted which models met the criteria and which combinations of predictor variables were candidates for the final predictive model. I also noted which predictor variables were included in the acceptable models and which predictor variables would be eliminated.

Stage 3. In Stage 3, I ran a series of backward and forward stepwise regression analyses using the two automated SPSS methods. Stepwise regression was an iterative process that built the model by adding or removing predictors one by one. Each time the regression outcomes were evaluated to consider the predictor variables' influence and overall contribution to the regression model (based on statistical significance and adjusted R^2). Each stepwise method, in some cases, resulted in a different model (different set of predictor variables). Again, I noted which predictor variables were included in the final model of each stepwise regression procedure and the adjusted R^2 of each of the final models. I did not rely on any single automated stepwise analysis when eliminating a predictor variable and instead considered the cumulative evidence.

Stage 4. During Stage 4, a purposeful sequential regression involved conducting a series of regression analyses in SPSS using the enter method with the remaining predictor variables. After each run, I noted the change in adjusted R^2. If there was a decrease, I noted the eliminated predictor that caused the change and considered its *p*-value. I also noted the *p*-value for each predictor. I decided to eliminate the predictor based on its *p*-value greater than α. If all *p*-values were less than α, I stopped. Otherwise, the predictor with the highest *p*-value was eliminated. Then I ran the next model. I used the elimination criteria (adjusted R^2 and *p*-value) iteratively until all the predictor variables were significant and the adjusted R^2 was no longer increased by eliminating a predictor variable.

Stage 5. In Stage 5, I compared the evidence from Stage 2 (best-subsets regression), Stage 3 (stepwise regression), and Stage 4 (purposeful sequential regression). I noted the predictor variables that were consistently included or excluded. I ran different combinations, checked for an increase in R^2, and noted which models improved adjusted R^2. Consistently significant predictor variables were noted.

Stage 6. A final model was selected using the cumulative evidence from the previous five stages of the model-building process based on these criteria:

- Predictor variables and 2FIs ($p < .05$)
- Combination of predictor variables and 2FIs best meeting the criteria of Mallows's C_P near and less than $k + 1$ and the highest adjusted R^2

- Fewest predictor variables while balancing highest adjusted R^2 (parsimony)
- Assessment of predictor variables as individual model contributors or as moderating variables that are part of 2FIs

Two-factor Interactions. Researchers evaluate data to make sure that there is no interaction effect between variables. A 2FI indicates that the influence of one predictor variable on the response variable depends on the value of a second predictor variable (Warner, 2013). I assessed 2FIs starting in Stage 2 and continuing forward in the regression model-building process. The 2FIs assessed were pairs of predictor variables remaining after the variable screening. The influence or predictability of any predictor variable (whether a country culture or a country demographic variable) depends on the presence of other variables, and there is often significant interaction among them.

Threats to Validity

Validity is the extent to which research measures what it intends to measure. Dooley (2001) argued that correlation studies should avoid reverse causation and spuriousness to support validity. I used social media research perspectives to define, explain, and manage potential threats to my study’s external, internal, and construct validity. This section concludes with an overview of how I addressed ethical procedures in my study.

External Validity

External validity is the extent to which research results can be generalized outside the context of a research study (Malhotra, 2018). Specific threats to external validity for a correlation study can include an interaction of effects with units, treatments, outcomes, and settings (Schenker & Rumrill, 2004). Paschek (2015) and Wijnhoven and Bloemen (2014) extended the definitions of external validity for social media research to include demographic bias, inconsistency, biased application, and biased settings (see Table 10).

To address demographic bias, I matched my purposive sample criteria to my API keywords, thus ensuring I reached my target audience. To minimize inconsistency, I ensured alignment between my research questions and the data by selecting Yelp as my social media platform because Yelp provides global eWOM valence data. Settings bias was minimized using the Yelp platform data for all country markets.

Table 10

Extending External Validity to Social Media Research

External validity threat	Application of threat in validity to social media research	Management of threat to validity
Interaction of effects with units	Demographic bias	Ensure match between sample and target audience
Interaction of effects with treatments	Inconsistency of social media	Ensure alignment between data mined and research questions
Interaction of effects with outcomes	Biased application of results	Ensure transparency in result reporting
Interaction of effects with settings	Settings bias	Use the same platform across samples

Note. This table shows the alignment between Schenker and Rumrill, 2004, Paschek (2015), and Wijnhoven and Bloemen (2014). I added the third column to demonstrate how I addressed external validity in my study.

Biased application of results relates to the inability to generalize the results of an eWOM study beyond the sample population. As mentioned in the literature, a platform's eWOM users are not representative of the total population, nor are a platform's eWOM users considered representative of all eWOM platforms (Choi, 2020; Janetzko, 2016; Quan-Haase & Sloan, 2016). While Mayr and Weller (2016) stated that a platform's users might not represent the entire population, they advocated that generalizations can be made to platform users. Moreover, Yang et al. (2017) indicated that Yelp's large and active restaurant user base allows for strong samples of online restaurant reviews and ratings. Therefore, the results of my study provide insights into the influence of country culture on restaurant eWOM valence and may be generalized to restaurants that use the

Yelp platform. Finally, to address biased results reporting, I was as clear and transparent as possible when communicating my research results.

Internal Validity

Internal validity examines if the research results could have been caused by variables other than the treatment variables (Malhotra, 2018). My study's threats to internal validity included reverse causation, spuriousness, historical flaws, statistical regression pitfalls, and missed variable bias. In the following paragraphs, I briefly explain these threats and how they can be addressed.

Reverse causation, a threat to internal validity, is an opposite causation of direction from the hypothesized relationship (Dooley, 2001). The researcher must transpose the predictor and response variables to address this threat. Historical flaws occur when some event has caused the population to change in an unmeasurable manner (Wrench et al., 2018). To address this threat, I reviewed the news media for any geopolitical events occurring during the time frame corresponding to the eWOM data access. I discovered no significant events, and the absence of historical flaws was noted in the limitation of the research.

Statistical regression threats occur when the regression model is not properly validated. To address this, I used an F-test each time a variable was added to the model during my stepwise and sequential regression analyses (Sobol, 1991). I also checked for concurrent validity using the coefficient of determination as adjusted R^2 (Sobol, 1991). These steps helped protect against spuriousness, ensure that the equation was fitted to the original data, provided a good fit for other sample data, and checked for predictive validity using adjusted R^2 to determine how well a characteristic determines future results.

Construct Validity

Construct validity assesses how well a research measurement measures a construct or concept it is purporting to capture (Wrench et al., 2018). Brown et al. (2018) noted that construct validity is one of the most challenging types to establish because it must reflect the construct and demonstrate a correlation with other items or constructs in the research. Three criteria can be used to address threats to construct validity. First, a measure must have convergent validity, that is, a high positive correlation between a measure and other measures of the same construct (Brown et al., 2018). Second, the measure must have discriminant validity, a high correlation between a measure and other related constructs (Brown et al., 2018). Finally, the measure must have nomological validity, demonstrated by theoretical relationships between the measure and other constructs (Brown et al., 2018).

To achieve construct validity, I ensured that the variables were informed by data that measured what they were intended to measure. I carefully defined my constructs based on prior research. Each construct was carefully matched with data (that is, as objectively as possible) that best represented the construct and was based on prior research studies. Additionally, I removed records that did not align with the variables they were intended to measure. This exclusion included removing three types of records for eWOM ratings: (a) those that were not for restaurants, (b) those for which there were no data on the type of establishment, or (c) where the data were missing. Additionally, records were removed where the predictor variable Yelp percent spill-in was greater than 15% to ensure the data represented the host country and was not diluted by out-of-country tourists or travelers. These processes helped to support construct validity and minimized the potential for human subjectivity or variation.

Ethical Procedures

Ethical consideration is essential in research. I analyzed archival data, and because I was using aggregate data, I maintained confidentiality. No identifying marks could be traced to human subjects. My proposal was approved by Walden University's Institutional Review Board (IRB; number 09-21-22-0047226). Additionally, I followed the ethical procedures set by Walden University and Yelp's terms of service. The collected data will be kept on one computer's hard drive and a backup external flash drive. The computer where the data are stored has regularly updated antivirus software. The data will be maintained for a minimum of 5 years, after which it will be destroyed.

Summary

In Chapter 3, I presented this quantitative correlation study's research design, methodology, and data analysis strategies. My research questions examined the relationship between the predictor variables (country culture, country demographics) and the response variable (restaurant eWOM valence ratings). The theoretical research population was defined as all countries with restaurants with eWOM for all time, and the sampling unit was a country. The target population consisted of 32 countries with restaurants with eWOM, for which Yelp has eWOM data. Because Yelp controls the data, the target population size was unknown. My sampling frame was all 32 countries with restaurant eWOM valence ratings provided via the Yelp Fusion API on October 3, 2021. My API calls included the keywords *restaurants* and *country name* to filter the data.

The Yelp Fusion API returns data for a maximum of 200 restaurants per country. Thus, the maximum sample size was $N = 6{,}400$. A G*Power a priori power analysis was computed to determine the minimum sample size using the F-test, multiple linear regression: fixed model, a small effect size of $f^2 = 0.02$, $\alpha = .05$, and 18 predictors. The resulting minimum required sample size was $N = 1{,}496$, which is significantly smaller than the sample provided by the potential sampling frame. Additionally, a G*Power sensitivity analysis was conducted. With the probability of Type I and Type II errors at .01, I detected a true effect size of 0.0074, which is more precise than Cohen's (1988) small effect size. Thus, my analysis appeared to be precise and reliable. I outlined how SPSS was used to conduct correlation analyses and MLR on the data. Finally, I explained the threats to the validity of my study and detailed plans to minimize those threats. In Chapter 4, I present my research results, including the results of my statistical analysis. In Chapter 5, I present a summary of my research findings.

Chapter 4: Results

The purpose of this quantitative correlational study was to examine the relationship between measures of country culture, country demographics (predictor variables), and restaurant eWOM valence ratings (response variable) for all countries on the Yelp platform with eWOM restaurant valence ratings. The first two research questions examined the significance of a relationship between (a) country culture variables and restaurant eWOM valence ratings and (b) country demographic variables and restaurant eWOM valence ratings. Correlation coefficients were calculated for the stated variables to test the hypotheses.

The third research question examined the significance of the relationship between country culture and country demographic variables on restaurant eWOM valence ratings. The null hypothesis was that there was no statistically significant relationship; the alternative hypothesis was that there was a significant relationship, as determined by statistically significant correlations. Correlation coefficients were calculated for the stated variables to test the hypotheses. Finally, the fourth research question asked what country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings. The null hypothesis was that no country culture or country demographic variable is a significant predictor of restaurant eWOM valence ratings; the alternative hypothesis was that there are country culture variables or country demographic variables that are significant predictors of restaurant eWOM valence ratings. Hypothesis testing was conducted through MLR.

In Chapter 4, I describe the data collection process, including the timeframe, response rates, and any discrepancies with the data collection plan presented in Chapter 3. This chapter also presents the study results, including descriptive statistics, statistical assumptions, statistical analysis findings, and post-hoc analyses. The statistical output is evaluated and presented in tables or figures, and Chapter 4 concludes with a summary and transitions to Chapter 5.

Data Collection

Publicly available secondary data from multiple websites were used in this study. The response variable data represented restaurant eWOM valence ratings from 32 countries and as many as 200 restaurants per country for a potential 6,400 records in my target population. The measurement dates for the predictor variables were aligned as closely as possible to the response variable's extraction date (see Table 11).

Table 11

Data Sources and Dates of Measurement

Data	Source	Date of Measurement
Restaurant eWOM valence ratings	Yelp	October 3, 2021
Power Distance Index	Hofstede	October 2021
Individualism/Collectivism	Hofstede	October 2021
Uncertainty Avoidance Index	Hofstede	October 2021
Masculinity/Femininity	Hofstede	October 2021
Long/Short-term Orientation	Hofstede	October 2021
Indulgence versus Restraint	Hofstede	October 2021
Population	United Nations	December 2021
Gross domestic product per capita	World Bank	December 2021
Mobile Device Penetration	Kepios	December 2021
Internet Penetration	Kepios	December 2021
Social Media Use	Kepios	December 2021
Restaurant Units	Barnes Reports	December 2020
Restaurant Sales	Barnes Reports	December 2020
Yelp Visits	Semrush	June 2021
Yelp Unique Visitors	Semrush	June 2021
Yelp Pages Per Visit	Semrush	June 2021
Yelp Average Visit Duration	Semrush	June 2021
Yelp Percent Spill-In	Semrush	June 2021

Following approval by Walden University IRB, the data were downloaded into a Microsoft Excel spreadsheet with columns for each relevant piece of information about each record (identifiers, predictor variable, values for the response variable). The original dataset contained 6,018 records. Each row in the Microsoft Excel spreadsheet was a record representing one restaurant. The data were cleaned to correct for various anomalies, including missing data. Records were eliminated for the following reasons:

- Records were not included for data that did not represent restaurants (i.e., museums) or for which the establishment type was not included.

- Records were not included where values for the predictor variable Yelp percent spill-in were greater than 15% for a country. The exclusion was done to ensure that the Yelp data reflected ratings posted by consumers living in the host country. Spill-in is a variable that measures the percentage of traffic originating outside the host country (Semrush, 2021). I followed the recommendation of Marucci (2009) and maintained spill-in at or lower than 15%.
- Records with missing data for three predictor variables (Internet penetration, social media use, and mobile device penetration) were excluded.
- Outliers were considered any value ± 3 standard deviations from the mean (Badiou et al., 1988). Because there were relatively few outliers and a large sample size, and because the data were realistic country data, I decided no records would be excluded as an outlier (see Table 12).

Table 12

Number of Outliers ± 3 Standard Deviations From Mean

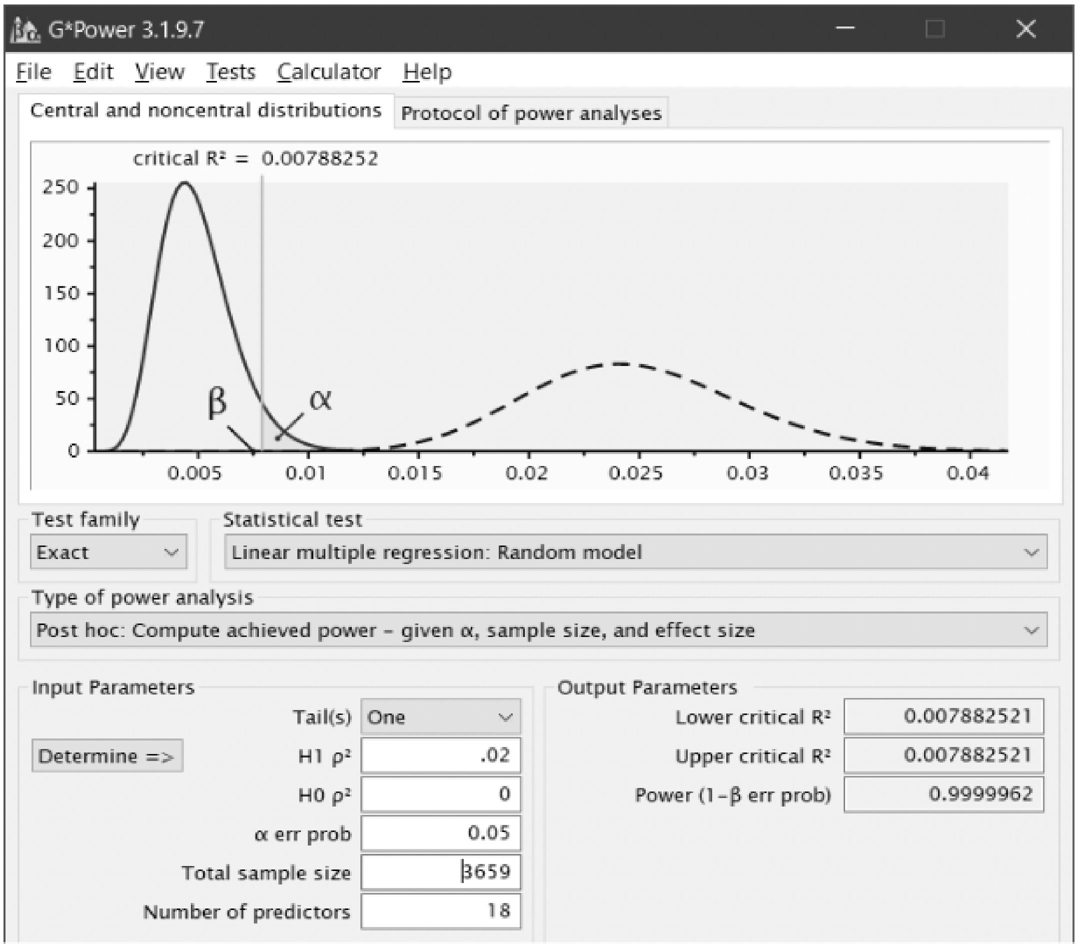
Variable	Count
Population	187
Yelp Unique Visitors	172
Yelp Average Visit Duration	192
Restaurant Units	187
Restaurant Sales	187

Note. The final total dataset N = 3,659; therefore, the number of outliers for each variable concerning the sample is relatively small.

The final data set represented restaurant eWOM valence ratings from 21 countries and was a census of valid records, N = 3,659, which exceeded the minimum calculated sample size. A post hoc computation of statistical power = $1 - \beta > .999$ based on an actual sample of $N = 3{,}659$ records was conducted. This indicated, given the desired confidence of $1 - \alpha = .95$, a small effect size of $\rho^2 = .02$, and a sample size of $N = 3{,}659$, a Type II statistical error was probable (false negative) of nearly zero (see Figure 4). Another method of assessing the final sample size was to compute the precision (sensitivity) of the statistical test given the sample size of $N = 3{,}659$ and the same parameters used in the a priori sample size calculation with desired power of $1 - \beta = .95$. The precision test with the actual sample size resulted in an effect size of $\rho^2 = .008$, which is a more precise test (ability to detect a smaller effect with a desired statistical power and confidence) than the minimum sample size would have yielded.

Figure 4

Post Hoc Sample Size



Study Results

The following sections include the results of my analysis. First, I report the descriptive statistics to provide an overview of my sample's characteristics. Second, I present the results of RQs 1, 2, and 3 (correlation analyses). Third, I present the results of RQ4 (MLR analysis). The results include comments evaluating the statistical assumptions appropriate for each research question, the exact statistics, and associated probability values. Finally, I state whether I accept or reject the null hypothesis.

Descriptive Statistics

Descriptive statistics were calculated for each variable. All predictor variables (measures of country culture and country demographics) were continuous, numerical variables. The response variable (restaurant eWOM valence ratings) was also a continuous numerical variable. To capture measures of central tendency, I calculated the number $N = 3{,}659$, mean, and median for each variable (see Table 13).

Q-Q plots were used to evaluate normality. Q-Q plots display data residual quintiles rather than each record; thus, they are easier to interpret with larger datasets. The variables' residuals followed relatively normal distributions except for population, Yelp visits, restaurant units, and restaurant sales, which had left skewed tails (see Figures 5 through 23). Due to the large dataset size ($N = 3{,}659$), the violations of normality could be ignored (Ghasemi & Zahediasl, 2012). The reason to overlook normality is based on the central limit theorem; if samples are from hundreds of observations, the data distribution can be ignored (Altman & Bland, 1995).

