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Social Media Platforms: Investigate Sentiment Analysis For Transforming Business Decisions In Car Segments

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Abstract. The automotive industry is one of the most significant global economic drivers. There has been a steady rise in both the expectations and the level of competition. Thus, to attain a better competitive advantage in the market, the companies carefully analyze the consumers' opinions on social media platforms to enhance business decisions. Existing studies have shown various analyses of consumer opinion towards brands or products, particularly on one social media platform. Yet, limited studies have explored sentiment analysis in social media text and reviews of preferences of car brands. This research aims to investigate the impact of social media sentiment analysis on business choices involving automotive companies. In this study, a dataset has been taken from a total of five car brand models of Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra with three social media platforms, namely Twitter, Facebook, and Instagram. Sentiment analysis has been applied to explore the user's opinions and reviews about five brand car models. By the utilization of Natural Language Processing (NLP), sentiment analysis evaluates the emotional polarity status of users. It showed that the brand Hyundai has achieved a much higher positive polarity sentiment score than the other model. Further, it showed that it achieved a strong correlation between business decisions and sentiment in the social media platform of Facebook, where all the brand models attained strong correlations.

Keywords: Sentiment Analysis; Social Media; Business Decision; Twitter; Instagram; Facebook; Automobile

1. Introduction

In the present century, the age of the internet has commutated the way people express their opinions and views. Social media platforms such as Twitter, Facebook, Instagram, YouTube, etc. have enabled millions of individuals to express themselves and share their thoughts, feelings, and opinions on their everyday life (Rasool et al., 2019). Social media provides a chance for companies by allowing them to engage with their consumers for advertising purposes (Farid et al., 2024). A great deal of emotion is therefore expressed on social media in many forms such as status updates, blog entries,

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reviews, tweets, comments, etc (A. & Sonawane, 2016). For this reason, sentiment analysis has grown in popularity as a tool for studying people's emotions (Batrinca & Treleaven, 2015). Opinion mining, often known as sentiment analysis, is a computer approach to studying how individuals feel about a certain thing (Medhat et al., 2014). Sentiment analysis can determine if someone is positive, neutral, or negative based on their attitude (Udayana et al., 2023). To analyze unstructured material and extract important ideas from it, it may be built using machine learning and Natural Language Processing (NLP). Figure 1 is an illustration of the sentiment analysis process from the perspective of making business choices.

