

Unveiling Temporal Dynamics of Consumer Emotions in Online Reviews: An Emotion Mining Approach Using Ekman's Emotion Model

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Abstract—Currently, business organizations are using Electronic Word-of-Mouth (EWOM) from consumer-opinion platforms to elevate their marketing strategies using semantic analysis and emotion mining. Existing efforts are devoted to analyzing EWOM using fine-grained emotion classification; however, the well-known and well-established emotion models that provide a basic set of psychological and biological emotions are not targeted in these studies. Further, the existing literature is unable to present temporal dynamism and volatility of consumers' emotions according to emotion categories that have an inescapable impact on consumers and corporate decision-making process. Therefore, this study tries to address this gap by extracting, classifying, summarizing, and tracking consumers' emotions for corporate and consumers' decision-making processes based on widely used and well-established Ekman's emotions model. Therefore, the current work aims to provide consumers' emotions temporal dynamism and volatility at product and feature levels by using binary and fine-grained emotion classifications based on Ekman's basic psychological and biological emotions. Online reviews from amazon.com are used for experimental purposes. The results of the study exhibited that consumers predominantly expressed joy emotion to the camera. However, the picture feature of the camera evoked negative emotions, namely, fear, anger, and sadness. Temporal analysis unveiled shifting emotional expressions in quarter 1 and quarter 2. The results of the study will assist corporates in shaping their decision-making process and marketing strategies. Moreover, the findings of the study provide valuable insights into consumers to improve their purchase decisions by pinpointing the advantages and disadvantages of critical product features through emotional clues.

Keywords—*Emotion; emotion mining; semantic analysis; online reviews*

I. INTRODUCTION

The proliferation of online review platforms has transmuted content publishing from corporates towards consumers [1]. The web offers highly scalable and accessible platforms to consumers for the creation and dissemination of Electronic Word-of-Mouth (EWOM) such as wikis, discussion forums, tweets, blogs, and online review websites. EWOM is a positive or negative statement about an object such as product, people, service, topic, organization, set by the potential, actual or former consumers which is available online to a vast audience [2]. Currently, consumers are connected globally to online platforms to express their emotions, evaluations, opinions, and judgments to a broad spectrum of individuals [3][4]. Therefore, fast-growing EWOM provides unstructured, trustworthy, and freely

available valuable decision-oriented data that can address the diverse needs of corporates and consumers by providing insights into consumers' behaviour, and preferences[5][6][7]. This powerful source of emotions leverages corporates in various business intelligence tasks, namely, sale prediction, risk analysis, enterprise strategies, and benchmarking. On the other hand, it assists consumers in their purchase decisions by highlighting the advantages and disadvantages of a target product [8][9].

Although there are many online platforms for consumers to express their opinions, evaluations, and emotions; however, online reviews are considered more credible and trustworthy [10]. Further, the characteristics of Web 2.0, such as scalability, accessibility, and enhanced users' participation, allow consumers all over the world to express their emotions by writing reviews that result in the explosive growth of online reviews [11]. The massive freely available online reviews present valuable insight into critical features of a target product that play an important role in consumers' purchases and business strategies [7][12][13]. Therefore, corporates are targeting consumers' online reviews from different sources for their decision-making process [14][15]. Major retailers' websites provide a star rating of a product and the helpfulness of the review such as amazon.com, ebay.com, and aliexpress.com. On the other hand, cnet.com presents the rating of a product and its prominent features. However, the emotions expressed by consumers are not considered and published by these websites. Further, it is difficult to extract consumers' emotions manually on critical features of a product due to the volume, distribution, length, structure, multidimensional data and dynamic nature of the online reviews[7][16].

Early efforts and attempts of opinion mining focused on the classification of online reviews into positive or negative opinion categories [17][18]. Later, online reviews are classified into fine-grained opinion categories [19][20][7]. However, the fine-grained opinion categories are unable to provide a perception of consumers' emotions. The classification of EWOM into emotion categories may provide an enhanced understanding of consumers' state of mind, evaluation, and judgment about a particular product. Further, limited attempts are also performed to provide fine-grained emotion classification of online reviews that provide a deeper understanding of consumers' opinions, sentiments, emotions, and evaluations about a target product or feature. However, the existing studies do not classify emotions into well-known and well-established basic psychological and biological emotions as there is a limited number of emotions that

are biologically and psychologically basic to human beings [21]. Further, consumers' emotions may change with time, that is, positive emotions change into negative emotions and vice versa as exhibited by Twitter data [22]. Existing studies [23][24], are not reporting this temporal dynamism and volatility of consumers' emotions according to emotion categories that have an enormous impact on corporate and consumers' decision-making process. Therefore, it is vital to track this shift in the emotions of consumers of a particular feature or a product over time based on psychological and biological emotions, and the reason behind this change should be identified to make appropriate decisions. Consequently, there is a need to extract, classify, summarize, and track consumers' emotions according to basic psychological and biological emotions for corporate and consumer decision-making.

The aim of this work is to extract, classify, and summarize consumers' emotions expressed in online reviews, and to present the temporal dynamism and volatility of consumers' emotions according to well-established and widely used basic psychological and biological emotions [25] that impacts corporate planning and the consumers' decision-making process significantly. Specifically, the current study 1) classifies and summarizes consumers' online reviews into binary and fine-grain classes according to the well-known psychological and biological emotions at the product level, 2) classifies and summarizes consumers' online reviews into binary and fine-grain classes according to the well-known psychological and biological emotions at the feature level, 3) provides temporal dynamism and volatility of consumers' emotions according to psychological and biological emotions at the product level, and 4) provides temporal dynamism and volatility of consumers' emotions according to psychological and biological emotions at the feature level. A dataset consisting of real online reviews from amazon.com is used for the experimental purpose in this study.

This study has the following contributions:

- The classification of consumers' emotions into well-known six basic psychological and biological emotions categories: anger, fear, disgust, joy, surprise, and sadness defined by Ekman [25] is presented by the study.
- The study highlights six basic psychological and biological consumers' emotions for target products that show the strengths and weaknesses of target products reported by the actual users of products.
- The six basic psychological and biological consumers' emotions for prominent features of target products are also reported by the study that can play a decisive factor in the purchase decision of consumers.
- The temporal dynamism and volatility of six basic psychological and biological consumers' emotions are observed and presented by the study that is helpful to understand the change in consumers' emotions over time. The temporal dynamism of consumers' emotions is highlighted at two levels: product and feature in the study.

The rest of the paper is organized as follows: Existing emotion models and related work are reviewed in Section II. Section III discusses the proposed methodology. Section IV described the experimental results and discussion. Section V presents the research implications. Lastly, Section VI concludes the paper.

II. LITERATURE REVIEW

A. Emotion Models

Emotions are strong positive or negative motivational stimuli that comprise experiences such as love, hate, anger, joy, and grief. To study the emotions expressed by humans, various emotion models are presented in the literature of Psychology. And these emotion models are a critical component of emotion mining systems [26]. Therefore, this section reviews the state-of-the-art emotion models by focusing on key emotion categories and their associated descriptors. These descriptors play a crucial role in the measurement of emotions. Moreover, basic emotions are the motions having no other emotional constituent parts. Table I provides a summary of existing emotion models.

TABLE I. EXISTING EMOTION MODELS

Reference	Basic Emotions
[27]	Anger, disgust, elation, fear, subjection, tender-emotion, wonder
[28]	Fear, love, rage
[29]	Anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness
[30]	Pain, pleasure
[31]	Joy, Anguish, Fear, Anger, Disgust, Surprise, Interest, Shame
[25]	Joy, Sadness, Fear, Anger, Disgust, Surprise
[32]	Interest, joy, surprise, sadness, anger, disgust, contempt, self-hostility, fear, shame, shyness, guilt
[33]	Acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise
[34]	Expectancy, fear, rage, panic
[35]	Happiness, sadness
[36]	Desire, happiness, interest, surprise, wonder, sorrow
[37]	Love, Joy, Surprise, Anger, Sadness, Fear
[31]	Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise
[38]	Fear, Worry, Anger, Joy, Sadness, Discontent, loneliness, Peacefulness, Excitement, Optimism, Surprise, Shame, Guilt, Romantic Love, Love, Contentment, Envy
[39]	Fear, Anger, Enjoyment, Distress, Disgust, Surprise, Contempt
[40]	contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame

While researchers and psychologists have proposed various emotion models, however, Ekman's model [25] with six basic emotions is considered the most widely accepted and used model in computer science and natural language processing research areas [26][41][42][43]. This model presents six basic emotions: anger, fear, disgust, joy, surprise, and sadness. Later, Ekman expanded these basic emotions by introducing additional positive and negative emotion dimensions [40]. Due to widespread adoption and validation of Ekman's basic emotion model, the current study utilized this model to classify the

emotion expressed by consumers into the six basic emotion categories.