Table 13

Summary of Measures of Central Tendency

Variable	*N*	*M*	*Mdn*
Power Distance Index	3,659	50.48	50.00
Individualism/Collectivism	3,659	61.76	68.00
Masculinity/Femininity	3,659	53.20	56.00
Uncertainty Avoidance	3,659	57.46	58.00
Long-Term/Short-Term Orientation	3,659	51.72	41.00
Indulgence versus Restraint	3,659	56.79	62.00
Country Total Population	3,659	48,009	20,097
Country Gross Domestic Product Per Capita	3,659	$42,824	$41,597
Country Internet Penetration	3,659	0.90	0.91
Country Social Media Use	3,659	0.80	0.80
Country Mobile Device Penetration	3,659	1.24	1.23
Country Yelp Visits	3,659	74.00	32.40
Country Yelp Unique Visitors	3,659	57.23	23.90
Country Yelp Pages Per Visit	3,659	2.39	2.18
Country Yelp Average Visit Duration	3,659	3.00	2.57
Country Yelp Percent Spill-In	3,659	0.02	0.00
Country Total All Restaurant Units	3,659	89,996	53,181
Country Total Annual All Restaurant Sales	3,659	$62,618	$17,989
Restaurant eWOM Valence Ratings	3,659	4.19	4.00

To capture measures of variability, I calculated the range, minimum, maximum, standard deviation (s), and variance (s^2) for each of the variables (see Table 14).

Table 14

Summary Measures of Variability

Variable	Range	Min.	Max.	*SD*	Var.
Power Distance Index	82	18	100	21.9	478.7
Individualism/Collectivism	74	17	91	22.3	495.6
Masculinity/Femininity	90	5	95	20.5	418.8
Uncertainty Avoidance	86	8	94	24.3	591.8
Long-Term/Short-Term Orientation	73	20	93	23.9	573.3
Indulgence versus Restraint	68	29	97	14.6	212.3
Population	252,526	4,984	257,510	59,415	3,530,190,566
Gross Domestic Product Per Capita	$83,799	$3,301	$87,100	$22,445	$503,762,047
Internet Penetration	0.310	0.670	0.980	0.07	0.01
Social Media Use	0.202	0.679	0.881	0.06	0.00
Mobile Device Penetration	0.700	0.890	1.590	0.20	0.04
Yelp Visits	342.9	6.800	349.700	96.68	9,346.1
Yelp Unique Visitors	287.3	5.1	292.400	76.79	5,897.1
Yelp Pages Per Visit	3.390	1.280	4.670	0.84	0.71
Yelp Average Visit Duration	11.2	0.220	11.460	2.33	5.41
Yelp Percent Spill-In	0.124	0.000	0.1244	0.04	0.00
Restaurant Units	546,281	7,894	554,175	123,270	15,195,427,843
Restaurant Sales	$571,429	$6,062	$577,491	$125,138	$15,659,552,709
Restaurant eWOM Valence Ratings	4.00	1.00	5.00	0.50	0.25

Note. Valid N = 3,659, minimum (Min.), maximum (Max.), variance (Var.).