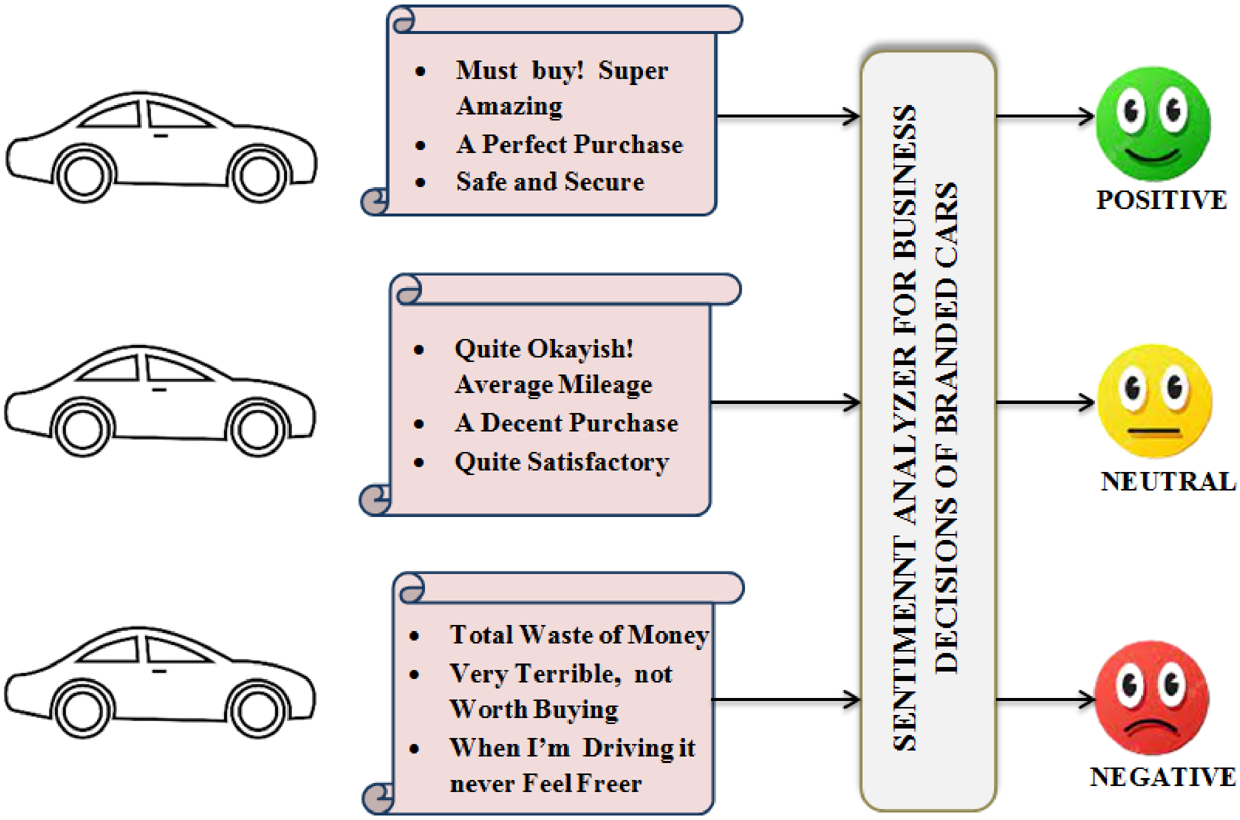

Figure 1 Sentiment analyzer for business decisions of branded cars

It can be used in various contexts of commercial and non-commercial and significant purposes for business decisions (Kauffmann et al., 2019). For transforming better business decision, people mainly depends upon user-generated content over online to a great extent (Yadav, 2023). In light of these realities, businesses are making adjustments to meet the rising need for disseminating the choices and values that drive and maintain their operations. According to research, the expansion of a brand's fan base is the best indicator of how positively people feel about that brand on digital social media platforms, where the automobile sector is highly regarded (Devi, 2015). However, it is becoming more difficult to sift through all of the data generated every day in order to reach a conclusion since the volume of data is enormous and always increasing.. There is a lack of research contributions in addressing sentiment analysis on people's feedback regarding the automobile industry, particularly in car segments. Furthermore, the gap between customers and business decisions is bridged through sentiments in a social media text, which will lead to a better understanding of customer needs and business decisions. Prior studies have paid little attention to sentiment analysis because of the intricacy of the data produced by social media sites. Hence, Twitter, Facebook, and Instagram were the three social media sites used in this research. This research aims to delve into the use of sentiment analysis on certain social media platforms to influence business choices, particularly in the automotive industry. This research used sentiment analysis to look at how people feel about several competing car manufacturers and what variables influence public opinion.

Wang designed to examine public opinion towards autonomous cars by mining social media data via sentiment analysis (Wang et al., 2022). Data pertaining to autonomous cars has been retrieved from 954,151 tweets using a web scraping approach. Then, to calculate the sentiment scores of public attitudes, sentiment analysis has been used. Further, to examine the impacting factors by the subjectivity levels of tweets and the selection of preliminary candidates of independent variables, a linear mixed model and random forests algorithm has been applied. Findings indicated that public sentiment towards autonomous cars was rather positive. Then, “blind spot,” “drunk,” and “mobility” were major variables in shaping public opinion. The other relevant components, such as locations and personal information, were not shown in this study, which just examined the 53 affecting aspects.

Yue Ding examined how autonomous vehicles are influenced by sentiments using an analysis of Twitter feeds (Ding et al., 2021). A Twitter dataset has been collected by using a tool of Apollo social sensing. Next, a thorough model of the framework was put into place to identify the key dates associated with sentiment changes, classify sentiments, and investigate sentiment fluctuations. The study concluded that the sentiment of the general was positive towards the autonomous vehicle, while the users of social media had sentiment biases towards different autonomous terms. The population at large, however, was more attuned to social events than the most engaged users. Additionally, some relevant tweets may have been missed since the data retrieval keyword was not exhaustive. Vasile-Daniel Pavaloaia researched how social customer relationship management (sCRM) technology, along with customer-centric management solutions, may help businesses grow sustainably (Pavaloaia et al., 2019). Using sentiment analysis of user preferences, two beverage firms were investigated, and the study's results were assessed. Information was culled from Pinterest, Twitter, Facebook, Google+, and YouTube. The study indicated that depending on the type of post, the users were found to tend to express their sentiments differently. Further, it demonstrated that the emotional reaction of users of social media influences customer purchasing decisions. However, this research study does not engage with an examination of the negative impact of bots and fake likes on brand social media channels.

Amit Singh investigated the performance of automobile manufacturers with online customer reviews (Singh et al., 2020). A dataset has been taken for the CarWale portal in India. An examination of the integrated house of quality (HoQ)-TOPSIS was conducted using sentiment analysis and quantifying customer opinions inherent in reviews. In addition, a Pareto chart was used to determine which manufacturers were considered as having the weakest performance by consumers. Finding the worst-performing manufacturers and their poor qualities in the mid-size automobile category was the conclusion of the result. Negative feelings were viewed as an outlier, or a flaw in the current outcome, from a customer demand perspective. Sarah E. Shukri looked at the use of Twitter sentiment analysis for the car sector. Using the Twitter API, data from three thousand tweets was retrieved. Afterwards, text mining and sentiment analysis were used to sift through Twitter's unstructured messages, identify emotional classifications, and investigate the polarity towards several vehicle classes, including Audi, Mercedes, and BMW. Finally, the study showed that the category of “Joy” has achieved better emotions for BMW than the Audi and Mercedes. Further, compared to BMW, the “Sadness” has gained higher in Mercedes and Audi. Thus, compared to 18% for Mercedes and 16% for Audi, only 8% of negative polarity has been attained in BMW. However, the study considered limited companies of car segments only with a social media platform of Twitter.

