Cultural differences in customer emotions

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Abstract

E-commerce platforms have emerged as leading arenas for fostering customer engagement, offering unique pathways for gauging customer satisfaction through reviews and enabling diverse approaches to analyzing content. This inquiry arises from the increasing inclination toward incorporating customer feedback into cultural examinations, addressing a research gap in cultural studies centered on e-commerce platforms across various societies. What sets this study apart is its focus on scrutinizing the emotional expressions of both Eastern and Western consumers as depicted in their online feedback. The findings revealed 27 distinct emotions discernible in both sets of reviews, with notable variations in their distributions. Theoretically, the research posited and verified a novel conceptual correlation between emotions and cultures. On a practical level, it provided businesses with insights into their customers' emotional experiences, facilitating more culturally targeted approaches to customer engagement.

1. Introduction

The rise and widespread use of e-commerce represent the most prominent facets of business development (Felbermayr & Nanopoulos, 2016). This contemporary paradigm facilitates rapid customer feedback across e-commerce sites, ushering in a plethora of activities, including the manipulation of consumer reviews. Despite the longstanding existence of similar analytical processes in social networks, the emergence of e-commerce sites and new machine learning-based emotion detection techniques offer unique opportunities for business analysis just recently (Abbassy & Abo-Alnadr, 2019).

The e-commerce sites, not only aid in establishing and maintaining brand awareness but also serve as a vital arena for diverse customer feedback and innovative storytelling through online reviews (Haque et al., 2018). The platforms play a pivotal role in fostering customer feedback and introducing novel storytelling methods. In this sense, customer reviews facilitate cross-language conversations, eliminating linguistic and geographic barriers and providing researchers access to expansive and in-depth topics (Haque et al., 2018).

However, the purpose of the previous research was to examine individuals' opinions on a particular subject (Alhadlaq & Alnuaim, 2023). Their main objective was to categorize a collection of texts automatically, determining whether they express positivity, negativity, or neutrality. By amalgamating methodologies such as data mining, machine learning, and natural language processing (NLP), previous sentiment analysis studies aimed to uncover and extract subjective insights from extensive unorganized datasets (Wang et al., 2019).

The popularity of e-commerce sites recently generated other substantial sets of data, offering diverse avenues for the analysis of customer experience (Hossain et al., 2022). Little, however, has been done about this kind of dataset, especially in the area of emotional analysis (Guo et al., 2020). The benefit of a potential understanding of the customer experience emotionally is enormous and should motivate more research in this promising area (Pashchenko et al., 2022).

In line with that, this study aims to understand how customer emotions are distinctly identified. It further seeks to explore cross-national differences in the expression of emotions, particularly about culture. In the past, few academics have delved into this topic but faced challenges due to linguistic complexities, psychological theories, and technological constraints (Alhadlaq & Alnuaim, 2023).

The linguistic landscape, encompassing languages like Japanese, poses formidable challenges for natural language processing (NLP) due to their intricate structures (Ariely et al., 2023).

This challenge is compounded by the grammatical complexity of these languages, their diverse dialects, and the scarcity of reliable data sources, resulting in a dearth of hieroglyphs-language research in NLP, especially in emotion classification (Raharjana & Fatichah, 2021). Similar challenges are observed in other countries in the East, which have limited resources in machine learning (ML). Consequently, this region witnessed a scarcity of successfully developed NLP algorithms, often reliant on established ML foundations (Qiu, 2020).

The contemporary development of psychological theories has also put another obstacle. In specific, a recent study conducted by researchers at the University of California, Berkeley challenges the conventional belief in psychology that human emotions primarily fit into limited universal categories of just happiness, sadness, anger, surprise, fear, and disgust (Demszky et al., 2020). The study, which involved analyzing responses from emotionally evocative video clips, revealed the existence of 27 distinct categories of emotions, suggesting a more nuanced and complex understanding of human emotions beyond traditional categories (Demszky et al., 2020).

Consequently, most of the technologies today can only translate human messages into Ekman's six basic emotions. Some can successfully convert texts to eight emotions following Plutchik's model (Plaza-del-Arco et al., 2022). However, converting to 27 emotions is still a technical challenge, partly because of the missing reliable training data and a valid fine-tuned model (Demszky et al., 2020).

This study tackles the outlined challenges by presenting a technological solution designed to identify 27 emotions within customer reviews and assess the disparities in their distribution across Eastern and Western cultures.

2. Literature Review

This study is related to customer emotions and cultural dimensions. The recent studies in those areas will be first reviewed. In each area, the literature gaps are first identified before the hypotheses will accordingly be formulated accordingly.

2.1. Customer emotions

Pashchenko et al. (2022) claimed that customer reviews, often intense and multifaceted, have the power to leave indelible imprints on consumers' minds. They possess a unique ability to linger in consumers' memories, influencing consumers' thoughts and behaviors long after the experience itself has passed. Positive moments can create lasting memories that bring forth feelings of warmth, contentment, and gratitude when recalled, having a long impact on consumers' future repurchase behaviors (Yusifov & Sineva, 2022).

Conversely, negative moments can leave scars that impact people's lives in profound ways (Pashchenko et al., 2022). The sentiments associated with such experiences can be overwhelming and challenging to process, yet they often contribute to personal growth and resilience. They can teach us valuable lessons, foster empathy, and provide a deeper understanding of ourselves and others. These experiences, though painful, often become integral parts of our identity and contribute to the richness of our experience (Abebe, 2023).

Furthermore, Yusifov and Sineva (2022) found that experiences are not only confined to human interactions; they also shape our relationships with various facets of life, including art, nature, and shopping. A breathtaking piece of art, a serene natural landscape, or a useful product can evoke powerful feelings, transcending language and cultural barriers, and resonating with people on a profound sentimental level (Yusifov & Sineva, 2022)

Similarly, Zanwar et al. (2022), the influence of experiences reaches far into the realms of decision-making and cognition. This neuroscience study has shown that previous experiences play a critical role in decision-making and purchasing processes. Customer experiences can influence their judgments, perceptions, and decision-making, often guiding their actions and preferences in ways that reason alone cannot (Zanwar et al., 2022).

Other studies, e.g. Chuah and Yu (2021), found that the significance of customer experiences extends beyond the individual. They are the threads that weave the intricate tapestry of connections. Shared experiences can create powerful bonds between individuals, forming the basis for empathy, understanding, and solidarity as found by Widyaningrum et al. (2019). Celebrating moments of collective joy or supporting each other through shared grief creates a sense of community and strengthens the connections between people (Demszky et al., 2020).

Furthermore, according to the appraisal theory, experiences can be transmitted, suggesting that exposure to evaluations rooted in consumer sentiment can evoke similar feelings in readers (Pashchenko et al., 2022). The theory posits that sentiments form the bedrock of all interactions, aiding cognitive processes and helping potential consumers comprehend their experiences (Ghasemaghaei et al., 2018). That means the crucial attributes of online reviews that impact a customer's perception of usefulness play a vital role in shaping consumer behavior (Meek et al., 2021).

In the context of e-commerce, a study Umasuthan et al. (2017) found that in the absence of sincere customer reviews, service satisfaction lacks significance and feels inadequate. Considering the impersonal nature of e-commerce and the significance users attribute to electronic Word-of-Mouth (eWOM) assessments, monitoring reviews have emerged as a crucial task for every business for that reason (Ramachandran et al., 2022).

According to Zhao et al. (2018), customer reviews exemplify electronic Word-of-Mouth (eWOM), serving as a reliable information source for businesses to gauge consumer sentiment towards their products and services. Understanding customer reviews and strategies to influence eWOM behavior has become indispensable for businesses aiming to bolster product sales. These sentimental evaluations, alongside consumer ratings, wield significant influence on a company's sales by providing insights into buyer experiences (Batat, 2019).