Figure 5

Power Distance Q-Q Plot

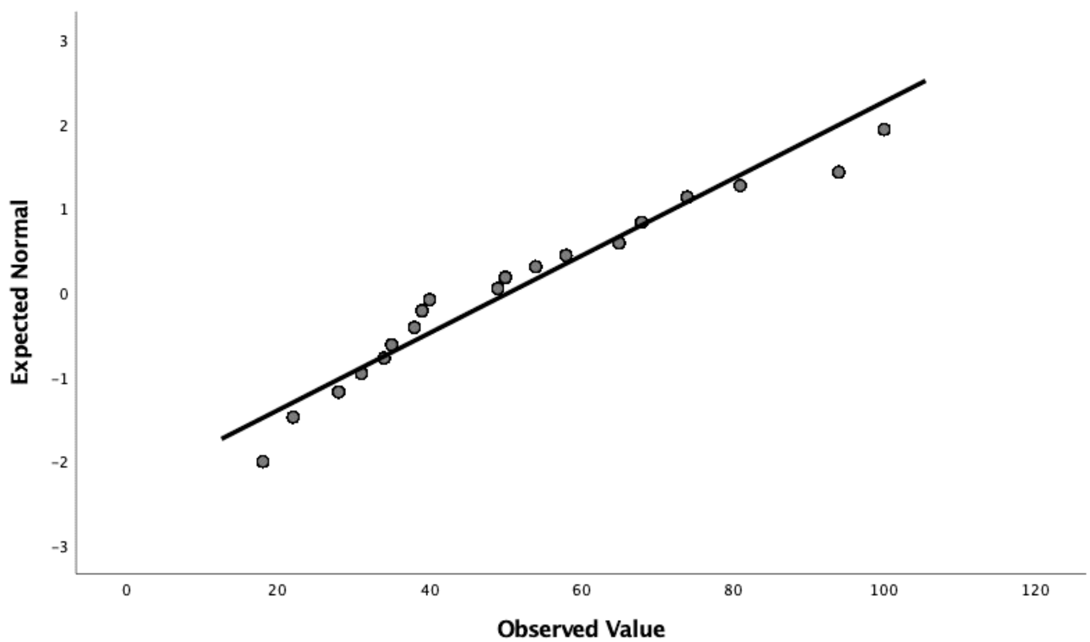


Figure 6

Individualism/Collectivism Q-Q Plot

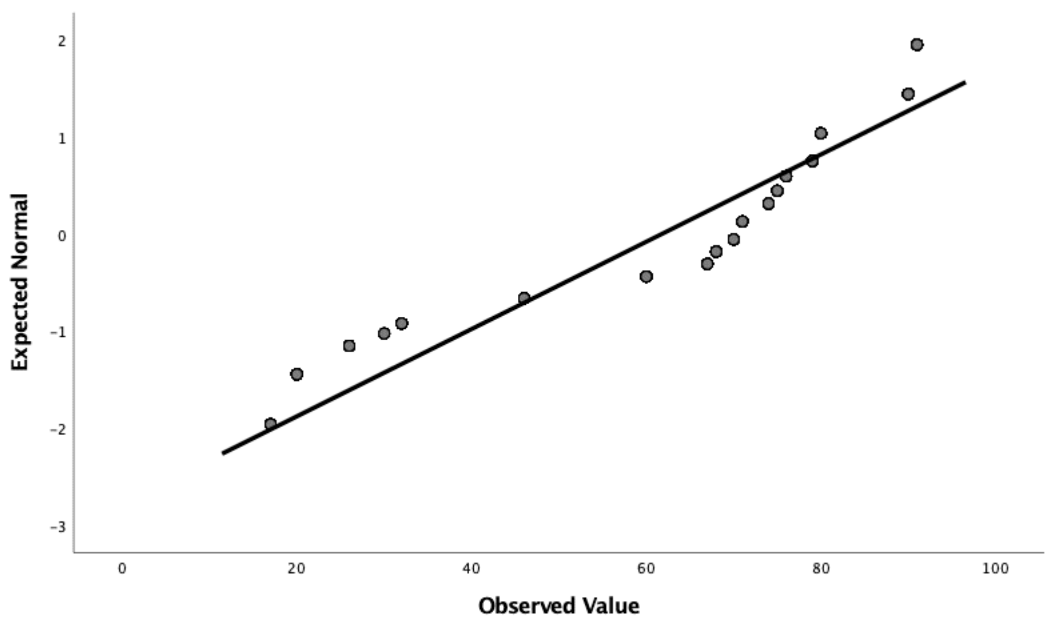


Figure 7

Masculinity / Femininity Q-Q Plot

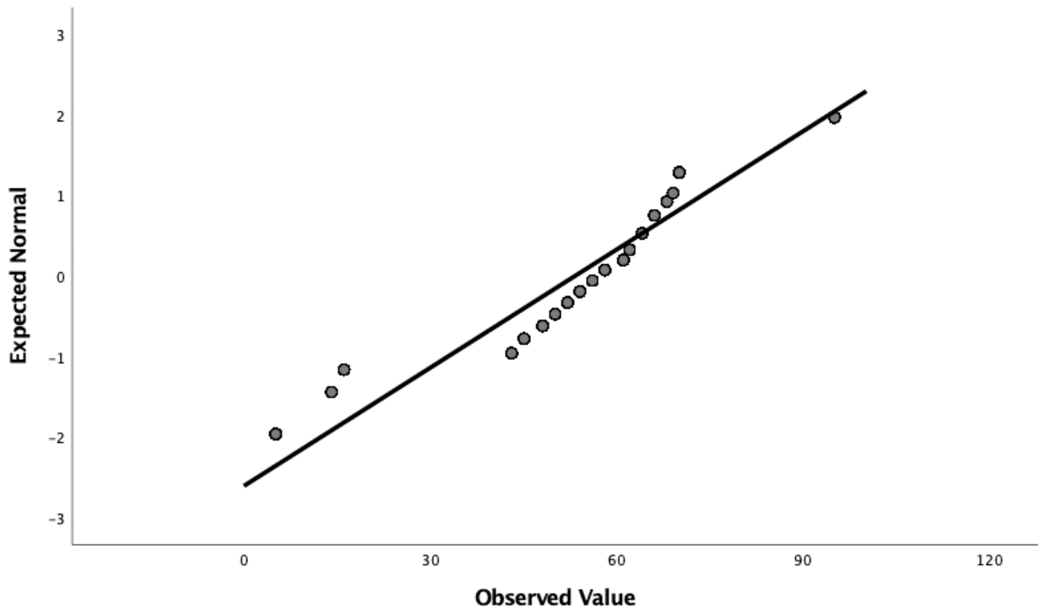


Figure 8

Uncertainty Avoidance Q-Q Plot

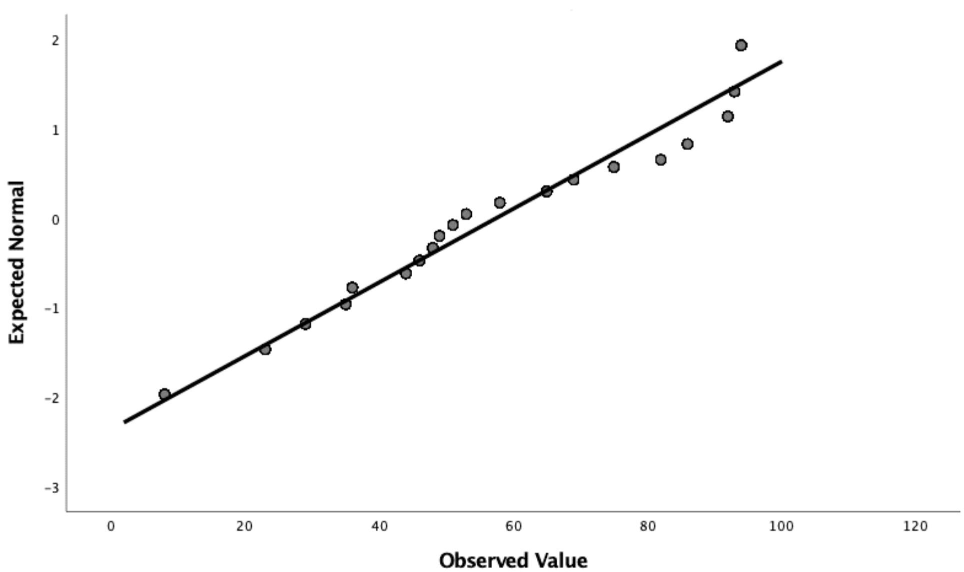


Figure 9

Long/Short-Term Orientation Q-Q Plot

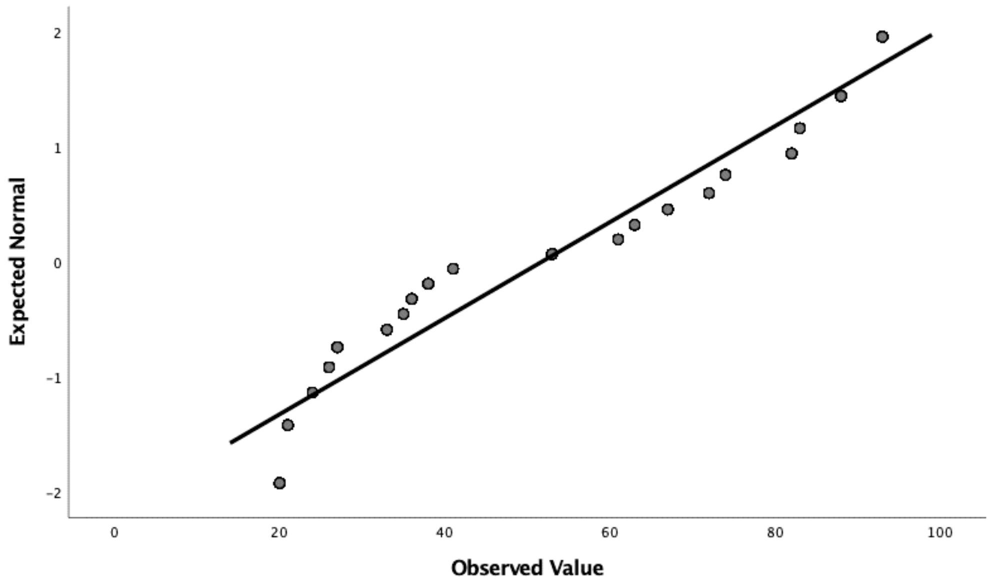


Figure 10

Indulgence Versus Restraint Q-Q Plot

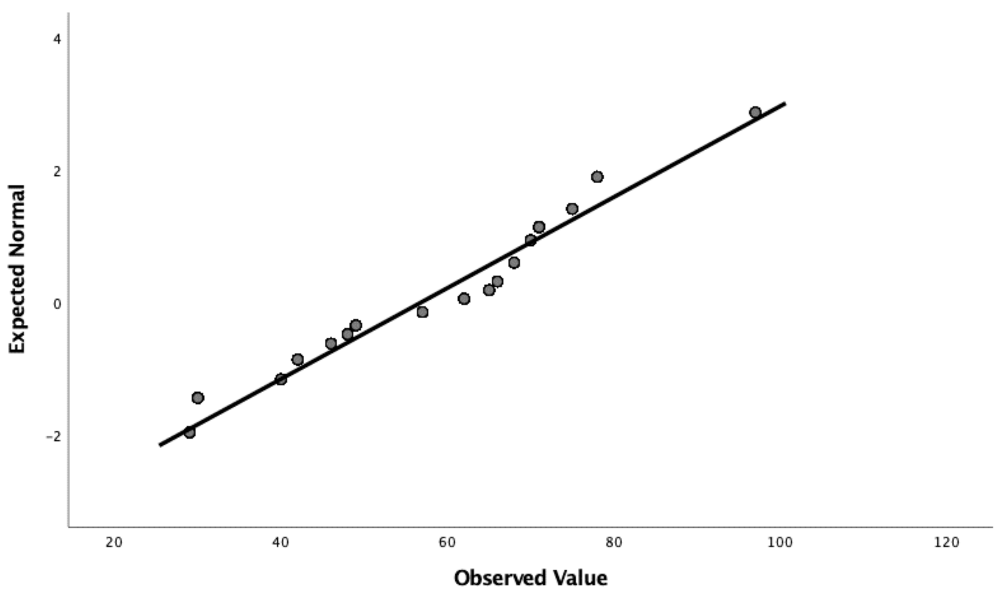


Figure 11

Country Population Q-Q Plot

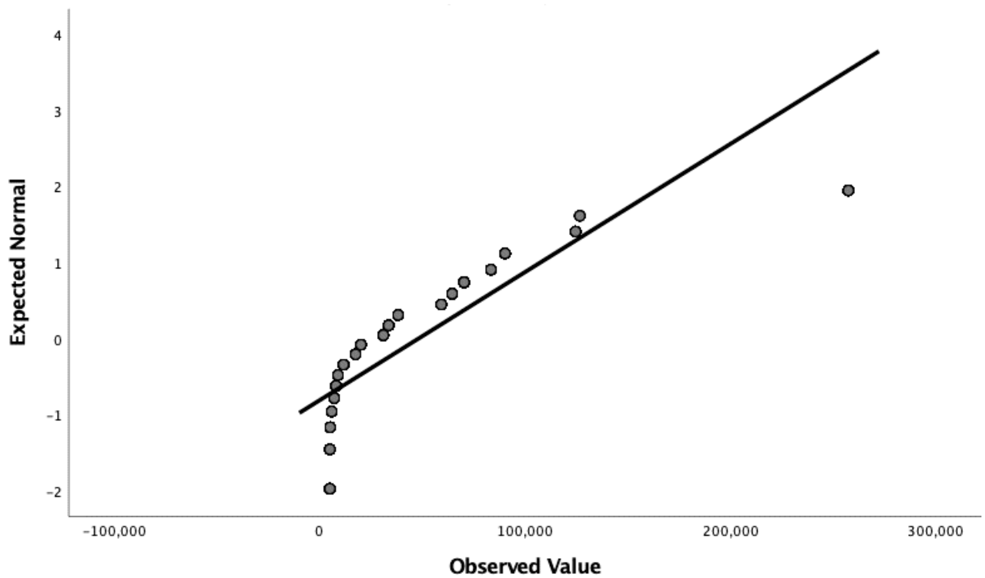


Figure 12

Gross Domestic Product per Capita Q-Q Plot

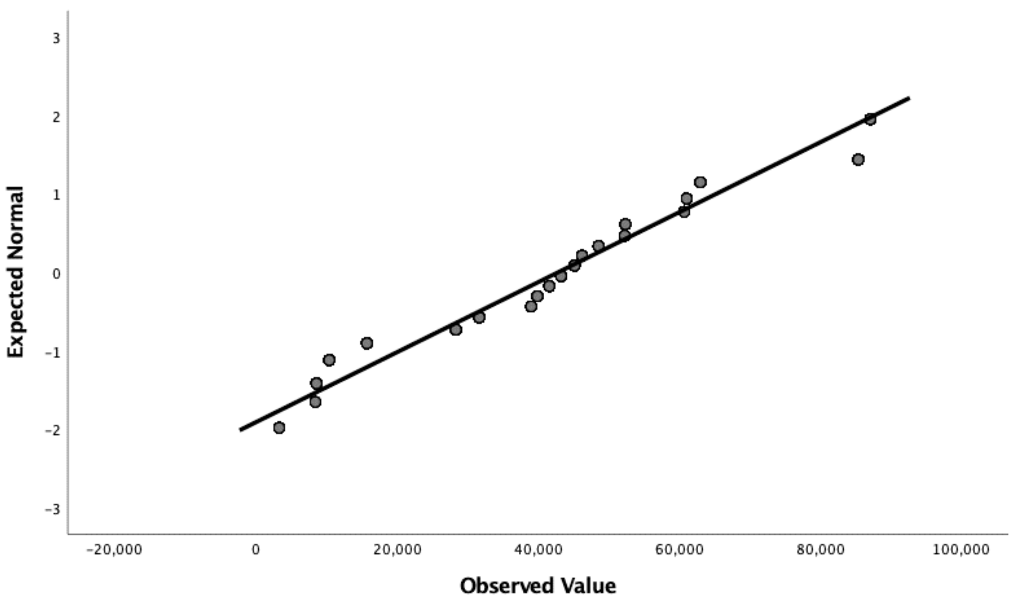


Figure 13

Internet Penetration Q-Q Plot

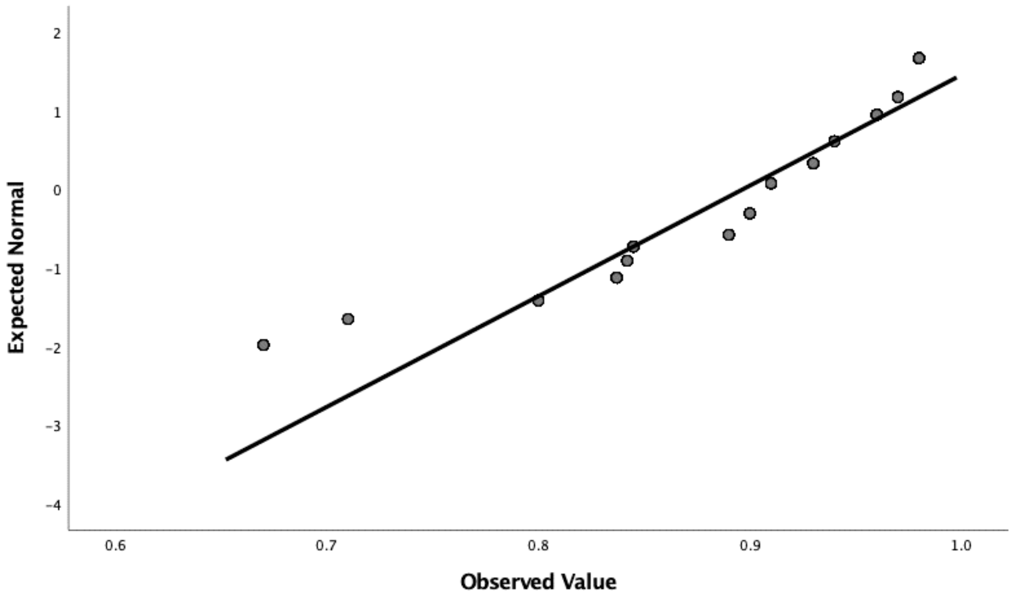


Figure 14

Social Media Use Q-Q Plot

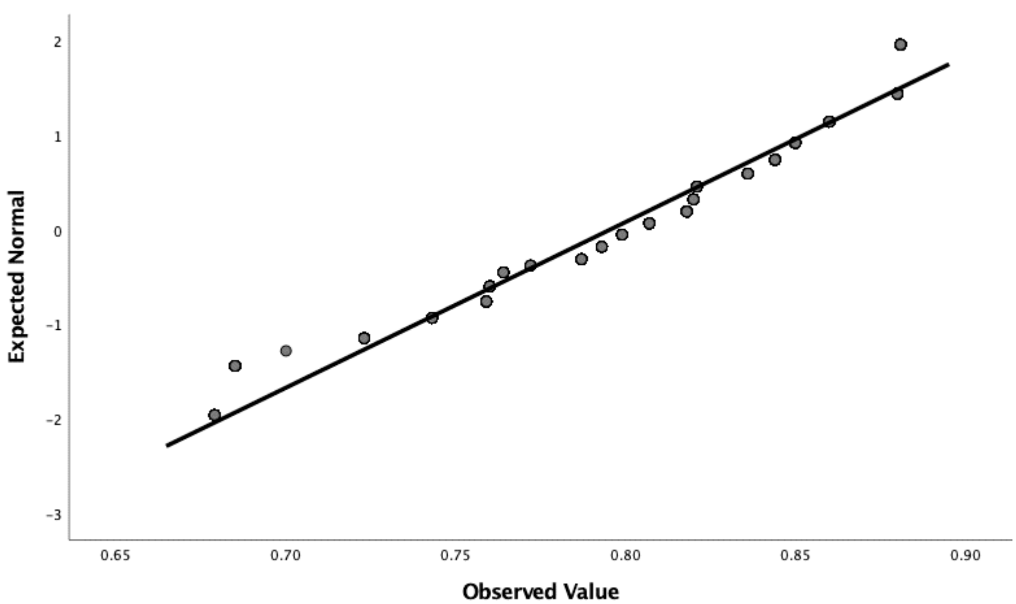


Figure 15

Mobile Device Penetration Q-Q Plot

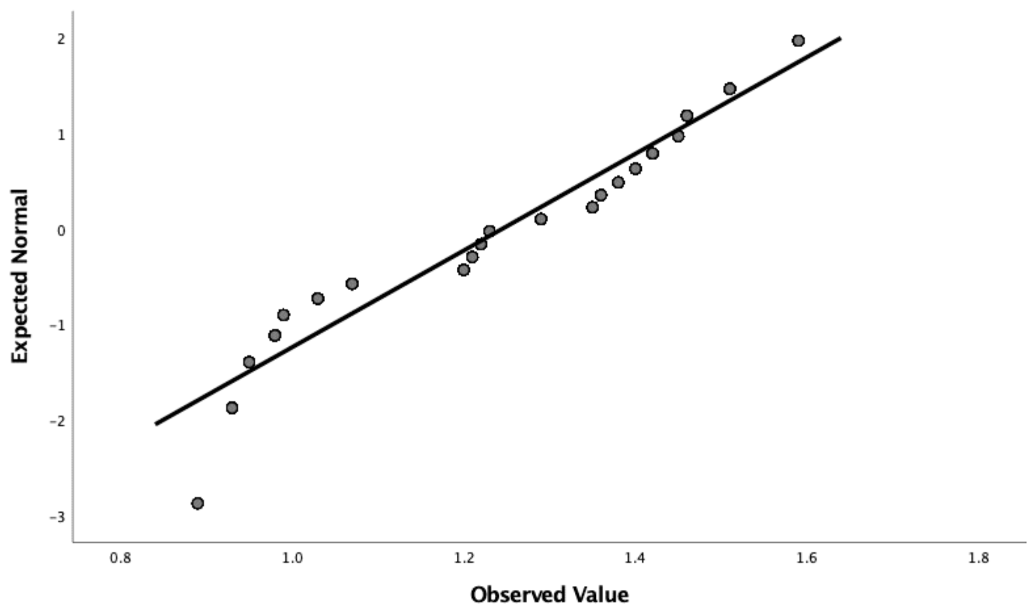


Figure 16

Yelp Visits Q-Q Plot

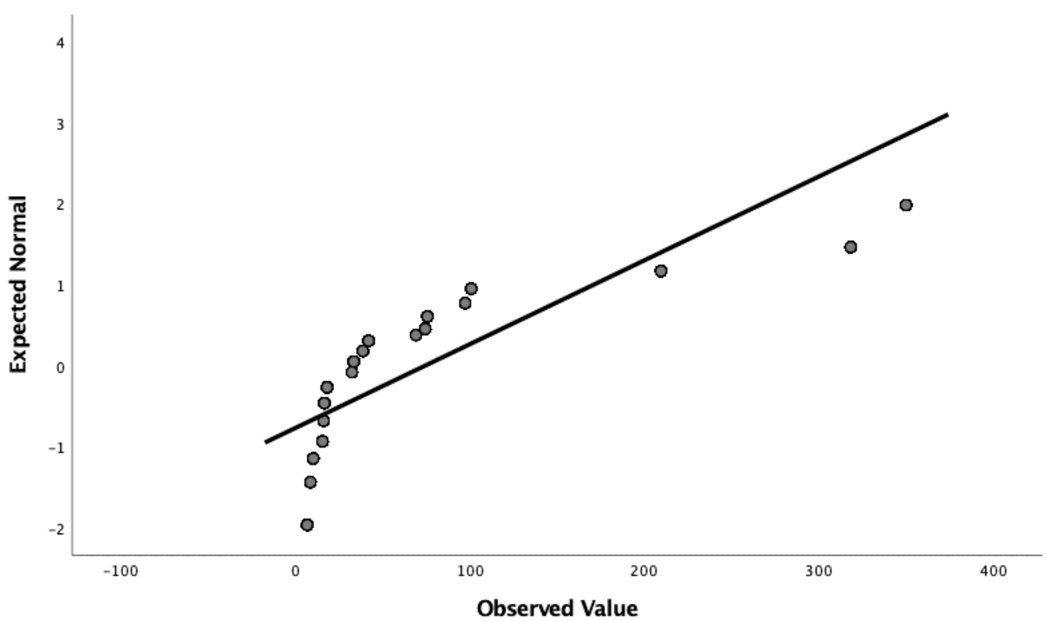


Figure 17

Yelp Unique Visitors Q-Q Plot