Zain Asghar intended to examine the analysis of sentiment on automobile brands like Audi, BMW, Honda, Mercedes, and Toyota (Asghar et al., 2019). A study data has been taken from Twitter data. By using sentiment analysis and text mining, the breakdown of unstructured Twitter tweets of the polarity of automobile classes has been analyzed. The result indicated that Audi (87%) has achieved the highest percentage of positive tweets than the 84% for Honda, 81% for Mercedes, 74% for BMW, and 70% for Toyota. The finding of the study was not similar to the other social media platforms. Umair Liaquat Ali analyzed the competitive mood of tweets from Samsung, Nokia, and Oppo, three Android mobile brands. Using web-crawling and API, research data was gathered on the social media site Twitter in May 2018. Data mining, text mining, and sentiment analysis were used to examine the gathered data. The study showed that compared to Samsung, Nokia was more famous on Twitter, whereas, Samsung has been connected more with the customers. However, the generalizability of the result might affect other Android brands on other platforms.

Shrawan Kumar Trivedi and Amrinder Singh examined the sentiment analysis of Twitter for applications that are based on the online meal delivery services like UberEats, Swiggy, and Zomato (Trivedi & Singh, 2021). R-studio and lexicon-based sentiment analysis were used to examine data from social media networks where customers tweeted about three different organizations. Zomato had the lowest amount of negative feelings at 12% and the highest percentage of good sentiments at 26%, outperforming Swiggy and UberEats, according to the survey. Certain limitations have occurred in this study, first, the study only considered the social media platform of Twitter, whereas other platforms like Instagram, Facebook, etc have not been considered. Second, the locations were also not considered to take care in this study. Dagmar Babcanova identified the perception and presentation of selected automotive brands (Babčanová et al., 2021). Sample of a data has been considered from the social media sites of Twitter and YouTube from the selected brands of KIA, Citroen, Toyota, Peugeot, Skoda, and VW by using sentiment analysis. Then, by applying the qualitative and quantitative analysis tools, the perception and presentation of selected automotive brands were analyzed. The result concluded that the consumer's positive opinions and attitudes have attained a positive polarity with the name of the brand. Compared to other car brands of KIA, Citroen, VW, Peugeot, and Skoda, Toyota has achieved the test position. The flaws in the VADER vocabulary, which does not take into account all the positive and negative polarity of terms in twitter messages, were a drawback of this research.

Anna Baj-Rogowska intended to analyze the sentiment analysis of Facebook posts of Uber and examined the opinions on sentiments of classification as phrases with positive, neutral, and negative emotional tones (Baj-Rogowska, 2017). Data has been considered from the relevant social media sites of Facebook posts of Uber during the period of July 2016 to July 2017. Then, to explore the importance of opinion mining, sentiment analysis has been applied for analysis. The findings indicated that the customer sentiment has been perfectly reflected by the tool of sentiment analysis and efficiently deliver an attractive and innovative offer. A limitation of this study was that the data has been obtained only from the social media posts from Facebook, whereas the other platforms, namely Instagram, Twitter, etc were not considered in this study. Fadhilah Az-Zahra investigated the connection between stock price and public mood in the car business via correlation analysis (Az-Zahra et al., 2021). The study's sample was compiled from remarks made by official accounts on Instagram and Facebook for the Volkswagen, General Motors, and Chrysler brands of cars. By using a Plantombuster, data has been collected, whereas the stock price has been collected from January to February 2020. Finally, it demonstrated that there was a strong and significant correlation between headline news with the rise and fall in stock prices and public sentiment in social media. However, this study considered limited brands of cars, and this study had limited time constraints.

2. Methods

The research study is intended to examine the sentiment analysis on social media platforms for achieving better business decisions in car segments (De Oliveira et al., 2023). Thereafter, it investigated the consumer reviews of various competitive automobile brands and explored impacting factors on public attitudes through sentiment analysis (Yadav, 2023). From the popular automobile brand pages like Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra, it was assumed that there would be a sufficient number of customer reviews generated over the years. Further, it had a sufficient number of users who have contributed a large amount of unstructured content regarding automobile brands like Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra.