Xu et al. (2020) also claimed that customer reviews unveil perceptions regarding specific product and service features, empowering company management to improve these aspects. Different types of reviews evoke varied emotional responses from reviewers, reflecting the long-term impact of consumer experiences with goods and services (Xu et al., 2020). The study, together with others, has confirmed the importance of customer reviews and their sentiments in businesses. The challenge is how to quantify the customer reviews and extract an abstract meaning from them (Pashchenko et al., 2022).

Quantifying customer reviews involves employing a range of methodologies to extract meaningful data from qualitative feedback (Felbermayr & Nanopoulos, 2016). One approach is sentiment analysis, which utilizes natural language processing techniques to assess the emotional tone of reviews. By assigning numerical scores to positive, negative, or neutral sentiments expressed in the text, sentiment analysis provides a quantitative measure of overall customer sentiment (Yang & Yu, 2013). Additionally, feature-based analysis breaks down reviews into specific aspects of the product or service, such as quality, price, or customer service. By quantifying the sentiment or rating associated with each feature separately, businesses can identify areas of strength and areas for improvement (Lai et al., 2021).

Another method to quantify customer reviews is through text analytics, which involves extracting quantitative data from textual reviews (Wu, 2021). Text mining techniques can be used to count the frequency of specific words or phrases related to certain sentiments or topics, providing insights into the most commonly mentioned aspects of the product or service. Additionally, topic modeling algorithms can categorize reviews into topics or themes and quantify the prevalence of each topic across reviews. By aggregating these metrics, businesses can gain a comprehensive understanding of customer feedback, enabling them to make data-driven decisions to enhance their products, services, and overall customer experience (Batat, 2019).

However, quantifying customer reviews extends beyond merely assessing their ratings, sentiments, or topics; it encompasses the deeper realm of emotions and feelings conveyed within them (Cordaro et al., 2018). Despite the strides made in sentiment analysis and topic modeling, the intricacies of customer emotions have remained relatively underexplored in previous studies (Vyas et al., 2023). Understanding and quantifying these emotions within customer reviews can offer invaluable insights into the underlying motivations and preferences driving consumer perceptions and actions, thereby enriching the depth and accuracy of analytical approaches in the realm of customer feedback analysis (Mesquita, 2022).

Emotions, the intricate tapestry of human experience, are complex and multifaceted, encompassing a wide range of feelings. They play vital roles in shaping human perception (Serra-Cantallops et al., 2018). In the meantime, individuals' thoughts and actions are influenced by their emotions, serving as guiding forces in their behavior (Gendron et al., 2018). These feelings and emotions assist potential consumers in understanding their surroundings and facilitating cognitive processes (Chuah & Yu, 2021).

Silvan Tomkins and Robert McCarter developed an influential model of emotions that emphasizes the fundamental role emotions play in human behavior and experience. Tomkins, a pioneering psychologist, proposed that emotions are primary motivational systems that drive human behavior more powerfully than other drives such as hunger or sex. His work, complemented by McCarter, helped form a comprehensive theory of emotions (Tomkins & McCarter, 1964).

Paul Ekman's seminal work centers on the identification of universal facial expressions associated with basic emotions. His research, based on cross-cultural studies, proposed six fundamental emotions: happiness, sadness, fear, disgust, anger, and surprise. Ekman's primary methodology involved the development of the Facial Action Coding System (FACS), a tool that classifies facial expressions into specific action units (Ekman, 1993).

The universality of Ekman's findings has been both a strength and a point of contention in the current literature. While his work laid the foundation for emotion recognition and understanding, critics argue that cultural nuances and individual differences might influence the interpretation of facial expressions by just a limited set of universal emotions (Plaza-del-Arco et al., 2022).

Robert Plutchik's contribution expands the emotional landscape beyond basic (facial) emotions, introducing the "Wheel of Emotions." Plutchik identified eight primary emotions arranged in a circular diagram, emphasizing the dynamic nature of emotional experiences. His model allows for the combination and intensification of emotions, offering a more nuanced understanding of human feelings (Plutchik, 2001). The Wheel of Emotions has been praised for capturing the complexity of emotional experiences. However, critics argue that the model might still oversimplify the intricate nature of emotions and interactions when the number of emotions identified is still too limited (Alkaabi et al., 2022; Cortis, 2021).

Both Ekman and Plutchik made significant contributions to the understanding of emotions and how they are expressed and experienced. Ekman's work is often associated with facial expressions linked to basic emotions, while Plutchik's model provides a more nuanced view of the complex interplay between emotions. Compared with Ekman, Plutchick offered a more systematic way of organizing emotions, especially through its one-dimensional pairs (Tesfagergish et al., 2022).

Model	**Type of model**	**Emotional states**	**No. of states**
Tomkins model (Tomkins & McCarter, 1964)	Distinct	Disgust, surprise-Startle, anger-rage, anxiety, fear-terror, contempt, joy, shame, interest, excitement	9
Ekman model (Ekman & Oster, 1979)	Distinct	Anger, disgust, fear, joy, sadness, surprise	6
Plutchik Wheel of Emotions (Plutchik, 1980)	2- Dimensional	Joy, pensiveness, ecstasy, acceptance, sadness, fear, interest, rage, admiration, amazement, anger, vigilance boredom, annoyance, submission, serenity, apprehension, contempt, surprise, disapproval, distraction, grief, loathing, love, optimism, aggressiveness, remorse, anticipation, awe, terror, trust, disgust	–
Russell's circumplex model (Russell, 1980)	2- Dimensional	Sad, satisfied, Afraid, alarmed, frustrated, angry, happy, gloomy, annoyed, tired, relaxed, glad, aroused, astonished, at ease, tense, miserable, content, bored, calm, delighted, excited, depressed, distressed, serene, droopy, pleased, sleepy	–
Shaver model (Shaver et al., 1987)	Distinct	Sadness, joy, anger, fear, love, surprise	6
Izard model (Izard, 1992)	Distinct	Anger, contempt, disgust, anxiety, fear, guilt, interest, joy, shame, surprise	10
Lövheim Model (Lövheim, 2012)	3- Dimensional	Anger, contempt, distress, enjoyment, terror, excitement, humiliation, startle	–

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Table 1: Emotion models

James A. Russell proposed a two-dimensional model of emotional experience, organizing them along two independent dimensions: valence and arousal (Posner et al., 2005). The circumplex model, representing the interplay between these dimensions, provides a broader perspective on customer emotions. Lim (2016) claimed that valence and arousal stand as two key dimensions used in psychology to categorize and understand the nature and intensity of emotions.

Shaver's model of emotions focuses on the hierarchical organization of emotions and their relationships with each other (Shaver et al., 1987). Izard developed the Differential Emotions Theory (DET), which posits that emotions are discrete, fundamental, and biologically rooted in humans (Izard, 1992). Lövheim's model maps emotions onto a cube defined by three neurochemical axes: dopamine: Associated with pleasure and reward, influencing emotions like joy and interest, noradrenaline: linked to arousal and alertness, affecting emotions such as fear and anger, serotonin: related to mood regulation, impacting emotions like sadness and contentment (Lövheim, 2012).

However, critiques highlight potential limitations in capturing the full spectrum of emotional experiences, as the model predominantly relies on arousal and valence, neglecting other potentially relevant dimensions (Cowen & Keltner, 2017). The number of emotions is also not complete as the purpose of Russel’s work was not to list out all the possible emotions and at least to verify their distinction (Cortis, 2021).