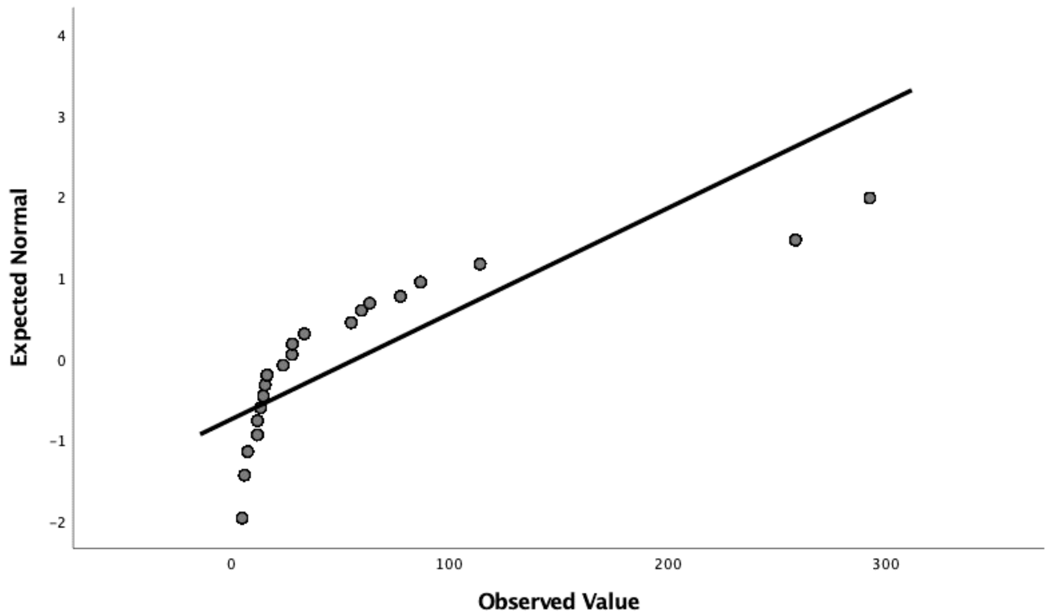


Figure 18

Yelp Pages Per Visit Q-Q Plot

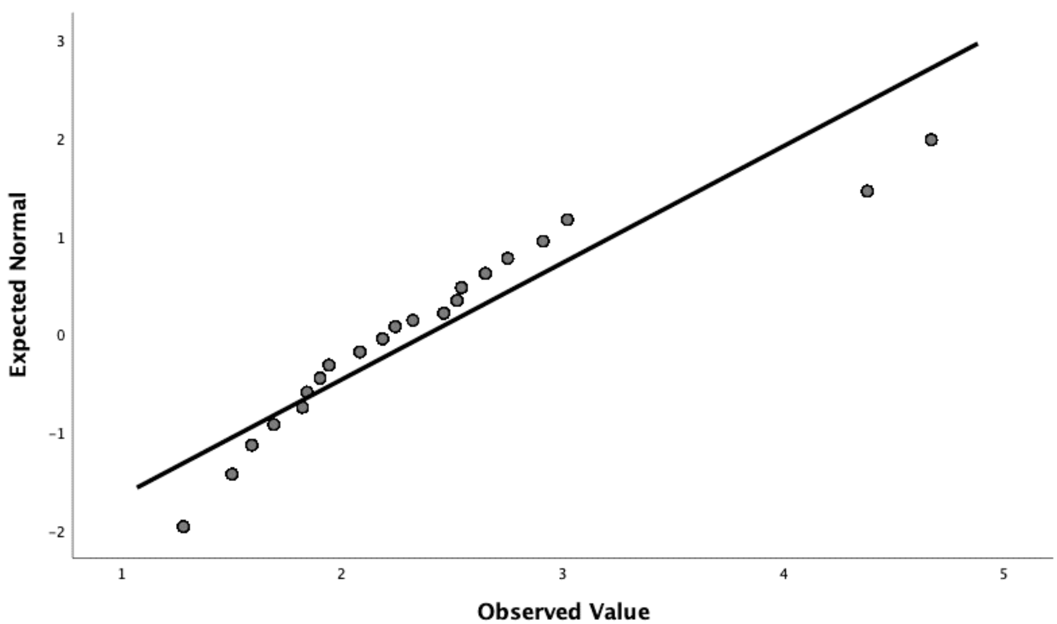


Figure 19

Yelp Average Visit Duration Q-Q Plot

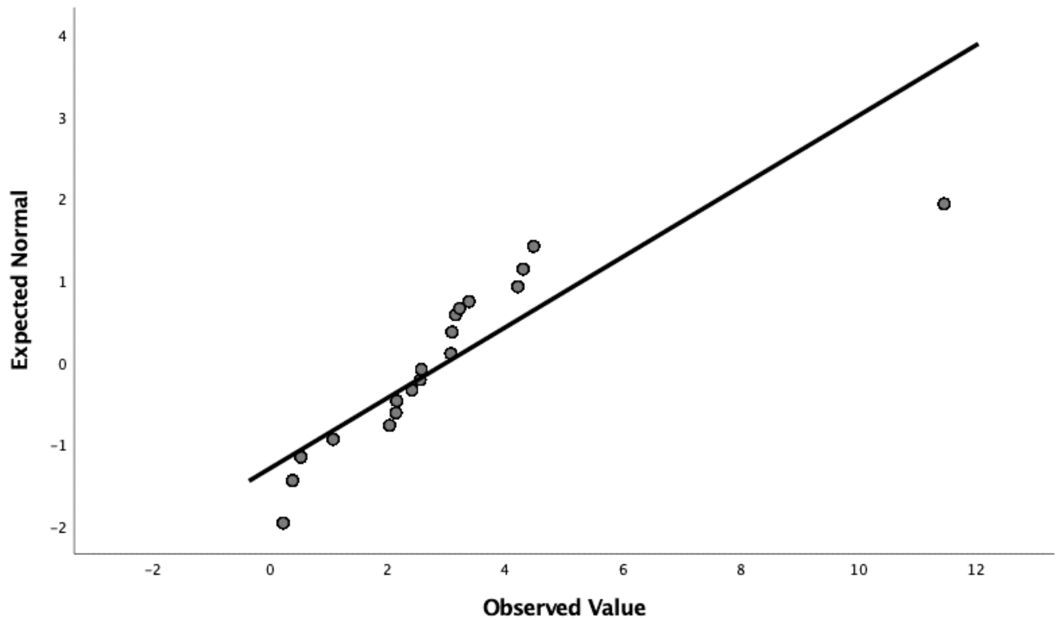


Figure 20

Yelp Percent Spill-in Q-Q Plot

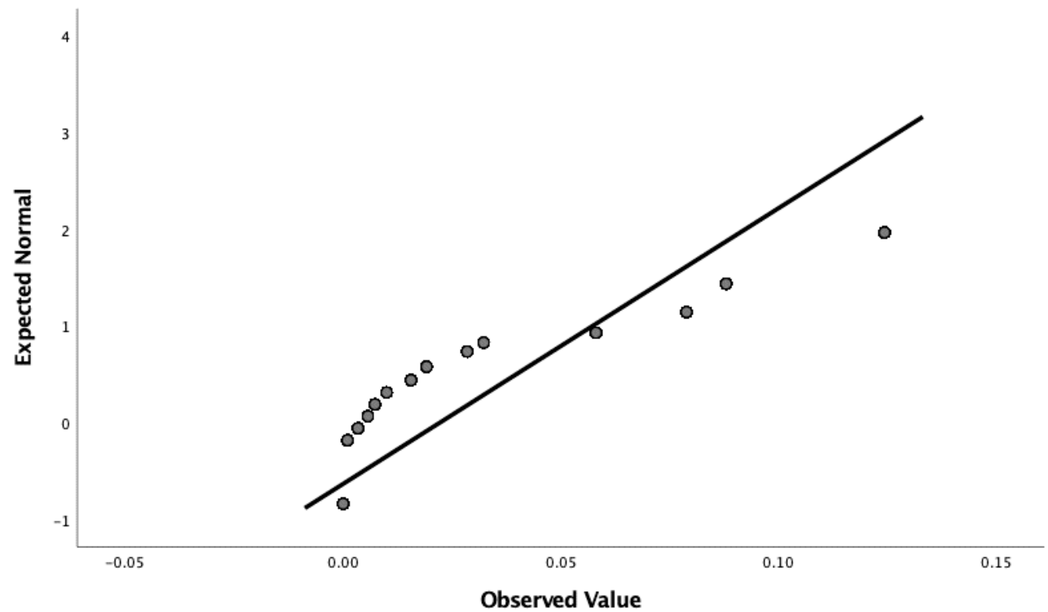


Figure 21

Restaurant Units Q-Q Plot

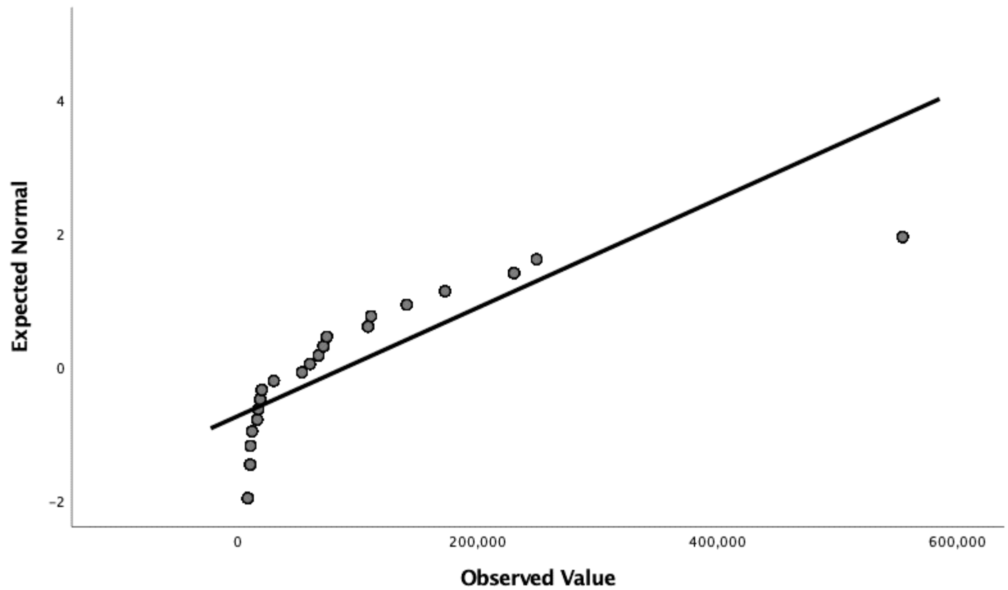


Figure 22

Restaurant Sales Q-Q Plot

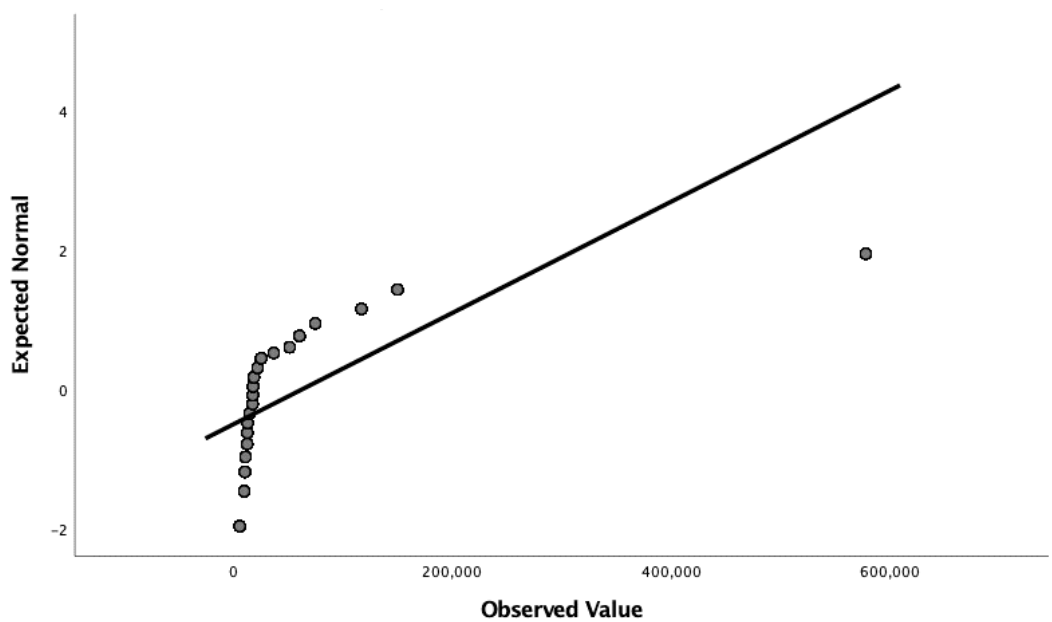
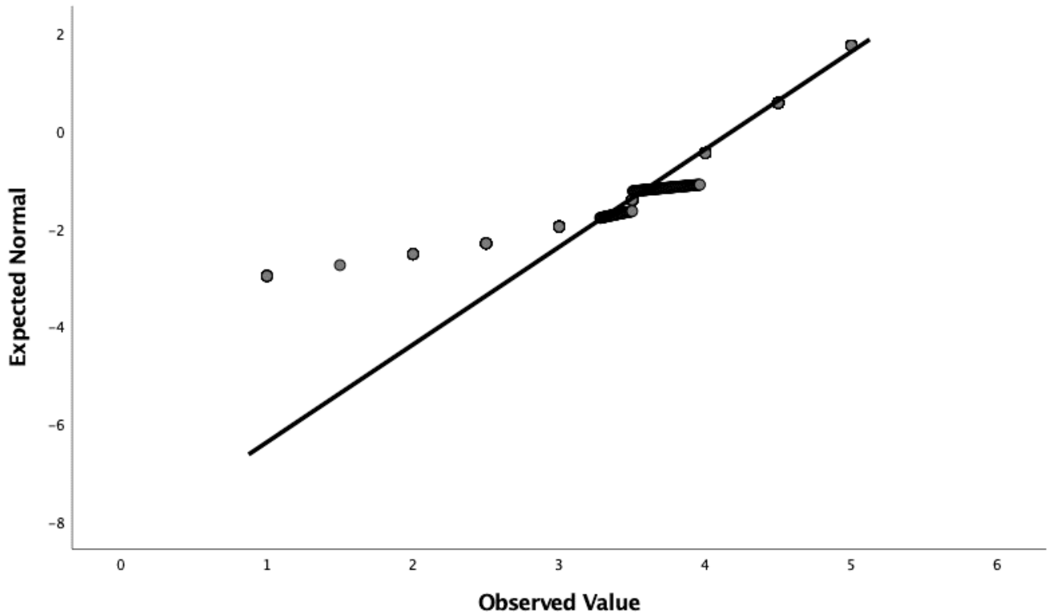


Figure 23

Valence Q-Q Plot



A visual review of the scatterplots evaluated linearity. The scatterplots showed no obvious nonlinear relationships or patterns between the predictor (measures of country culture and country demographics) and response (restaurant eWOM valence ratings) variables. Homoscedasticity was also assessed by visual inspection of the scatterplots of restaurant eWOM valence ratings versus the predictor variables (measurements of country culture and country demographics). The data were homoscedastic because of the absence of funneling (see Figures 24 through 41).