2.1. Data collection

In social network sites, Twitter, Facebook, and Instagram are the most used sites by people (Samir et al., 2023). As a result, these sites have dominated the social media landscape, including daily content creation and sharing by millions of users. Utilizing data from three different social media platforms increased the validity and reliability of the results and provided the possibility of more generalizable findings in this study. The rich social media platform data collected from the automobile industries of branded car segments of Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra of official Twitter, Facebook, and Instagram accounts were central to the research design. These platforms have evolved into treasure troves of user-generated content due to the sheer number of users and the resulting engagement; sifting through this material can provide light on how the general public feels about certain topics covered by social media. Instagram and Facebook contributed 197 tweets and 798 user comments, emoticons, and other types of feedback. Facebook has a far larger user base than Instagram and Twitter combined, which makes it easier to collect a huge amount of data for corpus creation. This would lead to a more engaging and specific product or service selection. By using #hashtags and keywords, the data has been collected in English only. A collection covered a period of six months ranging from the beginning of January 2023 to the end of June 2023.

2.2. Data extraction

Through web scraping, data has been analyzed (Giannakis et al., 2022). Web data extraction and web scraping are synonyms (Smetanin & Komarov, 2022). This method may be used to store information from any website to local files on a computer. In most cases, users will not be able to download or save the material seen on websites. However, by scrapping them programmatically from the social media platform of Instagram, Twitter, and Facebook, the users can collect the data. Instagram, Facebook, and Twitter users may directly engage with other online or application blogs using the Application Programming Interface (API) service. Using a data mining method to collect customer feedback is an additional perk. Then, social media networks also allow for the analysis of user attributes.

2.3. Data Analysis and Sentiment Analysis

Using the API and a Python script, the previously mentioned goal of saving the gathered sample to an Excel file was accomplished. As an output, this script will generate several Excel files including all the retrieved posts, emojis, and comments. Additionally, it can count how many reactions each post receives from users and saves that data to an Excel spreadsheet. The data must undergo preprocessing after labeling and extraction in order to proceed to the next stage. The data retrieved from social media sites like Instagram, Facebook, and Twitter is in a very difficult-to-manage unstructured format. Short phrases, web addresses, blanks, mentions, special characters, and duplication might all be among the retrieved comments. As a result, cleaning and preparing the data is necessary before moving on with sentiment analysis. After that, the cleaned and labelled dataset underwent feature extraction prior to being fed into the classification models and the performance of the models identified. Because of the importance of precisely representing the characteristics of the items mentioned by users in sentiment analysis, feature extraction is crucial for selecting the subsets of features. A lot of people have started using sentiment analysis on user or follower-generated content like comments, reviews, and survey answers. Using natural language processing, sentiment analysis determines the user's emotional polarity. As a result, it has been put to good use in several instances when recommendations were culled from product reviews. In addition, it classifies evaluations as either favorable, neutral, or negative and assesses the level of interaction between the client and the business. By using a lexicon-based analysis, the polarity (Positive, Negative, and Neutral) of sentiment has been classified.

A diagrammatic representation of the research phases is shown in Figure 2,

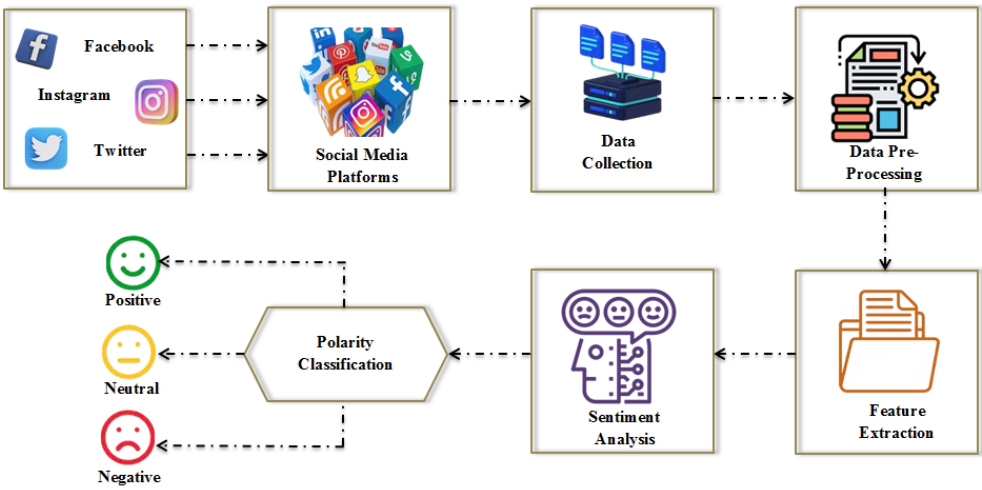

Figure 2 Flowchart of Research phases

2.4. Followers of branded cars on social media platforms

Initially, the followers of each brand of car segments of Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra on social media platforms, namely Twitter, Facebook, and Instagram were examined. This follower indicates how the engagement happens in their business decision. If somebody finds your social media page interesting and wants to stay up-to-date on promotions, news, and material, they may show their interest by like it. In Table 1 you can see how many people follow each automobile brand.