Even though there are numerous models of emotion, only a select few treat emotions as discrete entities. Among these are the models developed by Tomkins, Ekman, Shaver, and Izard. These theorists assert that emotions are fundamental, distinct categories that are universally recognizable and biologically rooted. Tomkins' model emphasizes innate affect programs, Ekman's work focuses on universal facial expressions, Shaver categorizes emotions into hierarchical structures, and Izard's Differential Emotions Theory identifies ten basic, discrete emotions. Together, these models underscore the idea that certain emotional responses are hardwired into human nature, distinct from the more continuous or dimensional approaches seen in other emotion theories.

As shown in Table 1, these models identify a core set of basic, universal emotions, emphasizing their biological and evolutionary foundations. However, the distinct emotions recognized in these models are still too limited to capture the full spectrum of human emotional experience. The complexity and diversity of emotions go beyond the foundational categories these models propose, indicating a need for more comprehensive frameworks that can encompass the wide range of emotional states people experience.

Scientists at UC Berkeley have recently expanded our understanding of distinct human emotions, challenging the notion that we experience only six or eight primary ones. Contrary to the traditional belief in happiness, sadness, anger, surprise, fear, and disgust, the researchers identified 27 distinct human emotions. These include not only well-known emotions but also others like confusion, romance, nostalgia, and sexual desire. The findings are presented on an interactive map, highlighting the broader and more diverse range of emotions that humans can feel universally and distinctly (Cowen & Keltner, 2017).

The emergence of 27 distinct human emotions has prompted inquiry into whether customers exhibit a similar range of emotions when interacting with companies' products and services, as evidenced by their reviews. Customer emotions are different from human emotions and are a crucial aspect of customer experience management. Researchers have found that the intensity of emotions expressed by customers in a service context can have significant interpersonal effects (Cheshin et al., 2018). Specifically, customers' emotional expressions that are perceived as appropriate for the context are more likely to elicit favorable responses than expressions that are deemed inappropriate (Manthiou et al., 2020).

Moreover, customer emotions are different from human emotions in the sense that customers are not passive victims of their emotions and can actively regulate them. Customers who use reappraisal, a form of emotion regulation, experience a reduction in the negativity of an emotional experience (Manthiou et al., 2020). They may, for instance, conceal a negative emotion to gain a reward or better service (Manthiou et al., 2020). Customers also can tolerate and control their emotions, such as when a positive outcome outweighs a negative emotion experienced during an encounter. Interestingly, customers may even feel mixed emotions during a service experience, particularly when the event has both pleasant and unpleasant aspects (Cheshin et al., 2018).

Previous research has established the intricate nature of customer emotions, each possessing unique attributes. Instead of oversimplifying customer emotions into a binary framework of positive and negative, it is imperative to acknowledge the intensity and management of these emotions as pivotal elements influencing customer reactions and results. With the recent confirmation that the array of distinct emotions is far broader than previously understood, there arises a necessity to reassess the differentiation of customer emotions.

This study, therefore, hypothesized that:

Hypothesis 1: The 27 emotions extracted from customer reviews are significantly distinct.

2.2. Cultural dimensions

Emotions are a fundamental aspect of the human experience, yet the way they are expressed, perceived, and understood can vary significantly across cultures. While some researchers have argued for the existence of universal, basic emotional categories, such as happiness, anger, fear, and sadness, others have highlighted the profound influence of cultural norms and beliefs on how emotions are categorized and experienced (Mesquita & Walker, 2003).

One perspective suggests that while the core emotional experiences may be pancultural, the specific ways in which they are labeled, expressed, and interpreted are heavily influenced by cultural contexts (Posner et al., 2005). For example, in Western cultures, emotions are often seen as intrapsychic phenomena that occur within the individual, whereas in other cultural contexts, emotions may be understood as emerging from the dynamic interactions between individuals and their social environments. These cultural differences in emotional conceptualization can lead to variations in the prevalence and societal valuation of different emotional states (Marcos-Nájera et al., 2021).

Hofstede's cultural dimensions theory, developed by Dutch social psychologist Geert Hofstede, is a widely recognized framework for understanding cultural differences in various societies (Hofstede, 2011). The model identifies six cultural dimensions: Power Distance, Individualism vs. Collectivism, Masculinity vs. Femininity, Uncertainty Avoidance, Long-Term Orientation vs. Short-Term Normative Orientation, and Indulgence vs. Restraint. These dimensions help analyze how different cultures approach issues such as authority, individualism, gender roles, tolerance for uncertainty, time orientation, and indulgence in pleasure (Hofstede, 2011).

Hsu et al. (2021) claimed that the countries and more generally the regions are grouped not by their geographical locations but also by their cultural dimensions. Cultural dimensions in countries exhibit distinct characteristics that shape societal norms, behaviors, and values (Li, 2014). In some countries, individualism stands as a prominent cultural dimension, emphasizing personal autonomy, independence, and self-expression. Those societies value individual achievement, personal rights, and the pursuit of one's goals. This ethos fosters a competitive spirit and encourages people to strive for uniqueness and personal success. According to Cordaro et al. (2018), egalitarianism is deeply ingrained in Western culture, promoting equality of opportunity and the belief in meritocracy. People in the West, typically value fairness, justice, and inclusivity, striving to create environments where individuals have equal access to resources and opportunities regardless of their background as found by Nakayama and Wan (2018).

Conversely, cultural dimensions in other countries, often in the East, often emphasize collectivism as a core value. Family, community, and group harmony take precedence over individual desires or ambitions (Hampden-Turner et al., 2020). Confucian principles heavily influence Eastern cultures, emphasizing hierarchical relationships, respect for authority, and duty to the collective. Maintaining social harmony and preserving the group's interests are paramount in Eastern societies, leading to strong social cohesion and interconnectedness among individuals (Oyserman et al., 2002). Additionally, Eastern cultures often prioritize long-term orientation, valuing perseverance, thriftiness, and tradition. These values contribute to a sense of continuity and stability within Eastern societies, fostering resilience in the face of challenges and promoting sustainable development over time as found by Oyserman et al. (2002).

Trompenaars and Hampden-Turner expanded Hofstede’s cultural model and developed the Seven Dimensions of Culture model, which provides a more comprehensive understanding of cultural diversity. The seven dimensions include Universalism vs. Particularism, Individualism vs. Communitarianism, Specific vs. Diffuse, Neutral vs. Affective, Achievement vs. Ascription, Sequential vs. Synchronic, and Internal vs. External Control (Hampden-Turner et al., 2020). This model delves into aspects like how cultures approach rules, relationships, communication styles, attitudes toward time, and control over one's environment. As shown in Table 2, the Hampden-Turner and Trompenaars model offers a nuanced perspective on cultural differences, emphasizing the importance of understanding the underlying values that shape customer behaviors (Hampden-Turner et al., 2020).

Dimension	**One Extreme**	**Other Extreme**
Identity	Individual	Group
Power	Egalitarian	Hierarchal
Gender	Feminine	Masculine
Uncertainty	Ambiguity	Structure
Orientation	Short term	Long term
Time	Task	Relationship
Direction	External	Internal

Table 2: Cultural dimensions

In the context of social networks, based on those conceptual frameworks, Sudirjo et al. (2023) studied an uncharted realm of sentiments embedded in discussions about one topic of Urban Green Spaces (UGS) across different cultures. By analyzing sentiment values in English and German tweets, the study brought to the fore the distinct emotional responses elicited by various types of UGS. This observation suggests a cultural divergence in the preferences and emotional associations related to specific UGS, highlighting the importance of cultural dimensions in understanding emotional responses on a particular topic (Sudirjo et al., 2023).