Figure 24

Power Distance Versus Valence Scatterplot

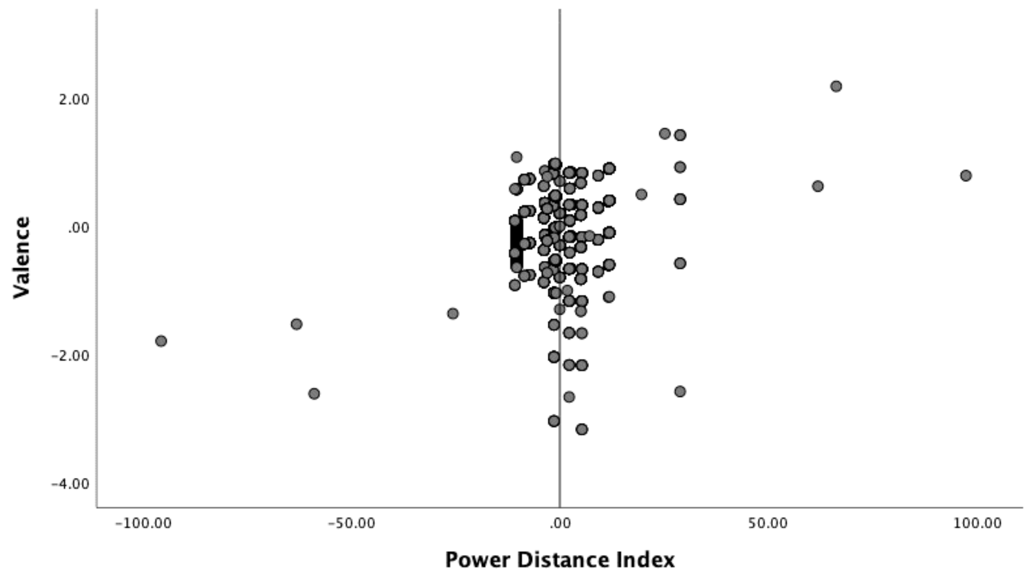


Figure 25

Individualism/Collectivism Versus Valence Scatterplot

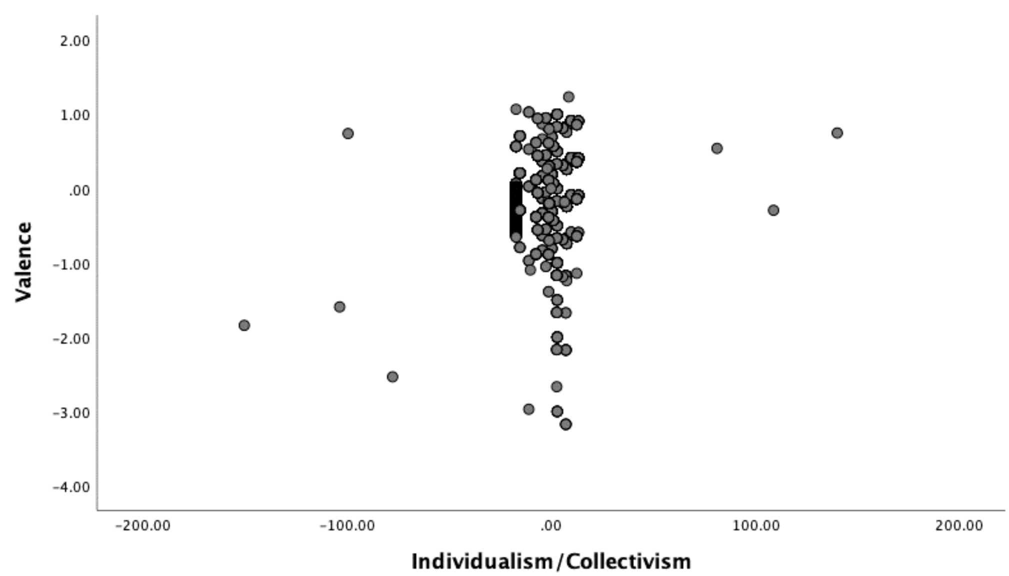


Figure 26

Uncertainty Avoidance Versus Valence Scatterplot

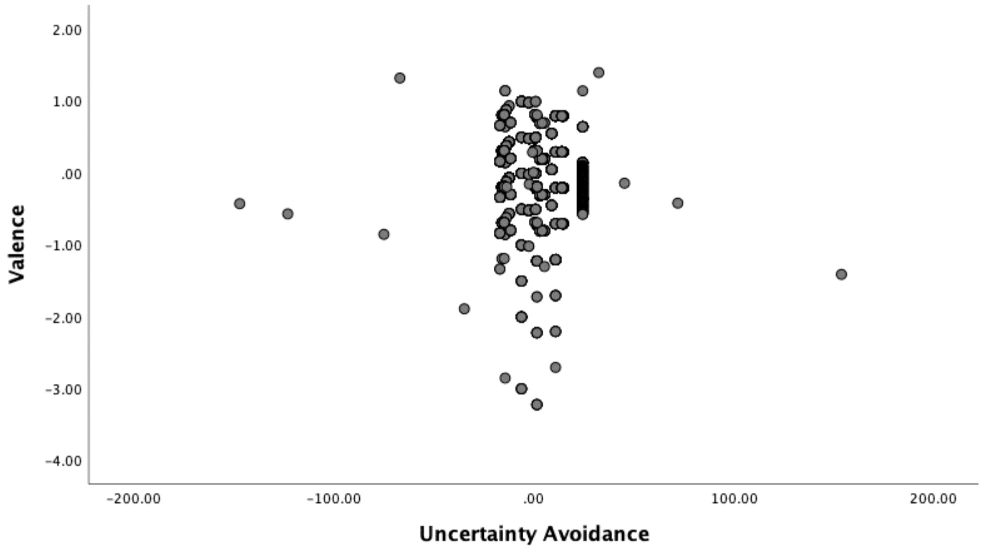


Figure 27

Masculinity/Femininity Versus Valence Scatterplot

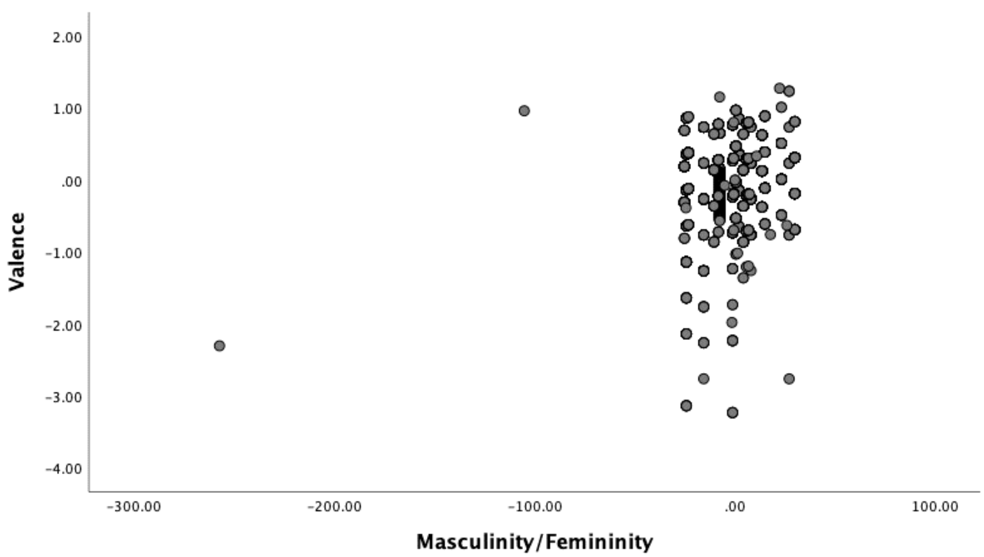


Figure 28

Long/Short-Term Orientation Versus Valence Scatterplot

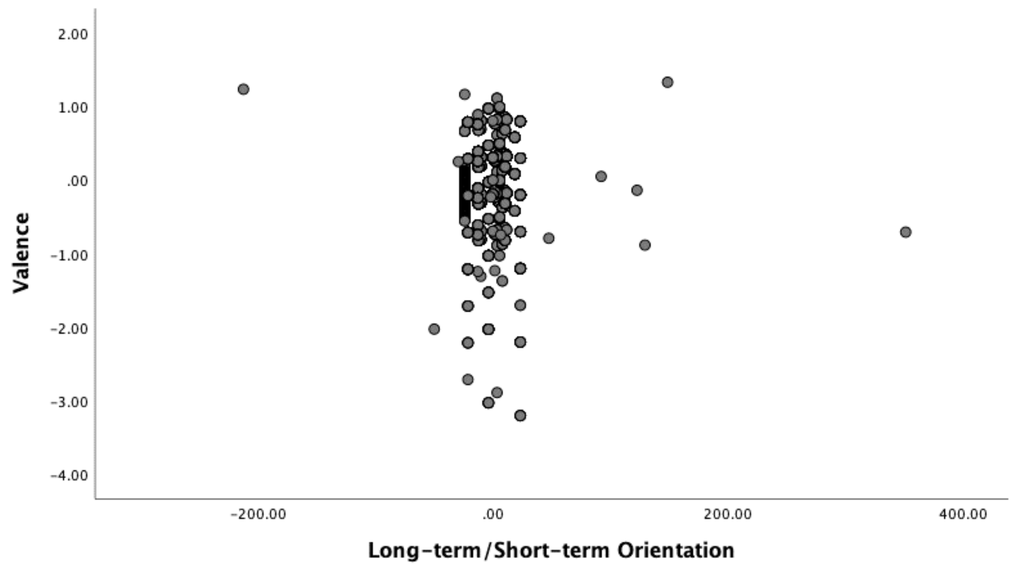


Figure 29

Indulgence Versus Restraint Scatterplot

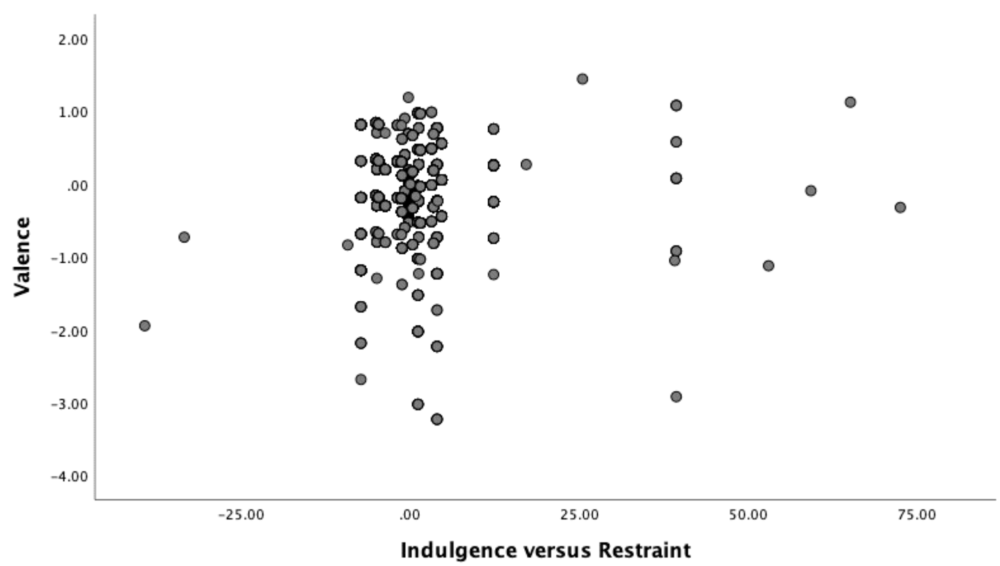


Figure 30

Population Versus Valence Scatterplot

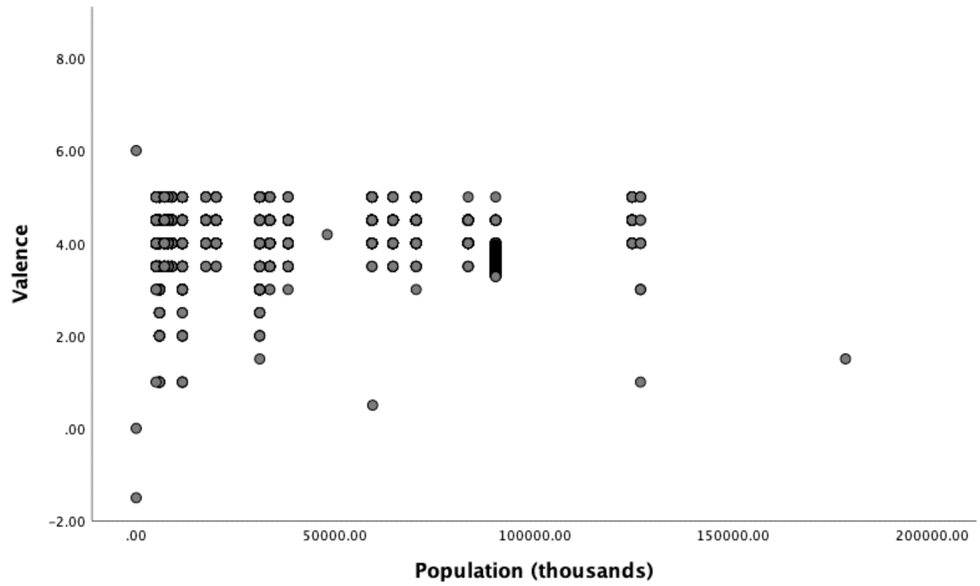


Figure 31

Gross Domestic Product per Capita Versus Valence Scatterplot

Figure 32

Mobile Device Penetration Versus Valence Scatterplot

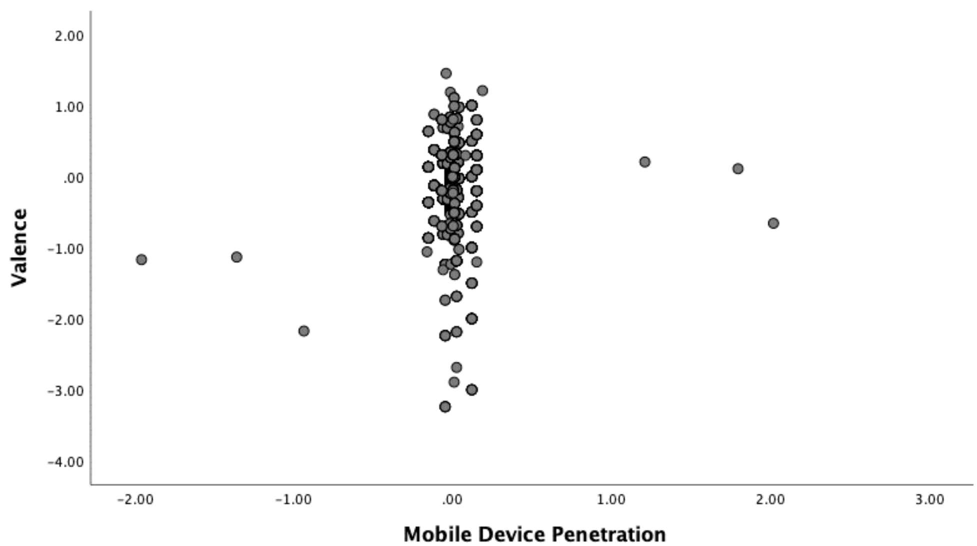


Figure 33

Internet Penetration Versus Valence Scatterplot

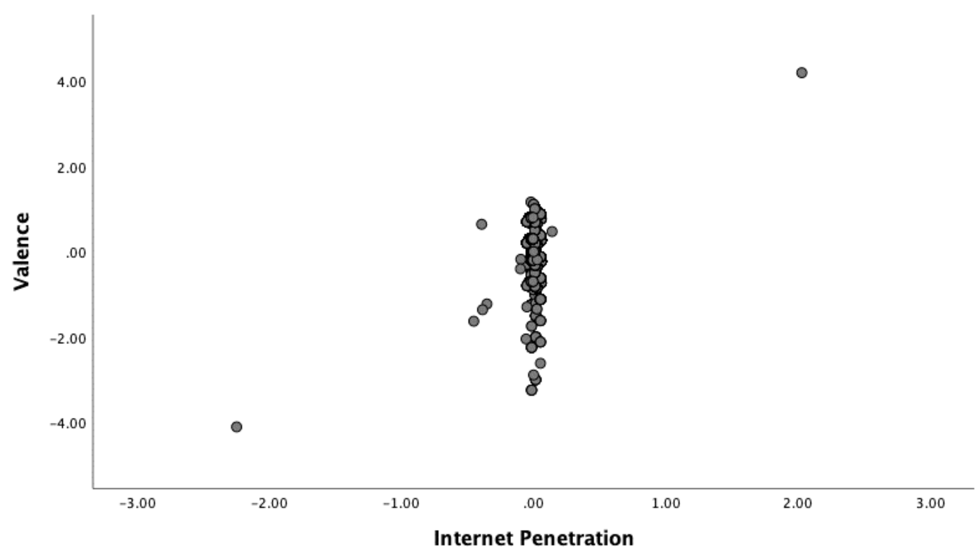


Figure 34

Social Media Use Versus Valence Scatterplot

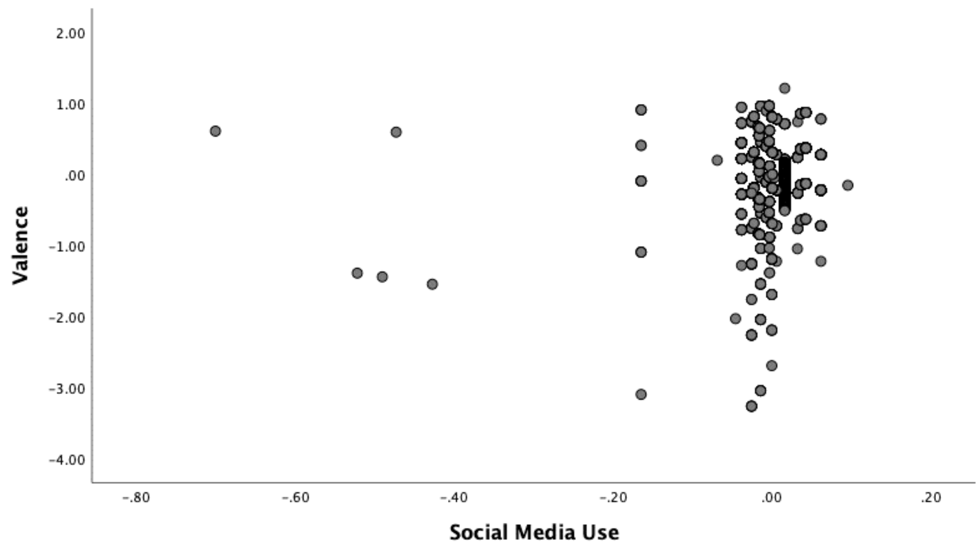


Figure 35

Restaurant Units Versus Valence Scatterplot

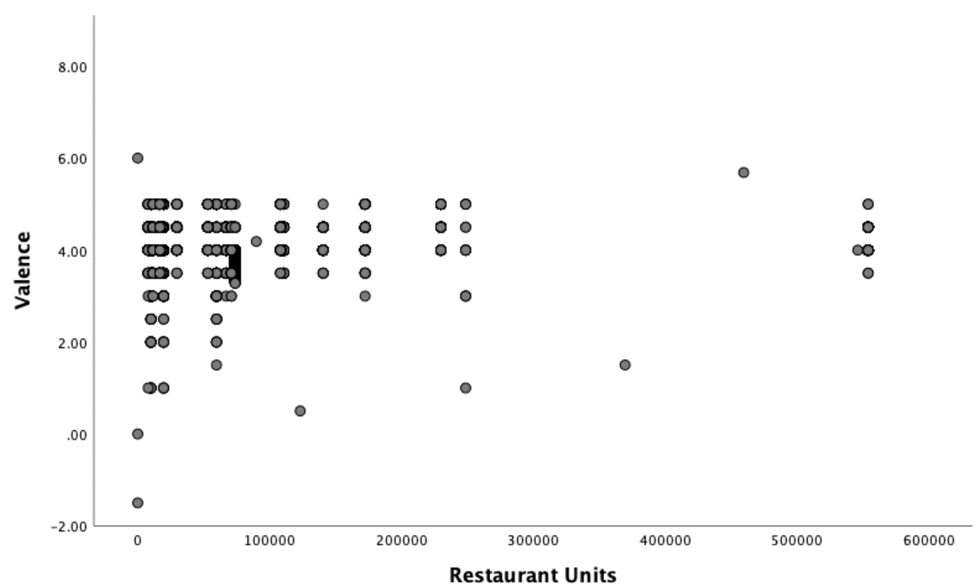


Figure 36

Restaurant Sales Versus Valence Scatterplot

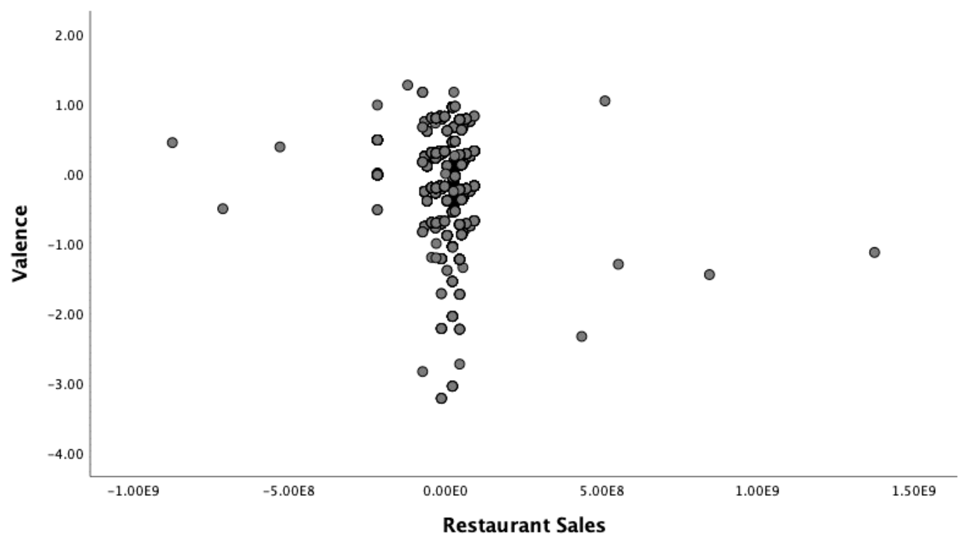


Figure 37

Yelp Visits Versus Valence Scatterplot

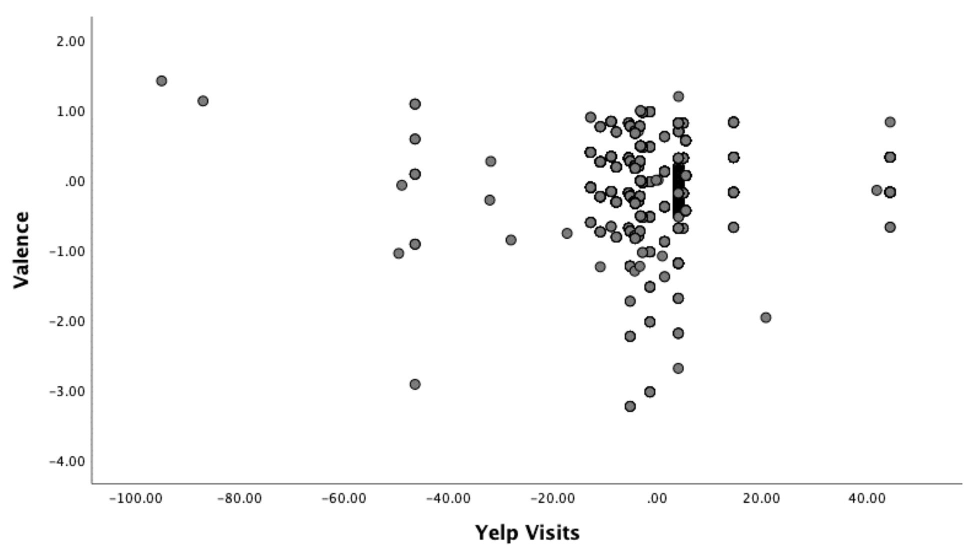


Figure 38

Yelp Unique Visitors

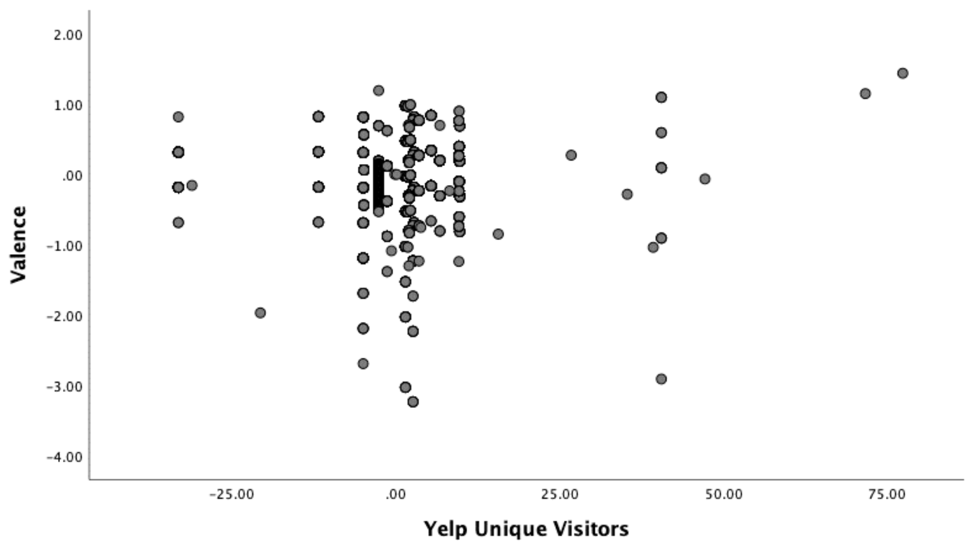


Figure 39

Yelp Pages per Visit Versus Valence Scatterplot

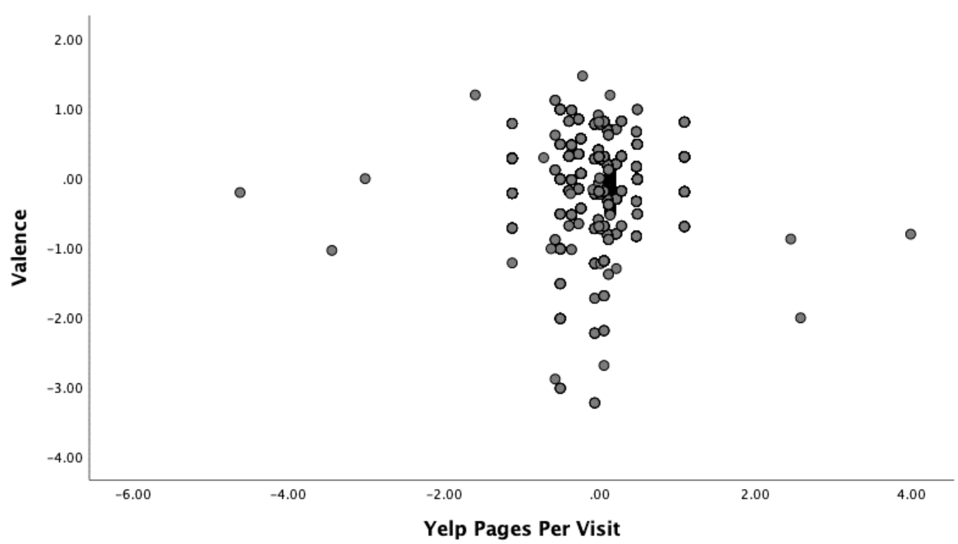


Figure 40

Yelp Average Visit Duration

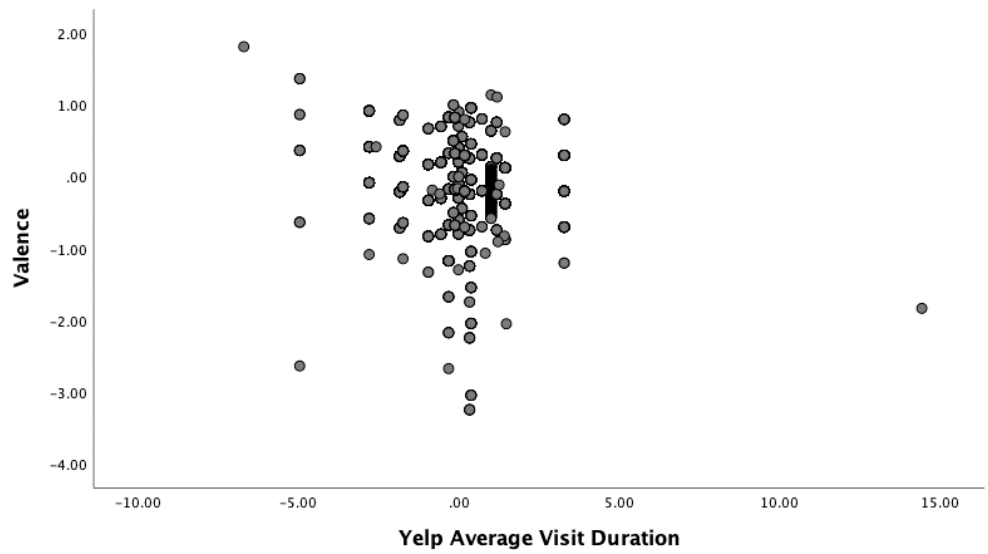
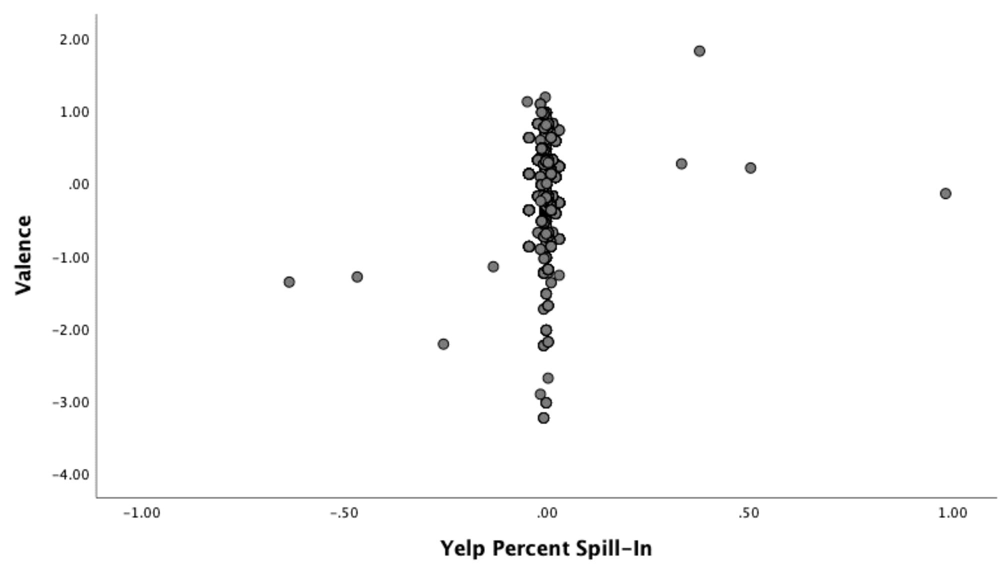


Figure 41

Yelp Spill-In Versus Valence



Research Question 1

The first research question was, what is the relationship between country culture and restaurant eWOM valence ratings? The null hypothesis was that there is no significant relationship between country culture and restaurant eWOM valence ratings. The alternative hypothesis was that there is a significant relationship between country culture and restaurant eWOM valence ratings. A Pearson product-moment correlation was conducted using SPSS to determine the relationship and significance between six measures of country culture and one measure of restaurant eWOM valence ratings (N = 3,659). Prior analyses met the correlation assumptions for two continuous variables, linearity, no concern with significant outliers, and normality.

The results suggest that 17 out of 21 correlations were statistically significant and were greater or equal to a small correlation of $r(3,657) = +.08$, $p < .05$. The relationship between power distance and individualism/collectivism had the strongest correlation with $r(3,657) = -.68$, $p < .05$. In general, the results suggested that measures of country culture including masculinity/femininity, long/short-term orientation, and indulgence/restraint had a relationship with restaurant eWOM valence ratings; however, power distance, individualism/collectivism, and uncertainty avoidance did not have a relationship with restaurant eWOM valence ratings (see Table 15). Because there were statistically significant relationships between some of the measures of country culture and restaurant eWOM valence ratings, I rejected the null hypothesis.

Table 15

Pearson Correlations for Country Culture Variables and eWOM Valence Ratings

	VAL	PDI	IDV/CLV	MF	UAI	LTO/STO
PDI	0.02					
IDV/CLV	0.01	-0.68				
MAS/FEM	0.11	0.19	-0.10			
UAI	0.02	0.15	0.08	0.44		
LTO/STO	0.16	0.11	-0.27	0.04	0.30	
IVR	-0.10	-0.54	0.41	-0.47	-0.45	-0.38

Note. N = 3,659; correlation is significant when bold.

Research Question 2

The second research question was, what is the relationship between country demographics and restaurant eWOM valence ratings? The null hypothesis was that there is no significant relationship between country demographics and restaurant eWOM valence ratings. The alternative hypothesis was that there is a significant relationship between country demographics and restaurant eWOM valence ratings. A Pearson product-moment correlation was conducted using SPSS to determine the relationship and significance between 12 measures of country demographics and one measurement for restaurant eWOM valence ratings to determine the relationship between the stated variables with N = 3,659. Prior analyses met the correlation assumptions for two continuous variables, linearity, no concerns from significant outliers, and normality.

The results suggested that 68 out of 78 correlations were statistically significant and were greater or equal to a small correlation $r(3,657) = -.023$, $p < .05$. The relationship between restaurant units and restaurant sales had the strongest correlation $r(3,657) = +.945$, $p < .05$. In general, the results suggested that measures of country demographics including population, gross domestic product, social media use, Yelp unique visitors, Yelp average visit duration, Yelp percent spill-in, restaurant units, and restaurant sales have relationships with restaurant eWOM ratings valence. However, Internet penetration, mobile device penetration, Yelp visits, and Yelp pages per visit did not have a relationship with restaurant eWOM ratings valence (see Table 16). Because there were statistically significant relationships between some of the measures of country demographics and restaurant eWOM valence ratings, I rejected the null hypothesis.