Table 1 Total followers of selected car brands on social media platforms

Branded cars	Twitter followers	Facebook followers	Instagram followers
Kia	360.8K	574K	689K
Hyundai	425.1K	12M	1M
Toyota	200K	22M	5.7M
Maruti Suzuki	153.5K	583.9K	213K
Mahindra	1.3M	926K	155K

Table 1 shows that when compared to other social media platforms, Facebook has the most users. The brand Toyota has the largest fan base on Facebook and Instagram, i.e. 22M followers on Facebook and 5.7M followers on Instagram. However, its Twitter followers are the lowest. Then, the brand Hyundai has the second largest fan base on Facebook and Instagram, which are 12M followers on Facebook and 1M followers on Instagram. Thereafter, the Facebook followers of Mahindra have achieved the third highest fan base, which is 926K, whereas, its Instagram followers are the lowest. However, its Twitter followers are higher than the other brand car segments. Next, the brand Kia has achieved the third highest fan base on Instagram, i.e. 689K, while Maruti Suzuki brand followers on Twitter attained the lowest followers fan base, which is 153.5K.

2.5. Sentiment analysis with the context of car segments for business decisions

To review the user comments, emojis, and other comments for exploring the context of car segments of business decisions, sentiment analysis has been applied. It finds out just how sentimental a view is. Each entity in the document or phrase can have its sentiment analysis result computed in textual data. It is possible to classify the sentiment as neutral, negative, or positive.

Table 3 Positive polarity sentiment analysis in car segments

Word Kia comment	Word Hyundai comment	Word Toyota comment	Word Marutisuzuki comment	Word Mahindra comment
*:	*:	*:	*:	*:
Great	Congratulations	Love	Like	Prize
save	Great	(*	Welcome	Like
Amazing	Champion	:*	Great	Best
(*	Proud	Free	Good	Great

Congratulations	Superb	Best	Congratulations	Win
gt	Best	Happy	Love	Good
Best	Hope	*)	(*	Love
*)	Good	congratulations	Best	Superb
Free	(*	Save	Happy	:*

The word comment that received the greatest favorable score for certain automobile manufacturers is summarized in Table 3. In this context, it is common to employ certain emotions to convey feelings. As a result, the positively charged word "Best" is connected with the chosen brand of automobiles within the framework of the name. Additionally, the terms "Great" are linked to the Kia, Hyundai, Maruti Suzuki, and Mahindra automobile brands. The terms "ground tour" (gt) and "superb" (Mahindra) are used interchangeably while discussing this topic.

Table 4 Negative polarity sentiment analysis in car segments

Word Kia comment	**Word Hyundai comment**	**Word Toyota comment**	**Word Marutisuzuki comment**	**Word Mahindra comment**
Accidents	Low life	Bad	Disappointing	Emergency
Missing	Lowered	Limited	Negative	Trouble
Killed	Damages	No	Nasty	Fight
Severely	Miss	Killer	Dead	Faults
Limited	Stop	Shocks	Faulty	Gravel
No	Low	Accidents	Avoid	Death
Prisoners	Missed	Dirty	Sick	Battle
War	Scandal	Stop	No	Bloody
Faults	No	Scary	Bad	Broken
Died	Beaten	Low	Kill	No

Table 4 summarizes ten words with the highest negative score for each car brand. The highest score for any of the brands was "No" in this case. Then, "Low" became synonymous with the Hyundai and Toyota brands, while "Bad" became synonymous with the Maruti Suzuki and Toyota brands. With that in mind, the term "dead" was associated with the Kia brand, "stop" with Toyota, and "faults" with Mahindra. On the other hand, Kia achieved the greatest negative polarity score with the chosen terms.

Table 5 Neutral polarity sentiment analysis in car segments

Word Kia comment	**Word Hyundai comment**	**Word Toyota comment**	**Word Marutisuzuki comment**	**Word Mahindra comment**

Okay	Acceptable	Better	Alright	Decent
Alright	Decent	Vice	Filled	Okay
Serious	Okay	Weak	Acceptable	Use
Detached	Limit	Crime	Flaw	Different
Skeptical	Invent	Alright	Liable	Acceptable
Decent	Expensive	Lessen	Better	Flaw
Acceptable	Better	Okay	Tenacious	Weak
Coarse	Alright	Acceptable	Decent	Listless
Solemn	Imperfect	Flaw	Selective	Better
Listless	Fail	Decent	Okay	Alright

Table 5 summarizes ten words with the highest neutral score for each car brand of Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra. In this context, the word "okay", "alright", "decent", and "acceptable" were commonly associated will all the car brands. Further, the word "expensive" was associated with the brand Hyundai, "lessen" was associated with the brand Toyota, the word "filled" with Maruti Suzuki, and "use' was the next neutral word of the brand Mahindra.

2.6. Emotions classification of car segments

On brand pages of social media platforms, the users express their opinions or emotions through emojis like positive, negative, surprise, anger, unknown expression, fear, joy, trust, disgust, and anticipation. From the five different brands, various emotions are classified, which are mentioned in Table 3.

