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Emotional Differences in Product and Service Reviews: A Sentiment and Emotion Analysis

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Article

Emotional Differences in Product and Service Reviews: A Sentiment and Emotion Analysis

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Abstract: This study investigates the emotional and sentiment differences in customer reviews of products and services on e-commerce platforms. Unlike prior research that treats customer reviews as a single entity, this study distinguishes between products, which fulfil fundamental needs, and services, which cater to higher-level experiential desires. The analysis reveals that customer sentiment and emotional expressions vary significantly between these two categories, reflecting their distinct roles in consumer decision-making. One of the key findings is that products tend to receive reviews centred around functionality, reliability, and value for money, often characterized by a more neutral or pragmatic tone. In contrast, services evoke stronger emotional responses, as they involve direct interactions, subjective experiences, and personal satisfaction. Customers express a wider range of emotions, including joy, frustration, and disappointment, when reviewing services compared to products as detected by recently developed machine learning techniques. Cultural differences further amplify these distinctions. Consumers from collectivist cultures, as identified by Hofstede's cultural dimensions, tend to emphasize group consensus and social harmony in their reviews, often using more moderated language. Meanwhile, those from individualist cultures are more likely to provide direct and emotionally intense feedback. Interestingly, gender does not significantly influence sentiment differences, suggesting that product and service categorization and cultural background are the primary drivers of variation in reviews. Theoretically, this study extends Maslow's hierarchy of needs and Hofstede's cultural framework by applying them to consumer reviews, offering a conceptual model of how these factors shape customer experiences. From a practical perspective, businesses can leverage these insights to refine their marketing and customer engagement strategies, tailoring their communication and service approaches to align with customer expectations based on product and service offerings and cultural context.

Keywords: emotion; product; service; customer review; sentiment

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Introduction

The rapid expansion of e-commerce platforms has transformed consumer behaviour, influencing how individuals purchase and review products and services. Customer reviews serve as a vital source of information for both businesses and potential buyers, shaping purchasing decisions and brand perceptions (Chevalier & Mayzlin, 2006; Zhu & Zhang, 2010). Prior research has extensively examined the role of online reviews in driving sales, enhancing consumer trust, and predicting purchase behaviour (Filieri, 2015; Floyd et al., 2014; Mudambi & Schuff, 2010). However, most studies have treated customer reviews as a homogeneous dataset, failing to differentiate between products and services despite their fundamental distinctions in consumer expectations and consumption experiences (Vargo & Lusch, 2004; Zeithaml, 1988). This oversight represents a critical gap in the literature, as the factors that shape customer reviews may differ significantly depending on whether the review pertains to a product, which fulfils tangible and functional needs, or a service, which caters to experiential and relational needs (Sudirjo et al., 2023).

Existing research on online reviews has primarily focused on their impact on consumer decision-making and brand reputation management (Filieri et al., 2018; You et al., 2015). Studies have analyzed review valence, volume, and credibility to understand their influence on purchase behaviour

(Dellarocas et al., 2007; Hennig-Thurau et al., 2004). However, these studies have largely neglected the inherent differences in consumer expectations and emotional responses when reviewing products versus services. Given that products primarily fulfil physiological and safety needs, while services address higher-order psychological and social needs (Maslow, 1943), it is plausible that consumer sentiments and emotions in reviews would differ across these categories (Chiu et al., 2012). Despite this theoretical basis, empirical investigations into these differences remain scarce, leaving an important gap in the understanding of how consumer expectations shape review sentiment and emotional expression.

Another limitation in the literature is the narrow focus on sentiment polarity (positive, negative, neutral) rather than a nuanced analysis of emotions. While studies in sentiment analysis have explored basic emotions (joy, anger, sadness, etc.), few have examined emotions beyond valence and arousal (Guo et al., 2024; Pang & Lee, 2008). Recent advancements in psychological and computational emotion research suggest that a more comprehensive framework—including valence, arousal, and dominance (VAD) alongside advanced discrete emotional categories—provides a deeper understanding of consumer sentiment (Buechel & Hahn, 2017). Despite these advancements, limited research has applied this expanded emotional framework to customer reviews in e-commerce settings, particularly in differentiating between product and service evaluations (Truong, 2022) . Addressing this gap, this study seeks to analyze a more detailed spectrum of emotional expressions across product and service reviews.

Cultural variations in consumer behaviour further complicate how sentiments and emotions are expressed in online reviews. Hofstede (2011)'s cultural dimensions theory suggests that individualism, uncertainty avoidance, and long-term orientation influence communication styles and consumer decision-making. Prior research indicates that collectivist cultures emphasize social harmony, leading to more restrained and indirect expressions of dissatisfaction, while individualistic cultures tend to provide explicit and detailed feedback (Park et al., 2007; Schuckert et al., 2015). Additionally, high-context cultures, which rely on implicit communication, may express emotions through subtle linguistic cues rather than direct sentiment words (De Kock et al., 2018). While these cultural differences have been studied in customer feedback contexts (Liu et al., 2023), there is limited research examining how they moderate the emotional expression of product versus service reviews. This study aims to fill this gap by investigating the extent to which cultural backgrounds shape the sentiment and emotional intensity of customer reviews based on purchase category.