B. Related Work

Emotion mining has been explored in various contexts, including blogs [41], health [42], social media platforms like Facebook [43] and Twitter [44], news headlines [45] [46], online reviews [21], customer emails [47], and stock exchange [48]. These applications aim to extract and analyze emotions expressed by individuals or groups, providing valuable insights into human behavior and sentiment.

Significant work in the area of emotion classification is performed on Twitter data to analyze emotional content in tweets. Recently, [22] classified the public tweets into binary classes as well as into the basic emotions. Similarly, [49] exploited machine learning techniques for the classification of tweets in basic emotion categories. Further, the work analyzed the changes in emotions over time. Likewise, the artificial intelligence methods are utilized in [50] to analyze 73,000 public conversations on Twitter associated with the Corona pandemic using basic emotions proposed by [51]. [52] classified 9,000,000 tweets from a specific time frame into six moods: tension, anger, depression, vigor, confusion, and fatigue using the proposed profile of mood states method. On the other hand, [53] utilized hashtags of tweets as emotion labels for the classification of emotions expressed in tweets. A linear classifier is used to classify 2,500,000 tweets using hashtags as emotion labels into seven emotions: anger, joy, fear, love, sadness, thankfulness, and surprise. The comparison of manually labeled tweets and hashtags labels showed acceptable agreement. Further, the result of experiments conducted using different features like unigrams, bi-grams, POS tags, adjectives, and lexicons exhibited that unigrams, bi-grams, and POS tags provide the best emotion detection results. Moreover, the findings of the study suggested that the increased size of the training dataset has a direct impact on the accuracy of the classifier. In [54], the authors also used hashtags to classify a dataset of 134,000 tweets. They compared hashtags with manual tags assigned by two groups: a group of people and a group of psychologists. The findings of [53] [54] suggest that larger training datasets and features like uni-grams, bi-grams, and POS tags can improve emotion detection accuracy.

In the context of blogs, [55] [56] classified online diary entries into 1 of 40 moods of the writer using a support vector machine. Mood classification is considered similar to emotion classification; however, emotions are more intense in nature. The previous work was enhanced by [38] by capturing and aggregating the moods of writers from a large number of blog posts in a certain period. Similarly, [46] analyzed the emotional content in online news.

In [57], the authors identified emotion passages from the children's fairy tales dataset and then classified these emotions into positive and negative valence. The results from their linear classifier (Sparse Network of Winnows) are not very promising; however, their dataset is extensively utilized by the emotion mining community. Fine-grained classification of emotions from text is performed by [58]. In this work, the authors targeted the 600 notes of persons who committed suicide and predicted a label for each note from 15 emotions such as love, hopelessness,

thankfulness, sorrow, and anger. Another work on fine-grained emotion classification of text is presented in [59]. The authors classified the emotions from a pre-defined emotion set that includes six emotions: Joy, Fear, Anger, Disgust, Sadness, and Surprise using a Vector Space Model [60].

In the context of consumers' emotions in online reviews, [61] explored the relationship between three emotion classes (positive, negative, and mixed emotions) with product attitude. On the other hand, [62] identified Plutchick's basic emotions [51] by using the NRC emotion lexicon in online movie reviews from IMDb. Unlike previous studies, [62] analyzed negative emotions in online reviews in a different perspective by exploring the association between two negative emotions (regret and frustration) with the helpfulness of review, reviewer rationality, and price fairness in online review and their empirical results confirmed a positive relationship between these negative emotions and helpfulness of review and price fairness, however, the positive impact of the negative emotions on reviewer rationality was not established. The authors in [47] focused on the customer care domain by identifying customers' emotional emails complaining about services or products to provide timely and pertinent responses to the sender of emotional emails in order to increase customer satisfaction and retention. They used the boosting method and performed experiments on 1077 customers' emails. Their method, based on salient features, outperforms the baseline method based on the unigram feature. [63] analyzed the correlation between helpfulness, unhelpfulness, rating, positive score, and the negative score of product reviews from amazon.com. The impact of the emotional score is not found to be significant on helpfulness in this study; however, a negative correlation is established between emotional score and rating. The emotional score is divided into positive and negative; positive emotion score (1 to 5), whereas negative emotion score (-1 to -5). The distribution of positive and negative scores over time is also highlighted in the study. In contrast, [64] found an association between emotional score and helpfulness of a review. The existing emotion models are not applied in this work for the extraction of emotions. Further, [65] classified emotions expressed in online reviews into positive, negative, and neutral categories. Also, [66] classified online reviews into positive, negative and neutral sentiment using machine learning techniques. Moreover, binary emotion classification is considered by [67] [68]. On the other hand, in [69] [70], the authors focused on positive, negative, and neutral emotions. Different experiments were conducted to investigate the link between emotional expressions in reviews and their impact on product evaluation in [71]. [72] investigated the relationship between additional online reviews and sales volume. [21] presented the distribution of positive and negative emotions over time.

Extensive literature has been available targeting 'emotions' in various contexts, like Twitter, online news, and blogs. According to the best of our knowledge, little work has been conducted to extract fine-grained emotion classification according to well-known and widely used six basic psychological and biological emotions in the context of amazon.com at product and feature levels. Moreover, the temporal dynamism and volatility of consumers' emotions are

not tracked by existing work according to basic psychological and basic emotions. Therefore, the current work focuses on the extraction, classification, and tracking of basic psychological and biological emotions: anger, fear, disgust, joy, surprise, and sadness, proposed by [22] from online reviews of amazon.com.

III. RESEARCH DESIGN

A. Research Framework

Let document D contain n reviews $R = [r_1, r_2, r_3, \dots, r_n]$. Each review r_k is represented by a tuple having two elements: metadata (MD_{r_k}) and body (B_{r_k}) of the review (r_k). This study extended the tuple of [23]. This tuple is termed as the review tuple. The tuple is shown in Fig. 1 and is presented as follows:

$$r_k = [MD_{r_k}, B_{r_k}]$$

The metadata of the review (r_k) is decoded as MD_{r_k} and is comprised of a review rating ($Rating_{MD_{r_k}}$), review title ($Title_{MD_{r_k}}$) and date ($Date_{MD_{r_k}}$) whereas B_{r_k} signifies a set of sentences in r_k as shown below:

$$MD_{r_k} = [Rating_{MD_{r_k}}, Title_{MD_{r_k}}, Date_{MD_{r_k}}]$$

$$B_{r_k} = [S_1, S_2, S_3, \dots, S_m]$$

$$\forall S_i \in B_{r_k}, S_i = [B_{r_k} S_i F_j, B_{r_k} S_i F_j E_{Cat}, B_{r_k} S_i F_j E_w, B_{r_k} S_i F_j E, B_{r_k} S_i Content]$$

Every sentence S_i in B_{r_k} encloses a feature ($B_{r_k} S_i F_j$), emotion category of emotion ($B_{r_k} S_i F_j E_{Cat}$), emotion word

($B_{r_k} S_i F_j E_w$), emotion expressed on F_j ($B_{r_k} S_i F_j E$) and contents of S_i ($B_{r_k} S_i Content$).

Every review (r_k) embodies a set of feature-emotion pairs (F_j, E_w). This pair includes a feature (F_j) and associated emotion word (E_w). Every feature F_j may have more than one associated E_w in document D.

The emotion expressed in the feature F_j in sentence S_i classified into two categories: positive ($B_{r_k} S_i F_j E_{Cat}^{Pos}$) or negative ($B_{r_k} S_i F_j E_{Cat}^{Neg}$). In other words, $B_{r_k} S_i F_j E_{Cat}$ is either positive or negative. $B_{r_k} S_i F_j E_{Cat}^{Pos}$ have two positive emotions: Joy ($B_{r_k} S_i F_j E_{Cat}^{Pos.Joy}$) and surprise ($B_{r_k} S_i F_j E_{Cat}^{Pos.Surprise}$). On the other hand, anger ($B_{r_k} S_i F_j E_{Cat}^{Neg.anger}$), fear ($B_{r_k} S_i F_j E_{Cat}^{Neg.Fear}$), disgust ($B_{r_k} S_i F_j E_{Cat}^{Neg.Disgust}$) and sad ($B_{r_k} S_i F_j E_{Cat}^{Neg.Sad}$) are negative emotions that belong to $B_{r_k} S_i F_j E_{Cat}^{Neg}$.

$$B_{r_k} S_i F_j E_{Cat} = [B_{r_k} S_i F_j E_{Cat}^{Neg}, B_{r_k} S_i F_j E_{Cat}^{Pos}]$$

$$B_{r_k} S_i F_j E_{Cat}^{Pos} = [B_{r_k} S_i F_j E_{Cat}^{Pos.Joy}, B_{r_k} S_i F_j E_{Cat}^{Pos.Surprise}]$$

$$B_{r_k} S_i F_j E_{Cat}^{Neg} = [B_{r_k} S_i F_j E_{Cat}^{Neg.anger}, B_{r_k} S_i F_j E_{Cat}^{Neg.Fear}, B_{r_k} S_i F_j E_{Cat}^{Neg.Disgust}, B_{r_k} S_i F_j E_{Cat}^{Neg.Sad}]$$

Table II illustrates the description of notations used in the proposed review tuple.