Table 16

Pearson Correlations for Country Demographic Variables and eWOM Valence Ratings

	VAL	POP	GDP	INP	SMU	MDP	VIS	UVI	PPV	AVD	PSI	RU
POP	**0.050**											
GDP	**0.049**	**-0.121**										
INP	0.018	**-0.229**	**0.727**									
SMU	**-0.030**	**-0.447**	**0.060**	**0.241**								
MDP	0.021	**-0.061**	**-0.195**	**-0.073**	**-0.050**							
VIS	0.058	**0.135**	0.151	**0.109**	**0.183**	**0.161**						
UVI	**0.059**	**0.368**	**-0.056**	**-0.065**	**-0.278**	**-0.177**	0.481					
PPV	0.005	**-0.067**	**0.313**	**0.220**	**0.121**	**0.281**	**-.023**	-0.032				
AVD	**-0.094**	**0.086**	**-0.273**	**-0.294**	**0.095**	**-0.193**	**-.067**	**0.126**	**0.185**			
PSI	**0.032**	**0.046**	**0.466**	**0.131**	**0.116**	**-0.403**	**-.300**	**-0.087**	0.016	0.024		
RU	**0.088**	**0.973**	**-0.052**	**-0.206**	**-0.419**	**-0.063**	**-.210**	**0.343**	0.001	**0.103**	**0.094**	
RS	**0.065**	**0.910**	**0.195**	**0.063**	**-0.380**	**-0.145**	**.447**	**0.309**	**0.091**	**0.073**	**0.197**	**0.945**

Note. *N* = 3,659; correlation significant when bold.

Research Question 3

The third research question was, what is the relationship between country culture and country demographics on restaurant eWOM valence ratings? The null hypothesis was that there is no significant relationship between country culture and country demographics on restaurant eWOM valence ratings. The alternative hypothesis was that there is a significant relationship between country culture and country demographics on restaurant eWOM valence ratings. A Pearson product-moment correlation was conducted using SPSS to determine the relationship and significance between 12 measures of country demographics and one measurement for restaurant eWOM valence ratings to determine the relationship between the stated variables (N = 3,659). Prior analyses met the correlation assumptions for two continuous variables, linearity, no concerns from significant outliers, and normality.

The results suggested that 156 out of 171 correlations were statistically significant and were greater or equal to a small correlation $r(3{,}657) = -.023$, $p < .05$. The relationship between restaurant units and restaurant sales had the strongest positive correlation $r(3{,}657) = +.945$, $p < .05$. In general, the results suggested that measures of country culture including masculinity/femininity, long/short-term orientation, and indulgence vs. restraint have relationships with restaurant eWOM valence ratings; however, power distance, individualism/collectivism, and uncertainty avoidance did not have relationships with restaurant eWOM valence ratings. Additionally, measures of country demographics, including population, gross domestic product per capita, social media use, Yelp unique visitors, Yelp average visit duration, Yelp percent spill-in, restaurant units, and restaurant sales, have relationships with restaurant eWOM valence ratings. Internet penetration, mobile device penetration, and Yelp pages per visit did not have a relationship with restaurant eWOM valence ratings (see Table 17). Because there were statistically significant relationships between some of the measures of country culture and country demographics on restaurant eWOM valence ratings, I rejected the null hypothesis.

Table 17

Pearson Correlations for Country Culture and Country Demographics on Restaurant eWOM Valence Ratings

	VAL	PDI	IDV /CLV	MAS /FEM	UAI	LTO /STO	IVR	POP	GDP	INP	SMU	MDP	VIS	UVI	PPV	AVD	PSI	RU
PDI	0.020																	
IDV/CLV	0.006	**-0.682**																
MAS/FEM	**0.111**	**0.191**	**-0.104**															
UAI	0.020	**0.152**	**0.079**	**0.436**														
LTO/STO	**0.156**	**0.108**	**-0.269**	**0.035**	**0.298**													
IVR	**-0.103**	**-0.543**	**0.410**	**-0.468**	**-0.449**	**-0.383**												
POP	**0.050**	**0.071**	**0.117**	**0.368**	**0.224**	**-0.139**	**-0.130**											
GDP	**0.049**	**-0.649**	**0.471**	**-0.086**	**-0.387**	**0.154**	**0.431**	**-0.121**										
INP	0.018	**-0.690**	**0.457**	**-0.351**	**-0.179**	**0.375**	**0.447**	**-0.229**	**0.727**									
SMU	**-0.030**	-0.025	**-0.333**	**-0.544**	**-0.534**	**0.108**	**0.493**	**-0.447**	**0.060**	**0.241**								
MDP	0.021	0.014	**-0.291**	**0.103**	**-0.169**	**0.028**	**-0.254**	**-0.061**	**-0.195**	**-0.073**	**-0.050**							
VIS	**0.058**	**0.135**	**0.151**	**0.109**	**0.183**	**0.161**	**-0.309**	**0.481**	-0.023	**-0.067**	**-0.300**	**-0.210**						
UVI	**0.059**	**0.139**	**0.116**	**0.103**	**0.220**	**0.214**	**-0.359**	**0.368**	**-0.056**	**-0.065**	**-0.278**	**-0.177**	**0.987**					
PPV	0.005	**-0.157**	**0.303**	**-0.329**	**-0.475**	**-0.223**	**0.422**	**-0.067**	**0.313**	**0.220**	**0.121**	**0.281**	0.001	**-0.032**				
AVD	**-0.094**	**0.551**	**-0.167**	**-0.069**	**-0.245**	**-0.306**	**0.058**	**0.086**	**-0.273**	**-0.294**	**0.095**	**-0.193**	**0.164**	**0.126**	**0.185**			
PSI	**0.032**	**-0.174**	0.027	**0.062**	**-0.461**	**-0.196**	**0.177**	**0.046**	**0.466**	**0.131**	**0.116**	**-0.403**	**-0.043**	**-0.087**	0.016	0.024		
RU	**0.088**	**0.096**	**0.127**	**0.340**	**0.119**	**-0.119**	**-0.118**	**0.973**	**-0.052**	**-0.206**	**-0.419**	**-0.063**	**0.469**	**0.343**	0.001	**0.103**	**0.094**	
RS	**0.065**	**-0.120**	**0.309**	**0.227**	0.025	**-0.098**	**0.045**	**0.910**	**0.195**	**0.063**	**-0.380**	**-0.145**	**0.447**	**0.309**	**0.091**	**0.073**	**0.197**	**0.945**

Note. N = 3,659; correlation is significant when bold.

Research Question 4

The fourth research question was, what country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings? The null hypothesis was that there are no country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings. The alternative hypothesis was that there are country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings. I conducted my analysis for RQ4 over six stages of MLR analysis using SPSS. The following section details my regression analysis, model-building process, and the appropriate statistical results.

Stage 1

Prior analyses satisfactorily addressed the MLR assumptions for two continuous variables, linearity, homoscedasticity, and no concerns from significant outliers. While the prior analyses found some variables appeared to have slightly skewed distributions due to the large sample size and the central limit theorem, there was no concern for violations of normality. The remaining MLR assumptions for independence and multicollinearity were assessed in Stage 1 of the RQ4 analysis.

- Independence: Independence was assessed using the Durbin-Watson test on all predictor and response variables. The Durbin-Watson statistic of 1.691 (see Table 18) is considered within an acceptable range for independence (Field, 2009); therefore, the data met the assumption for independence.

Table 18

Stage 1 Assumption Screening Model Summary

Model	*R*	R^2	Adjusted R^2	*SE*	Durbin-Watson
1	.303	0.092	0.087	0.4782	1.691

Note. Predictors: RS, UAI, INP, MDP, UVI, AVD, PPV, MAS/FEM, LTO/STO, SMU, PSI, IDV/CLV, PDI, IVR, GDP, POP, RU, VIS. Response Variable: VAL.

- Multicollinearity: During the Stage 1 MLR analysis, several predictor variables were found to be highly correlated with each other. I used a combination of the highest VIF, high correlation, and subject matter expertise to sequentially eliminate predictor variables that appeared to duplicate information in another predictor variable: Yelp visits, restaurant units, population, indulgence vs. restraint, and mobile device penetration. After six rounds of SPSS standard regression, all VIFs < 10.

After confirming that my data met the assumptions for MLR, the SPSS enter method was used to conduct a final screening of my predictor variables. Twelve predictors remained, and the initial overall regression model was significant, $F(12, 3646) = 25.9$, $p < .001$, $R^2 = .079$ (see Tables 19 and 20). When evaluating the individual predictor variables, two were found to be not significant, INP and PPV; however, all VIF factors were < 10 (see Table 21).

Table 19

Stage 1 Final Screening Model Summary

Model	*R*	R^2	Adjusted R^2	*SE*
1	.280	0.079	0.076	0.4813

Note. Predictors: RS, UAI, INP, AVD, PPV, LTO/STO, MAS/FEM, PSI, SMU, IDV/CLV, GDP, PDI

Table 20

Stage 1 Final Screening ANOVA Table

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	71.990	12	5.999	25.900	<.001
	Residual	844.522	3646	0.232		
	Total	916.513	3658			

Note. Predictors: RS, UAI, INP, AVD, PPV, LTO/STO, MAS/FEM, PSI, SMU, IDV/CLV, GDP, PDI. Response variable: VAL.

Table 21

Stage 1 Final Screening Summary of Coefficients

Model		Unstandardized coefficients β	Unstandardized coefficients *SE*	Standardized coefficients β	*t*	Sig.	Collinearity statistics Tolerance	Collinearity statistics VIF
1	Constant	3.376	0.326		10.370	0.000		
	PDI	0.004	0.001	0.164	3.419	0.001	0.109	9.153
	IND/CLV	0.007	0.001	0.321	9.260	0.000	0.211	4.741
	MAS/FEM	0.005	0.001	0.196	8.184	0.000	0.439	2.276
	UAI	-0.005	0.001	-0.243	-7.132	0.000	0.218	4.595
	LTO/STO	0.006	0.001	0.307	9.233	0.000	0.229	4.365
	GDP	-3.817	0.000	-0.171	-4.576	0.000	0.181	5.536
	INP	-0.454	0.295	-0.065	-1.541	0.123	0.144	6.935
	SMU	0.596	0.231	0.068	2.580	0.010	0.363	2.752
	PPV	0.022	0.013	0.037	1.670	0.095	0.517	1.933
	AVD	-0.036	0.006	-0.167	-5.813	0.000	0.307	3.254
	PSI	0.921	0.327	0.065	2.813	0.005	0.479	2.086
	RS	1.464	0.000	0.037	1.947	0.052	0.715	1.398

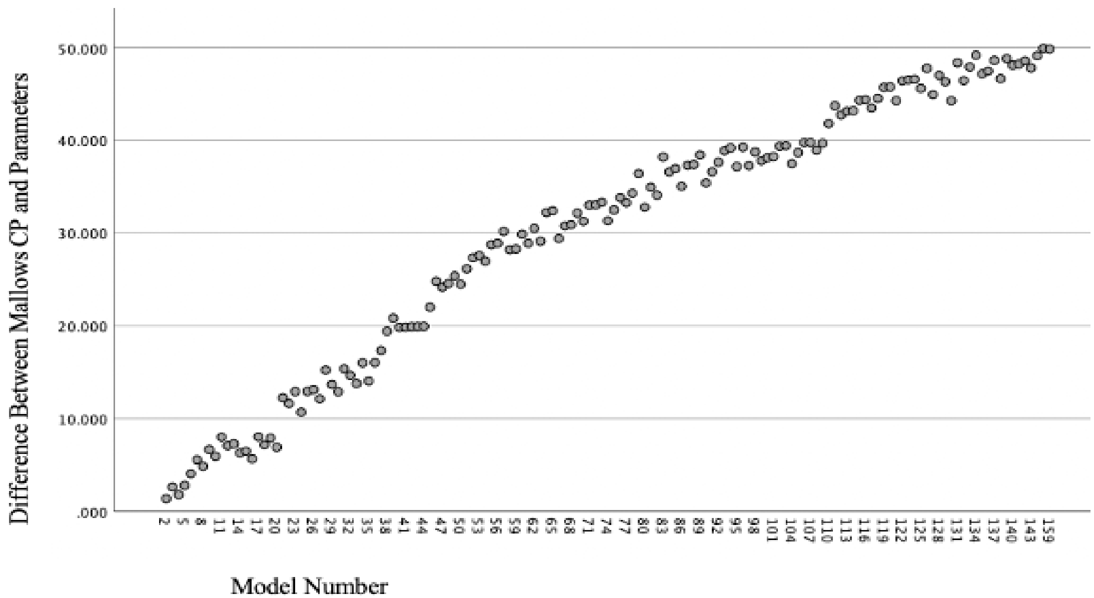
Note. Response variable: VAL

Stage 2

In Stage 2, a best-subsets regression analysis was conducted to find the best interim combination of predictor variables based on three criteria: Mallows's C_P, adjusted R^2, and a combination of parsimony and residual analysis (see Figure 42). After each round, the models meeting the criteria were noted. Specifically included were combinations of predictor variables that could be candidates for the final model.

Figure 42

Stage 2 Best-Subsets Regression



Stage 3

During Stage 3, a series of statistical stepwise regression analyses were conducted (backward and forward), which resulted in four models. All four models statistically significantly predicted restaurant eWOM valence ratings. Additionally, all four models had an R^2 of nearly 15% with an adjusted R^2 of 14% (see Tables 22 and 23). I evaluated the significance of Stage 3 individual predictor variables (see Table 24). In the first model, one predictor variable and five 2FI's were found to be not significant. In the second model, one predictor variable and three 2FI's were not significant. In the third model, four 2FI's were found to be not significant. In the fourth model for Stage 3, one 2FI was found to be not significant.

Table 22

Stage 3 Model Summary

Model	R	R^2	Adjusted R^2	SE
1	.385	0.148	0.143	0.4633
2	.384	0.148	0.143	0.4633
3	.384	0.148	0.143	0.4633
4	.384	0.147	0.143	0.4633

Note. Response variable for all models: VAL

Model 1. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, SMU, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, IDV/CLV_AVD, PDI_LTO/STO, MAS/FEM_PPV, UAI_PSI, PDI_AVD, MAS/FEM_UAI
Model 2. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, SMU, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, PDI_LTO/STO, MAS/FEM_PPV, UAI_PSI, PDI_AVD, MAS/FEM_UAI

Model 3. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, PDI_LTO/STO, MAS/FEM_PPV, UAI_PSI, PDI_AVD, MAS/FEM_UAI

Model 4. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, PDI_LTO/STO, UAI_PSI, PDI_AVD, MAS/FEM_UAI

Table 23

Stage 3 ANOVA Table

	Model	*SS*	*df*	*MS*	*F*	Sig.
1	Regression	135.524	20	6.776	31.565	<.001
	Residual	780.988	3638	0.215		
	Total	916.513	3658			
2	Regression	135.435	19	7.128	33.210	<.001
	Residual	781.078	3639	0.215		
	Total	916.513	3658			
3	Regression	135.282	18	7.516	35.018	<.001
	Residual	781.231	3640	0.215		
	Total	916.513	3658			
4	Regression	135.079	17	7.946	37.023	<.001
	Residual	781.434	3641	0.215		
	Total	916.513	3658			

Note. Response variable all models: VAL

Model 1. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, SMU, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, IDV/CLV_AVD, PDI_LTO/STO, MAS/FEM_PPV, UAI_PSI, PDI_AVD, MAS/FEM_UAI
Model 2. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, SMU, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, PDI_LTO/STO, MAS/FEM_PPV, UAI_PSI, PDI_AVD, MAS/FEM_UAI
Model 3. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, PDI_LTO/STO, MAS/FEM_PPV, UAI_PSI, PDI_AVD, MAS/FEM_UAI
Model 4. Predictors: PSI_RS, UAI_PPV, INP, LTO/STO_AVD, MAS/FEM_LTO/STO, GDP_PSI, SMU_PPV, IDV/CLV_MAS/FEM, IDV/CLV_LTO/STO, PDI_GDP, LTO/STO_PSI, LTO/STO_RS, PDI_IDV/CLV, PDI_LTO/STO, UAI_PSI, PDI_AVD, MAS/FEM_UAI

Table 24

Stage 3 Summary of Coefficients

Model		Unstandardized coefficients		Standardized coefficients		
		β	*SE*	Beta	*t*	*Sig.*
1	(Constant)	3.686	0.475		7.763	0.000
	INP	-1.395	0.342	-0.198	-4.074	0.000
	SMU	0.465	0.487	0.053	0.954	0.340
	PDI_IDV/CLV	0.000	0.000	-0.308	-3.212	0.001
	PDI_LTO/STO	0.000	0.000	1.118	8.654	0.000
	PDI_GDP	-1.303	0.000	-0.249	-2.774	0.006
	PDI_AVD	0.002	0.000	1.098	9.440	0.000
	IDV/CLV_MAS/FEM	0.000	0.000	0.768	8.990	0.000
	IDV/CLV_LTO/STO	0.000	0.000	0.973	9.285	0.000
	IDV/CLV_AVD	0.000	0.000	0.047	0.647	0.518
	MAS/FEM_UAI	5.023	0.000	0.207	1.514	0.130
	MAS/FEM_LTO/STO	0.000	0.000	-0.908	-3.574	0.000
	MAS/FEM_PPV	-0.001	0.001	-0.167	-1.425	0.154
	UAI_PPV	-0.002	0.001	-0.204	-1.984	0.047
	UAI_PSI	-0.084	0.045	-0.227	-1.872	0.061
	LSO_AVD	-0.006	0.001	-1.368	-10.564	0.000
	LSO_PSI	0.089	0.034	0.267	2.631	0.009
	LSO_RS	3.911	0.000	0.336	4.757	0.000
	GDP_PSI	6.711	0.000	0.341	3.553	0.000
	SMU_PPV	0.330	0.039	0.464	8.550	0.000
	PSI_RS	-1.378	0.000	-0.202	-2.771	0.006

		Unstandardized coefficients		Standardized coefficients		
	Model	*β*	*SE*	Beta	*t*	*SE*
2	(Constant)	3.698	0.474		7.794	0.000
	INP	-1.351	0.336	-0.192	-4.026	0.000
	SMU	0.402	0.477	0.046	0.842	0.400
	PDI_IDV/CLV	0.000	0.000	-0.328	-3.588	0.000
	PDI_LTO/STO	0.000	0.000	1.156	10.044	0.000
	PDI_GDP	-1.243	0.000	-0.238	-2.700	0.007
	PDI_AVD	0.002	0.000	1.061	10.459	0.000
	IDV/CLV_MAS/FEM	0.000	0.000	0.778	9.231	0.000
	IDV/CLV_LTO/STO	0.000	0.000	0.977	9.340	0.000
	MAS/FEM_UAI	5.932	0.000	0.244	1.974	0.049
	MAS/FEM_LTO/STO	0.000	0.000	-1.004	-4.856	0.000
	MAS/FEM_PPV	-0.001	0.001	-0.130	-1.271	0.204
	UAI_PPV	-0.002	0.001	-0.228	-2.373	0.018
	UAI_PSI	-0.067	0.036	-0.181	-1.844	0.065
	LTO/STO_AVD	-0.006	0.000	-1.309	-14.257	0.000
	LTO/STO_PSI	0.076	0.027	0.228	2.799	0.005
	LTO/STO_RS	4.125	0.000	0.354	5.479	0.000
	GDP_PSI	6.337	0.000	0.322	3.524	0.000
	SMU_PPV	0.336	0.038	0.472	8.914	0.000
	PSI_RS	-1.432	0.000	-0.210	-2.922	0.003