Another unresolved question in sentiment analysis research is whether gender plays a significant role in moderating the emotional expressions found in product and service reviews. Prior studies suggest that men and women process emotions differently due to biological, psychological, and social factors, influencing how they articulate satisfaction and dissatisfaction in consumer contexts (Brody, 2008; Fischer & Manstead, 2000). Women have been found to express emotions more vividly in online communication, while men tend to adopt a more neutral tone (Purnawirawan et al., 2015; Thelwall et al., 2010). However, it remains unclear whether this gendered pattern holds across different types of online reviews, particularly in distinguishing between product and service evaluations. Given the potential implications for personalized marketing strategies, this study seeks to determine whether gender differences influence how consumers express emotions in product versus service reviews across cultural contexts.

Overall, despite the growing interest in sentiment analysis and customer review mining, there remains a lack of conceptual frameworks that integrate both category-based differences (products vs. services) and cultural variations in emotional expression. Existing studies have focused predominantly on polarity classification (positive, neutral, negative) and aspect-based sentiment detection (Liu et al., 2012; Pang & Lee, 2008), but few have explored the interactions between review content, customer expectations, and cultural influences. This study aims to bridge this gap by conceptualizing the roles of product/service categorization and cultural dimensions in shaping customer experiences and review sentiments. Specifically, this study addresses the following research questions:

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- Do customer emotional experiences differ significantly based on two categories of products and services?
- Does the impact of category differences on customer emotional experiences vary by gender and across cultures?

The remainder of this paper is structured as follows: Section 2 provides a comprehensive literature review on category-based differences in customer emotional experiences and the moderating roles of culture and gender, with hypotheses formulated at the end of each subsection. Section 3 outlines the research design and methodology, detailing the data collection and analysis processes. Section 4 presents the study's results and findings, followed by a discussion in Section 5, which explores the significance of the findings, study limitations, and directions for future research. Finally, Section 6 concludes the paper with key takeaways and implications for theory and practice.

Literature Review

This section reviews existing literature on categorical differences in customer emotional experiences, emphasizing key insights and contrasting viewpoints. It examines how product and service categories shape emotional expression in online reviews, focusing on sentiment, valence, arousal, dominance scores, and distinctions across both basic and complex emotion categories. Furthermore, it explores cultural and gender-based variations in emotional articulation, considering both traditional assumptions and shifting digital communication patterns. By identifying gaps in prior research—such as conflicting findings, methodological constraints, and the limited use of multidimensional emotion analysis—this review establishes a foundation for developing hypotheses that will be empirically tested later on.

Category Differences

Understanding customer emotional experiences in online reviews is a critical area of inquiry for both academic research and business practice. Prior studies have established that consumer sentiment plays a crucial role in shaping purchasing decisions, influencing brand reputation, and predicting customer satisfaction (Berger et al., 2020). Sentiment analysis techniques have been widely applied to assess the polarity of customer reviews, typically classifying them as positive, negative, or neutral (Pang & Lee, 2008). However, recent research underscores the importance of moving beyond simple sentiment classification to examine more nuanced emotional dimensions, such as valence (pleasure), arousal (intensity), and dominance (control) (Preoţiuc-Pietro et al., 2016; Russell, 2003). While sentiment analysis has traditionally treated product and service reviews collectively, emerging evidence suggests that emotional experiences may systematically differ based on the nature of the purchase, warranting further theoretical and empirical investigation (Rasappan et al., 2024).

Theoretical perspectives from consumer psychology and behavioural economics provide a strong foundation for understanding the emotional differences between product and service reviews. One of the earliest and most influential theories, Maslow's hierarchy of Needs suggested that consumer behaviour is driven by a hierarchy of psychological and physiological expectations (McLeod, 2007). Products, particularly utilitarian goods, often fulfil basic physiological and safety needs, whereas services, particularly experience-based and relational services, tend to fulfil higher-order social and self-actualization ones (Hoffman & Novak, 2018). This distinction suggests that customer emotions associated with services may be more intense, given their connection to social and psychological fulfilment.

Another relevant theoretical framework is Zeithaml and Parasuraman (2004)'s goods-services continuum, which differentiates between goods and services based on their tangible versus intangible characteristics. This model posits that services involve greater variability, perishability, and inseparability of production and consumption, leading to heightened emotional responses compared to product purchases, which are often evaluated based on functional attributes such as durability, reliability, and price (Vargo & Lusch, 2004). Furthermore, theories of customer satisfaction suggest that negative service experiences provoke more intense dissatisfaction and stronger negative

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emotions than negative product experiences, primarily due to the personal and relational aspects of service consumption (Bateson & Hoffman, 2011).

Empirical studies reinforce these theoretical distinctions by demonstrating that emotional expressions in service reviews tend to be more polarized and emotionally charged. For example, Li et al. (2020) found that service reviews on platforms like TripAdvisor and Yelp exhibit a higher degree of emotional intensity compared to product reviews on Amazon. This pattern aligns with previous findings that service failures trigger stronger emotional responses due to higher consumer expectations for personalized interactions and seamless experiences (Sparks & Browning, 2011). Additionally, research suggests that customers rely more on experiential and affective language when reviewing services, whereas product reviews tend to focus on cognitive and attribute-based evaluations (Yin et al., 2014).