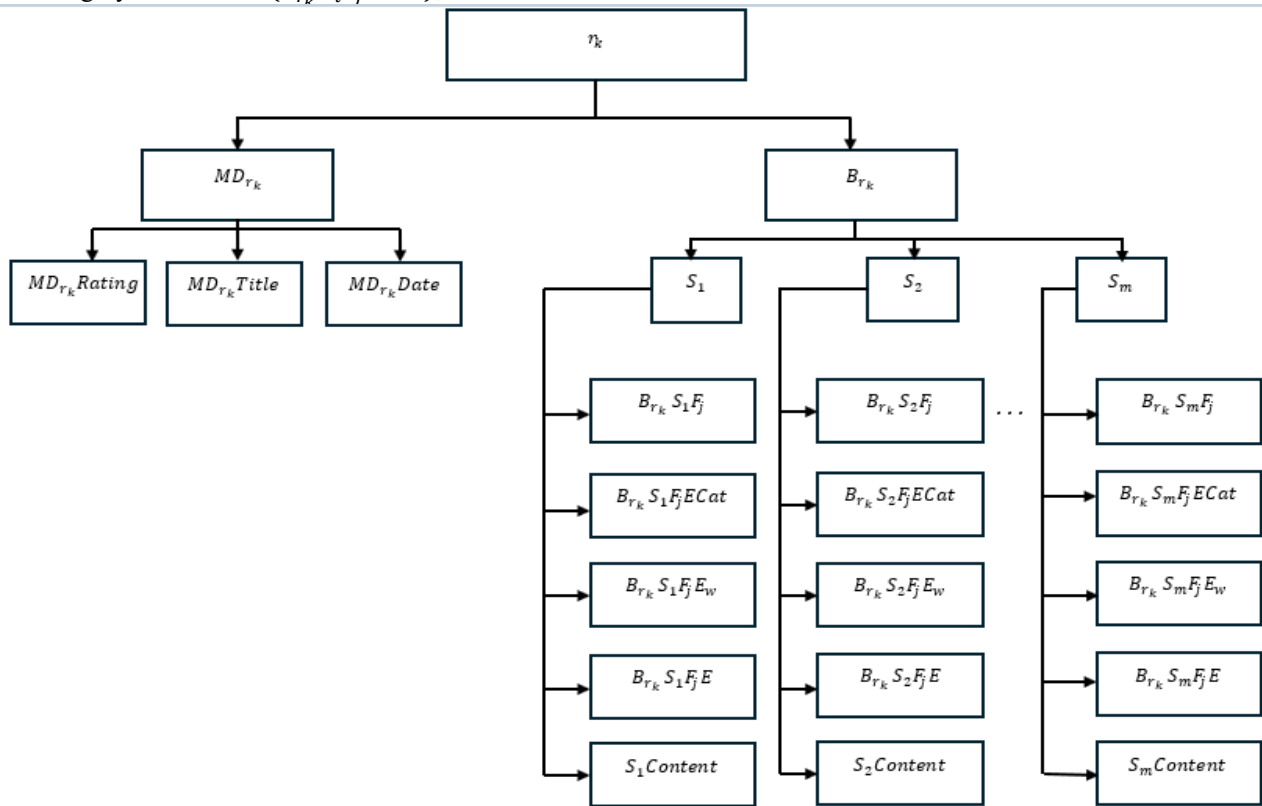


Fig. 1. Proposed tuple.

TABLE II. DESCRIPTION OF NOTATIONS

Notations	Description
D	Document having n product reviews
r_k	Review k
MD_{r_k}	Metadata of Review k
B_{r_k}	Body of Review k
$MD_{r_k} Rating$	Rating of Review k in the metadata of review
$MD_{r_k} Title$	Title of Review k in the metadata of review
$MD_{r_k} Date$	Date of Review k in the metadata of review
$B_{r_k} S_i F_j$	A product feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j ECat$	Emotion category (Positive/Negative) of emotion word E_w associated with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j E_w$	Emotion word E_w associated with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j E$	Emotion E associated with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i Content$	The content of S_i in body of review k
$B_{r_k} S_i F_j ECat^{Pos}$	Indicates emotion category of emotion word E_w associated with feature (F_j) in sentence S_i in body of review k is Positive
$B_{r_k} S_i F_j ECat^{Neg}$	Indicates emotion category of emotion word E_w associated with feature (F_j) in sentence S_i in body of review k is Negative
$B_{r_k} S_i F_j ECat^{Pos_Joy}$	Indicates Joy emotion expressed on with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j ECat^{Pos_Surprise}$	Indicates Surprise emotion expressed on with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j ECat^{Neg_anger}$	Indicates Anger emotion expressed on with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j ECat^{Neg_Fear}$	Indicates Fear emotion expressed on with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j ECat^{Neg_Disgust}$	Indicates Disgust emotion expressed on with feature (F_j) in sentence S_i in body of review k
$B_{r_k} S_i F_j ECat^{Neg_Sad}$	Indicates Sad emotion expressed on with feature (F_j) in sentence S_i in body of review k

B. System Architecture

The architecture of the proposed system is discussed in this section. A system called Emotion Analyzer is developed in this work to provide fine-grained emotion classification at product and feature levels, and to track temporal dynamism and volatility of consumers' emotions. The system is comprised of four components: data preprocessor, feature and emotion extractor, emotion classifier, and emotion visualizer, as shown in Fig. 2 and discussed below.

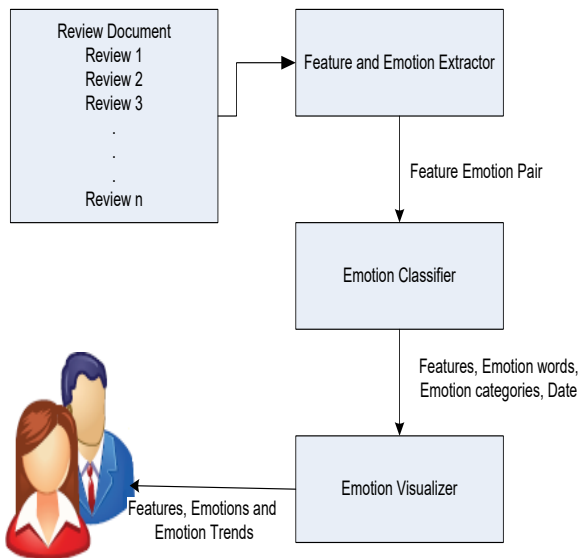


Fig. 2. Proposed system.

1) *Data pre-processor*: Data pre-processor performs a variety of operations to formulate document D containing n reviews for feature and emotion extraction. The following operations are performed by the component. Data processing is performed to increase classification accuracy.

- The symbols, special characters, and punctuations are removed from document D .
- Stop words are discarded from document D .
- The inflected or derived words are converted to their root form by utilizing Word stemming to enhance the efficiency and accuracy of mining.
- Spell checking is performed to eliminate noise from document D .
- Part-of-speech tagging is applied to label each word with its corresponding category, i.e., noun, verb, and adjective.

2) *Feature and emotion extractor*: Feature and emotion extractor identifies critical product features with their associated emotion words. The input to feature and emotion extractor is document D consisting of n reviews of a target product. A file containing all feature-emotion pairs is the output of feature and emotion extractor. In order to create this file, in the first step, the decisive features of a target product are extracted by the feature and emotion extractor. The candidate's features are derived from frequent nouns. All frequent nouns are obtained from document D and stored in a list called

Nounlist[]. Then, a weight is assigned to each noun in Nounlist [].

