International Journal of Business Analytics and Intelligence
11 (1) 2023, 47-58
http://publishingindia.com/ijbai/

Examining Consumer Sentiments in Online Purchase Reviews on Social Media Platforms

Riktesh Srivastava*, Rajita Srivastava**

Abstract

Consumers are increasingly turning to online product reviews for direction when it comes to making decisions about the products they want to purchase. Reviewing products and providing feedback on those reviews is becoming more popular on social media. It is possible that looking at consumer product evaluations on social media might prove to be a highly beneficial resource for businesses. This is because consumers post reactions on social media regarding their most recent purchases. Nevertheless, it is challenging to scan social media for evaluations and gather them all together in one place. A conceptual framework called 4A (anxious, apart, ardent and active) is presented in the research to classify results into one of four possible categories. The framework's flexibility makes it simple for businesses to use, since it effectively classifies results into one of four categories. This allows businesses to gauge the public's reaction and adjust their marketing strategy accordingly. Despite the fact that businesses have not yet embraced the proposed framework, the findings are favourable.

Keywords: 4A Framework, Naïve Bayes Algorithm, Amazon India, Flipkart, Snapdeal, Myntra, eBay

Introduction

It is anticipated that the Indian e-commerce business can reach $350 billion by 2030 (Forbes, 2022). The growth of e-commerce in India is due to an increase in the number of smartphones, and it is expected that one billion of these devices will be in use by the year 2026 (Outlook, 2022). Mobile phone usage has become so pervasive in India that the devices are now widely recognised as the single most democratic method of accessing technology in the country. More than that, it has helped in many ways to foster the expansion of electronic commerce in India. As a result, mobile phones and especially smartphones, have become a crucial medium for fostering the development of e-commerce in India (Chawla & Kumar, 2022; Nougarahiya et al., 2021; Rathod, 2020). Businesses have difficulty matching the consumer interactions they have with their business plans as a result of the continuous maturing of mobile shopping (Vaidyanathan & Henningsson, 2022). As a consequence of this, they use social media to strengthen their interactions with consumers and increase brand recognition via digital marketing (Appel et al., 2020; Dwivedi et al., 2021; ElAydi, 2018). Because social media has such a large presence, it is reasonable to anticipate that it may increase sales. In addition, when these companies communicate with their consumers through social media platforms, they are able to gain instant feedback, which provides them with a fast grasp of what it is that their consumers desire (Kumar & Pradhan, 2018; Ogunmola & Kumar, 2019; Susanto et al., 2021). Consumers are not only venting their annoyance or irritation on social media, rather also use them as a source to provide feedback (Verhoef et al., 2021; Vidili, 2021). Social media is becoming a favoured avenue for consumer service interactions; nevertheless, this also presents a unique set of challenges. Consumers are growing more demanding of prompt replies at all hours of the day and night. As stated, when consumers have a negative experience, half of them complain about it openly on social media. And if they don't get a response at all, 81% of consumers say they won't recommend that business to their friends (Johansen et al., 2016).

The current study focuses on an analysis of the responses by consumers on Twitter for India's five most successful

* Associate Professor, City University, Ajman, UAE. Email: r.srivastava@cuca.ae
** PhD (Management), Banasthali University, India. Email: rajitariktesh@gmail.com

online retailers: Amazon India, Flipkart, Snapdeal and Myntra, as well as eBay India. The feedback research used the tweets made by these companies on Twitter from January 1, 2022, through August 31, 2022, as its primary source of data. The investigation model is referred to as the 4A (anxious, apart, ardent and active) conceptual framework. The experiment employs 1,500 tweets and the Naïve Bayes algorithm to categorise the responses into one of the four quadrants of the model. These companies may choose to accept and implement the general social media tactics presented in the research, which were adopted based on the results presented in the study.

The remainder of the components of the paper at the beginning with the introduction, are going to be organised as follows: In the second section, we conduct a review of the literature that is presently accessible about the usage of social media by the Indian retail sector to respond to customer feedback and apprehensions. This was done so that the research gap could be identified, and progress could be made towards the overall goal of the study. The next section (Section 3) is then offered, and it is in this section that our proposed conceptual framework for 4A is outlined. The results are shown in Section 4, with a breakdown that takes into account whether the tweets had a positive or negative polarity. Section 5 of the study contains the recommendations that have been compiled.