Beyond overall sentiment, researchers have explored specific emotional dimensions, such as valence, arousal, and dominance, in customer reviews. The circumplex model of the effect (Russell, 1980) posits that emotions can be mapped onto these three dimensions, offering a more granular understanding of customer emotional responses. Studies applying this model to online reviews indicate that service-related emotions tend to exhibit higher arousal and lower dominance levels, reflecting the heightened intensity and lower sense of control consumers feel in service encounters (Xu et al., 2023). Conversely, product reviews, particularly for utilitarian goods, are often characterized by lower arousal and higher dominance, as consumers evaluate them in a more rational and controlled manner (Yin et al., 2017).

Despite these insights, significant gaps remain in the literature. First, while many studies have examined sentiment polarity, relatively few have systematically integrated valence-arousal-dominance scores into sentiment analysis models. Additionally, findings on emotional expression in online reviews remain inconsistent across studies (Truong, 2023). For instance, while some research suggests that service reviews exhibit stronger emotional intensity (Li et al., 2020), other studies indicate that certain product categories, such as luxury goods, elicit emotions comparable to services due to their hedonic nature (Chitturi et al., 2008). Furthermore, emerging evidence suggests that factors such as reviewer personality traits, review context, and cultural background may moderate emotional expression in ways that have yet to be fully explored (Hong et al., 2016). Moreover, studies using different sentiment analysis techniques have produced conflicting results. Some research relying on lexicon-based approaches (e.g., Liu et al. (2012) suggests clear distinctions between product and service emotions, while others using deep learning-based methods report more complex and overlapping emotional structures (Wang et al., 2022).

In addition to sentiment polarity and dimensional affect scores, emotional categorization models have been employed to differentiate between 6 basic emotions (e.g., joy, anger, sadness) and up to 27 advanced emotions (e.g., gratitude, disappointment, nostalgia) (Cowen & Keltner, 2017). Research has demonstrated that service reviews contain a wider range of both basic and advanced emotions, with a greater prevalence of gratitude and disappointment due to the inherently relational nature of service experiences (Jang & Kim, 2011). By contrast, product reviews tend to emphasize emotions such as trust and surprise, which are linked to product reliability and performance expectations (Eslami et al., 2022). However, an integrated framework that combines these three dimensions—sentiment polarity, valence-arousal-dominance scores, and basic and advanced emotion categories—has not yet been systematically developed in the literature.

Building on these insights, this study proposes the following hypothesis:

H1: Customer emotional experiences differ significantly between product and service reviews, as measured by sentiment polarity, valence-arousal-dominance scores, and sentiment, basic, and advanced emotion categories.

Methodology

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This section will introduce the conceptual model for the study, followed by a discussion on the data collection process and the statistical techniques employed for analysis.

Conceptual Model

The conceptual model as shown in Figure 1 illustrates the relationships of Category, in shaping Emotional Experiences. Emotional experiences are categorized into three components: Sentiment, Dimensional Emotions, and Categorial Emotions, which are measured through various scores and classifications.

The Category variable differentiates between classifications of offerings, specifically products and services. According to the model, Category is hypothesized to have a direct impact on Emotional Experiences (H1), implying that consumers exhibit distinct emotional responses depending on whether they engage with a product or a service. This distinction suggests that the nature of the offering itself influences the intensity, valence, and complexity of emotional reactions in consumer evaluations.

The Emotional Experiences section in the model is divided into three key components. The Sentiment aspect includes Sentiment Scores and Sentiment Categories, which classify emotions into positive, negative, or neutral valence. This approach is often used in sentiment analysis to determine the overall affective tone of a given stimulus.

The Dimensional Emotions framework uses Valence Scores, Arousal Scores, and Dominance Scores to represent emotions in a continuous space. Valence refers to the positivity or negativity of an emotion, arousal indicates its intensity, and dominance reflects the level of control or submissiveness associated with the emotion (Truong & Hoang, 2022). This approach aligns with the Valence-Arousal-Dominance (VAD) model, which is widely used in emotion research.

The Categorial Emotions section classifies emotions into Basic Emotion Categories (such as joy, sadness, anger, fear, disgust, and surprise) and Advanced/Complex Emotion Categories, which may include emotions like nostalgia, pride, or envy. These categories help differentiate between fundamental emotional states and more nuanced affective experiences influenced by cognitive and social factors.