Existing literature presents a multitude of schemes for feature weight calculation, such as word frequency-inverse document frequency (TF-IDF), chi-square test, and information gain. However, among the aforementioned schemes, TF-IDF is regarded as the most ubiquitous and efficient scheme since it can reflect the importance of words within a collection of documents [79]. Therefore, the current work utilized and enhanced this scheme for feature weight calculation. The formula of TF-IDF utilized in the current study is shown in Eq. (1) – (3).

$$f_j f(f_j, r_k) = \frac{f_{f_j, r_k}}{\sum_{f_j' \in r_k} f_{f_j', r_k}} \quad (1)$$

$$idf(f_j, D) = \text{Log} \left(\frac{|R|}{n_{f_j}} \right) \quad (2)$$

$$f_j f \cdot idf(f_j, r_k, D) = \frac{f_{f_j, r_k}}{\sum_{f_j' \in r_k} f_{f_j', r_k}} * \text{Log} \left(\frac{|R|}{n_{f_j}} \right) \quad (3)$$

In Equation 1, f_{f_j, r_k} is the number of times f_j occurs in r_k and is calculated using Eq. (4).

$$f_{f_j, r_k} = \sum_{i=1}^n \text{Count } f_j \text{ occurrence in } r_k \quad (4)$$

The denominator in Equation 1 shows the total number of features in r_k .

$|R|$ in Eq. (2) shows the total number of reviews in D . $n_{f_j} = |\{r_k \in D : f \in r_k\}|$: number of reviews in which the f_j appears where $\text{tf}(t, d) \neq 0$ and computed using equation below:

$$n_{f_j} = \sum_{i=1}^n [f_j \text{ Exist in } r_k = \text{True}] \quad (5)$$

Eq. (6) and (7) compute the weight of features by introducing a new variable into TF-IDF calculation, that is, the number of emotion words associated with f_j ($f_j E_w \text{Count}$). The introduction of the new variable rests on the assumption that more emotions expressed toward a feature indicate frequent discussion of that feature, thus justifying a higher relative weight compared to other features.

Eq. (8) exhibits the computation of $f_j E_w \text{Count}$.

$$f_j W = f_j f \cdot idf(f_j, r_k, D) + f_j E_w \text{Count} \quad (6)$$

$$f_j W = \frac{f_{f_j, r_k}}{\sum_{f_j' \in r_k} f_{f_j', r_k}} * \text{Log} \left(\frac{|R|}{n_{f_j}} \right) + f_j E_w \text{Count} \quad (7)$$

$$f_j E_w \text{Count} = \sum_{k=1}^n \text{Count } E_w \text{ associated with } f_j(r_k) \quad (8)$$

Eq. (7) is used to compute the weight of a feature f_j . Nouns in NounList[] having $f_j W$ above a threshold α are considered as potential features as shown in Eq. (9).

$$F = [f_1, f_2, f_3, \dots, f_n] \quad (9)$$

After this, E_w associated with each feature are extracted by exploiting a window-based approach in which E_w conversed within K words of f_j are selected as associated emotion words ($f_j E_w$). At the end, a feature emotion list is created that contains all features and associated emotion words as shown below:

If f_j is a feature in the F , then $f_j E_w = \{F_j E_{w_1}, F_j E_{w_2}, \dots, F_j E_{w_n}\}$. The feature-opinion pairs (FW) are stored in a ragged array represented below:

$FW \in \mathbb{R}^{\{n \times m_i\}}$ where $n = \sum_{x \in F} 1$ and m_i is the number of column in i^{th} row.

3) *Emotion classifier*: The task of emotion classification is performed by the emotion classifier. The input to the emotion classifier is FW and the output is the classification of emotions. Extensive emotion mining systems rely on emotion lexicon (dictionary-based approach) for the classification of emotions, and some emotion lexicons are available in the literature for the classification of emotions, such as Wordnet Affect [74]. The Linguistic Inquiry and Word Count (LIWC) [75], NRC emotion lexicon [76], Clean Balanced Emotional Tweets (CBET)[76] [77]. Recently, [78] utilizes the NRC lexicon to classify public tweets into the emotion categories of Ekman. Therefore, the current study also utilized the NRC emotion lexicon [73].

Given the feature-emotion pairs FW, the emotion classification function f classifies $F_i W_j$ to an emotion category e_k using lexicon L .

Formally, f can be defined as:

$$f \triangleq (FW_{ij}, L) \mapsto L(e_{ij}) = e_k$$

where,

$$FW_{ij} = (f_i, E_{w_j}) \in FW, E_{w_j} \in E_w, L(E_{w_j}) = e_k \in E$$

$$FW_{ij} \subseteq F \times E_w$$

$L \in \mathbb{R}^{(n \times m)}$, where n is the number of words in the lexicon and m is the number of emotion categories.

$E = \{e_1, e_2, e_3, e_4, e_5, e_6\}$ where $e_1 = \text{Joy}$, $e_2 = \text{surprise}$, $e_3 = \text{anger}$, $e_4 = \text{fear}$, $e_5 = \text{disgust}$, $e_6 = \text{sad}$.

In other words,

$f: FW_{ij} \rightarrow E$, where $g(E_w) = \text{argmax}_{e \in E} (P(e|E_w))$, and $P(e|E_w)$ is the probability of emotion e given the word E_w

The classified emotions are aggregated at the feature using the following equations:

$$\text{Count } f_j e_1 = \sum_{r=1}^m \sum_{i=1}^{\text{sentence}(r)} [S_i f_j E_w = e_1]$$

$$\text{Count } f_j e_2 = \sum_{r=1}^m \sum_{i=1}^{\text{sentence}(r)} [S_i f_j E_w = e_2]$$

$$\text{Count } f_j e_3 = \sum_{r=1}^m \sum_{i=1}^{\text{sentence}(r)} [S_i f_j E_w = e_3]$$

$$\text{Count } f_j e_4 = \sum_{r=1}^m \sum_{i=1}^{\text{sentence}(r)} [S_i f_j E_w = e_4]$$

$$Count_{f_j e_5} = \sum_{r=1}^m \sum_{i=1}^{sentence(r)} [S_i f_j E_w = e_5]$$

$$Count_{f_j e_6} = \sum_{r=1}^m \sum_{i=1}^{sentence(r)} [S_i f_j E_w = e_6]$$

The classified emotions are then aggregated at the feature and product levels using the following equations:

$$Feature\text{-}level\ aggregation: F_e = \sum_{w \in W} P(e|w) / |W|$$

$$Product\text{-}level\ aggregation: P_e = \sum_{f \in F} F_e / |F|$$

where, F_e is the feature-level emotion score, P_e is the product-level emotion score, and $|W|$ and $|F|$ are the number of words and features, respectively.

The emotion classifier provides a file to the emotion visualizer that consists of a list of features, associated emotion words, emotion categories, and the date on which this emotion category was expressed by the consumer. This can be represented as a tuple (F, W, E, D) , where F is the set of features, W is the set of emotion words, E is the set of emotion categories, and D is the set of dates.

4) *Emotion visualizer*: The visual summary of consumers' basic biological and psychological emotions is presented by the emotion visualizer. It utilizes two types of visualizations: bar charts and line graphs to display emotions expressed in online reviews. A bar chart visualization is used to present the classification and summarization of consumers' biological and psychological emotions at product and feature levels. To display the temporal and volatility of reviews, a line graph visualization is utilized by the emotion visualizer. It takes the file containing features, emotion words, and emotion categories from the emotion classifier and aggregates these emotions according to the emotion categories at the product and feature levels. Then, it plots the temporal dynamism and volatility of emotions using a line graph.

IV. EXPERIMENTAL DATASET, RESULTS, AND DISCUSSION

This section presents the details of the experimental dataset, the results of experiments performed on the experimental dataset, and a discussion of the results.

A. Experimental Dataset

The proposed system is evaluated on online reviews from amazon.com. This dataset was used by many studies, including [23][7][73][80]. The data set contains consumers' reviews of five diverse digital products: two digital cameras (Canon G3 and Nikon Coolpix 4300), one mobile phone (Nokia 6610), one MP3 player (Creative Labs Nomad Jukebox Zen Xtra 40GB), and one DVD player (Apex AD2600 Progressive-scan DVD player). However, the date metadata of the reviews is not available in this dataset. The authors added the metadata to the dataset.

B. Experimental Results and Discussion

This section presents the aggregated consumers' emotions at product and feature levels, along with the change in the consumers' emotions over time.

1) *Consumers' emotion categories at the product level*: The results of fine-grained and binary emotion classifications of the Canon G3 camera at the product level are presented in this section. Fig. 3 shows the fine-grained consumers' basic emotions classification of the Canon G3 Camera. The joy emotion is in the first position, having a value of 157, as consumers expressed the Joy emotion more compared to other emotions. Joy is considered a positive emotion; therefore, it can be inferred that consumers enjoyed the use of the Canon G3 camera. The anger emotion is in second position with a value of 102 which is less than the value of joy emotion depicting the consumers' dissatisfaction. Consequently, consumers also expressed other negative emotions: sadness, fear, and disgust with the values of 89, 80, and 50, respectively. In contrast, some consumers defined Canon G3 with surprise emotion (81 value). It can be concluded from Fig. 3 that most consumers are happy with the camera as the frequency of Joy is very high compared to other emotions. Fig. 4 represents the binary emotion classification of the Canon G3 camera presenting that consumers are not satisfied with the camera as they expressed negative emotions (anger, fear, disgust, and sadness) more than positive emotions (joy and surprise).