Literature Review

In previous research, the concept of sentiment analysis has been described as a method for deducing information about the feelings of consumers. It does it by examining the responses that consumers provide to surveys (positive or negative). It has been shown that sentimental analysis may be put to use in a wide variety of settings, some of which have already been covered. Mamgain et al. (2016) stated that consumers commonly use Twitter to voice their thoughts. Twitter data is very valuable, but its size and disorganisation make analysis difficult. Ranjan et al. (2018) did the Sentiment analysis was performed on 153,651 tweets mentioning five major Indian telecom brands: Aircel, Bharti Airtel, Idea Cellular, Reliance Jio and Vodafone India. Businesses may utilise the findings of sentiment analysis to take prompt action to enhance future customer experiences and reduce customer turnover. According to research (Khajuria & Rachna, 2017), the impact of Facebook on brand communication among Indian consumers is far-reaching. There is a lack of study on how social media strategies affect consumers' perceptions of a business, despite the fact that these platforms routinely provide very effective tools for organisations to communicate with their target audiences. Thomas et al. (2018) examines the mediating role of trust in the relationship between online website cues (such as product display and perceived engagement) and Generation Z's propensity to make a purchase. The study's findings indicated that all the relevant signals taken into account had a significant effect on purchase intent when trust was a moderating variable. Wase et al. (2018) conducted research on data mining by using sentiment analysis for three firms in India that are involved in electronic commerce. They analysed the reviews of products that were purchased online and posted on popular e-commerce websites such as Amazon, Rediff.com and Flipkart.com. According to the findings of the research, a negative reaction has a significant influence on the purchasing decisions of consumers. According to Gupta et al. (2020), text mining is becoming an increasingly important field of study in the business realm of finance. This article takes a text-mining approach to examine a variety of financial issues, including financial forecasting, banking and corporate finance among others. In addition to this, it undertakes an examination of the existing literature on text mining in financial applications and provides a summary of some recent research that has been published. Rendering to the findings of the study, investigating how customers react to content posted on social media that relates to financial apps is an important field of research. Rajeswari et al. (2020) conducted research on the opinions of customers on products that are both kind to the environment and contribute to a shift in the consumer attitudes towards safer products. The relevance of reviews and demographic data to a consumer's experience is two factors that impact their replies. Sundaram (2020) evaluated the sentiment of investors on mutual funds in the Indian market using assets under management (AUM) as an indicator to analyse the impact of news items referring to the mutual fund business during the COVID-19 epidemic. This was done using AUM. By evaluating the sentiment score, the study goes on to demonstrate a considerable statistical correlation between sentiment scores and AUM. This is in addition to the previous finding, which demonstrates that sentiment scores are related to AUM. P & Sivakumari (2021) constructed a model that employs sentimental analysis to help stock market investors make decision making techniques for Sensex stocks in India. We hypothesise that, sentiment analysis of news headlines and tweets has an effect on the value of stocks and other securities. Wankhade et al. (2022) presents an in-depth description of the process through which sentiment analysis is carried out. In the findings, it was contended that natural language processing and text mining are used in sentiment analysis in order to recognise and retrieve opinion information from the text. Modi et al. (2022) did the research that seeks to generalise Twitter sentiment analysis. Support Vector Machines, Naive Bayes and Decision Tree Classifiers analyse sentiment for three sectors: enterprises and sports clothing and multimedia. The research found that social media involvement boosts brand growth. Ahmed et al. (2022) concentrated on the performance of businesses, and we will use AI techniques in the form of machine learning (ML) and deep learning (DL) and paying particular attention to sentiment analysis. The findings showed that doing sentiment analysis for consumer response on social media enhances the business performance. Dixit et al. (2022) mentioned that because data is both free and available to the public, Twitter is frequently utilised as a tool for gaining insights on popular mood. The purpose of this article is to give a lexicon-based sentiment analysis of the top competitors operating within the electronics industry in India. They stated that comments and opinions posted by customers through social media platforms have a great deal of weight, both for end users and for businesses that operate on such platforms. Adak et al. (2022) used food delivery service (FDS) providers as a case study and collected feedback and complaints from consumers through social media. The purpose of this study was to investigate ML and DL models to better anticipate the feelings of consumers in the FDS sector. According to the findings of the research, consumers are highly active on social media and generating information that have to be taken into account while maintaining a constructive frame of mind. Yaqub et al. (2022) did the study to investigate, display and evaluate the most recent findings in the field of sentiment analysis as it relates to the tourist business. There was a notable rise in the amount of emphasis placed on sentiment analysis for the tourism industry.

The current body of research on the subject of sentiment analysis with alignment of business offerings and responses is taken into consideration and subjected to an assessment with Indian context. Through recent study, a number of publications associated with the application of sentiment analysis to the financial markets and the stock market and macroeconomics or the tourism sector have been unearthed. There hasn't been a lot of study done on the subject of sentiment analysis in the retail business in India, especially in regard to the feedback customers provide about purchases or the after-sales assistance they experience.

Table 1 gives the detail listing of the research gap and objective that is carried out in the study.

Table 1: Research Gap and Objectives for the Study

Research Gap	*Research Objective*
There does not seem to be a sufficient amount of published research on the sentiment analysis of the Indian retail industry's presence on social media.	The purpose of this research is to investigate, with the help of the 4A framework that has been established, how the reactions of customers on social media impact businesses.

A Conceptual Framework

According to the findings, the objective of the research is twofold: first, we need to categorise the feelings and perspectives of customers using sentiment analysis. During the course of this investigation, it was found that each of these businesses keeps two separate Twitter accounts updated (except for eBay). The first is the official source, which is where these firms post new information, bargains, and offers; the second is for giving customers with assistance when they have issues about a product or service. Table 2 outlines the current standing of all of these companies' Twitter accounts, which can be seen here.

Table 2: Twitter Status (as on 31/08/2022)

Company	*Twitter Account(s)*	*Tweets (n=1500) (Feedback Collected)*	*Total Tweets*	*Total Followers*
Amazon	@amazonIN	1500	21.7K	637K
	@AmazonHelp	1500	1.31M	103K
Flipkart	@Flipkart	1500	32.8K	1.48M
	@Flipkartsupport	1500	332K	63.4K
Snapdeal	@Snapdeal	1500	26.2K	696K
	@Snapdeal_Help	1500	217K	24K
Myntra	@Myntra	1500	80.9K	350K
	@MyntraSupport	818	29.4K	16.7K
eBay	@ebayindia	1199	84K	210K

Steps for Sentiment Analysis

The procedures involved in analysing social media are divided into two distinct parts in Fig. 1. The first section is a compilation of the tweets from all five of the aforementioned firms' Twitter accounts. Because tweets often include a lot of noise and bits that aren't very helpful, they need to be cleaned up using pre-processing. This is accomplished in Part 2 of the framework, and it consists of five phases. The Naïve Bayes theorem is used in the analysis of the texts that are presented in Part 2.