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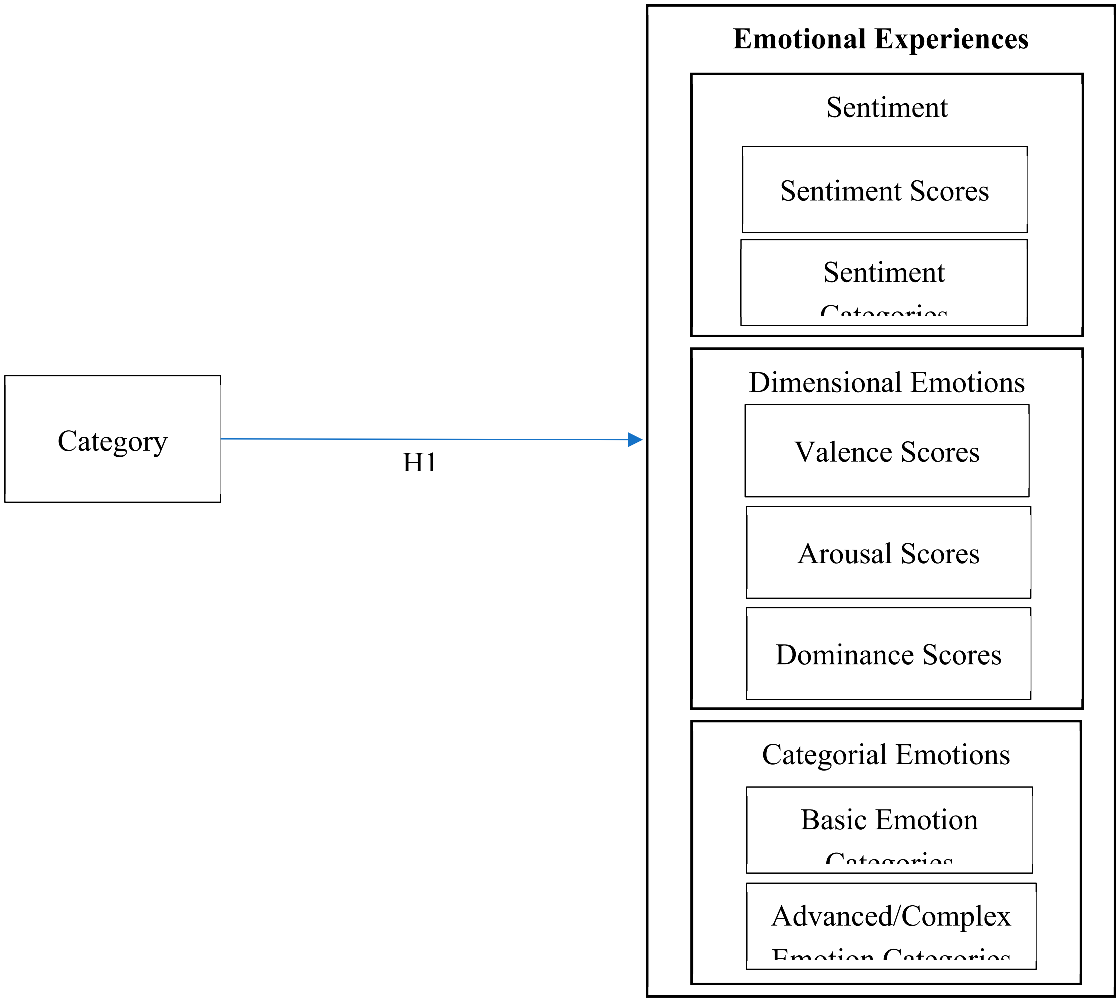

Figure 1. The conceptual model of this study.

This conceptual model basically explores how Category, Culture, and Gender influence Emotional Experiences, outlining three hypotheses (H1, H2, and H3) that describe their interactions. Category (products vs. services) is proposed to have a direct impact on emotional responses (H1), suggesting that different offerings evoke distinct levels of emotional intensity and complexity. Culture acts as a moderator (H2), shaping how consumers from different cultural backgrounds perceive and express emotions, with collectivist cultures emphasizing social harmony and individualistic cultures focusing on personal achievement. Gender (H3) further modifies emotional responses, as research suggests men and women differ in emotional sensitivity, expression, and regulation. Emotional Experiences are classified into Sentiment, Dimensional Emotions, and Categorial Emotions, assessed through sentiment scores and classifications, which help determine the affective tone of consumer evaluations.

Data Collection

In pursuit of the mentioned objectives, this study proposed a comprehensive method for extracting and categorizing customer emotions, consisting of several steps.

In the initial stage of gathering customer experiences, this study focused on collecting reviews from open-source platforms. A key selection criterion was the inclusion of category, cultural and gender background information, as these demographic details are essential for analyzing the effect of category and the moderating effects of culture and gender on emotional responses. By prioritizing

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datasets that provide this information, the study ensures a comprehensive and diverse representation of consumer perspectives across platforms, industries, and product categories.

Several publicly available datasets provide valuable insights into product and service reviews, facilitating research on consumer sentiment and emotional expression. These datasets often include user-generated reviews from e-commerce platforms, online marketplaces, and service-based websites, capturing diverse consumer experiences across different categories. Examples include the Amazon Reviews Dataset, which contains millions of product reviews with ratings and textual feedback, and the Yelp Dataset, which focuses on service-related experiences in restaurants, hotels, and other businesses. Additionally, datasets such as TripAdvisor Reviews and Google Reviews offer sentiment-rich textual data specifically for hospitality and local services (Haque et al., 2018). These resources enable researchers to analyze emotional patterns, sentiment trends, and category-based differences in consumer evaluations, providing a foundation for studies on how product and service reviews differ in emotional intensity, valence, and complexity.