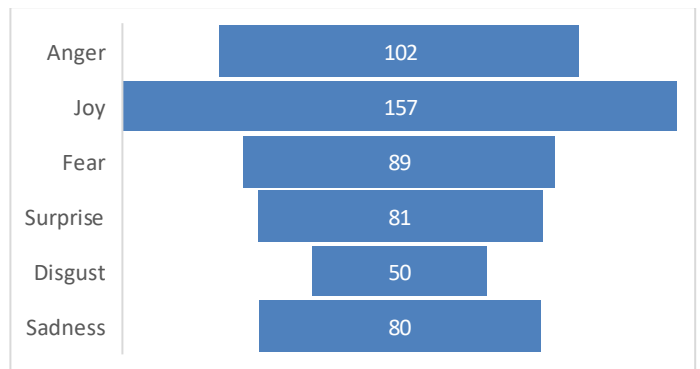


Fig. 3. Basic consumers' emotions on the Canon G3 camera.

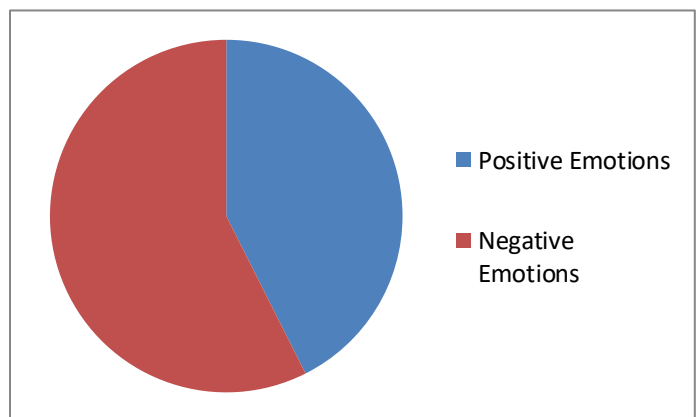


Fig. 4. Binary emotion classification of Canon G3 Camera.

2) *Consumers' emotion categories at feature level*: This section presents the basic consumers' emotions at the feature level. Due to the space limitations, we are presenting the fine-grained emotions classification of the top three features

(Camera, Picture, and Use) of the Canon G3 Camera (Fig. 5). Consumers expressed all emotions only through the camera feature. Disgust emotion is not mentioned by consumers for the picture and use features, highlighting that consumers like the picture and the use features of the camera. Moreover, only positive emotions (joy and surprise) are described by consumers for the use feature, showing the appreciation by the consumers towards the use of the camera. Further, it can be concluded that the camera is easy to use. All of these features are discussed using joy emotion remarkably as compared to other emotions. In other words, consumers are satisfied with these features tremendously. Specifically, for the camera, the highest discussed emotion is joy, with the highest value of 23 showing the endorsement of the camera by consumers. A few consumers are angry about the camera as shown by the value (4) of angry emotion. Also, other emotions (fear, surprise, disgust and sadness) are discussed by fewer consumers as indicated by a value of 3 for all features. Similarly, consumers exhibited mixed emotions (anger, surprise, and sadness) for the picture feature in a very small frequency of 3.

The binary emotion classification of the top three features is depicted in Fig. 6. All of these features received more positive emotions than negative emotions. The use feature received only positive emotions.

3) *Temporal dynamism and volatility of consumers' emotions at the product level:* This section describes the temporal dynamism and volatility of consumers' basic emotions are product level. Fig. 7 exhibited the temporal

dynamism and volatility of consumers' emotions at product level. Consumers expressed all basic emotions from Q1 to Q4. More emotions are expressed in Q1 as shown by the values of anger, joy, fear, surprise, disgust, and sadness. On the other hand, fewer emotions are expressed in other quarters of the year. Fig. 8 shows the temporal dynamism and volatility of consumers' emotions at product level over a period of one year. In the month of March, the joy emotions are expressed more by the consumers. It is also interesting to note that at the starting month, consumers described the Canon G3 camera with joy and emotion.

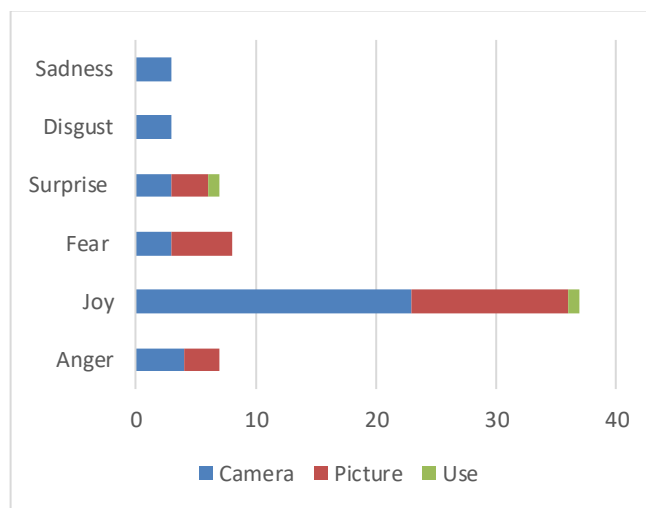


Fig. 5. Basic consumers' emotions at the feature level.

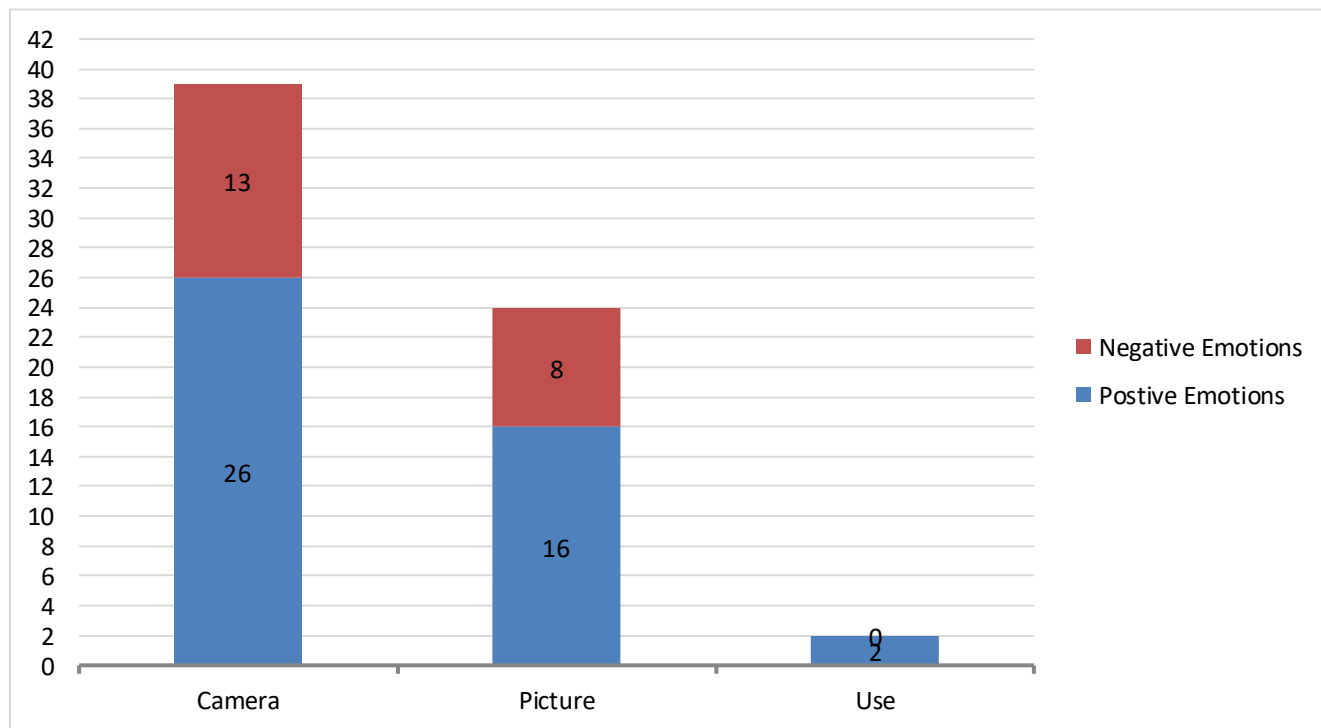


Fig. 6. Binary classification of the top three features.