Table 6 Classification of emotions using sentiment analysis

Emotions	Kia (%)	Hyundai (%)	Toyota (%)	Marutisuzuki (%)	Mahindra (%)
Surprise	7	8	10	9	10
Positive	21	24	26	18	20
Anger	13	14	9	10	7
Negative	10	16	14	15	13
Unknown	11	10	11	12	9
Fear	9	10	7	7	11
Joy	12	6	9	11	15
Trust	7	5	7	8	4
Disgust	5	3	4	6	5

Anticipation	5	4	3	4	6

Compared the five vehicle brands and computed percentages of emotions using all the data that the businesses provided. The distributions of good and negative emotions were taken into account to a greater or lesser extent. The brand Toyota, Hyundai, and Kia has gained the highest positive emotion of 26%, 24%, and 21%, respectively. Further, the negative emotions were highly achieved in the brand of Hyundai, Maruti Suzuki, and Toyota with an obtained value of 16%, 15%, and 14%, respectively. Thereafter, the unknown emotions attained the highest percentage in the brand of Maruti Suzuki, i.e. 12%. Finally, it showed that the brand Toyota performed better than the other selected car brands in terms of perceptions of users. A graphical representation of sentiment analysis of emotions classifications is shown in Figure 3,

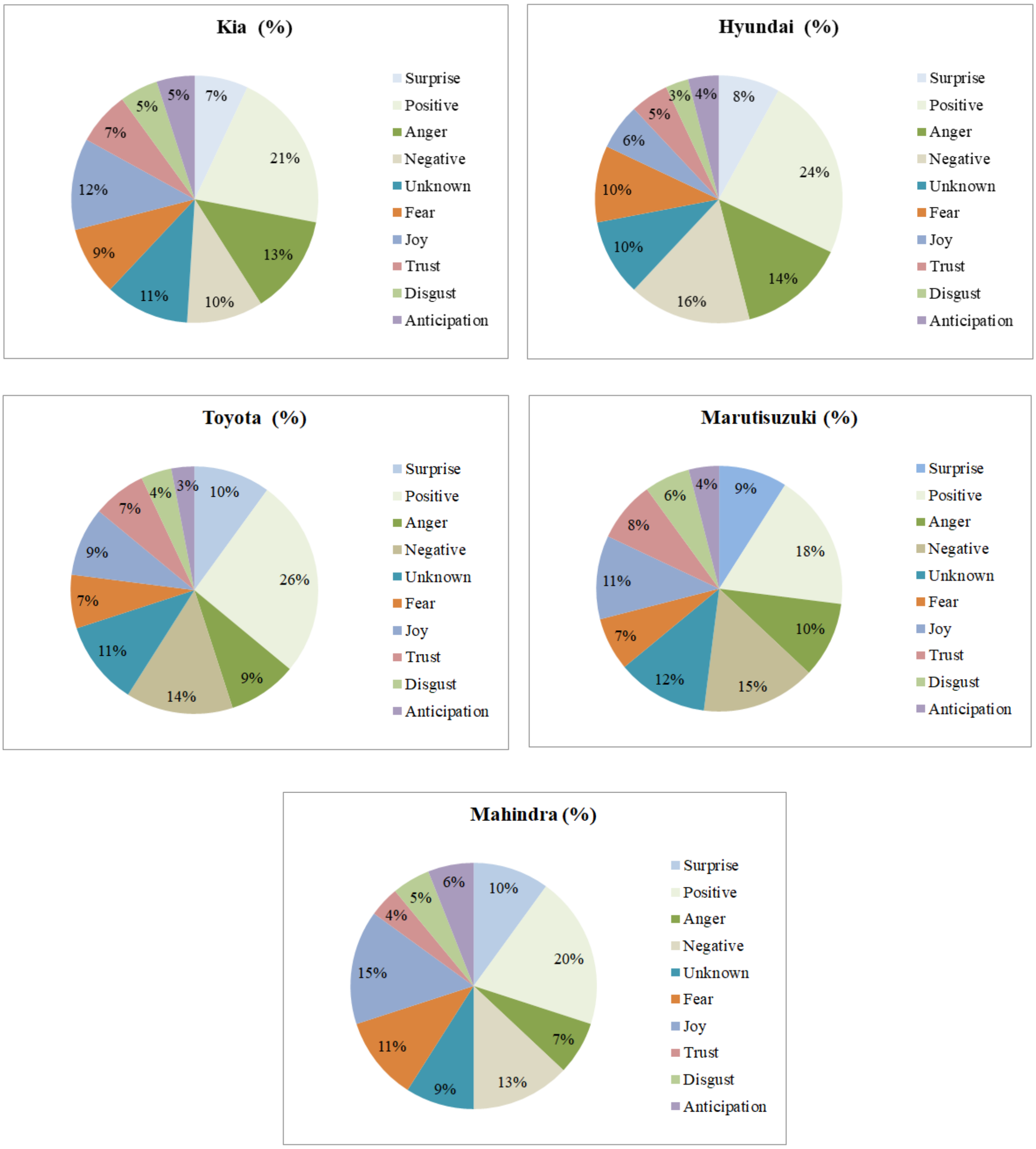

Figure 3 Sentiment analysis of the classification of emotions

2.7. Impacting factors of public attitudes towards car segments through sentiment analysis

For further analysis of sentiment scores of data related to automobile brand pages of the car segment, the most significant factors has been selected. Thus, the importance of impacting factors of public attitude towards automobile car brands was calculated, which was shown below in Table 4.