		Unstandardized coefficients		Standardized coefficients		
	Model	*β*	*SE*	Beta	*t*	*SE*
3	(Constant)	4.010	0.295		13.577	0.000
	INP	-1.297	0.329	-0.184	-3.938	0.000
	PDI_IDV/CLV	0.000	0.000	-0.368	-4.734	0.000
	PDI_LTO/STO	0.000	0.000	1.174	10.405	0.000
	PDI_GDP	-1.168	0.000	-0.223	-2.586	0.010
	PDI_AVD	0.002	0.000	1.076	10.783	0.000
	IDV/CLV_MAS/FEM	0.000	0.000	0.749	9.718	0.000
	IDV/CLV_LTO/STO	0.000	0.000	1.011	10.460	0.000
	MAS/FEM_UAI	6.108	0.000	0.251	2.037	0.042
	MAS/FEM_LTO/STO	0.000	0.000	-1.062	-5.452	0.000
	MAS/FEM_PPV	-0.001	0.001	-0.084	-0.973	0.331
	UAI_PPV	-0.002	0.001	-0.237	-2.488	0.013
	UAI_PSI	-0.052	0.032	-0.140	-1.642	0.101
	LTO/STO_AVD	-0.006	0.000	-1.316	-14.385	0.000
	LTO/STO_PSI	0.074	0.027	0.222	2.741	0.006
	LTO/STO_RS	4.144	0.000	0.356	5.506	0.000
	GDP_PSI	5.591	0.000	0.284	3.573	0.000
	SMU_PPV	0.324	0.035	0.455	9.285	0.000
	PSI_RS	-1.526	0.000	-0.224	-3.197	0.001

	Model	Unstandardized coefficients		Standardized coefficients		
		β	*SE*	Beta	*t*	*SE*
4	(Constant)	3.859	0.252		15.346	0.000
	INP	-1.116	0.272	-0.159	-4.100	0.000
	PDI_IDV/CLV	0.000	0.000	-0.376	-4.864	0.000
	PDI_LTO/STO	0.000	0.000	1.228	12.462	0.000
	PDI_GDP	-1.231	0.000	-0.235	-2.753	0.006
	PDI_AVD	0.002	0.000	1.035	11.475	0.000
	IDV/CLV_MAS/FEM	0.000	0.000	0.713	10.538	0.000
	IDV/CLV_LTO/STO	0.000	0.000	1.039	11.266	0.000
	MAS/FEM_UAI	7.612	0.000	0.313	2.962	0.003
	MAS/FEM_LTO/STO	0.000	0.000	-1.164	-7.105	0.000
	UAI_PPV	-0.003	0.001	-0.299	-4.178	0.000
	UAI_PSI	-0.044	0.030	-0.118	-1.432	0.152
	LTO/STO_AVD	-0.006	0.000	-1.289	-14.770	0.000
	LTO/STO_PSI	0.063	0.024	0.187	2.576	0.010
	LTO/STO_RS	4.254	0.000	0.365	5.719	0.000
	GDP_PSI	5.543	0.000	0.281	3.544	0.000
	SMU_PPV	0.318	0.034	0.447	9.257	0.000
	PSI_RS	-1.575	0.000	-0.231	-3.316	0.001

Note. Response variable all models: VAL

Stage 4

During Stage 4, a purposeful sequential regression analysis was conducted using the SPSS enter methods: backward and forward. The Stage 4 model (eight predictor variables and eight 2FIs) statistically significantly predicted restaurant eWOM valence ratings. In the Stage 4 model, $F(16, 3642) = 39.242$, $p < .001$, $R^2 = .147$, and adjusted $R^2 = .143$ (see Tables 25 and 26). When I evaluated the significance of Stage 4 individual predictor variables, three individual predictor variables were found to be not significant:

masculinity versus femininity, uncertainty avoidance index, and social media use (see Table 27).

Table 25

Stage 4 Model Summary

Model	*R*	R^2	Adjusted R^2	*SE*	Durbin-Watson
1	0.383	0.147	0.143	0.4633	1.803

Note. Predictors: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, MAS/FEM, SMU_PPV, SMU, SMU_PSI, PDI, UAI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Response Variable: VAL

Table 26

Stage 4 ANOVA Table

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	134.771	16	8.423	39.242	<.001
	Residual	781.742	3642	0.215		
	Total	916.513	3658			

Note. Response variable: VAL

Stage 5

In Stage 5, the best preliminary models based on the evidence from Stages 1 through 4 were selected for further analysis (met criteria of $Cp < k + 1$ and highest adjusted R^2 of .143 or .144). Four models were chosen, and all models were the same except for some combination of three predictor variables: masculinity versus femininity, uncertainty avoidance, and social media use. SPSS was used to run a series of regression analyses (purposeful sequential regression using the enter method) with various combinations of the remaining predictor variables and 2FIs. All four models statistically significantly predicted restaurant eWOM valence ratings (see Tables 28 and 29). When evaluating the significance of Stage 5 individual predictor variables, three were not significant: masculinity versus femininity, uncertainty avoidance index, and social media use (see Table 30).

Table 27

Stage 4 Coefficients Summary

	Unstandardized coefficients		Standardized coefficients		
Variable	β	*SE*	Beta	*t*	Sig.
(Constant)	3.157	0.458		6.891	0.000
PDI	0.029	0.005	1.262	6.092	0.000
IDV/CLV	0.017	0.001	0.740	14.884	0.000
MAS/FEM	-0.001	0.001	-0.045	-0.916	0.360
UAI	0.001	0.002	0.043	0.503	0.615
LTO/STO	0.024	0.002	1.129	11.654	0.000
GDP	-1.984	0.000	-0.890	-9.658	0.000
SMU	-0.170	0.378	-0.019	-0.449	0.654
AVD	-0.121	0.036	-0.560	-3.384	0.001
LTO/STO_AVD	-0.005	0.000	-1.019	-13.163	0.000
PDI_INP	-0.049	0.010	-1.654	-4.808	0.000
PDI_GDP	2.994	0.000	0.572	4.948	0.000
PDI_AVD	0.004	0.001	1.758	6.229	0.000
GDP_PSI	0.000	0.000	0.836	9.617	0.000
SMU_PPV	0.165	0.029	0.232	5.796	0.000
SMU_PSI	-6.205	1.690	-0.347	-3.671	0.000
UAI_LTO/STO	-3.985	0.000	-0.187	-1.869	0.062

Note. Response variable VAL

Table 28

Stage 5 Model Summary

Model	R	R^2	Adjusted R^2	SE
1	0.383	0.147	0.143	0.4632
2	0.383	0.147	0.143	0.4633
3	0.383	0.147	0.144	0.4632
4	0.383	0.147	0.144	0.4632

Note. Predictors Model 1: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, MAS/FEM, SMU_PPV, SMU_PSI, PDI, UAI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Predictors Model 2: SMU, GDP_PSI, AVD, SMU_PPV, LTO/STO, IDV/CLV, MAS/FEM, PDI_GDP, PDI, GDP, UAI_LTO/STO, LTO/STO_AVD, SMU_PSI, PDI_AVD, PDI_INP

Predictors Model 3: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, MAS/FEM, SMU_PPV, SMU_PSI, PDI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Predictors Model 4: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, SMU_PPV, SMU_PSI, PDI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Table 29

Stage 5 ANOVA Table

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	134.728	15	8.982	41.854	<.001
	Residual	781.785	3643	0.215		
	Total	916.513	3658			
2	Regression	134.717	15	8.981	41.85	<.001
	Residual	781.796	3643	0.215		
	Total	916.513	3658			
3	Regression	134.701	14	9.621	44.845	<.001
	Residual	781.812	3644	0.215		
	Total	916.513	3658			
4	Regression	134.554	13	10.350	48.247	<.001
	Residual	781.959	3645	0.215		
	Total	916.513	3658			

Note. Response variable: VAL

Model 1. Predictors: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, MAS/FEM, SMU_PPV, SMU_PSI, PDI, UAI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP
Predictors Model 2: SMU, GDP_PSI, AVD, SMU_PPV, LTO/STO, IDV/CLV, MAS/FEM, PDI_GDP, PDI, GDP, UAI_LTO/STO, LTO/STO_AVD, SMU_PSI, PDI_AVD, PDI_INP
Predictors Model 3: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, MAS/FEM, SMU_PPV, SMU_PSI, PDI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Predictors Model 4: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, SMU_PPV, SMU_PSI, PDI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Table 30

Stage 5 Coefficients Summary

		Unstandardized coefficients		Standardized coefficients		
Model		β	*SE*	Beta	t	Sig.
1	(Constant)	2.966	0.173		17.149	0.000
	PDI	0.028	0.004	1.212	6.985	0.000
	IDV/CLV	0.017	0.001	0.751	17.412	0.000
	MAS/FEM	-0.001	0.001	-0.028	-0.899	0.369
	UAI	0.001	0.002	0.028	0.355	0.722
	LTO/STO	0.024	0.002	1.129	11.663	0.000
	GDP	-1.959	0.000	-0.878	-9.914	0.000
	AVD	-0.111	0.029	-0.516	-3.872	0.000
	LTO/STO_AVD	-0.005	0.000	-1.007	-13.845	0.000
	PDI_INP	-0.046	0.008	-1.555	-5.892	0.000
	PDI_GDP	2.852	0.000	0.545	5.531	0.000
	PDI_AVD	0.003	0.000	1.669	8.324	0.000
	GDP_PSI	0.000	0.000	0.857	11.668	0.000
	SMU_PPV	0.159	0.024	0.223	6.484	0.000
	SMU_PSI	-6.781	1.097	-0.380	-6.179	0.000
	UAI_LTO/STO	-4.214	0.000	-0.198	-2.035	0.042

		Unstandardized Coefficients		Standardized Coefficients		
Model		β	*SE*	Beta	*t*	Sig
2	(Constant)	3.102	0.445		6.97	0.000
	PDI	0.027	0.004	1.196	7.493	0.000
	IDV/CLV	0.017	0.001	0.742	15.021	0.000
	MAS/FEM	-0.001	0.001	-0.031	-0.766	0.444
	LTO/STO	0.023	0.002	1.103	13.456	0.000
	GDP	-1.96	0	-0.88	-9.786	0.000
	AVD	-0.111	0.029	-0.513	-3.747	0.000
	LTO/STO_AVD	-0.005	0	-1.006	-13.747	0.000
	PDI_INP	-0.046	0.008	-1.543	-5.83	0.000
	PDI_GDP	2.87	0	0.548	5.208	0.000
	PDI_AVD	0.003	0	1.665	7.848	0.000
	GDP_PSI	0	0	0.839	9.674	0.000
	SMU_PPV	0.156	0.022	0.219	7.156	0.000
	SMU_PSI	-6.566	1.53	-0.368	-4.291	0.000
	UAI_LTO/STO	-3.47	0	-0.163	-1.854	0.064
	SMU	-0.095	0.348	-0.011	-0.273	0.785
3	(Constant)	2.989	0.161		18.621	0.000
	PDI	0.027	0.003	1.178	8.124	0.000
	IDV/CLV	0.017	0.001	0.749	17.489	0.000
	MAS/FEM	-0.001	0.001	-0.023	-0.827	0.408
	LTO/STO	0.023	0.002	1.109	14.137	0.000
	GDP	-1.950	0.000	-0.874	-9.950	0.000
	AVD	-0.107	0.026	-0.495	-4.143	0.000
	LTO/STO_AVD	-0.005	0.000	-1.001	-14.115	0.000
	PDI_INP	-0.045	0.007	-1.504	-6.806	0.000
	PDI_GDP	2.803	0.000	0.536	5.640	0.000
	PDI_AVD	0.003	0.000	1.627	10.016	0.000
	GDP_PSI	0.000	0.000	0.852	11.805	0.000
	SMU_PPV	0.154	0.020	0.216	7.591	0.000
	SMU_PSI	-6.863	1.073	-0.384	-6.395	0.000
	UAI_LTO/STO	-3.742	0.000	-0.176	-2.357	0.018

Model		Unstandardized Coefficients β	Stnd. Error	Standardized Coefficients Beta	*t*	Sig.
4	(Constant)	2.912	0.131		22.278	0.000
	PDI	0.025	0.003	1.106	9.55	0.000
	IDV/CLV	0.017	0.001	0.749	17.497	0.000
	LTO/STO	0.024	0.002	1.126	14.875	0.000
	GDP	-1.88	0	-0.842	-10.697	0.000
	AVD	-0.102	0.025	-0.472	-4.063	0.000
	LTO/STO_AVD	-0.004	0	-0.975	-15.367	0.000
	PDI_INP	-0.041	0.005	-1.387	-8.16	0.000
	PDI_GDP	2.54	0	0.485	6.682	0.000
	PDI_AVD	0.003	0	1.554	11.412	0.000
	GDP_PSI	0	0	0.847	11.778	0.000
	SMU_PPV	0.153	0.02	0.215	7.568	0.000
	SMU_PSI	-6.917	1.071	-0.387	-6.458	0.000
	UAI_LTO/STO	-4.55	0	-0.214	-3.636	0.000

Note. Response variable: VAL

Stage 6 Final Model

In Stage 6, I selected the final model using cumulative evidence from the previous five stages. The final model had five predictor variables and eight 2FIs (see Table 31). Three predictor variables were not significant predictors by themselves but were moderating variables and included as part of various 2FIs; they moderate the relationship between other predictor variables and the response variable.

Using the SPSS enter method, a standard regression analysis was run for the final regression model (all selected predictor variables and 2FIs). The final model statistically predicted VAL, $F(13, 3645) = 48.247$, $p < .001$, $R^2 = .147$, and adjusted $R^2 = .144$ (see Tables 32 and 33).

Table 31

Final Model Descriptive Statistics

Variable	*M*	*SD*	*n*
VAL	4.188	0.501	3,659
PDI	50.479	21.878	3,659
IDV/CLV	61.765	22.263	3,659
LTO/STO	51.716	23.945	3,659
GDP	42824.174	22444.644	3,659
AVD	2.998	2.325	3,659
LTO/STO_AVD	138.021	110.582	3,659
PDI_INP	44.187	16.769	3,659
PDI_GDP	1843080.013	956631.089	3,659
PDI_AVD	179.354	242.203	3,659
GDP_PSI	1312.097	2541.377	3,659
SMU_PPV	1.903	0.704	3,659
SMU_PSI	0.018	0.028	3,659
UAI_LTO/STO	3145.535	2353.334	3,659

Table 32

Final Model Summary

Model	*R*	R^2	Adjusted R^2	*SE* of the estimate	Durbin-Watson
1	.383[a]	0.147	0.144	0.4632	1.802

Note. Predictors: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, SMU_PPV, SMU_PSI, PDI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

Dependent variable: VAL

Table 33

Final Model ANOVA

Model		*SS*	*df*	*MS*	*F*	Sig.
1	Regression	134.554	13	10.350	48.247	<.001
	Residual	781.959	3645	0.215		
	Total	916.513	3658			

Note. Response variable: VAL

Predictors: UAI_LTO/STO, IDV/CLV, LTO/STO_AVD, PDI_GDP, SMU_PPV, SMU_PSI, PDI, GDP, AVD, GDP_PSI, LTO/STO, PDI_AVD, PDI_INP

The final model coefficients summary data (see Table 34) were used to write the regression equation for the predictive model. The regression equation predicting VAL is as follows:

VAL = 2.912 + .025(*PDI*) + .017(*IDV/CLV*) + .024(*LTO/STO*) – 1.878(*GDP*) - .102(*AVD*) - .004(*LTO/STO_AVD*) -.041(*PDI_INP*) + 2.538(*PDI_GDP*) + .003(*PDI_AVD*) + .001(*GDP_PSI*) +.153(*SMU_PPV*) – 6.917(*SMU_PSI*) – 4.549(*UAI_LTO/STO*)

Table 34

Final Model Coefficients Summary

		Unstandardized coefficients		Standardized coefficients		
Model		β	*SE*	Beta	*t*	Sig.
1	(Constant)	2.912	0.131		22.278	0.000
	PDI	0.025	0.003	1.106	9.550	0.000
	IDV/CLV	0.017	0.001	0.749	17.497	0.000
	LTO/STO	0.024	0.002	1.126	14.875	0.000
	GDP	-1.878	0.000	-0.842	-10.697	0.000
	AVD	-0.102	0.025	-0.472	-4.063	0.000
	LTO/STO_AVD	-0.004	0.000	-0.975	-15.367	0.000
	PDI_INP	-0.041	0.005	-1.387	-8.160	0.000
	PDI_GDP	2.538	0.000	0.485	6.682	0.000
	PDI_AVD	0.003	0.000	1.554	11.412	0.000
	GDP_PSI	0.001	0.000	0.847	11.778	0.000
	SMU_PPV	0.153	0.020	0.215	7.568	0.000
	SMU_PSI	-6.917	1.071	-0.387	-6.458	0.000
	UAI_LTO/STO	-4.549	0.000	-0.214	-3.636	0.000

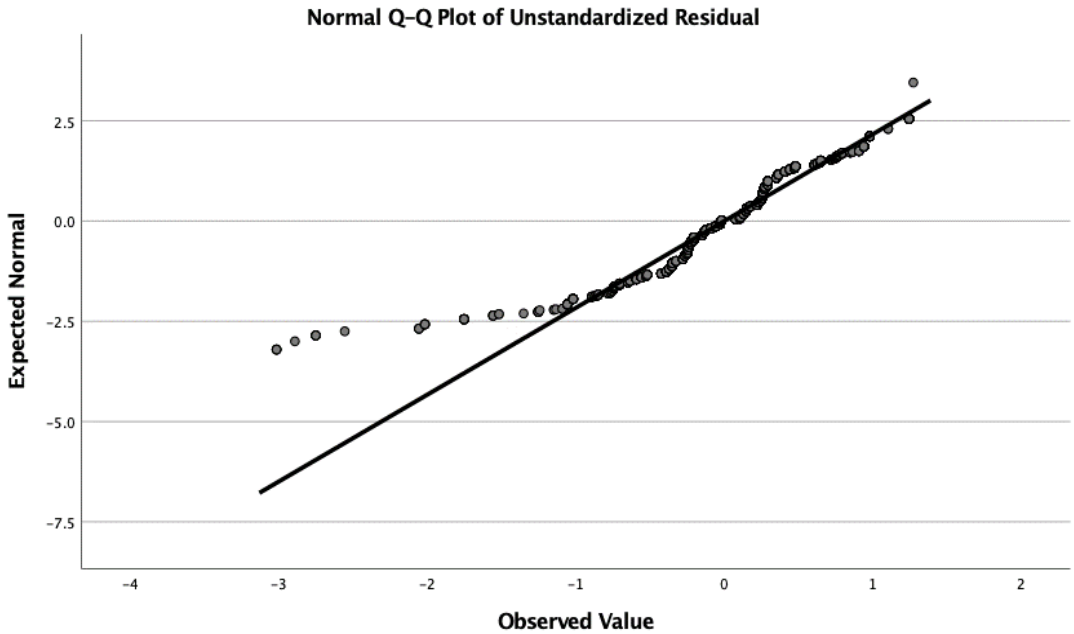
Note. Response variable: VAL

Final Model Assumptions

Once the final model was selected, the MLR assumptions were checked. The assumptions for measurement, outliers, linearity, and homoscedasticity remained valid. Normality was tested using a visual inspection of the Q-Q plots of the unstandardized residuals. Figure 43 shows a minor departure from normality.