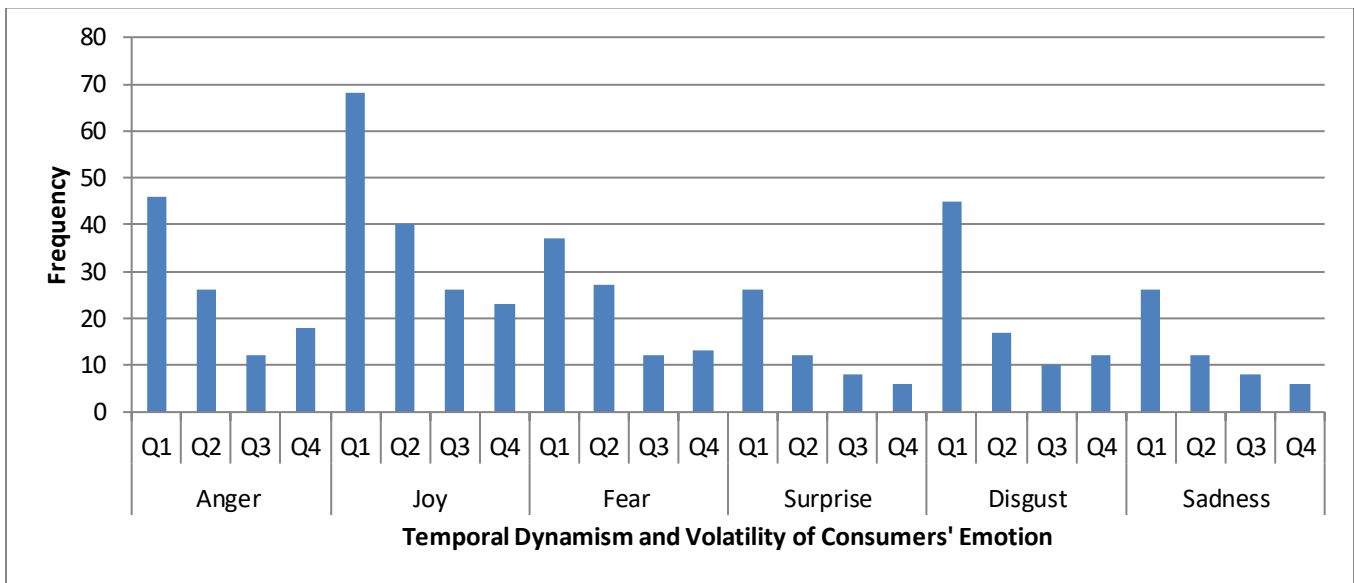


Fig. 7. Temporal dynamism and volatility of basic consumers' emotions at the product level.

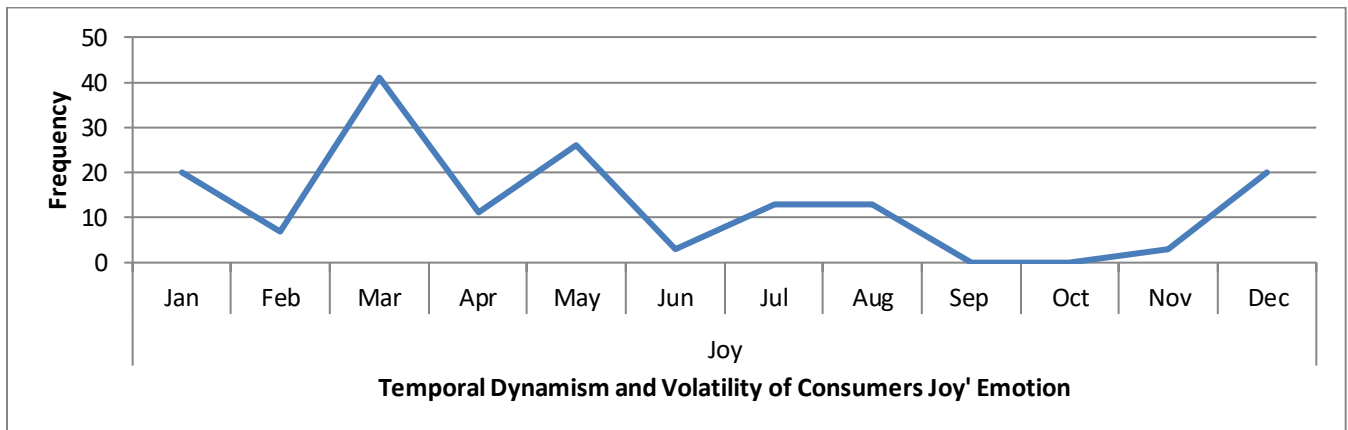


Fig. 8. Temporal dynamism and volatility of joy emotion at the product level.

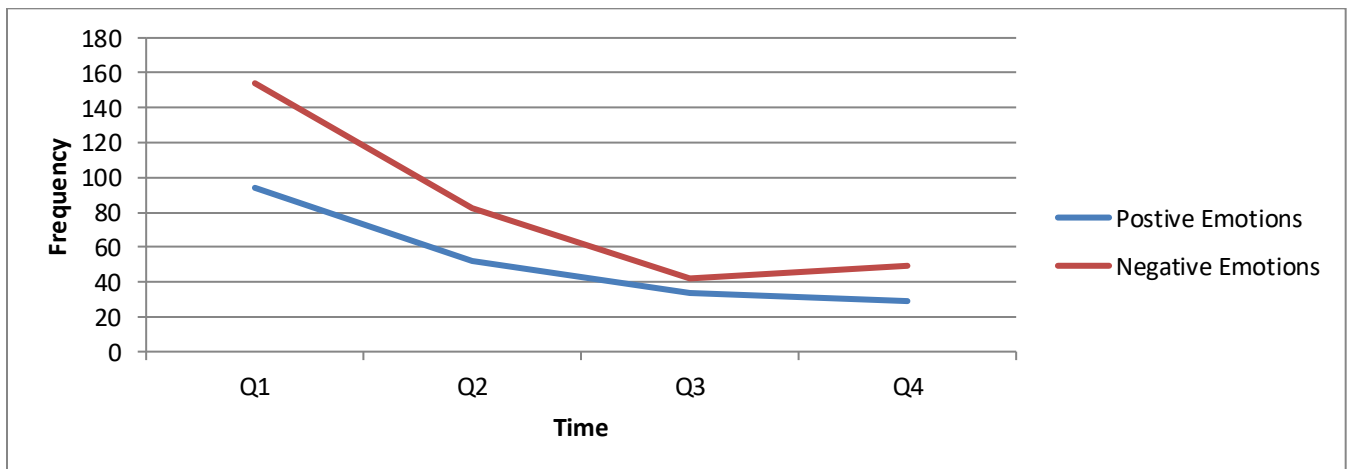


Fig. 9. Temporal dynamism and volatility of binary consumers' emotions at the product level.

Fig. 9 describes the temporal dynamism and volatility of binary consumers' emotions at the product level. It is important to note that more negative emotions are expressed in all quarters

of the year as compared to positive emotions. Therefore, it shows the consumers' dissatisfaction with the camera. There is a decreasing trend in both positive and negative emotions

expression. However, in Q1 and Q2, consumers are more expressive than in the other quarters of the year (Q3 and Q4).

4) *Temporal dynamism and volatility of consumers' emotions at the feature level:* Fig. 10 exhibited the temporal dynamism and volatility of consumers' emotions at the feature level. It can be seen from the figure that the picture feature is

discussed only in Q1. Therefore, it can be concluded that with the launch of the camera, the consumers expressed more emotions on prominent features like picture, battery, etc. However, with time, the focus of consumers' emotions is shifted to some less critical features.

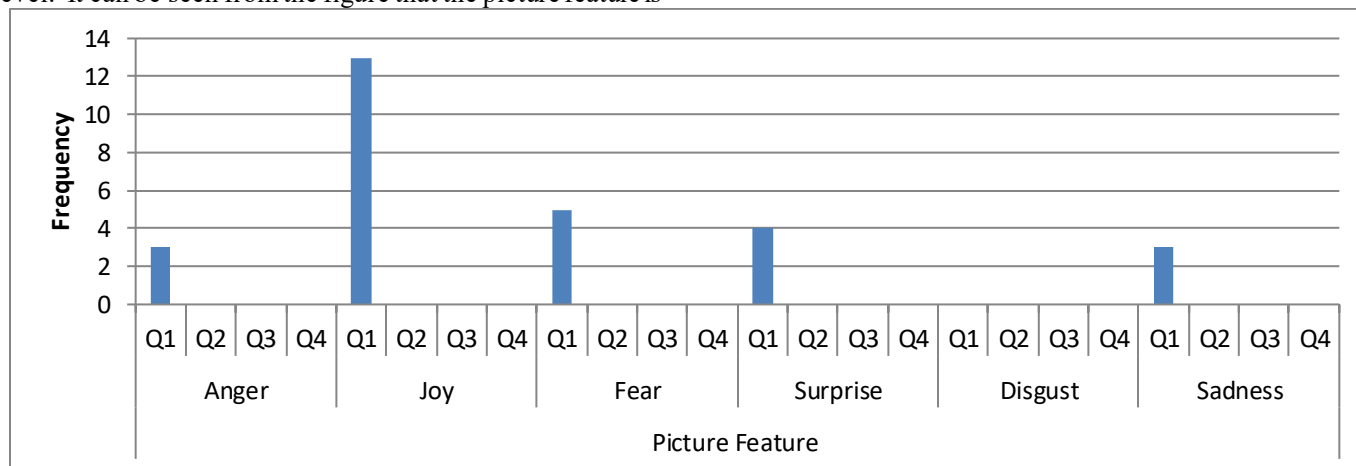


Fig. 10. Temporal dynamism and volatility of basic consumers' emotions at the feature level.