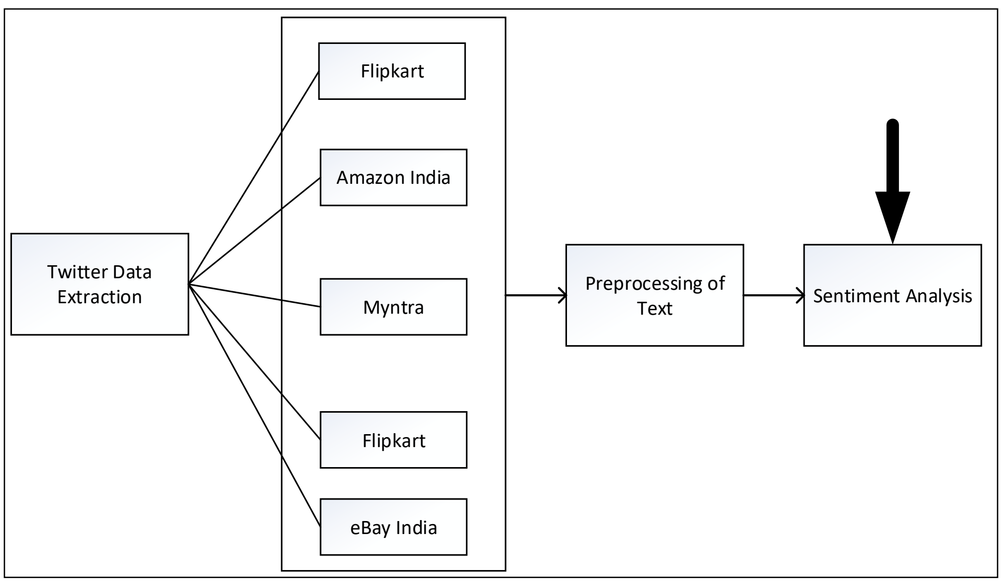

Fig. 1: Steps for Sentiment Analysis

Preprocessing Steps

In pre-processing, the initial step is to remove all words (not the texts, as some texts contain a mix of English and other language words). An in-depth description of the five stages procedure of pre-processing.

Step 1: Transformation

All of the gathered texts are raw and unprocessed. The process of transformation takes this raw, unstructured data and transforms it into something more suitable for analytical purposes.

The steps can be represented mathematically by equation (1) as:

$$\sum_{i=1}^{n}\prod_{j=1}^{m}t_{ij} = \sum_{i=1}^{n}\left[\prod_{j=1}^{m}\begin{bmatrix}(t_{11})\\(t_{12})\\ \vdots\\ \vdots\\ \vdots\\(t_{nm})\end{bmatrix}\right] = \sum_{i=1}^{n}\left[\prod_{j=1}^{m}\begin{bmatrix}(Word_{11}Word_{12}\dots Word_{1j})\\(Word_{21}Word_{22}\dots Word_{2j})\\ \vdots\\ \vdots\\ \vdots\\(Word_{n1}Word_{n2}\dots Word_{nm})\end{bmatrix}\right] \quad (1)$$

Where, i is number of texts where each texts contain j words. Notice from equation (1) that each word of texts is not disjointed and are embodied as sentences.

Step 2: Tokenisation

In their basic state, when all possible texts are available in digital forms and have no specific value and texts generated in step 1 are inappropriate for processing. Now, we may rewrite equation (1) as equation (2):

$$= \sum_{i=1}^{n}\left[\prod_{j=1}^{m}\begin{bmatrix}(Word_{11})(Word_{12})\dots\dots(Word_{1j})\\(Word_{21})(Word_{22})\dots\dots(Word_{2j})\\ \vdots\\ \vdots\\ \vdots\\(Word_{n1})(Word_{n1})\dots\dots(Word_{nm})\end{bmatrix}\right] \quad (2)$$

Observe that each text has been divided into expressive tokens.

Step 3: Normalisation

In the third step, all of the words that are referenced in the second equation are taken as input and then stemming and lemmatisation are performed. The process of stemming is an iterative continuation of removing affixes that are derived from other words. After stemming, there is a possibility that certain words may look unimportant while having been significant all along. Lemmatisation accomplishes this goal by using word analysis that is both morphological and vocabulary-based. In this stage, the Porter 2 Stemmer, which is also known as the Snowball stemmer is used. The words are made more complicated by adding affixes, and then they are stemmed and lemmatised as a result. The procedure is described by the following equation (3):

$$= \sum_{i=1}^{n}\left[\prod_{j=1}^{m}\begin{bmatrix}(Word_{11})(Word_{12})\dots\dots(Word_{1j})\\(Word_{21})(Word_{22})\dots\dots(Word_{2j})\\ \vdots\\ \vdots\\ \vdots\\(Word_{n1})(Word_{n1})\dots\dots(Word_{nm})\end{bmatrix}\right] = \begin{bmatrix}(w_{11},w_{12},\dots\dots,w_{1m})\leftarrow x_1\\(w_{21},w_{22},\dots\dots,w_{2m})\leftarrow x_2\\ \vdots\\ \vdots\\(w_{n1},w_{n2},\dots\dots,w_{nm})\leftarrow x_n\\ v_1,v_2,\dots\dots\dots v_m\end{bmatrix} \quad (3)$$

Where w_{11},w_{12}, … …, w_{1n} are words that have comparable affixes and are translated to x_1, w_{21},w_{22}, … …, w_{2n} are words that are allocated to x_2, and the words v_1, v_2, … …, v_m are words that are mapped to x_3 does not possess any positive affixes, and as a result it continues to be invariant.