Despite the abundance of online customer review datasets as shown above, a significant challenge was the lack of comprehensive demographic data. While some datasets included gender information, they often lacked cultural or nationality details, and vice versa. This limitation necessitated an extensive search and meticulous filtering process to identify datasets meeting the study's criteria. The difficulty in locating datasets that are both content-rich and demographically detailed highlights a broader gap in consumer feedback data availability.

Following an exhaustive search, six datasets were identified that satisfied the necessary conditions, as shown in Table 1. These datasets span various industries, offering a broad perspective on consumer behaviour in different contexts. The selected datasets include FashionNova (fashion), Amazon Reviews (electronics), Celsius Network (cryptocurrency trading), ASOS TrustPilot (cosmetics), Qatar Airways (airline services), and La Veranda (hospitality).

The FashionNova Customer Review Dataset contains feedback from an online fashion retailer, encompassing textual reviews, star ratings, timestamps, and demographic attributes like gender, age, and location. These reviews cover clothing, accessories, and footwear, offering insights into product quality, fit, and customer satisfaction. Similarly, the Amazon Reviews Dataset provides extensive consumer-generated reviews across various electronics products, featuring star ratings, written feedback, and metadata such as review dates and reviewer profile details (Haque et al., 2018).

The Celsius Network Customer Review Dataset includes user feedback on the cryptocurrency platform's usability, interest rates, security, and customer support. This dataset features textual reviews, ratings, and occasional demographic details (AlQahtani, 2021). Meanwhile, the ASOS TrustPilot Customer Review Dataset captures customer experiences with ASOS products and services, focusing on fit, style preferences, and delivery, along with demographic markers like age, gender, and location (Parker & Alexander, 2022) .

The Qatar Airways Customer Review Dataset compiles passenger feedback on in-flight services, comfort, punctuality, and customer support. Reviews include star ratings, text comments, and traveler demographics such as nationality, age, and travel class, making it a valuable resource for assessing sentiment and service quality in the aviation sector (Hamad MA Fetais et al., 2021). Likewise, the La Veranda Customer Review Dataset contains restaurant reviews evaluating food quality, ambiance, service, and pricing. Some records also include details about visit frequency and group size (Kondopoulos, 2014).

Table 1. Datasets with gender and culture information.

No	Dataset	Category
1	Fashionnova	Product
2	Amazon Reviews	Product
3	Celsius Network	Service
4	ASOS TrustPilot	Product

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5	Qatar Airlines	Service
6	La Veranda	Service

The inclusion of diverse datasets ensures a broad spectrum of communication styles and contextual influences, minimizing biases that could arise from overrepresentation in specific domains (Hewson et al., 2016). This diversity strengthens the study's ability to assess gender- and culture-driven variations in emotional responses across different industries.

Sentiment and Emotion Detection

After collecting customer reviews, advanced machine learning models was employed to analyze sentiment, valence, arousal, and dominance scores. Additionally, the reviews will undergo detailed classification to identify both basic and advanced emotions along with their intensities.

Multiple machine learning models are used to examine different aspects of emotional expression. The first step involves converting textual data into sentiment scores using tabularisai/multilingual-sentiment-analysis, a model designed to classify sentiment intensity across various languages. By assigning a numerical sentiment score to each review, this model effectively distinguishes between positive, negative, and neutral sentiments. Its multilingual capability ensures robust sentiment evaluation across diverse linguistic and cultural contexts, making it particularly useful for cross-cultural studies where traditional sentiment models may fall short (Rasappan et al., 2024).

For sentiment classification, VADER is utilized to categorize text into sentiment groups (positive, negative, and neutral). Unlike conventional sentiment analysis tools, VADER considers contextual intensities, punctuation, capitalization, and even emoticons, making it highly effective for analyzing informal and opinion-rich texts, such as customer reviews (Hutto & Gilbert, 2014).

To measure valence (emotional tone), arousal (intensity), and dominance (control level) in consumer feedback, the study employs hplisiecki/word2affect_english. This model assigns numerical values to these three emotional dimensions, providing a more nuanced understanding of consumer emotions than traditional sentiment analysis (Plisiecki & Sobieszek, 2024). By evaluating emotions on a 3D scale, the study can capture subtle differences in emotional expression across gender and cultural groups.

For identifying basic emotions such as happiness, sadness, anger, fear, surprise, and disgust, the study uses bhadresh-savani/bert-base-uncased-emotion. This transformer-based model is trained on large datasets to ensure high accuracy in emotion classification (Khalili et al., 2022). Analyzing basic emotions allows for comparisons between different consumer groups, shedding light on how gender and cultural backgrounds influence emotional expression.

To capture complex emotions, the study utilizes SamLowe/roberta-base-go_emotions, a model fine-tuned on the GoEmotions dataset (Demszky et al., 2020). This dataset includes 27 distinct emotion labels, such as admiration, amusement, pride, disappointment, and gratitude. By incorporating advanced emotion classification, the study provides a more granular view of consumer sentiment, uncovering patterns that basic models might overlook. This level of analysis is particularly valuable for understanding nuanced emotional expressions across demographics, an area where previous research has been limited.