V. RESEARCH IMPLICATIONS

A. Business Perspective

The implications of expected results from a business perspective are for corporate decision-makers. First, it aids corporate decision-makers to improve their products and services based on the negative EWOM consumers. Second, the critical product features (the features having a great impact on sales) can be identified and can be targeted in future decision-making. Thirdly, the critical identified features can be focused on in new product development to enhance future sales. Fourthly, the result employing positive EWOM can be utilized for the reputation management of the organization to attract more consumers. Further, new product advertisements having positive feedback from consumers may result in increased consumer loyalty and trust, along with new consumers. Lastly, the marketing strategies can be designed based on expected results to attain consumers' attention and retention.

B. Consumers' Perspective

From the consumers' perspective, the results can be exploited in two different ways. First, the results will highlight the relative strengths and weaknesses of the target product(s) on a deeper (fine-grained) level that facilitates consumers' decision-making process. Moreover, the outcomes will depict the true emotions, evaluations, opinions, and judgments of consumers without any bias, as the EWOM posed no constraints on free expression. Consequently, the outcomes support consumers in their purchase and product adoption decisions.

VI. CONCLUSION, LIMITATIONS, AND FUTURE DIRECTIONS

EWOM is remarkably and consistently increasing due to the active participation of consumers over different online forums, including online reviews. However, EWOM is unable to present consumers' emotions on different products and services.

Specifically, basic biological and psychological emotions need to be extracted, summarized, and visualized from EWOM to empower consumers and enterprises to make informed decisions. Therefore, this research presents emotion categories and the temporal dynamism of emotion expressed in online reviews. The study extracted, summarized, and presented six basic emotion categories: anger, fear, disgust, joy, surprise, and sadness of well-known emotion model. Joy emotion is expressed more by the consumers in the online reviews of the Canon G3 camera published on amazon.com, indicating the satisfaction of the consumers towards the camera. A few consumers criticize the picture feature of the camera by describing it with negative emotions (sadness, anger, and fear). The proposed system has some potential limitations. First, it is evaluated on 332 reviews of electronic products. Second, the reviews are from amazon.com. The future direction of work includes the analysis of the proposed system by using a large number of reviews. Further, the proposed system can be utilized to analyze online reviews from different domains, like movie reviews and hotel reviews.

FUNDING

This work was funded by the Deanship of Scientific Research (DSR), University of Jeddah, Jeddah, under grant No. UJ-02-074-DR. The authors, therefore, acknowledge with thanks DSR's technical and financial support.

REFERENCES

- [1] O'Brien, C., The emergence of media empowered consumer. *Irish marketing review*, 2011. 21(1/2): p. 32-40.
- [2] Hennig-Thurau, T., et al., Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? *Journal of interactive marketing*, 2004. 18(1): p. 38-52.
- [3] Na, J.C., T.T. Thet, and C.S. Khoo, Comparing sentiment expression in movie reviews from four online genres. *Online Information Review*, 2010.

- [4] Chatterjee, S., Drivers of helpfulness of online hotel reviews: A sentiment and emotion mining approach. *International Journal of Hospitality Management*, 2020. 85: p. 102356.
- [5] Fuad, Ammar, and Aida Fitri. "THE INFLUENCE OF DIGITAL MARKETING AND ELECTRONIC WORD OF MOUTH (E-WOM) ON PURCHASE INTENTION." *Global Research in Economics and Advanced Theory (GREAT)* 3.2 (2026): 91-101.
- [6] Anastasiei, Bogdan, Nicoleta Dospinescu, and Octavian Dospinescu. "Individual and product-related antecedents of electronic word-of-mouth." *Aslib Journal of Information Management* 78.2 (2026): 449-469.
- [7] Shamim, A., et al., Critical product features' identification using an opinion analyzer. *The Scientific World Journal*, 2014. 2014.
- [8] Wang, Shan, et al. "Content dissimilarity and online review helpfulness: Contextual insights." *Journal of Business Research* 187 (2025): 115068.
- [9] ADENIRAN, Adetayo Olaniyi, Goodness OLALEYE, and Ayobami Abdulmateen GBADEGESIN. "Influence of Online Reviews on Customer Satisfaction in E-Commerce Logistics Firm: Evidence from TEMU Nigeria." *Journal International Review of Research Studies* 1.04 (2026): 1-27.
- [10] Singh, Amit, et al. "Quantifying the effect of eWOM embedded consumer perceptions on sales: An integrated aspect-level sentiment analysis and panel data modeling approach." *Journal of Business Research* 138 (2022): 52-64.
- [11] Hao, M., et al. Visual sentiment analysis on twitter data streams. in 2011 IEEE Conference on Visual Analytics Science and Technology (VAST). 2011: IEEE.
- [12] Li, H.; Bruce, X.B.; Li, G.; Gao, H. Restaurant survival prediction using customer-generated content: An aspect-based sentiment analysis of online reviews. *Tour. Manag.* 2023, 96, 104707.
- [13] Ray, Rajeev Kumar, and Amit Singh. "From online reviews to smartwatch recommendation: An integrated aspect-based sentiment analysis framework." *Journal of Retailing and Consumer Services* 82 (2025): 104059.
- [14] Abbasi Moghaddam, S., Aspect-based opinion mining in online reviews. 2013, Applied Sciences: School of Computing Science.
- [15] Chen, C.; Zhang, D.; Zhang, F.; Zhang, F. The interaction effect of online composite reviews and time pressure on information persuasiveness: A heuristic-systematic perspective. *Electron. Commer. Res. Appl.* 2023, 59, 101269.
- [16] Lin, Y.; Jen, L. The impact of consumer heterogeneity in the product life cycle on the diffusion patterns of user reviews and sales. *J. Retail. Consum. Serv.* 2024, 76, 103558.
- [17] Eirinaki, M., S. Pisal, and J. Singh, Feature-based opinion mining and ranking. *Journal of Computer and System Sciences*, 2012. 78(4): p. 1175-1184.
- [18] Ahmad, T. and M.N. Doja, Rankings system for opinion mining of features from review documents. *International Journal of Computer Science Issues (IJCSI)*, 2012. 9(4): p. 440.
- [19] Zhang, L., et al. Extracting and ranking product features in opinion documents. in *Coling 2010: Posters*. 2010.
- [20] Zhang, K., R. Narayanan, and A.N. Choudhary, Voice of the Customers: Mining Online Customer Reviews for Product Feature-based Ranking. *WOSN*, 2010. 10: p. 11-11.
- [21] Gu, S., et al., A model for basic emotions using observations of behavior in *Drosophila*. *Frontiers in psychology*, 2019. 10: p. 781.
- [22] Khan, S.S., et al., CHALLENGES IN OPINION MINING, COMPREHENSIVE.
- [23] Shamim, A., et al., Multi-Attribute Online Decision-Making Driven by Opinion Mining. *Mathematics*, 2021. 9(8): p. 833.
- [24] Ullah, R., et al., From valence to emotions: Exploring the distribution of emotions in online product reviews. *Decision support systems*, 2016. 81: p. 41-53.
- [25] Ekman, P., An argument for basic emotions. *Cognition & emotion*, 1992. 6(3-4): p. 169-200.
- [26] Bruna, O., H. Avetisyan, and J. Holub. Emotion models for textual emotion classification. in *Journal of Physics: Conference Series*. 2016: IOP Publishing.
- [27] McDougall, William, "The hypothesis of inhibition by drainage." *Psychological Review* 33.5 (1926): 370.
- [28] Watson, John Broadus. "Behaviorism, rev." (1930).
- [29] Arnold, Magda B. "Emotion and personality." (1960).
- [30] Mowrer, Orval. "Learning theory and behavior." (1960).
- [31] Tomkins, Silvan S. "Surprise—startle: The resetting affect." (1962).
- [32] Izard, Carroll E. "Differential emotions theory." *Human emotions*. Boston, MA: Springer US, 1977.
- [33] Plutchik, Robert. "A general psycho evolutionary theory of emotion." *Theories of emotion*. Academic press, 1980. 3-33. 43-66.
- [34] Panksepp, Jaak. "Archaeology of mind." *Behavioral and Brain Sciences* 5.3 (1982): 449-467.
- [35] Weiner, Bernard, and Sandra Graham. "An attributional approach to emotional development." *Emotions, cognition, and behavior* (1984): 167-191.
- [36] Frijda, Nico H. "The emotions." *Studies in Emotion and Social Interaction* (1986).
- [37] Shaver, Phillip, et al. "Emotion knowledge: further exploration of a prototype approach." *Journal of personality and social psychology* 52.6 (1987): 1061.
- [38] Richins, Marsha L. "Measuring emotions in the consumption experience." *Journal of consumer research* 24.2 (1997): 127-146.
- [39] Derbaix, Christian, and Joëlle Vanhamme. "Inducing word-of-mouth by eliciting surprise—a pilot investigation." *Journal of economic psychology* 24.1 (2003): 99-116.
- [40] Ekman, Paul. "Are there basic emotions?." (1992): 550.
- [41] Yadollahi, A., A.G. Shahraki, and O.R. Zaiane, Current state of text sentiment analysis from opinion to emotion mining. *ACM Computing Surveys (CSUR)*, 2017. 50(2): p. 1-33.
- [42] Amini, R., C. Lisetti, and G. Ruiz, HapFACS 3.0: FACS-based facial expression generator for 3D speaking virtual characters. *IEEE Transactions on Affective Computing*, 2015. 6(4): p. 348-360.
- [43] Teijeiro-Mosquera, L., et al., What your face vlogs about: expressions of emotion and big-five traits impressions in YouTube. *IEEE Transactions on Affective Computing*, 2014. 6(2): p. 193-205.
- [44] Balog, K., G. Mishne, and M. Rijke. Rijke. why are they excited? identifying and explaining spikes in blog mood levels. in *In Proceedings 11th Meeting of the European Chapter of the Association for Computational Linguistics (EACL)*. 2006
- [45] Pennebaker, J.W., Writing about emotional experiences as a therapeutic process. *Psychological science*, 1997. 8(3): p. 162-166.
- [46] Zamani, N.A.M., et al. Sentiment analysis: determining people's emotions in Facebook. in *Proceedings of the 13th international conference on applied computer and applied computational science*. 2014.
- [47] Mohammad, S.M., et al., Sentiment, emotion, purpose, and style in electoral tweets. *Information Processing & Management*, 2015. 51(4): p. 480-499.
- [48] Bhowmick, P.K., A. Basu, and P. Mitra, Reader Perspective Emotion Analysis in Text through Ensemble based Multi-Label Classification Framework. *Computer and Information Science*, 2009. 2(4): p. 64-74.
- [49] Lei, J., et al., Towards building a social emotion detection system for online news. *Future Generation Computer Systems*, 2014. 37: p. 438-448.
- [50] Gupta, N., M. Gilbert, and G.D. Fabbriozio, Emotion detection in email customer care. *Computational Intelligence*, 2013. 29(3): p. 489-505.
- [51] Luo, B., J. Zeng, and J. Duan, Emotion space model for classifying opinions in stock message board. *Expert Systems with Applications*, 2016. 44: p. 138-146.
- [52] Min, H., et al., Using machine learning to investigate the public's emotional responses to work from home during the COVID-19 pandemic. *Journal of Applied Psychology*, 2021. 106(2): p. 214.
- [53] Adikari, A., et al., Emotions of COVID-19: Content Analysis of Self-Reported Information Using Artificial Intelligence. *Journal of Medical Internet Research*, 2021. 23(4): p. e27341.
- [54] Plutchik, R., A psycho evolutionary theory of emotions. 1982, Sage Publications.