Figure 43

Final Model Q-Q Plot of Unstandardized Residuals



The Kolomogoroz-Smirnov test with Lilliefors Significance correction and the Shapiro-Wilk test showed a departure from normality (see Table 35). While a normally distributed data set is desired, MLR is a statistical tool that is robust to violations of normality (Osborne & Waters, 2002). Additionally, the large dataset size, N = 3,659, and the central limit theorem allow normality violations to be excused (Altman & Bland, 1995; Ghasemi & Zahediasl, 2012).

Table 35

Final Model Normality Tests

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	*df*	Sig.	Statistic	*df*	Sig.
Unstandardized Residual	0.113	3,659	0.000	0.920	3,659	0.000

I assessed the independence of the final model with the Durbin-Watson statistic (from the Final Model Summary Table 32). The Durbin-Watson statistic for the final model was 1.8, which means the model met the assumption for independence. Finally, I assessed multicollinearity by reviewing the collinearity diagnostics table (see Table 36). Given that my final model had more than two predictors with a VIF greater than 10, I reviewed the collinearity diagnostics table. Because there were no cases with a condition index greater than 15 with more than one predictor (column) with a variance proportion greater than .90, the model met the assumption for multicollinearity.

Table 36

Final Model Collinearity Diagnostics Table

		Variance Proportions													
Dimension	Condition Index	(Constant)	PDI	IDV/ CLV	LTO/ STO	GDP	AVD	LTO/STO_ AVD	PDI_INP	PDI_GDP	PDI_AVD	GDP_PSI	SMU_PPV	SMU_PSI	UAI_ LTO/STO
1	1.000	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	2.423	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00
3	2.913	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	4.964	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01
5	6.803	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00
6	8.464	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.04	0.00	0.03
7	12.811	0.00	0.00	0.01	0.00	0.03	0.00	0.06	0.00	0.00	0.01	0.07	0.03	0.22	0.00
8	14.245	0.00	0.00	0.03	0.03	0.01	0.00	0.02	0.00	0.05	0.01	0.00	0.04	0.02	0.00
9	18.930	0.01	0.00	0.02	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.10	0.40	0.05	0.19
10	20.295	0.00	0.00	0.01	0.01	0.00	0.01	0.22	0.00	0.04	0.03	0.28	0.03	0.27	0.04
11	38.433	0.09	0.03	0.06	0.05	0.12	0.30	0.10	0.00	0.10	0.09	0.01	0.12	0.10	0.05
12	49.727	0.01	0.07	0.44	0.16	0.40	0.20	0.14	0.00	0.09	0.34	0.46	0.13	0.25	0.08
13	69.076	0.57	0.16	0.40	0.72	0.00	0.36	0.40	0.01	0.02	0.10	0.04	0.11	0.07	0.42
14	124.147	0.31	0.72	0.00	0.00	0.42	0.12	0.02	0.99	0.67	0.41	0.00	0.08	0.01	0.17

Research Question and Hypothesis Test

RQ4 used a series of MLR regression analyses in evaluating the predictor variables and 2FIs with the response variable.

RQ4: What country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings?

$H_0$4: There are no country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings.

H_a4: There are country culture variables or country demographic variables as significant predictors of restaurant eWOM valence ratings.

For each predictor variable and 2FIs in the final model, I rejected the null hypothesis (coefficient = 0) and concluded that there was sufficient evidence that the alternate hypothesis was true (coefficient ≠ 0). Among the original candidate variables, power distance, individualism/collectivism, long/short-term orientation, gross domestic product per capita, and Yelp average visit duration were proven to significantly influence eWOM restaurant valence ratings as individual contributors to the model. Uncertainty avoidance, Internet penetration, percent spill-in, social media use, and pages per visit were not individually significant; however, they moderated other variables and contributed to the model. The adjusted R^2 of this model was .144, indicating that 14.4% of the variance in restaurant eWOM valence ratings was explained by this predictive model.

Summary

The purpose of this quantitative correlational study was to examine the relationship between measures of country culture, country demographics (predictor variables), and restaurant eWOM valence ratings (response variable) for all countries on the Yelp platform with eWOM restaurant valence ratings. Secondary data were exclusively used in this study. A purposive sampling strategy was used, and the timeframe for the data access was selected to minimize collection bias across the data sources. A total of 6,018 records were accessed in the original dataset. After I screened and cleaned the data, 61% (N = 3,659) of the records remained in the analysis.

Initially, 19 variables were considered; 18 were predictor variables with one response variable. SPSS was used to analyze the data. RQs 1–3 required correlation analyses to assess the relationship between the two variables stated in each question. RQ4 used a series of MLR regression analyses in evaluating the predictor variables and 2FIs with the response variable.

RQs 1–3 tested the null hypotheses that no linear relationships existed between the variables. The alternative hypotheses were that there was a linear relationship. For each of RQs 1–3, I found statistically significant correlations between variables. Therefore, I rejected the null hypotheses, concluding that there is sufficient evidence that linear relationships existed. RQ4 involved testing the null hypothesis that no country culture variable or country demographic variable was a significant predictor of restaurant eWOM valence ratings. The alternative hypothesis was that country culture variables or country demographic variables were significant predictors of restaurant eWOM valence ratings. The final model consists of five predictor variables (power distance, individualism/collectivism, long/short-term orientation, gross domestic product per capita, Yelp average visit duration) and eight 2FIs (long/short-term and average visit duration, power distance, and Internet penetration, power distance and gross domestic product, power distance, and average visit duration, gross domestic product and percent spill in, social media use and pages per visit, social media use and percent spill in, uncertainty avoidance and long/short-term orientation) explained 14.4% of the variance in VAL $F(13, 3645) = 48.247$, $p < .001$, $R^2 = .147$. Therefore, I rejected the null hypothesis, concluding that there is sufficient evidence that county culture and country demographics are significant predictors of restaurant eWOM valence ratings.

In Chapter 5, I will interpret the data analysis results. This interpretation will include study limitations, the generalizability of the study results, recommendations for using the model to predict restaurant eWOM valence ratings, recommendations for future research, and implications for professional practice and positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative correlational study was to examine the relationship between measures of country culture, country demographics (predictor variables), and restaurant eWOM valence ratings (response variable) for all countries on the Yelp platform with eWOM restaurant valence ratings. I used a correlational research design to assess the strength and direction of the relationship between my quantitative variables. Additionally, correlation studies are used to test hypotheses when the unit of analysis cannot be randomly assigned, such as country culture, country demographics, and aggregate (country-level) restaurant eWOM valence ratings. In answer to RQs 1–3, I found statistically significant relationships between the predictor variables (measures of country culture and country demographics) and the response variable (restaurant eWOM valence ratings). I framed RQ4 to develop a model that included measures of country culture, country demographics, and 2FIs, which predicted 14.4% of the variance in restaurant eWOM valence ratings. In the following sections, I present the interpretation of the findings, limitations of the study, recommendations, implications, and conclusion.

Interpretation of Findings

Four research questions guided this research. RQs 1–3 examined the relationships between the predictor variables (measures of country culture and country demographics) and the response variable (restaurant eWOM valence ratings). Specifically, RQ1 addressed the relationship between measures of country culture and restaurant eWOM valence ratings. In RQ2, I examined the relationship between measures of country demographics and restaurant eWOM valence ratings. RQ3 addressed the relationship between measures of country culture and country demographics on restaurant eWOM valence ratings. Finally, using RQ4, I examined what country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings. This section includes information regarding how the findings of the study confirm, disconfirm, or extend existing knowledge regarding the relationship between country culture, country demographics, and restaurant eWOM.

Confirmation of Knowledge

I could find no prior studies that analyzed the relationship between country culture and restaurant eWOM valence ratings; however, researchers in different industries (retail, airlines) examined different aspects of eWOM (review sentiment, review helpfulness), which provided relatively consistent results with the findings of RQs 1–3. Empirical studies analyzing the influence of country culture on eWOM ratings within other industries revealed significant country differences in valence ratings (Barbro et al., 2020; Chiu et al., 2019). Moreover, prior research on eWOM reviews showed significant country cultural influences (Buzova et al., 2019; Nakayama & Wan, 2019). Research regarding the effect of culture on airline ratings found masculinity versus femininity and long versus short-term orientation to have significant results (Stamolampros et al., 2019).

The results of this study showed that measures of country culture had relationships with restaurant eWOM valence ratings. Specifically, RQ1 and RQ3 revealed that masculinity/femininity and long/short-term orientation had statistically significant small, positive relationships. Therefore, the results of this study appear consistent with the literature indicating that measures of country culture are influential on eWOM valence ratings.

Additionally, I could find no studies that examined the relationship between country demographics and restaurant eWOM valence ratings. Some researchers identified population and gross domestic product as key demographic considerations for organizational success (de Mooij, 2003; Kotler et al., 2017). Other research indicated that restaurant sales and restaurant units significantly influence business metrics (Biel, 2022). Prior research also demonstrated that spill-in influences media-testing market outcomes (Marucci, 2009) and that social media use represents the strength of a country's digital connections (Mariani & Predvoditeleva, 2019). Finally, in one study, site traffic (number of visitors) and site stickiness (visit duration) represented consumer brand interest (Tuten & Solomon, 2017).

The results of RQ2 and RQ3 appear to align with prior research examining aspects of country demographics. Specifically, the results of RQ2 and RQ3 indicated that measures of country demographics, including population, gross domestic product, restaurant units, restaurant sales, and Yelp percent spill-in, had statistically significant small positive relationships with restaurant eWOM valence ratings. Social media use, Yelp unique visitors, and Yelp average visit duration had statistically significant small negative relationships with restaurant eWOM valence ratings. Thus, the results of this research are consistent with the literature indicating that measures of country demographics are influential on eWOM valence ratings.

Disconfirmation of Knowledge

While the overall results of my research align with the body of literature presented in Chapter 2, there were several areas where I found slight differences. The results of RQ1 and RQ2 suggested that measures of country culture, including individualism/collectivism and uncertainty avoidance, had no statistically significant relationships with restaurant eWOM valence ratings. These results differ from research for cell phone ratings (Tang, 2017) and air travel ratings (Chatterjee & Mandal, 2020), which found that individualism/collectivism and uncertainty avoidance affected eWOM ratings. Additionally, this study found a statistically significant relationship between indulgence and restraint, which differs from research for airlines that found indulgence versus restraint did not significantly affect ratings (Stamolampros et al., 2019).

Regarding country demographics, RQ2 and RQ3 showed that Internet and mobile device penetration had no relationships with eWOM ratings valence. While I could find no research regarding Internet penetration, mobile device penetration, and eWOM, there was research regarding the growth of both measures. The global growth of Internet users (4%) has outpaced the world population growth (1%) (Kepios, 2022). Moreover, there are 1.54 mobile devices per unique user (Kepios, 2022). Both statistics may help explain why Internet penetration and mobile device penetration did not have relationships with eWOM ratings valence. Globally there is hyper saturation, so Internet and mobile device penetration potentially has lost social significance.

Extension of Knowledge

Scholars have inadequately examined the interplay between country culture, country demographics, and restaurant eWOM valence ratings. Although Hofstede's cultural dimensions are widely used in cross-cultural research (Obara et al., 2021; Stamolampros et al., 2019; Wang et al., 2019), in no previous study have they been used as measures of country culture in a study regarding restaurant eWOM valence ratings. The results of RQs 1–4 extended knowledge regarding Hofstede's (2001) cultural dimensions theory; I used Hofstede not only as the theoretical framework but also as the predictor variables (measures of country culture). Additionally, several researchers have included demographic variables relating to the industry (Stamolampros et al., 2019) or geography (Hong et al., 2016; Mariani & Predvoditeleva, 2019). However, no prior study has featured demographic variables relating to the social media platform I included in the study. This research used demographic variables, including visits, unique visitors, pages per visit, average visit duration, and percent spill-in related directly to the Yelp platform. By including platform demographics, I could better understand and refine my data.

I could not locate any prior research on RQ4, which asked: What country culture variables or country demographic variables are significant predictors of restaurant eWOM valence ratings? Thus, this study is the first attempt to use country culture and country demographics to build a predictive model for restaurant eWOM valence ratings. The results showed a final model consisting of five predictor variables (power distance, individualism/collectivism, long/short-term orientation, gross domestic product per capita, Yelp average visit duration) and eight 2FIs (long/short-term and average visit duration, power distance and Internet penetration, power distance and gross domestic product, power distance, and average visit duration, gross domestic product and percent spill-in, social media use and pages per visit, social media use and percent spill-in, uncertainty avoidance, and long/short-term orientation), which explained 14.4% of the variance in restaurant eWOM valence ratings.

Limitations of the Study

Although researchers weigh many considerations when designing a study, and there is no such thing as a perfect study, research quality must be upheld by disclosing limitations encountered during the research process. Several validity and reliability limitations arose during this study. The validity limitations included external and internal limitations; no construct limitations were noted. The reliability limitations resulted from the nature of the eWOM ratings data source. The validity and reliability limitations are detailed below.

External validity refers to the generalizability of the study's findings (Malhotra, 2018). The inclusion criteria for this study were all countries and restaurant establishments with an eWOM presence; however, no list of this population exists, nor would it be possible to create one. Therefore, a random study was not possible, which limits the generalizability of the study to restaurants on the Yelp platform.

Internal validity examines if the research results are based on the measures, research context, and research design, as opposed to a variable or factor that was not considered (Malhotra, 2018). Internal validity was potentially compromised because of the lack of normality in the final model; however, researchers have noted that the distribution of the data can be ignored in samples with hundreds of observations due to the central limit theorem (Ghasemi & Zahediasl, 2012), and this study had a large sample (N = 3,659). Additionally, Altman and Bland (1995) observed that the means of samples would have a normal distribution, and the restaurant eWOM valence ratings were aggregate means for each country. Therefore, the potential for internal validity to compromise this study's results is not a significant concern.

Reliability relates to a study's consistency, whether the study can be repeated with consistent results under similar conditions (Heale & Twycross, 2015). Given the nature of the Yelp Fusion API, the returned cases (restaurant data) vary from API to API call. Yelp controls the data released via the Fusion API; therefore, one cannot access the same set of restaurants. Furthermore, consumers continuously post ratings to Yelp, which causes the eWOM valence ratings to change over time. Thus, researchers who use social media data must weigh these considerations when comparing studies and evaluating limitations.

Recommendations

A strength of the research was the use of archival data from reliable, recognized, and easily accessible databases. More and similar data are freely available for future studies. For example, other researchers could access restaurant eWOM valence ratings from Yelp or other social media platforms. Replicating this study could help increase knowledge and understanding regarding the correlations between the predictor and response variables and the predictive model for country culture, country demographics, and eWOM valence ratings. In addition, the global restaurant sector comprises a variety of venues such as street food, cafes, and bars, quick-service, and full-service (Nastasi &

Nobili, 2020), with subcategories fulfilling different consumer needs. Future researchers could use archival data to examine the relationship between country culture, country demographics, and eWOM valence ratings for each subcategory.

I could not find any prior research regarding the relationship between country culture, country demographics, and restaurant eWOM valence ratings. Hence, I undertook the first attempt to research and understand the interplay of country culture, country demographics, and eWOM valence ratings for restaurants. Results of this study suggest that a model composed of measures of country culture, country demographics, and their 2FIs was a predictor of restaurant eWOM valence ratings. Currently, the model predicts 14.4% of the variance in restaurant eWOM valence ratings; however, future researchers could refine the model to increase its predictability (Lichy & Kachour, 2019).

Implications

This study's contribution is twofold, first to theory and second to professional practice. Both contributions offer positive social change. Theoretically, this study addresses multiple calls in the literature to understand how country culture influences eWOM. The study also fills a gap in the literature regarding eWOM valence ratings research in the restaurant sector. The lack of eWOM research analyzing multiple cultures leads to this study positively contributing to social change.

Additionally, research on eWOM valence ratings is an emerging domain. This study offers an important first step toward a systemic empirical methodology. Positive social change is created because future researchers can use the knowledge gained from this research when designing studies using eWOM or social media data.

From a practical perspective, this study offers guidance to restaurants regarding cultural and demographic influences on eWOM valence ratings. The proposed model identifies 14.4% of restaurant eWOM valence ratings variance. Given that eWOM ratings are considered a de facto measure of customer satisfaction, restaurants that monitor and manage their eWOM in the context of country culture and country demographics could find a competitive advantage. Thus, the study's results suggest that positive social change is created using the predictive model proposed in this research and then appropriately addressing eWOM ratings based on a stronger understanding of cultural and demographic influences.

Conclusions

When Ph.D. candidates embark on their dissertations, they start an incredible journey filled with twists, turns, ups, and downs. It is also a journey requiring a great deal of motivation and perseverance to complete. At the start of my dissertation, I was given some advice: picking a research topic is like picking a life partner because you will spend a lot of time together. So, when I reflect on the essence of this study, I return to the start of my journey and my motivation and reason for this topic.

Starting in the 1980s, I spent several decades working in the hospitality industry, including being a vice president of marketing for an international restaurant chain. First, I saw firsthand through this experience how business results can be negatively affected (such as a drop in sales) when brands make decisions without truly understanding the local culture. Second, Web 2.0 allows consumers to express their satisfaction through eWOM. The marketer in me realized the importance of these situations: a need for local cultural understanding and an opportunity to easily harness consumer satisfaction data for greater insights.

Thus, the essence of this study was to use eWOM data (a de facto for consumer satisfaction) to support positive social change for restaurants. Given the global nature of eWOM, it made sense to examine the relationship between country culture and country demographics with eWOM valence ratings. The model I developed does not account for all the variance in eWOM ratings; however, it does predict 14.4% of the variance in restaurant eWOM valence ratings.

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Appendix A: Yelp Terms of Service Right to Use Content

Our Right to Use Your Content. We may use Your Content in a few different ways, including by publicly displaying it, reformatting it, incorporating it into advertisements and other works, creating derivative works from it, promoting it, distributing it, and allowing others to do the same in connection with their own websites and media platforms ("Other Media"). As such, you hereby irrevocably grant us worldwide, perpetual, non-exclusive, royalty-free, assignable, sublicensable, and transferable rights to use Your Content for any purpose. Please note that you also irrevocably grant the users of the Service and any Other Media the right to access Your Content in connection with their use of the Service and any Other Media. Finally, you irrevocably waive, and cause to be waived, against Yelp and its users any claims and assertions of moral rights or attribution with respect to Your Content. By "use," we mean use, copy, publicly perform and display, reproduce, distribute, modify, translate, remove, analyze, commercialize, and prepare derivative works of Your Content (Yelp, 2021d).

Appendix B: Yelp API Terms of Service Permission for Use

Allowable non-commercial use of the Yelp Content. Notwithstanding the previous, you may use the Yelp Content to perform certain analysis for non-commercial uses only, such as creating rich visualizations or exploring trends and correlations over time, so long as the underlying Yelp Content is only displayed in the aggregate as an analytical output, and not individually. For example, this is an acceptable non-commercial analytical use of the Yelp Content. "Non-commercial use" means any use of the Yelp Content which does not generate promotional or monetary value for the creator or the user or such use does not gain economic value from the use of our content for the creator or user (i.e., you) (Yelp, 2021a).