The study by Park et al. (2014) previously took a groundbreaking approach by combining Twitter-emoticon-usage patterns with the cultural dimensions, providing a nuanced understanding of how cultural factors influence online emotional expression. Twitter, as a microblogging platform, serves as a rich source for observing spontaneous and real-time emotional reactions, making it an ideal medium for studying cross-cultural emoticon preferences (Alhadlaq & Alnuaim, 2023).

The research highlights a captivating distinction in emoticon usage between individuals from collectivistic and individualistic cultures. People from collectivistic cultures exhibit a preference for vertical and eye-oriented emoticons, whereas those from individualistic cultures lean towards horizontal and mouth-oriented emoticons. This finding not only underscores the diversity in emotional expression but also reveals the subtle ways in which culture shapes the non-verbal elements of online communication (Park et al., 2014).

Similarly, Li et al. (2019) embarked on an empirical study, leveraging a vast and diverse dataset from Twitter to delve into the intricate world of emoji usage. The authors employed distributional semantic models, a sophisticated analytical approach, to express the semantics of emojis. The study demonstrated that different cultural dimensions within countries exhibited considerably diverse uses of emojis to express emotions (Li et al., 2019).

In the current literature, there are more studies about cultural differences using emojis than texts, partly because the technique for emotion detection from texts was not there yet. Just recently, there was a study by Hsu et al. (2021), which revealed intriguing disparities in the emotional tones of Twitter messages by a machine learning technique based on Transformer. Accordingly, Japanese users were found to predominantly produce low arousal postings, aligning with the cultural tendency towards emotional restraint and subtlety (Nakayama & Wan, 2018).

In contrast, U.S. users were more inclined to generate positive, high-arousal posts, reflecting a cultural preference for optimism and positivity. This observation underscores how cultural values intricately shape the emotional expressions manifested in online text messages through their arousal scores. While the affective cultural values of Japanese users would suggest a greater sensitivity to negative high-arousal posts, the study found that Japanese users were, in fact, more affected by changes in others' high-arousal positive posts than their United States counterparts (Hsu et al., 2021).

However, this study, together with other ones, has a limitation of using only the valence and arousal scores of the texts, not the emotions themselves. Furthermore, other studies about cultural differences were mostly based on individualism and collectivism, but not on other dimensions, which might be more relevant to business (Hampden-Turner et al., 2020).

Recently, Lawrie et al. (2020) conducted a study revealed that cultures with a high tendency to avoid uncertainty often exhibit a greater inclination toward expressing negative emotions such as disappointment and fear. This finding sheds light on how cultural values and norms shape individuals' emotional expressions, illustrating the intricate interplay between societal context and emotional behavior. Understanding these cultural nuances is essential for effective communication and interaction across diverse cultural landscapes, as it allows for the recognition and interpretation of emotional cues within their cultural context (Lawrie et al., 2020).

Yan et al. (2020) explored the correlation between power distance orientation and the manifestation of approval or disapproval emotions within different cultural frameworks. Their research emphasized the significance of power dynamics in shaping emotional responses, indicating that individuals' perceptions of authority and hierarchy influence their emotional expressions. This underscores the importance of considering power differentials when analyzing emotional dynamics within cross-cultural contexts, as hierarchical structures can significantly impact individuals' emotional experiences and expressions.

Mesquita (2022) proposed the intriguing notion that cultures play a pivotal role in shaping the very nature of human emotions. According to the assertion, cultures possess the capability to not only influence how emotions are expressed and regulated but also to fundamentally create and define emotions themselves. This perspective challenges conventional understandings of emotions as universal and innate phenomena, suggesting instead that cultural factors exert a profound influence on the construction and interpretation of emotional experiences (Mesquita, 2022).

There is clear evidence of the correlation between emotions and cultures. This is not simply due to differences in psychological biases or environments but rather reflects the cultural construction of emotion categories. While there may be similarities in the basic physiological experiences of emotions across cultures, the meaning, expression, and regulation of these emotions can vary significantly (Casimir & Schnegg, 2002).

For instance, the Japanese emotion category of 'amae' has no direct equivalent in American culture (Lindquist et al., 2022). Similarly, Chinese Americans and European Americans living in the same country can describe emotional experiences differently in response to the same events (Lindquist et al., 2022). This suggests that even when cultures share similar core emotional themes, the specific meanings and associations of those emotions can be quite distinct (Kitayama et al., 2006).

The cultural shaping of emotion is evident in both the discrete categories used to label emotions, as well as the patterns of emotional experience. Studies have found that, compared to Japanese individuals, Americans tend to report experiencing emotions more intensely and for longer durations, and are less likely to mask their emotions (Atkins et al., 2016). In contrast, Japanese individuals show a greater tendency to experience socially engaging positive emotions, while Americans exhibit a stronger propensity for disengaging positive emotions (Kitayama et al., 2006).

Although cultural studies in the context of e-commerce have seen significant growth, there are still notable research gaps. Historically, research on cultural variances has predominantly centered on individualism and collectivism, overlooking other potentially pertinent dimensions crucial for businesses. Recent advancements in psychology further validate the existence of a broader spectrum of emotions. However, there remains a gap in our comprehension regarding whether cultural distinctions extend to all these emotions or are confined to only a subset, as previously explored.

Furthermore, the focus of previous studies was limited to distinguishing between just one or two emotions. While some studies have examined social networks, they have not specifically addressed e-commerce platforms and more specifically, customer emotions.

This study, therefore, hypothesizes that:

Hypothesis 2: There is a significant difference between the distributions of 27 emotions of Western and Eastern consumers.

3. Methodology

By addressing the gaps in the current literature, the present study aims to contribute to a more nuanced understanding of cross-cultural dynamics in the business landscape. The present study leverages the new machine learning techniques in analyzing Westerners' and Easterners' customer reviews on e-commerce sites. This approach goes beyond simplistic sentiment analysis, allowing for a more profound exploration of the underlying cultural influences shaping online communication emotionally.

In specifics, this study employed machine learning-based techniques to detect and analyze 27 emotions in customer reviews, focusing on their differences through the lens of cultural frameworks. Unlike previous studies, this research seeks to contribute to a more comprehensive understanding of cross-cultural differences by leveraging up-to-date machine-learning emotion detection techniques.

In pursuit of the mentioned objectives, this study proposed a comprehensive method for extracting and categorizing customer emotions, consisting of several steps. The workflow of the suggested method is visualized in Figure 1.

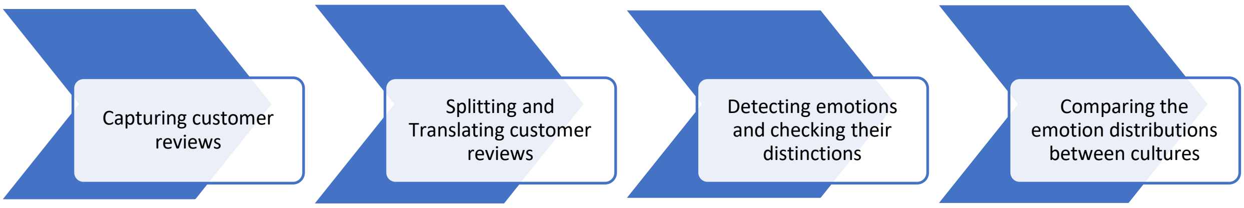

Figure 1: Proposed method workflow

Talking about cultures, Japan, often referred to as the Land of the Rising Sun, stands as a captivating representation of Eastern culture (Cordaro et al., 2018). Rooted in a rich history that spans thousands of years, Japanese culture is a seamless blend of tradition and modernity, where ancient customs coexist with cutting-edge technology. Japan's Eastern culture is a harmonious tapestry of ancient traditions and modern innovations, creating a unique and enduring identity. The nation's ability to preserve its cultural heritage while embracing progress showcases the resilience and adaptability inherent in Japanese society (Cordaro et al., 2018).