The equation might also be phrased as the following equation (4):

$$= \begin{bmatrix}(ws_{11},ws_{12},\dots\dots,ws_{1m})\\(ws_{21},ws_{22},\dots\dots,ws_{2m})\\ \vdots\\ \vdots\\ \vdots\\(ws_{n1},ws_{n2},\dots\dots,ws_{nm})\end{bmatrix} \quad (4)$$

Step 4: Filtering

Eliminating frequent words from an equation, commonly known as stopwords, is an essential part of the filtering process (equation 4). As can be seen in (equation 5), the addition of stop words results in a considerable decrease in the total amount of words.

$$= \sum_{i=1}^{n} \left[\prod_{j=1}^{k} \begin{bmatrix} (ws_{11}, ws_{12}, \dots\dots, ws_{1k}) \\ (ws_{21}, ws_{22}, \dots\dots, ws_{2k}) \\ \vdots \\ \vdots \\ \vdots \\ (ws_{n1}, ws_{n2}, \dots\dots, ws_{nk}) \end{bmatrix} \right] \quad (5)$$

Notice in equation (5) that amount of words are substantially concentrated from k to m, where $k << m$.

Step 5: ngram

The next stage is referred to as "ngram," and it is a series of n words that is utilised for filtering in order to extract essential phrases. In order to extract key phrases, a mix of statistical features (based on weighted betweeness centrality scores of words) and the strength of co-location relationships is used (based on nearest neighbour). As a consequence of the analysis, a combination of words is generated. These combinations of words are mostly comprised of a collection of words that appear together, and when calculating the ngram, normally one word is advanced. The following is an example of a generic encoding of ngram:

$$ngram_t = k - (t - 1) \quad (6)$$

where,

k = numbers of words in a text t, then

The study makes use of bigrams, often known as 2-grams and since it comprises characteristics consisting of sets of two adjacent words taken from the text. It has been discovered that unigrams are unable to capture phrases and other multi-word utterances, thereby discarding any word order dependencies. As an example, phrases such as "not enthusiastic" and "not satisfied" unequivocally communicate a negative attitude and yet, a unigram may fail to recognise this while a bigram is able to differentiate between these two meanings while conveying the precise mood of the text.

The outcome of equation (6) considering all the words from text is shown in equation (7).

$$= \sum_{i=1}^{n} \left[\prod_{j=1}^{l} \begin{bmatrix} (WD_{11}, WD_{13}, \dots\dots, WD_{1l}) \\ (WD_{21}, WD_{23}, \dots\dots, WD_{2l}) \\ \vdots \\ \vdots \\ \vdots \\ (WD_{n1}, WD_{n3}, \dots\dots, WD_{nl}) \end{bmatrix} \right] \quad (7)$$

Where, $l = \frac{k}{2}$ as two words in the corpus are now combined into one word.

When constructing a lexicon, firstly, seed words are generated which then identifies the mood state of responses grounded on these seed words. For the study, the lexicon analysis was done on the basis of sentiment scoring. The sentiments $P(t)$ maps each text to a three-dimensional mood vector $p \in R^3$ [*positive, negative, neutral*]. $P(t)$ matches the term extracted from of tweets, and set the sentiment adjectives for dimensions i,j, as denoted by set p_{ij}. Thus, sentiment scoring function can thus be defined as follows:

$$P(t) = p \in R^3 = \sum_{i=1}^{n} \left[\prod_{j=1}^{l} \begin{bmatrix} (WD_{11} \cap p_{11}, WD_{13} \cap p_{13}, \dots\dots, WD_{1l} \cap p_{1l}) \\ (WD_{21} \cap p_{21}, WD_{23} \cap p_{23}, \dots\dots, WD_{2l} \cap p_{2l}) \\ \vdots \\ \vdots \\ \vdots \\ (WD_{n1} \cap p_{n1}, WD_{n3} \cap p_{n3}, \dots\dots, WD_{nl} \cap p_{nl}) \end{bmatrix} \right] \quad (8)$$

The outcome of equation (8) can be then normalised to a vector p for each text t, to produce the unit mood vector,

$$\hat{p} = \frac{p}{\|p\|} \quad (9)$$

Equation (9) may be easily deciphered thanks to the fact that the matrix was converted into a vector. This is one of the many advantages of this transformation (considering A and B as two events for sample space).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{10}$$

where,

$P(A|B)$ Is the probability of A (class), given B (tweet).

$P(B|A)$ Is the probability of B (tweet), given A (class).

$P(A)$ Is the probability of A (class), and is independent of each other.

$P(B)$ Is the probability of B (tweet), and is independent of each other.