By leveraging these models, the study ensures a comprehensive, multidimensional analysis of consumer emotions, offering deeper insights into how gender and cultural factors shape emotional responses in digital communication.

Statistical Techniques

After the machine learning model identified and categorized emotions, statistical techniques were applied to analyze how emotional expressions varied across cultural and gender groups. Descriptive statistics, including means and standard deviations, were first used to assess data

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distribution and ensure normality. The dataset, consisting of a relatively equal representation of product and service reviews, male and female consumers, as well as Western and Eastern reviews, enabled balanced comparisons. Additionally, key emotional metrics—sentiment scores, as well as valence, arousal, and dominance scores—were evaluated for skewness and kurtosis, confirming that their distributions fell within acceptable statistical limits.

The reliability of the analysis was strengthened by the use of a large dataset comprising many customer reviews, which helped minimize biases and ensure a more representative sample. Normality was further supported by the even distribution of sentiment categories and both basic and complex emotion classifications. These preliminary statistical checks established a solid foundation for subsequent inferential analyses, allowing for more precise comparisons of emotional expression across demographic and cultural segments.

To further investigate differences in emotional expression across cultural and gender groups, inferential statistical techniques were employed. Univariate tests were conducted to determine whether significant differences existed in the distribution of emotions between these groups. Additionally, multivariate analysis techniques provided deeper insights into the complex relationships between culture, gender, and emotional intensity. Specifically, Multivariate Analysis of Variance (MANOVA) was used to simultaneously examine multiple dependent variables, such as sentiment scores and emotion categories, across cultural and gender groups. This comprehensive approach allowed for a more holistic assessment of how these factors interact (Saunders, 2015).

Moreover, a moderation regression test using Hayes' PROCESS macro was performed to investigate whether culture moderated the effect of gender on emotional expression (Hayes, 2017). This analysis helped determine whether cultural differences amplified, diminished, or altered gender-based emotional patterns, offering a more nuanced perspective on how emotions are shaped by both demographic factors.

The following section presents the key statistical findings and their implications, providing deeper insights into the interplay between culture, gender, and emotional expression.

Hypothesis Testing

The hypothesis testing results presented in Table 2 reveal significant findings regarding the relationship between emotional categories and key emotional metrics, such as sentiment score, valence, arousal, and dominance. The analysis demonstrates that category type has a statistically significant effect on sentiment scores, with a Type III Sum of Squares value of 70.343 and an F-value of 259.398 ($p < .001$). This indicates that different emotional categories exert a meaningful influence on the overall sentiment expressed in customer reviews. The significance of this result suggests that emotional category distinctions play a crucial role in shaping sentiment intensity, reinforcing the importance of categorizing emotions accurately in consumer analysis.

However, when analyzing the relationship between emotional category and sentiment category classification, the results show no statistical significance ($p = .614$). With a low F-value of 0.254, this finding suggests that emotional categories do not meaningfully impact sentiment classification into positive, negative, or neutral labels. This result implies that while emotional categories influence sentiment intensity (as indicated by the sentiment score analysis), they may not necessarily determine whether an emotion falls into broad sentiment classifications. The lack of significance in this case highlights potential limitations in sentiment classification models, which may not capture the nuanced effects of emotion categorization on consumer sentiment.

Table 2. Hypothesis 1 testing result.

Independent Variable	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Category	Sentiment Score	70.343	1	70.343	259.398	.000 (***)

	Sentiment Category	.466	1	.466	.254	.614
	Valence Score	.228	1	.228	7.234	.007 (***)
	Arousal Score	1.168	1	1.168	291.575	.000 (***)
	Dominance Score	.123	1	.123	11.965	.001 (***)
	Basic Emotion Category	.265	1	.265	.245	.621
	Complex Emotion Category	2333.084	1	2333.084	36.453	.000 (***)

Regarding the valence score, a statistically significant effect of category was observed, with a Type III Sum of Squares value of 0.228 and an F-value of 7.234 ($p = .007$). This result indicates that emotional category distinctions contribute to variations in valence, which represents the positivity or negativity of an emotion. Although the effect size is relatively small, the statistical significance suggests that categorizing emotions can provide insights into the valence of consumer sentiment, supporting the use of valence as a key emotional metric in sentiment analysis.

Arousal, which measures emotional intensity, exhibited a strong relationship with emotional category, as evidenced by an F-value of 291.575 ($p < .001$). The Type III Sum of Squares value of 1.168 suggests that emotional categories significantly impact the arousal levels expressed in customer reviews. This finding aligns with previous research indicating that emotions vary in intensity depending on their classification, emphasizing the importance of measuring arousal alongside sentiment and valence for a more comprehensive understanding of emotional expression in consumer feedback.

Similarly, dominance scores were significantly affected by emotional category, with a Type III Sum of Squares value of 0.123 and an F-value of 11.965 ($p = .001$). This result indicates that emotional category distinctions contribute to variations in the perceived level of control or dominance within consumer sentiment. The significance of this relationship suggests that certain emotions, depending on their classification, may evoke stronger or weaker perceptions of control, which can influence how consumers express their experiences and interactions with a brand or product.