On contrast, the Western culture of Spain is a rich tapestry woven with layers of history, tradition, and vibrant customs (Hampden-Turner et al., 2020). Influenced by centuries of diverse civilizations, including the Romans, Moors, and Visigoths, Spanish culture is characterized by its passionate flamenco music and dance, bullfighting spectacles, and colorful festivals such as the famous Running of the Bulls in Pamplona. Spaniards embrace a relaxed pace of life, savoring long meals with family and friends, often accompanied by lively conversations and copious amounts of delicious tapas and wine (Marcos-Nájera et al., 2021). The architecture reflects the country's varied heritage, with Moorish influences evident in the intricate designs of landmarks like the Alhambra in Granada, while Gothic cathedrals dot the landscape, epitomizing the grandeur of Spain's medieval past. Whether exploring the cobblestone streets of historic cities or basking in the sun on one of its picturesque beaches, the Western culture of Spain beckons visitors with its warmth, charm, and enduring spirit (Boyd, 2020).

By embracing cultural analysis, this methodology introduced a novel approach, comparing Japanese and Spanish-speaking communities as the two representatives of two different cultures. English is used as a translation language for both Spanish and Japanese to remove the bias due to the translation similar to the way previous studies were conducted (Alhadlaq & Alnuaim, 2023). The process commenced by collecting 400,000 Spanish and Japanese-speaking customer reviews on an e-commerce platform called Yelp.

Yelp, founded in 2004, has emerged as one of the most influential platforms for crowd-sourced reviews and recommendations, particularly within the realm of dining, hospitality, and local businesses (Nakayama & Wan, 2018). With its user-friendly interface and extensive database of reviews, Yelp provides a valuable resource for consumers seeking authentic insights into various establishments and services. Businesses, on the other hand, often rely on Yelp to engage with customers, manage their online reputation, and attract new clientele. Today, Yelp garners 70 million monthly views and 30 million monthly visits (Salehi-Esfahani & Kang, 2019). Studies indicate that Yelp customer reviews significantly shape the reputation and success of its merchandise (Anderson & Magruder, 2012; Nakayama & Wan, 2018).

Next, the emotion detection phase, facilitated by a GoEmotions fine-tuned model, provided a culturally guided assessment. The GoEmotions fine tuning approach represents an endeavor to develop a more resilient emotion detection model applicable to diverse NLP tasks, including semantic and propaganda analysis, where emotions play a significant role (Kamath et al., 2022). This methodology integrates a pre-trained and fine-tuned RoBERTa model, adapting it to a GoEmotions dataset containing 27 emotions offering the most comprehensive taxonomies available (Demszky et al., 2020).

ROBERTA, introduced in 2019, marked a significant leap in the field of natural language processing (NLP). It refined and optimized the pretraining process by using larger amounts of data and longer training times compared to the original BERT model. This approach helped ROBERTA achieve state-of-the-art performance in various language tasks and benchmarks (Kamath et al., 2022). The customer emotions identified by this model (Hypothesis 1) will then be tested to verify their distinctions with correlation coefficients.

Fine-tuning RoBERTa with the GoEmotions dataset, which took 7 days, involves adapting the pre-trained RoBERTa model to effectively classify a wide range of human emotions expressed in text. During the fine-tuning process, the RoBERTa model's weights are adjusted by training it on this dataset, enabling the model to learn the subtle linguistic cues associated with different emotions. This fine-tuning process enhances RoBERTa's ability to accurately identify and differentiate between the various emotion categories present in the GoEmotions dataset.

The following hyperparameters were used during training:

- learning_rate: 2e-05
- train_batch_size: 4
- eval_batch_size: 8
- seed: 42
- optimizer: Adam with betas = (0.9,0.999) and epsilon=1e-08
- lr_scheduler_type: linear
- num_epochs: 5

By leveraging the pre-trained knowledge from RoBERTa and the rich, diverse emotion annotations from GoEmotions, it achieves the following results on the evaluation set:

- Loss: 3.25
- Accuracy: 0.57
- F1: 0.56

Emotion scores are numerical values assigned by the fine-tuned model to indicate the intensity or presence of specific emotions within a given text. When a piece of text is processed by the fine-tune model, it outputs scores for each emotion category. These scores represent the model's confidence in the presence of each emotion (Kamath et al., 2022). For example, a text of "My son has received an excellent scholaship to study in the U.S but I am

```
Sadness 0.910, Disappointment 0.055, Grief 0.020, Admiration 0.002, Remorse 0.002, Caring
0.001, Approval 0.001, Love 0.001, Fear 0.001, Realization 0.001, Anger 0.001, Disgust 0.001,
Disapproval 0.001, Amusement 0.000, Joy 0.000, Annoyance 0.000, Optimism 0.000, Gratitude
0.000, Nervousness 0.000, Surprise 0.000, Desire 0.000, Relief 0.000, Embarrassment 0.000,
Curiosity 0.000, Pride 0.000, Confusion 0.000, Excitement 0.000
```

Figure 2: Sample emotion detection results

As shown in the output, the emotion scores typically range between 0 and 1, where values closer to 1 indicate a stronger presence of the emotion, and values closer to 0 indicate a weaker presence. These scores help in quantitatively analyzing the emotional tone of large datasets, including its correlations.

Correlation coefficients serve as numerical measures of the strength and direction of relationships between variables. Ranging from -1 to 1, these coefficients provide insights into the degree to which changes in one variable correspond to changes in another. In the context of customer emotion correlations, a low correlation coefficient suggests weak or minimal association, while higher coefficients indicate stronger relationships or lower distinctions (Padayachee, 2016).

Finally, the distributions of the emotion scores will then be put into an analysis of variance test. The ANOVA test is a statistical method used to compare the variances of two populations or more. It is often employed to determine if the means of several groups are equal. The test calculates the ratio of variances between groups to variances within groups. In essence, it assesses whether the differences among group means are due to true differences in population means or simply due to random variation (Hewson et al., 2016).

In the ANOVAT test, a high F-value suggests that the variation among group means is larger than expected by chance alone, leading to the rejection of the null hypothesis of equal population means. Conversely, a low F-value indicates that the variation among group means is similar to what would be expected by chance, thus failing to reject the null hypothesis. The ANOVA test is a fundamental tool in many statistical analyses, providing valuable insights into the significance of group differences (Saunders, 2015). A significant difference between groups (Hypothesis 2) is confirmed by a p-value of below 0.05 (Hewson et al., 2016).

4. Results

The emotion analysis employed the NLP approach, extracting and analyzing emotions from the text using the fine-tune model, which integrates the advanced ROBERTA approach. The model categorizes texts into 27 emotion categories. The analysis revealed that 27 emotions were extracted from translated customer reviews by the Spanish and Japanese-speaking customers as shown in Table 3. Out of the total customer reviews, 400,000 were collected over one year, 200,000 in Spanish, and 200,000 in Japanese were emotionally classified. Customer reviews with undetermined emotional context due to translation issues were excluded from the results.

The table presents a comparative analysis of the percentages of 27 emotions—ranging from admiration, amusement, anger, and annoyance to more nuanced states like pride, realization, relief, and remorse—expressed by two distinct groups of customers: those speaking Spanish and those speaking Japanese. This detailed breakdown provides valuable insights into the emotional landscapes of these cultural groups, highlighting similarities and differences in how emotions such as joy, sadness, excitement, and gratitude are articulated within their interactions. By examining the distribution of emotions like approval, caring, curiosity, and disappointment, the table underscores the cultural nuances and commonalities in emotional expression between Spanish and Japanese speakers, offering a comprehensive understanding of customer sentiment across these diverse linguistic groups.