- [55] Bollen, J., H. Mao, and A. Pepe. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. in Proceedings of the international AAAI conference on web and social media. 2011.
- [56] Wang, W., et al. Harnessing twitter big data for automatic emotion identification. in International Conference on Privacy, Security, Risk and Trust 2012
- [57] Hasan, M., E. Agu, and E. Rundensteiner. Using hashtags as labels for supervised learning of emotions in twitter messages. in ACM SIGKDD workshop on health informatics, New York, USA. 2014.
- [58] Mishne, G. Experiments with mood classification in blog posts. in Proceedings of ACM SIGIR 2005 workshop on stylistic analysis of text for information access. 2005.
- [59] Mishne, G. and M. De Rijke. Capturing Global Mood Levels using Blog Posts. in AAAI spring symposium: computational approaches to analyzing weblogs. 2006.
- [60] Alm, C.O., D. Roth, and R. Sproat. Emotions from text: machine learning for text-based emotion prediction. in Proceedings of human language technology conference and conference on empirical methods in natural language processing. 2005.
- [61] Luyckx, K., et al., Fine-grained emotion detection in suicide notes: A thresholding approach to multi-label classification. Biomedical informatics insights, 2012. 5: p. BII. S8966.
- [62] Jain, M.C. and V. Kulkarni, TexEmo: Conveying emotion from text-the study. International Journal of Computer Applications, 2014. 86(4).
- [63] Ho, D.T. and T.H. Cao. A high-order hidden Markov model for emotion detection from textual data. in Pacific Rim Knowledge Acquisition Workshop. 2012: Springer.
- [64] Zablocki, A., K. Makri, and M.J. Houston, Emotions within online reviews and their influence on product attitudes in Austria, USA and Thailand. Journal of Interactive Marketing, 2019. 46: p. 20-39.
- [65] Mokryn, O., et al., Sharing emotions: determining films' evoked emotional experience from their online reviews. Information Retrieval Journal, 2020. 23(5).
- [66] Garcia, D. and F. Schweitzer. Emotions in product reviews—empirics and models. in 2011 IEEE Third International Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third International Conference on Social Computing. 2011: IEEE.
- [67] Yin, G., Q. Zhang, and Y. Li, Effects of emotional valence and arousal on consumer perceptions of online review helpfulness. 2014.
- [68] Moghaddam, S. and M. Ester. Opinion digger: an unsupervised opinion miner from unstructured product reviews. in Proceedings of the 19th ACM international conference on Information and knowledge management. 2010
- [69] Tanase, D., et al., Emotions and activity profiles of influential users in product reviews communities. Frontiers in Physics, 2015. 3: p. 87.
- [70] Hossain, M.S.; Rahman, M.F. Customer sentiment analysis and prediction of insurance products' reviews using machine learning approaches. FIIB Bus. Rev. 2023, 12, 386–402.
- [71] Kim, J. and P. Gupta, Emotional expressions in online user reviews: How they influence consumers' product evaluations. Journal of Business Research, 2012. 65(7): p. 985-992.
- [72] Luo, Y.; Li, Y.; Ye, Q. Impacts of online additional reviews on the sales volume of cross-border pharmaceutical e-commerce platforms. J. Glob. Inf. Technol. Manag. 2022, 25, 83–101.
- [73] Yang, J.-Y., H.-j. Kim, and S.-g. Lee, Feature-based Product Review Summarization Utilizing User Score. J. Inf. Sci. Eng., 2010. 26(6): p. 1973-1990.
- [74] Castro, F., et al., Applying data mining techniques to e-learning problems, in Evolution of teaching and learning paradigms in intelligent environment. 2007, Springer. p. 183-221.
- [75] Arnold, K.E., Z. Tanes, and A.S. King, Administrative perceptions of data-mining software Signals: Promoting student success and retention. The Journal of Academic Administration in Higher Education, 2010. 6(2): p. 29-39.
- [76] Mohammad, Saif M., and Peter D. Turney. "Crowdsourcing a word-emotion association lexicon." *Computational intelligence* 29.3 (2013): 436-465
- [77] Ali, L., et al., Factors influencing beliefs for adoption of a learning analytics tool: An empirical study. Computers & Education, 2013. 62: p. 130-148.
- [78] Das, S. and A. Dutta, Characterizing public emotions and sentiments in COVID-19 environment: A case study of India. Journal of Human Behavior in the Social Environment, 2021. 31(1-4): p. 154-167.
- [79] Wen, Zhanming, et al. "Text Mining Based Approach for Customer Sentiment and Product Competitiveness Using Composite Online Review Data." *Journal of Theoretical and Applied Electronic Commerce Research* 19.3 (2024): 1776-1792.
- [80] Ruskanda, Fariska Zakhralativa, Dwi Hendratmo Widyantoro, and Ayu Purwaranti. "Efficient Utilization of Dependency Pattern and Sequential Covering for Aspect Extraction Rule Learning." *J. ICT Res. Appl* 14.1 (2020): 51.