Based on equation (10), positive and negative tweet are represented as:

$$P(positive|tweet) = \frac{P(tweet|positive)P(positive)}{P(tweet)} \tag{11}$$

$$P(negative|tweet) = \frac{P(tweet|negative)P(negative)}{P(tweet)} \tag{12}$$

It is observed that probability of tweets, $P(tweet)$ is constant, and can thus be ignored. Thus, equations (11) and (12) can be represented as:

$$P(positive|tweet) = P(tweet|positive)P(positive) \tag{13}$$

$$P(negative|tweet) = P(tweet|negative)P(negative) \tag{14}$$

The more precise notation of each class is thus given in equations (12), (13) and (14) respectively.

$$P(positive) = \sum_{j=1}^{m} \sum_{i=1}^{n} P(T_i|positive) \tag{15}$$

$$P(negative) = \sum_{j=1}^{m} \sum_{i=1}^{n} P(T_i|negative) \tag{16}$$

$$P(neutral) = 1 - [P(positive) + P(negative)]$$

(17)

Where,

$i = 1..n \rightarrow$ Total number of words for each tweet

$j = 1..m \rightarrow$ Total number of tweets

Proposed 4A Framework Explanation

The input of customers is a vital element in the operation of a profitable company, and the participation of customers via various social media platforms is becoming an even more significant role in the operation of profitable enterprises. One of the marketing tactics that has traditionally shown to be one of the most successful for organisations is word of mouth. However, "e-word of mouth," which refers to customers chatting to each other and offering more feedback via social media, has now eclipsed word of mouth as the most successful marketing method. This is because consumers are more likely to share their positive experiences on social media. As was discussed before, the importance of social media to organisations is expanding, and as was described earlier volume and impact and sentiment are three fundamental approaches that are nevertheless crucial for analysing social media. The method that was suggested is now being used in the investigation of the replies of customers that was carried out. This technique makes use of the idea of positive polarity in order to determine the degree of engagement, which these businesses now have with their customers. The criteria for evaluating the suggested 4A conceptual framework may be found in Table 3.

Table 3: Evaluation Table for 4A Framework

Positive Polarity (in %)		*4A States*
0	30	Anxious
31	60	Apart
61	80	Ardent
81	100	Active

An explanation of the following analysis is included in Fig. 2, which can be found here. The number of positive polarities present in the model is used to identify which of the four quadrants each part belongs in when the model is divided up. It is easy to assess the current stage of the adoption of social media and the approaches that should be implemented in the event that they are required when the findings are put into these quadrants.

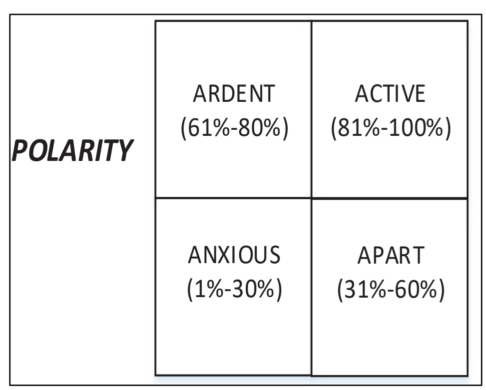

Fig. 2: Feedback Analysis

Results and Discussion

Based on equations (15), (16), and (17), Fig. 3 reveals the polarity of tweets.

Twitter Account(s)	*Polarity*		
	+	+/-	-
@amazonIN	66.87%	14.80%	18.33%
@AmazonHelp	54.87%	17.73%	27.40%
@Flipkart	66.60%	8.20%	25.20%
@Flipkartsupport	46.67%	20.00%	33.33%
@Snapdeal	56.20%	16.73%	27.07%
@Snapdeal_Help	54.93%	18.87%	26.20%
@Myntra	76.67%	11.67%	11.67%
@MyntraSupport	72.13%	14.67%	13.20%
@ebayindia	78.32%	12.93%	9.17%

Fig. 3: Polarity Status

Using data that is freely accessible to the public through the Twitter API, the Twitter graphs for each business are pieced together in phases. Only the comments on which consumers have provided feedback are gathered from the list of tweets sent by each company. This eliminates the possibility of gaining insight from unidentified customers who did not submit feedback and is ,thus unlikely to provide helpful information. Also, because of the high pace of growth on Twitter, the polarity tends to spread swiftly. As a result, the overall polarity is a representation of the firms' current social standing rather than the specific status that existed at the time that the tweet was posted. The feedback from these customers was collected during the course of the time period beginning on June 1, 2022 and ending on August 31, 2022, with a maximum of 1500 tweets being received.

Fig. (3-8) shows the feedback polarity breakdown for these companies.