The intricate relationship between culture and consumer behavior comes to the forefront of the analysis, offering a nuanced exploration of emotions associated with Spain and Japanese consumers. Beyond a mere assessment of product and service preferences, the findings reveal distinct emotional expressions linked to cultural nuances, shedding light on the diverse ways individuals from different regions engage with and respond to products and services they receive.

No	Emotion	Spain	Japan
1	admiration	27.14%	11.13%
2	amusement	0.64%	1.44%
3	anger	0.25%	0.23%
4	annoyance	1.38%	1.32%
5	approval	21.09%	29.82%
6	caring	1.08%	1.99%
7	confusion	2.16%	3.95%
8	curiosity	0.74%	2.28%
9	desire	0.46%	1.33%
10	disappointment	5.47%	6.72%
11	disapproval	18.62%	9.16%
12	disgust	2.19%	2.24%
13	embarrassment	0.94%	1.80%
14	excitement	0.56%	0.44%
15	fear	0.85%	1.52%
16	gratitude	1.48%	1.88%
17	grief	0.00%	0.01%
18	joy	2.53%	2.84%
19	love	3.94%	3.47%
20	nervousness	0.12%	0.63%
21	optimism	1.55%	1.30%
22	pride	0.01%	0.02%
23	realization	4.94%	9.34%
24	relief	0.09%	0.48%
25	remorse	0.19%	0.97%
26	sadness	0.50%	0.71%
27	surprise	1.07%	2.97%

Table 3: Descriptive results

The following sections present the outcomes of the hypothesis testing.

4.1. Hypothesis 1

It is found that the average correlation coefficients of all the emotions are in the range of -0.2 and 0.2 as shown in Table 4. That means those customer emotions are lowly correlated.

	admiration	amusement	anger	annoyance	approval	caring	confusion	curiosity	desire	disappointment	disapproval	disgust	embarrassment	excitement	fear	gratitude	grief	joy	love	nervousness	optimism	pride	realization	relief	remorse	sadness	surprise
admiration	1																										
amusement	-.04	1																									
anger	-.04	.00	1																								
annoyance	-.09	.00	.14	1																							
approval	-.19	-.04	-.04	-.07	1																						
caring	-.06	-.01	.00	-.01	-.03	1																					
confusion	-.08	-.01	-.01	-.01	-.08	-.02	1																				
curiosity	-.05	-.01	-.01	-.01	-.05	-.01	.04	1																			
desire	-.05	.00	-.01	-.01	-.01	-.01	-.01	.02	1																		
disappointment	-.15	-.02	.00	.00	-.13	-.03	-.03	-.02	-.02	1																	
disapproval	-.24	-.03	-.01	-.02	-.21	-.05	-.05	-.04	-.04	-.05	1																
disgust	-.10	-.01	.05	.09	-.08	-.02	-.03	-.02	-.02	-.02	.03	1															
embarrassment	-.06	-.01	.01	.02	-.06	-.01	-.01	-.01	-.01	.02	-.03	.04	1														
excitement	-.03	.00	-.01	-.01	-.03	-.01	-.01	.05	.02	-.02	-.05	-.02	-.01	1													
fear	-.06	-.01	.01	.03	-.05	.01	-.01	-.01	-.01	-.01	-.03	.05	.00	-.01	1												
gratitude	-.01	-.01	-.01	-.02	-.06	.01	-.02	.01	-.01	-.03	-.06	-.02	-.01	.00	-.01	1											
grief	-.01	.00	.01	.00	-.02	.03	.00	.00	.00	.00	-.01	.00	.00	.00	.01	.00	1										
joy	-.07	.06	-.01	-.02	-.04	.00	-.03	-.01	-.01	-.04	-.08	-.03	-.02	.02	-.02	-.02	.00	1									
love	-.05	-.01	-.01	-.03	-.08	-.02	-.03	-.02	.00	-.05	-.08	-.03	-.02	-.01	-.02	-.03	.00	.00	1								
nervousness	-.05	-.01	.00	.03	-.02	.01	.01	.00	.00	.01	-.03	-.01	.01	.05	.12	-.01	.01	-.01	-.02	1							
optimism	-.06	-.01	-.01	-.02	.01	.02	-.02	-.01	.04	-.04	-.08	-.03	-.01	-.01	-.02	-.01	.00	-.02	-.03	.01	1						
pride	.01	.00	.02	.02	-.01	-.01	-.01	-.01	.04	-.01	-.03	.01	.05	.02	.00	-.01	.01	.00	-.01	.01	.01	1					
realization	-.15	-.02	-.02	-.01	-.10	-.03	-.01	-.02	-.02	-.02	-.09	-.04	-.01	-.02	-.02	-.04	.01	-.04	-.05	.01	-.03	.01	1				
relief	-.03	-.01	-.01	-.01	.04	.06	-.01	-.01	-.01	-.02	-.04	.00	.00	.00	.00	.02	.01	.04	-.02	.04	.05	.06	.00	1			
remorse	-.03	.00	.00	.00	-.03	.00	-.01	.00	.00	.02	-.01	-.01	.04	.00	.00	.00	.02	-.01	-.01	.00	.00	.01	.00	.00	1		
sadness	-.06	-.01	.01	.00	-.05	.00	-.01	.00	.00	.07	-.03	-.01	.00	-.01	.02	-.01	.14	-.02	-.02	.04	-.02	.00	-.01	-.01	.05	1	
surprise	-.06	-.01	-.01	-.01	-.06	-.01	.00	.00	.00	.00	-.05	-.02	-.01	.03	-.01	-.01	.02	-.02	-.02	.01	.00	.01	.03	.00	-.01	-.01	1

Table 4: Correlation coefficients

In fact, more than 90% of the correlation coefficients in the 27 x 27 correlation matrix are in the range of -0.01 and 0.01, meaning they are very highly distinct. Almost all the correlation coefficients among the 27 categories of customer emotions are consistently close to zero. This finding suggests that these emotional categories are significantly distinct entities.

The near-zero correlation coefficients among the 27 emotional categories underscore the intricate and individual nature of customer emotions, which were not reported in previous studies. Each emotional category appears to exist independently, suggesting that they represent distinct facets of the vast spectrum of customer feelings. This lack of correlation reinforces the notion that customer emotions are multifaceted and diverse, showcasing the richness of customer emotional experiences. From joy to sadness, from excitement to fear, each emotion brings its unique essence to the intricate tapestry of human interactions, particularly within the context of buying and selling.

This diversity in emotional categories serves to emphasize the complexity of customer emotions and their role in decision-making processes, especially in the business context. The absence of strong correlations between emotional categories suggests that individuals may experience a wide array of emotions simultaneously or sequentially when engaged in buying or selling activities. Furthermore, it implies that each emotional experience holds its significance and influence, contributing uniquely to the overall emotional landscape of business transactions.

Understanding the distinctiveness of each emotional category within the realm of buying and selling can offer valuable insights for marketers, advertisers, and businesses aiming to connect with consumers on an emotional level. By recognizing and appreciating the diversity of emotional experiences, businesses can tailor their strategies to resonate with specific emotional triggers, effectively tapping into the nuanced dynamics of consumer behavior. Ultimately, acknowledging the complexity and richness of customer emotions can lead to more authentic and impactful interactions between businesses and consumers in the marketplace.