Interestingly, when analyzing the relationship between emotional category and basic emotion classification, no significant effect was observed ($p = .621$). With an F-value of 0.245, this suggests that emotional categories do not strongly impact how emotions are classified into basic emotions such as happiness, sadness, or anger. This may indicate that basic emotions are relatively stable across categories and that more granular emotional distinctions are necessary to capture meaningful differences in emotional expression.

In contrast, the relationship between emotional category and complex emotion classification was highly significant, with a Type III Sum of Squares value of 2333.084 and an F-value of 36.453 ($p < .001$). This strong effect suggests that emotional categories are crucial in distinguishing between complex emotions, such as admiration, gratitude, or disappointment. This finding underscores the importance of using advanced emotion classification models to capture the depth and complexity of consumer emotions, which may not be fully represented by basic sentiment or emotion classifications alone.

The differences between product and service categories in customer emotional experiences are particularly pronounced when analyzing complex emotion categories, as illustrated in Figure 2. The distribution of emotions between the two categories reveals that services tend to elicit a higher proportion of complex emotions compared to products. This is evident in emotions such as love, excitement, amusement, optimism, and admiration, where service-related experiences dominate. The nature of services, which often involves human interaction, personalized experiences, and direct engagement, likely contributes to the heightened emotional responses observed in these categories.

Conversely, product-related experiences generate a greater share of emotions like relief, pride, and caring. These emotions suggest that customers feel reassured and satisfied when a product meets their expectations, provides a solution to a problem, or enhances their daily lives. Unlike services, which often require real-time performance and interpersonal exchanges, products offer a tangible and often long-term source of utility. The prevalence of relief in product experiences indicates that customers may associate products with problem-solving and functional reliability, whereas services tend to evoke more dynamic emotional responses.

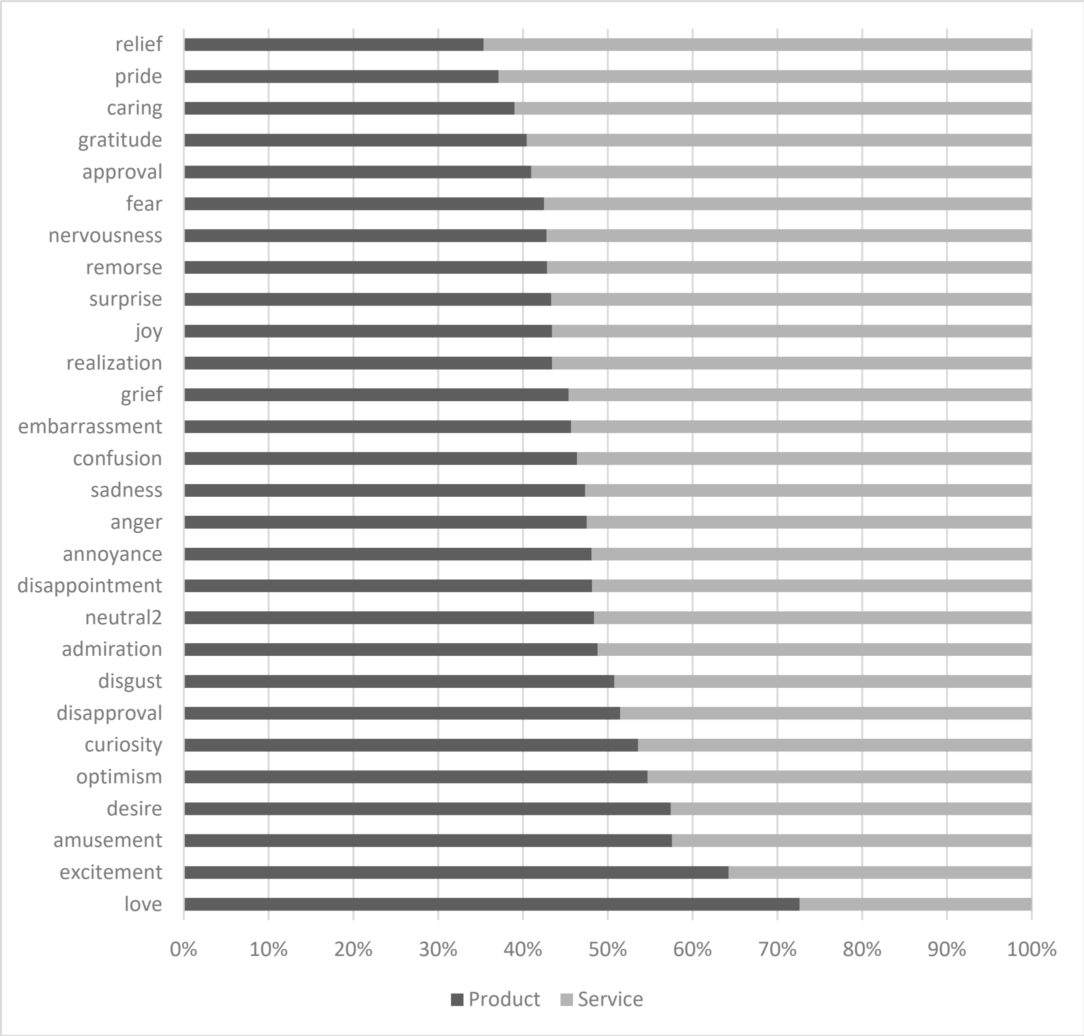

Figure 2. Categorical differences in advanced emotion categories.