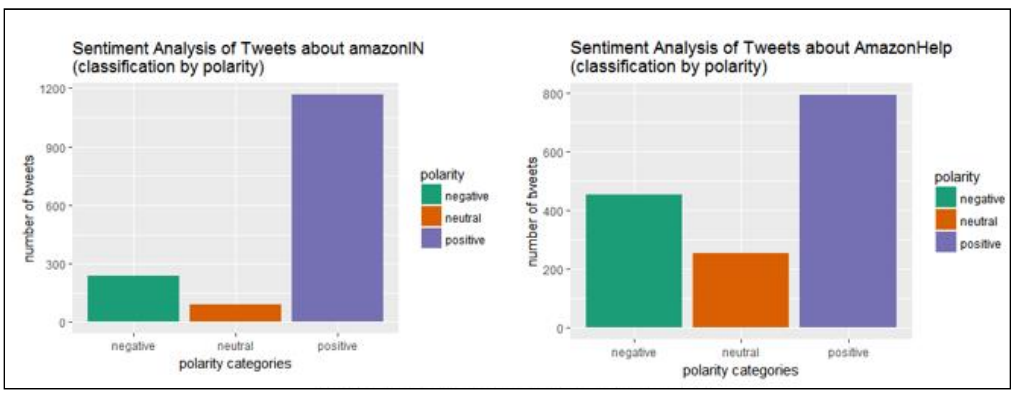

Fig. 4: Amazon Twitter Status

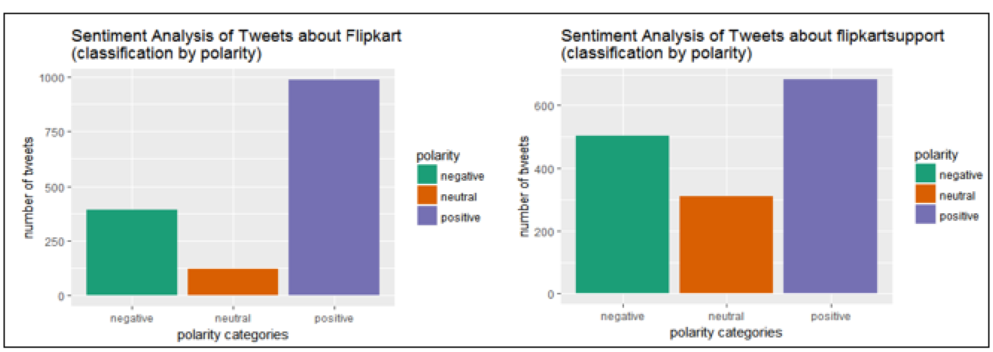

Fig. 5: Flipkart Twitter Status

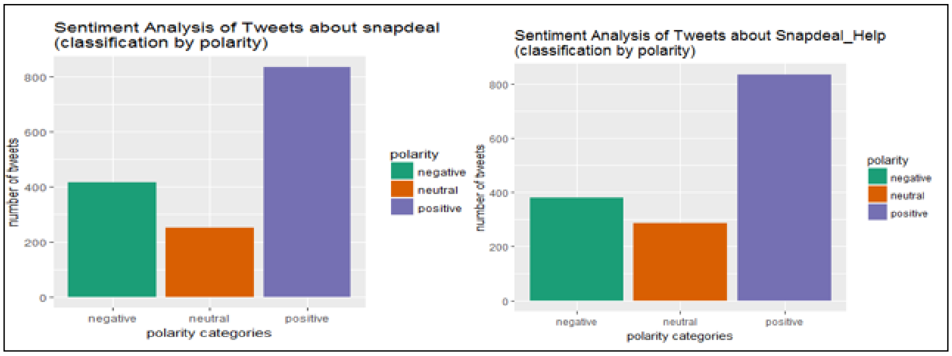

Fig. 6: Snapdeal Twitter Status

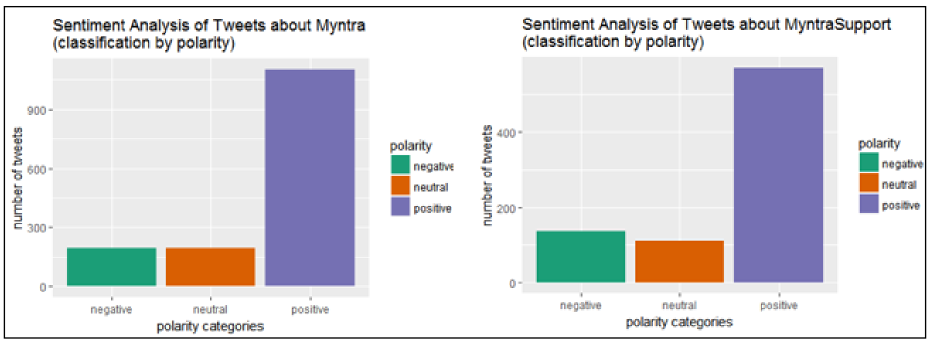

Fig. 7: Myntra Twitter Status

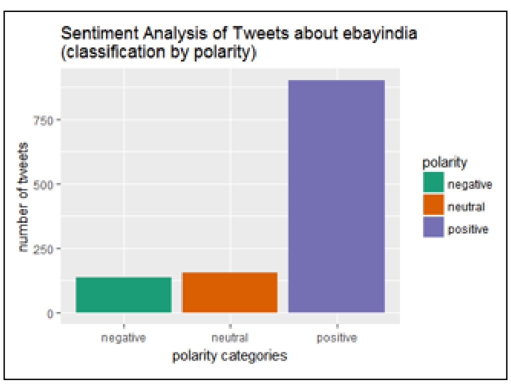

Fig. 8: eBay India

Implication of 4A Framework for the Observed Outcomes

The section highlights the implication of results in the proposed 4A framework. Fig. 9 depicts the results of the experiment undertaken.

Surprisingly, the response for tweets is just in two states– apart and nervous. Also, none of these businesses fall into an “anxious” condition, which suggests that these companies have adopted Twitter and utilise it for updates and comments relatively often. However, curiously, none of these firms have achieved an “active” condition, even after years of Twitter adoption which is astounding.