The confirmation of the distinction among 27 customer emotions and the confirmation of the hypothesis 1 is significant in both qualitative and quantitative aspects; and is the foundation for the testing of the hypothesis 2.

4.2. Hypothesis 2

From the emotion scores derived from 400,000 customer reviews, the study calculates the average scores for each emotion. The results are summarized in Table 5. Using this table, a comparison between the two groups will be conducted.

When checking with the test result in Table 5 afterwards, it is evident that the two distributions of 27 emotions are markedly distinct ($F=2.03$, $p=0.039$). The group test has yielded a p-value significantly below the conventional threshold of 0.05, indicating an extremely low probability that the observed difference in emotions between the two distributions of Eastern and Western customers is due to random chance alone. This result underscores the robustness of the observed distinction, suggesting that the variations in emotional responses among the groups are unlikely to be explained by inherent randomness or sampling variability. Therefore, we can confidently assert that there exists a substantial and meaningful difference in emotional distribution between the Spanish and Japanese-speaking groups or Western and Eastern customers in general.

When comparing the distributions side by side, it becomes evident that significant disparities exist between the two. This observation underscores the distinct emotional tendencies exhibited by each group. Through a visual inspection of the data, it becomes apparent that the frequencies of various emotions diverge notably between the two distributions of Spanish and Japanese-speaking customers’ emotions. This visual contrast serves as an initial indicator of the dissimilar emotional landscapes experienced by the two cultures in general.

	Spain	**Japan**
admiration	0,20262528	0,01854312
amusement	0,00514454	0,00914793
anger	0,00293066	0,00870418
annoyance	0,013009	0,0302014
approval	0,16946644	0,07523684
caring	0,0093184	0,01876944
confusion	0,01733558	0,05309264
curiosity	0,00621181	0,03252626
desire	0,00479127	0,00783772
disappointment	0,04413585	0,1145668
disapproval	0,14010196	0,13743961
disgust	0,01815074	0,04731947
embarrassment	0,00784945	0,02585673
excitement	0,00530653	0,00309973
fear	0,00675462	0,02153405
gratitude	0,01296807	0,0045618
grief	0,00017785	0,00050343
joy	0,01951987	0,00428621
love	0,02963763	0,00844692
nervousness	0,00169537	0,00645904
optimism	0,01695623	0,00834944
pride	0,0004596	0,00065846
realization	0,04334316	0,10897391
relief	0,00182897	0,00250602
remorse	0,00179333	0,01888553
sadness	0,00510018	0,01523497
surprise	0,00847874	0,03119653

Table 5: Average emotion scores

This outcome holds critical implications for understanding the underlying factors influencing emotional expression and perception within these groups. The significant difference identified by the F-test suggests that there may be distinct mechanisms, experiences, or external factors shaping the emotional landscape of each group. Furthermore, the statistical analysis provides quantitative validation of these observed differences. This statistical confirmation underscores the magnitude of the discrepancy and affirms the significance of the observed differences. Such findings bolster the understanding that the emotional expressions of the two groups are not merely random fluctuations but rather reflect systematic differences rooted in cultural factors as shown in Figure 3.

Figure 3 provides deeper insights into the distinct emotional tendencies of consumers in Spanish and Japanese-speaking groups, highlighting specific emotions that are more strongly correlated with each cultural group. The data underscore that Spanish-speaking customers are particularly inclined to express emotions such as joy, realization, approval, and annoyance. These emotions align with the individualistic nature of Western culture, where personal fulfillment and autonomy are highly valued. Joy and approval signify positive experiences and satisfaction with products or services, while realization reflects a critical engagement with information or experiences. Additionally, the presence of annoyance suggests a willingness to express dissatisfaction or frustration when expectations are not met, reflecting a consumer base that is assertive in asserting preferences and boundaries.

In contrast, Japanese-speaking consumers exhibit a different emotional profile, with a tendency to convey emotions centered around grief, relief, pride, and caring. These emotions reflect the collectivist orientation and strong emphasis on social harmony in Japanese culture. Grief and relief signify emotional responses to significant events or experiences, while pride reflects a sense of accomplishment or satisfaction derived from personal or collective achievements. Moreover, the presence of caring underscores the importance of empathy and interpersonal relationships in Japanese society, suggesting a consumer base that values products or services that foster connections and foster a sense of community that was not observed that much in other cultures.

With the test, hypothesis 2 has been confirmed, revealing significant insights beyond the mere differences in one or two emotions between the two cultures. This confirmation highlights a broader divergence in the entire emotional spectrums of the cultures studied. Instead of isolated variations, the results indicate distinct patterns and distributions across a wide range of emotions, suggesting that each culture possesses a unique emotional profile. This comprehensive understanding of cultural emotional spectrums underscores the complexity of emotional expression and perception across different cultural contexts, affirming that emotional experiences and their manifestations are deeply rooted in cultural norms and values.

The finding is significant in the sense that it comes from a comparative analysis between two groups of emotions, which were confirmed as distinct in hypothesis 1, and detected directly from the context of business transactions with its high applicability. More discussion on the significance and applicability of these findings will be presented in the next section.