Negative emotions also exhibit interesting distinctions between the two categories. Disgust, disappointment, disapproval, and sadness are more strongly associated with services than products. This suggests that negative service experiences, such as poor customer service, unmet expectations, or service failures, lead to stronger emotional reactions than product-related dissatisfaction. Unlike products, where dissatisfaction might be mitigated through returns or replacements, service failures are often more immediate and harder to rectify, leading to stronger negative sentiment.

Furthermore, emotions related to uncertainty, such as confusion and embarrassment, are also more prevalent in service experiences. This trend suggests that customers may feel more vulnerable or unsure when navigating service interactions, especially in cases where processes are complex or expectations are unclear. In contrast, products generally provide a more straightforward experience, reducing the likelihood of these emotions. The higher presence of fear and nervousness in service-related experiences further underscores the emotional sensitivity surrounding service engagements, where trust, competence, and reliability play critical roles.

Overall, the distinctions in emotional experiences between products and services highlight the fundamental differences in how consumers interact with and perceive these two categories. While products tend to elicit emotions related to reliability, functionality, and relief, services generate a broader range of emotional responses, particularly in complex and interpersonal emotions. This suggests that businesses in the service industry must be especially mindful of emotional management, ensuring that customer interactions foster positive experiences while mitigating the risks of strong negative emotions.

Discussion

The results of this study confirm that emotional expressions in online customer reviews differ significantly between product and service categories. This finding aligns with theoretical expectations derived from Maslow's hierarchy of needs and the goods-services continuum, suggesting that services, being more experiential and relational, elicit more intense and diverse emotional responses than products. Service reviews exhibited higher levels of emotional arousal and a broader range of complex emotions, such as admiration, gratitude, disappointment, and amusement. In contrast, product reviews were more grounded in emotions like relief and trust, which are associated with functional reliability and performance.

This distinction underscores the psychological and situational differences in how consumers experience and evaluate services versus products. Services often involve direct interaction, co-production, and personalized experiences, which heighten emotional engagement and vulnerability (Truong et al., 2020) . As a result, consumers are more likely to express strong feelings, whether positive or negative, in service reviews. The elevated presence of negative emotions like disappointment, disapproval, and sadness in service contexts suggests that service failures may carry more emotional weight than product defects, which are often perceived as more transactional or resolvable.

Furthermore, the significance of the valence-arousal-dominance (VAD) scores in distinguishing emotional experiences suggests that traditional sentiment polarity classifications (positive, negative, neutral) may be insufficient for capturing the full spectrum of consumer sentiment. The findings demonstrate that category influences not only sentiment scores but also emotional complexity and intensity, which have practical implications for how businesses analyze and respond to customer feedback. Particularly in service industries, where emotional engagement is high, understanding the nuances of customer sentiment through advanced emotion models can improve customer experience strategies and response mechanisms.

The lack of significant influence of category on basic emotion categories (e.g., joy, sadness, anger) but strong influence on complex emotion categories highlights the importance of moving beyond traditional six-emotion models. Consumers articulate their experiences using a wide range of nuanced emotions, particularly in service contexts. This calls for businesses and sentiment analysis systems to adopt more sophisticated emotion detection frameworks, such as those based on the 27-category GoEmotions model used in this study.

This study contributes to the growing body of literature on sentiment and emotion analysis by demonstrating that product and service categories significantly shape the emotional tone and complexity of customer reviews (Truong, 2024). By integrating multidimensional emotion models—including sentiment scores, VAD dimensions, and both basic and complex emotion categories—this research provides a more comprehensive understanding of how consumers express satisfaction and dissatisfaction across different purchase experiences.

Theoretically, the study extends existing consumer behaviour models by empirically validating that services, which fulfil higher-order psychological needs, evoke richer and more intense emotional expressions than products. It also underscores the importance of using advanced emotion detection frameworks to capture the full range of consumer sentiment, moving beyond binary or simplistic sentiment analysis approaches.

Practically, the findings offer valuable guidance for businesses seeking to enhance customer satisfaction and manage brand reputation. Service providers, in particular, must recognize the emotional volatility inherent in their interactions and tailor their customer engagement strategies accordingly. Tools that detect emotional nuance in customer feedback can help companies proactively address dissatisfaction and foster stronger emotional connections with customers.

Future research should explore the dynamic interactions between product/service categories and other moderating variables, such as brand trust, purchase context, and user personality. Additionally, more culturally and demographically diverse datasets could shed light on how emotional responses vary across global consumer segments. As sentiment analysis technologies continue to evolve, adopting more context-sensitive and psychologically grounded frameworks will be essential to understanding and responding to the emotional dimensions of consumer experience.

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