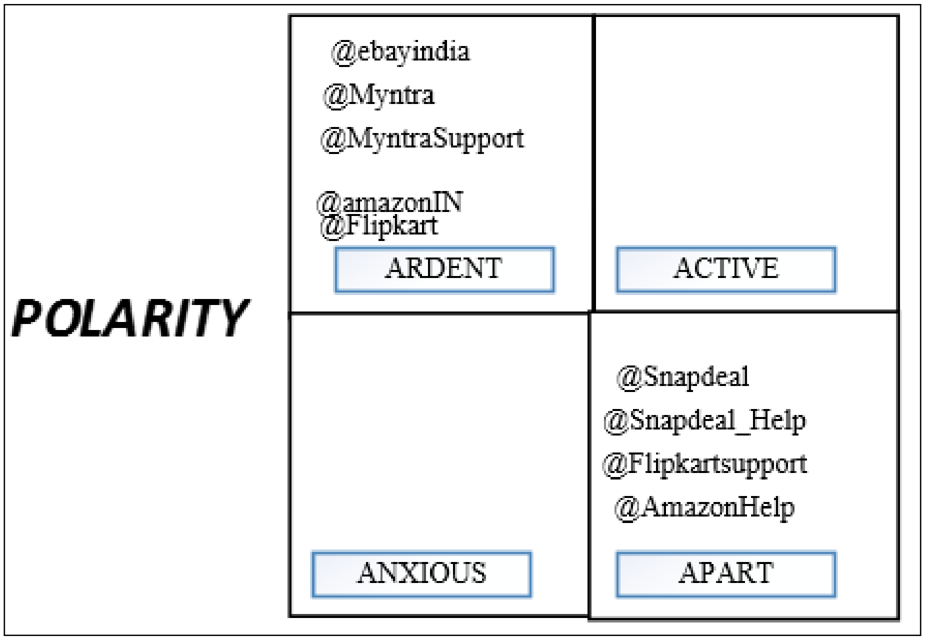

Fig. 9: Outcomes of Twitter Adoption by Indian E-Commerce Retail Sector

Also, the average response for ardent state is 72.12% and for other state is 53.17%. The research further emphasises that consumers are not content with the response they are receiving online from these businesses. Thus, the help/support component of Twitter accounts by these businesses is not benefiting consumers. A social media strategy should be in place to help these businesses to deal with consumer queries and respond appropriately.

Recommendations

There were several observations obtained throughout the research. Based on the findings, various recommendations include the following:

- Online rating and review systems allow users to make decisions on the basis of peer reviews.
- Documentation of consumer experiences on social networks. These networks foster peer-to-peer consumer engagement and let consumers communicate.
- Inclusion of social media plugins may be introduced to a website to expand the advantages beyond the social networking arena.
- Content management may be used to enhance consumer connection via social media.

Author's Contributions

Not applicable.

Financial Support

This study does not have any financial funding or sponsorship of any kind.

Acknowledgement

Not applicable.

Conflicts of Interest

This is to bring to your kind attention that there are no potential conflicts of interest with regard to this research endeavour.

References

Adak, A., Pradhan, B., & Shukla, N. (2022). Sentiment analysis of customer reviews of food delivery services using deep learning and explainable artificial intelligence: Systematic review. *Foods*, *11*(10). doi:https://doi.org/10.3390/foods11101500

Ahmed, A. A. A., Agarwal, S., Kurniawan, Im. G. A., Anantadjaya, S. P. D., & Krishnan, C. (2022). Business boosting through sentiment analysis using artificial intelligence approach. *International Journal of System Assurance Engineering and Management*, *13*(1), 699-709. Retrieved from https://ideas.repec.org/a/spr/ijsaem/v13y2022i1d10.1007_s13198-021-01594-x.html

Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. *Journal of the Academy of Marketing Science*, *48*(1), 79-95. doi:https://doi.org/10.1007/s11747-019-00695-1

Chawla, N., & Kumar, B. (2022). E-commerce and consumer protection in India: The emerging trend. *Journal of Business Ethics*, *180*(2), 581-604. doi:https://doi.org/10.1007/s10551-021-04884-3

Dixit, R. S, Choudhary, S. L, Jain, S, & Srivastava, R. (2022). Public sentiment analysis of the major competitors in the electronics sector in the Indian context. *Journal of Management Information and Decision Sciences*, *25*(3S), 1-6. Retrieved from https://www.abacademies.org/abstract/public-sentiment-analysis-of-the-major-competitors-in-the-electronics-sector-in-the-indian-context-14396.html

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., Jain, V., Karjaluoto, H., Kefi, H., Krishen, A. S., Kumar, V., Rahman, M. M., Raman, R., Rauschnabel, P. A., Rowley, J., Salo, J., Tran, G. A., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International Journal of Information Management*, *59*, 102168. doi:https://doi.org/10.1016/j.ijinfomgt.2020.102168

ElAydi, H. O. (2018). The effect of social media marketing on brand awareness through Facebook: An individual-based perspective of mobile services sector in Egypt. *Open Access Library Journal*, *5*(10), Article 10. doi:https://doi.org/10.4236/oalib.1104977

Forbes. (2022). The changing trajectory of e-commerce in India. Retrieved from https://www.forbesindia.com/article/brand-connect/the-changing-trajectory-of-ecommerce-in-india/79447/1

Gupta, A., Dengre, V., Kheruwala, H. A., & Shah, M. (2020). Comprehensive review of text-mining applications in finance. *Financial Innovation*, *6*(1), 39. doi:https://doi.org/10.1186/s40854-020-00205-1

Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 168-177. doi:https://doi.org/10.1145/1014052.1014073

Hu, N., Bose, I., Koh, N. S., & Liu, L. (2012). Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems*, *52*(3), 674-684. doi:https://doi.org/10.1016/j.dss.2011.11.002

Hu, X., Tang, L., Tang, J., & Liu, H. (2013). Exploiting social relations for sentiment analysis in microblogging. *Proceedings of the Sixth ACM International Conference on Web Search and Data Mining*, pp. 537-546. doi:https://doi.org/10.1145/2433396.2433465