Table 7 Factors impacting public attitudes towards car brand

Impacting factors	Importance
Blind spot	0.113
Mobility	0.217
Testing	0.036
Sleepy	0.048
Safety	0.044
Design	0.135
Spaciousness	0.056
Brake	0.034
Speed	0.042
Income	0.061

The impacting factors of blind spot, mobility, testing, sleep, safety, design, spaciousness, brake, speed, and income were considered in this study. The importance of all these factors might affect the attitudes of the public toward the automobile brand of car. The selected factors have been analyzed through sentiment scores of comments and reviews. Here, the impacting factors of mobility have gained the highest score of importance i.e. 0.217. Thereafter, the design gained the second highest sentiment score, which is 0.135. However, the factor brake has obtained the lowest sentiment score, i.e. 0.034. A graphical representation of impacting factors and their sentiment score is shown in Figure 4,

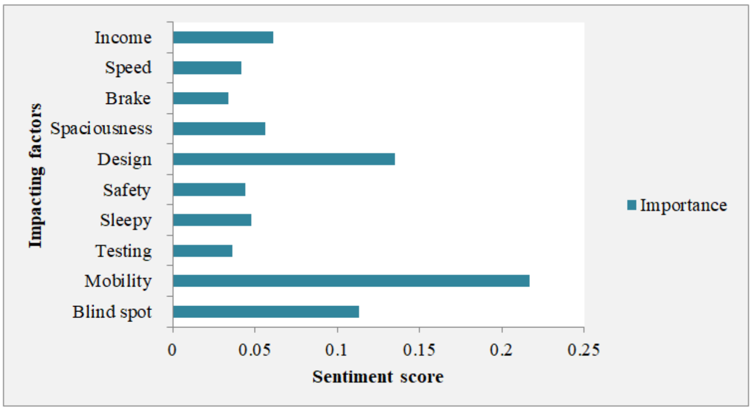

Figure 4 Impacting factors and their significance score

3. Results and Discussion

In this section, the collected data from three social media platforms of related brands of car segments were analyzed and discussed. The sentiment distributions of the car model by user ratings were analyzed through sentiment analysis. Moreover, the Pearson correlation has been applied to analyze the business decision and sentiment, and the overall sentiment analysis of the polarity of car brands with respective social media platforms has been analyzed and discussed.

3.1. Sentiment classes and rating of users in car models

The sentiment distribution values of all the selected automakers are examined using sentiment categorization. An analysis was conducted on the total and mean of user ratings and sentiment based on sentiment classes. Thus, the analysis of sentiment distribution of brands of cars is shown in Table 5.

Table 8 Analysis of sentiment distribution of selected brands

Brand	Sum rating	Mean rating	Sentiment_by_rating
Kia	1023.5	3.967	1.775
Hyundai	1178.5	4.486	1.987
Toyota	2481.0	4.313	1.804
Maruti Suzuki	1716.0	3.950	1.752
Mahindra	916.5	3.908	1.671

The selected brands of Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra have been considered to analyze the sentiment distribution of brands. Compared to all other brands, the brand Hyundai has gained the highest sentiment distribution on mean rating and sentiment by rating, which is 4.486 and 1.987, respectively. Then, the brand Toyota secured the second highest position, the obtained value of Mean and sentiment by ratings are 4.313 and 1.804. In mean rating and sentiment by rating, the brand Mahindra has attained the lowest rating value, which is 3.908 and 1.671, respectively. In sum rating, Toyota has achieved the highest rating (2481.0), whereas, Mahindra has obtained the lowest rating value (916.5).

3.2. Correlation analysis of business decision and sentiment

To investigate the relationship between sentiment analysis and business, a Pearson correlation was used to examine how several automakers fared on Instagram, Facebook, and Twitter.