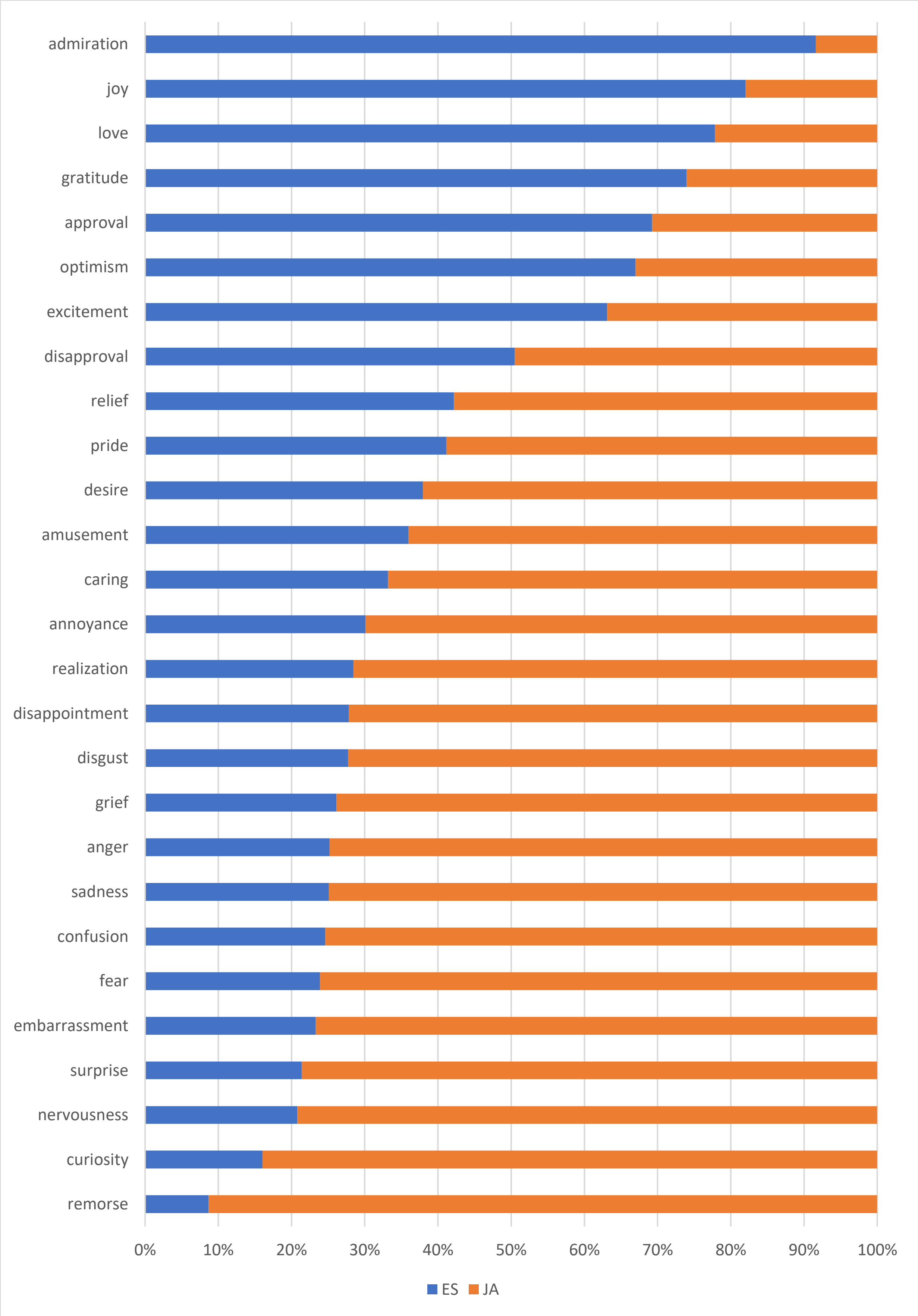

Figure 3: Emotion distributions

5. Discussion

The above findings confirmed the distinction of 27 emotions in 400,000 customer reviews. This is one of the first studies on e-commerce sites with this large amount of data and with this well-fine-tuned machine-learning model. That is highly applicable to businesses when they need to understand their customers emotionally. With the correlation coefficients all close to zero, it is strongly evident that the emotions are correctly and distinctly detected. Customers when shopping online, regardless of their locations all expressed the same set of emotions universally.

Even there were some studies on the distinction of 27 emotions observed in other platforms, like Reddit or X (formerly Twitter) (Alhadlaq & Alnuaim, 2023; Chen et al., 2022), this is one of the first studies that put e-commerce's customer reviews under the test. The number of messages is also much higher than those in previous studies. This finding is significant in the sense that even in the domain of shopping and purchasing, humans still express as many emotions as they do in other daily activities.

Not only so, this study also confirmed that different groups of customers could express their emotions differently, based on their cultures. The revelation that Spanish and Japanese-speaking customers express different sets of emotions transcends a mere acknowledgment of cultural variations; it encapsulates the profound impact of societal values on emotional articulation. Easterners, represented by the Japanese consumers in this context, do not merely differ in the intensity of emotions expressed; they showcase a unique set of emotional responses grounded in collectivism, long-term orientation, and uncertainty avoidance. Caring, pride, relief, and grief emerge as prominent emotional expressions, underlining the significance of communal values in Japanese and Eastern culture.

Conversely, Westerners, typified by U.S. consumers, lean towards emotional expressions rooted in individualism, power closeness, and result-oriented. Approval, disappointment, and excitement take precedence, emphasizing the importance of personal experiences and individual perspectives in shaping emotional responses. This cultural dichotomy highlights that emotional expressions are not uniform but are deeply embedded in the cultural fabric that shapes individuals' worldviews.

The observation that Westerners are more prone to excitement and approval suggests a cultural inclination toward celebrating personal achievements and individual success. This aligns with the broader cultural emphasis on autonomy and self-expression found in many Western societies. On the other hand, the Eastern tendency to express caring and desire highlights the importance of interpersonal relationships and communal well-being, mirroring the collective values ingrained in Eastern cultural contexts. The relevance of these cultural nuances extends to the realm of customer reviews, where consumer sentiments are articulated and shared. The distinct emotional expressions identified in the analysis underscore the need for a culturally sensitive lens when interpreting and responding to customer feedback from different markets.

Previously, Hofstede's model distinguished nations based on various values, with individualism vs. collectivism being a significant dimension. The literature suggests that both Japanese- and Spanish-speaking individuals reside in collectivistic cultures, although cultural variances exist, with Spanish-speaking communities exhibiting lower collectivism scores than the Eastern world. This study aligns with broader cross-cultural research indicating stronger collectivist beliefs in Eastern countries, Eastern Europe, Africa, and, to a lesser extent, Latin America (Cordaro et al., 2018). It further explored other cultural dimensions and investigated a large range of emotions in the context of customer experiences.

Also, even there were some studies on the cultural differences in the past. Most were based on the sentimental scores to judge the difference. Some were on the emojis quantitatively. The number of studies on actual emotions was limited mostly because of the readiness of emotion detection techniques and the psychological advancements on universal and discrete emotions. The number of emotions according to the previous theories was not limited to make the comparison between their distribution possible. This study is one of the first to verify the significant difference between the two emotion spectrums on a large scale.

Theoretically, this study contributed to a more comprehensive understanding of the interplay between emotions and cultural dimensions and shed light on the nuanced differences that exist between cultural regions, highlighting the varying emotional landscapes that individuals navigate based on their cultural backgrounds. A novel and insightful approach has emerged in this study, where researchers empirically connected these two realms by grouping emotions within the context of cultural dimensions.

Practically, this study highlighted the importance of considering cultural nuances and contextual factors when interpreting emotional data and designing strategies tailored to diverse audiences. By acknowledging and leveraging these differences, organizations can develop more targeted and effective approaches to communication, product development, and customer engagement. Moreover, such understanding fosters greater cultural sensitivity and inclusivity, enabling businesses to build stronger connections with their audience segments and cultivate relationships based on mutual understanding and respect.

The implications of these findings extend far beyond the realm of consumer preferences. They underscore the necessity for businesses to recognize and adapt to the emotional landscape of diverse markets. Crafting marketing strategies that resonate with the cultural nuances of specific regions becomes crucial for fostering authentic connections with consumers. In the era of global connectivity and cross-cultural interactions, understanding the subtleties of emotional expression across different cultures is becoming increasingly crucial.

6. Conclusions

This research endeavors to decipher the emotions conveyed in Yelp customer reviews by Spanish and Japanese-speaking customers, conversing in distinct languages. The objective is to gain deeper insights into how customer reviews mirror the cultural attributes of both cultures. All Japanese and Spanish customer reviews were translated into English beforehand. This objectively facilitated the use of pre-existing English-based machine-learning techniques for sentiment and emotion analysis.

This study explores the findings of a data analysis revealing distinct emotional tendencies in customer reviews universally. With a high confidence level, this study has confirmed the distinction of 27 emotions in customer reviews observed in different markets. In the future, businesses can apply this methodology in detecting emotions from their customer feedback and have a new mechanism to understand their customer intelligently.

This study also highlights that certain emotions are more strongly associated with one culture than another. Westerners, for instance, exhibit a higher likelihood of expressing feelings of excitement and approval, reflecting the individualistic and achievement-oriented values often prevalent in Western societies. In contrast, Easterners are more inclined to openly demonstrate their caring and desire, aligning with the collective and interdependent nature characterizing many Eastern cultures.

Significantly, this study found that the distribution of the two groups of customer emotions in Eastern and Western cultures is different as a whole. It has not only bridged the gap between emotions and cultural dimensions but has also unveiled stark differences in emotional experiences across diverse cultural regions. The empirical evidence presented in the research underscores the profound impact that cultural context has on the way customers perceive, express, and experience emotions in general not just individually.

The study links the current developments in both psychology and culture studies into one big picture and opens the door for future research in this promising area. Notably, the study demonstrated the feasibility of recognizing and understanding customers emotionally from their customer reviews. The study also opens avenues for targeting customers more precisely, culturally, and locally for long-term benefits.

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