Johansen, B. F., Johansen, W., & Weckesser, N. M. (2016). Emotional stakeholders as "crisis communicators" in social media: The case of the Telenor customer complaints crisis. *Corporate Communications: An International Journal*, *21*(3), 289-308. doi:https://doi.org/10.1108/CCIJ-05-2015-0026

Khajuria, M. I., & Rachna, D. (2017). Impact of social media brand communications on consumer - Based brand equity. *Indian Journal of Commerce and Management Studies*, *8*(3), Article 3. Retrieved from https://www.ijcms.in/index.php/ijcms/article/view/178

Kumar, V., & Pradhan, P. (2018). Trust management issues in social-media marketing [Chapter]. S*ocial Media Marketing: Breakthroughs in Research and Practice. IGI Global*. doi:https://doi.org/10.4018/978-1-5225-5637-4.ch036

Mamgain, N., Mehta, E., Mittal, A., & Bhatt, G. (2016). *Sentiment analysis of top colleges in India using Twitter data* (pp. 525-530). doi:https://doi.org/10.1109/ICCTICT.2016.7514636

Modi, A., Shah, K., Shah, S., Patel, S., & Shah, M. (2022). Sentiment analysis of Twitter feeds using flask environment: A superior application of data analysis. *Annals of Data Science*, 1-22. doi:https://doi.org/10.1007/s40745-022-00445-1

Nougarahiya, S., Shetty, G., & Mandloi, D. (2021). A review of e-commerce in India: The past, present, and the future (SSRN Scholarly Paper No. 3809521). Retrieved from https://papers.ssrn.com/abstract=3809521

Ogunmola, G., & Kumar, V. (2019). Social media analytics: A tool for the success of online retail industry. *International Journal of Services Operations and Informatics*, *10*, 79. doi:https://doi.org/10.1504/IJSOI.2019.100630

Outlook. (2022). *E-commerce in India: Industry overview, entrepreneurs, government action, future growth*. Retrieved from https://www.outlookindia.com/business-spotlight/e-commerce-in-india-industry-overview-entrepreneurs-government-action-future-growth-news-234435

Nitha, K. P., & Sivakumari, D. S. (2021). Sentimental analysis for Sensex stocks using Vader algorithm - An approach for investment recommendations in Indian stock market. *Turkish Online Journal of Qualitative Inquiry*, *12*(6), Article 6. Retrieved from https://www.tojqi.net/index.php/journal/article/view/1413

Rajeswari, B., Madhavan, S., Venkatesakumar, R., & Riasudeen, S. (2020). Sentiment analysis of consumer reviews - A comparison of organic and regular food products usage. *Rajagiri Management Journal*, *14*(2), 155-167. doi:https://doi.org/10.1108/RAMJ-05-2020-0022

Ranjan, S., Sood, S., & Verma, V. (2018). Twitter sentiment analysis of real-time customer experience feedback for predicting growth of Indian telecom companies. *2018 4th International Conference on Computing Sciences (ICCS)*, pp. 166-174. doi:https://doi.org/10.1109/ICCS.2018.00035

Rathod, J. (2020). Use of mobile/smart phone for e-commerce in India: An empirical investigation. *Journal of Management Information and Decision Sciences, 23*(4), 304-316.

Sundaram, A. (2020). Sentiment analysis of major mutual fund related news articles in India amid the COVID-19 outbreak, to obtain investor sentiment in mutual funds & to forecast assets under management (AUM), a mutual fund market indicator (SSRN Scholarly Paper No. 3746846). Retrieved from https://papers.ssrn.com/abstract=3746846

Susanto, H., Fang Yie, L., Mohiddin, F., Rahman Setiawan, A. A., Haghi, P. K., & Setiana, D. (2021). Revealing social media phenomenon in time of COVID-19 pandemic for boosting start-up businesses through digital ecosystem. *Applied System Innovation*, *4*(1), Article 1. doi:https://doi.org/10.3390/asi4010006

Thomas, M. R., Kavya, V., & Monica, M. (2018). Online website cues influencing the purchase intention of generation Z mediated by trust. *Indian Journal of Commerce and Management Studies*, *9*(1), Article 1. Retrieved from https://www.ijcms.in/index.php/ijcms/article/view/150

Vaidyanathan, N., & Henningsson, S. (2022). Designing augmented reality services for enhanced customer experiences in retail. *Journal of Service Management*, (ahead-of-print). doi:https://doi.org/10.1108/JOSM-01-2022-0004

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889-901. doi:https://doi.org/10.1016/j.jbusres.2019.09.022

Vidili, I. (2021). *C*ustomer experience: The new competitive advantage for companies that want their customer at the center of their business [Chapter]. *Handbook of Research on User Experience in Web 2.0 Technologies and Its Impact on Universities and Businesses. IGI Global*. doi:https://doi.org/10.4018/978-1-7998-3756-5.ch011

Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review*, *55*(7), 5731-5780. doi:https://doi.org/10.1007/s10462-022-10144-1

Wase, K., Ramteke, P., Bandewar, R., Badole, N., & Kumar, B. (2018). Sentiment analysis of product review. *International Journal of Innovations in Engineering and Science*, *3*(5), 8-13.

Yaqub, A., Thalib, H., Brahimi, T., & Sarirete, A. (2022). A bibliometric of sentiment analysis in tourism industry during COVID-19 pandemic. *Proceedings of the International Conference on Industrial Engineering and Operations Management,* Istanbul, Turkey, March 7-10.