Table 9 Analysis of Pearson correlation

Social media platform	Branded cars	Correlation coefficient	p-value
Twitter	Kia	0.416	0.117

	Hyundai	0.433	0.009
	Toyota	0.482	0.203
	Maruti Suzuki	0.397	0.041
	Mahindra	0.409	0.023
Facebook	Kia	0.523	0.009
	Hyundai	0.517	0.005
	Toyota	0.613	0.037
	Maruti Suzuki	0.505	0.020
	Mahindra	0.499	0.048
Instagram	Kia	0.698	0.005
	Hyundai	0.714	0.141
	Toyota	0.797	0.001
	Maruti Suzuki	0.812	0.038
	Mahindra	0.783	0.125

Table 9 shows the relationship between public opinion and corporate choices regarding five different automakers. There is a strong association if the p-value is less than 0.05; no correlation if the p-value is more than 0.05. Here, Toyota was statistically significant and it has a correlation between business decisions and sentiment analysis. On Twitter, the brand Kia and Toyota does not obtain a strong correlation, whereas, on Instagram, the brand Hyundai and Mahindra does not obtain a strong correlation. The above table concludes that all five brands had strong correlation findings, indicating a connection between business actions and Facebook sentiment research.

3.3. Overall sentiment analysis

The polarity of sentiment scores of positive, negative, and neutral has been calculated for given brands of Kia, Hyundai, Toyota, Maruti Suzuki, and Mahindra with selected social media platforms. Here, Hyundai has achieved the highest positive polarity of the other brands, where it obtained 87% of positive polarity, and a minimum percentage in negative and neutral polarity, which are 8% and 5%, respectively. Then, the second highest positive polarity sentiment score was achieved in the brand Toyota, i.e. 71%, and its negative and neutral sentiment score is 20% and 9%, respectively. However, the brand Kia has attained the lowest positive polarity sentiment score, which is 54%, whereas, it gained the highest sentiment score in negative and neutral polarity i.e. 26% and 20%, respectively. Thus, the graphical representation of the sentiment score of given brands is shown in below Figure 5,

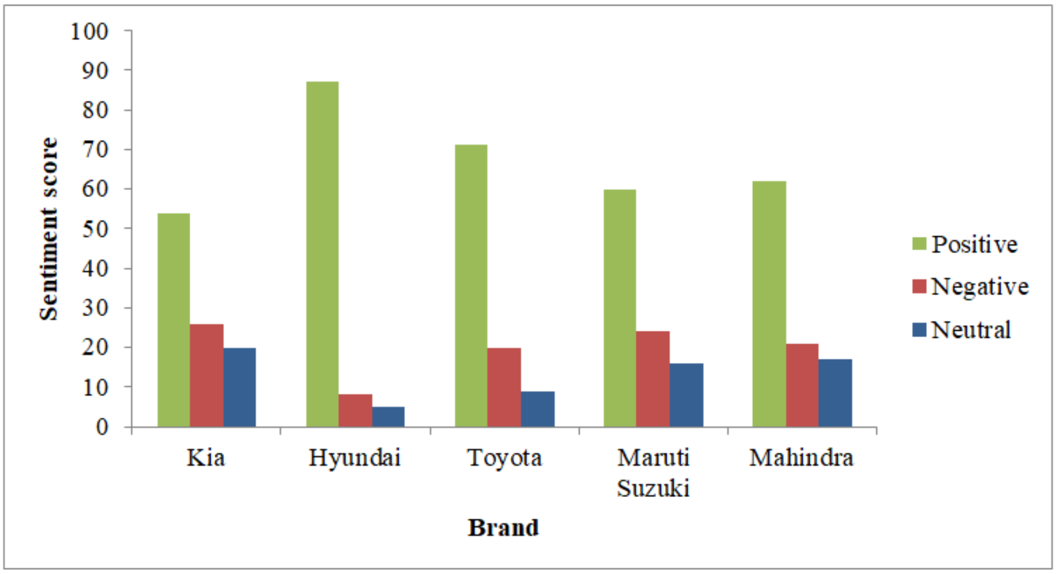

Figure 5 Sentiment score distribution of all selected brands

4. Conclusion

This research study is intended to identify the sentiment analysis on selected social media platforms for enhancing business decisions with special reference to car segments. Further, it examines the emotion of users and impacting factors on public attitudes through sentiment analysis. Data from five different automakers across three social media sites—Instagram, Facebook, and Twitter—was examined. Data has been extracted and analyzed through the NLP method, whereas sentiment analysis is employed to extract unstructured data and emotion classification in social media sites. It concluded that the emotions of the “positive” and “joy” categories were better in Toyota, Hyundai, and Mahindra. The polarity of sentiment score is highly achieved in the brand Hyundai, which is 87%, and its negative and neutral score is 8% and 5%. Then, the Pearson correlation revealed that all selected brands were strongly correlated with the business decision and sentiment in the platform of Facebook; thus, the p-values are 0.009 (Kia), 0.005 (Hyundai), 0.037 (Toyota), 0.020 (Maruti Suzuki), and 0.048 (Mahindra). Thus, this will help the users to compare buying a car with five brand models based on users’ opinions and enhance the business decision of companies with an examination of users’ opinions. This study collected data from only three social media platforms with limited car brands. In the future, it will be extended by considering other social media platforms like YouTube, google trends, etc. by analyzing other branded cars or other automobile vehicles.

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