A Text Analytics Framework for Performance Assessment and Weakness Detection from Online Reviews

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Abstract

Customer reviews pertaining to the automobile industry are rich in qualitative information. We propose a framework that integrates aspect-level sentiment analysis with multi-criteria decision making (TOPSIS) and control charts to uncover hidden quality patterns. While sentiment analysis quantifies consumer opinions corresponding to various product features, TOPSIS uses the sentiment scores to rank manufacturers based on their relative performance. Finally, U and P control charts assist in discovering the weak aspects and corresponding attributes. To extract aspect-level sentiments from reviews, we developed the ontology of passenger cars and designed a heuristic that connects the opinionbearing texts to the exact automobile attribute. The proposed framework was applied to a review dataset collected from a well-known car portal in India. Considering five manufacturers from the mid-size car segment, we identified the weakest and discovered the aspects and attributes responsible for its perceived weakness.

Keywords: Weakness detection, user generated content, online reviews, ranking, defect discovery, sentiment analysis, TOPSIS, control charts, consumer review, automobile industry, text mining, artificial intelligence

Conflict of interest:

The authors declare that there is no conflict of interest.

1. Introduction

Products such as automobiles may have both safety and performance defects. Government regulations and exposure to severe brand-value and financial losses compel manufacturers to be proactive in detecting and eradicating safety defects. Traditionally, safety defects are identified through process improvement tools and service center feedbacks. Such approaches not only suffer from high cost, and incomprehensiveness; their applicability is limited in the case of performance defects (Law et al., 2017; Y. Liu et al., 2018). In this regard, massive product review data generated from the web has turned out to be an important source to comprehend user experiences, reactions, and perceptions. While prospective consumers use them to analyse the peers' experience with the product, the organizations mine it to identify user requirements and expectations (Singh, Jenamani, & Thakkar, 2020). However, it is beyond human cognition to scan the available reviews manually, summarize them, and use them for sensible decision making.

In this regard, artificial intelligence in general (Dwivedi, et al., 2019; Grover, et al., 2019; Dwivedi et al., 2020 Stieglitz, et al., 2020) and sentiment analysis (SA) in particular has emerged as a tool to mine information from text. Its usefulness is well tested and validated in domains such as product promotions and marketing (Ting et al., 2014), demand and sales forecasting (Archak et al., 2011; Chong et al., 2017; Geva et al., 2013; Hou et al., 2017; Zhang, et al., 2020), supply-chain performance evaluation (Swain & Cao, 2019), and product quality assessment (Abrahams et al., 2015; Law et al., 2017). Specifically, it assists the businesses in decision making in automotive industry (Abrahams et al., 2012, 2013, 2015; Gruss et al., 2018) electronic products (Abrahams et al., 2015), dishwasher appliances (Law et al., 2017), body wash products (W. Zhang et al., 2012), entertainment industry (Chintagunta et al., 2010; Yang & Chao, 2015) travel industry (Chang & Chen, 2019; Choi & Lee, 2017; Sann, & Lai, 2020), books (Singh, et al., 2017), and the toy industry (Winkler et al., 2016; Saumya, Singh, & Dwivedi, 2019). However, there has been almost no effort to connect these results with traditional quality-control tools with which the manufacturing community is acquainted. Moreover, most of such studies focus on document or sentence level. More recently, aspect-level sentiment analysis (ASLSA) has emerged as a tool to identify product defects, more precisely targeting specific attributes and context (Schouten & Frasincar, 2016). In this research, we have contributed to

this growing field by proposing an integrated automobile-defect detection framework that connects ASLSA with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and traditional quality-control tools. The framework answers following research questions:

- RQ1: What are the important product features, which customers frequently discuss in online reviews?
- RQ2: How feature level consumer sentiments be used to quantify manufacturers' perceived performance rating?
- RQ2: Are review embedded consumer sentiments useful in discovering products' perceived weakness?

The proposed framework consists of three phases. In *Phase-I*, we extract attribute-level consumer sentiments indices for specific car aspects. We define aspects with various systems and subsystems of a car, and attributes to the more specific parts, features, or service of the system under consideration. For example, regarding *EXTERIOR* as an aspect, we can consider *bumper* as an underlying attribute. In *Phase-II*, the TOPSIS, a multi-criteria decision-making tool, compare extracted sentiments to compute manufacturers' relative performance index. Traditionally, TOPSIS requires inputs from experts. In this research, expert inputs are replaced by the sentiments scores mined from reviews. In this phase, we compute a performance score for each manufacturer based on overall consumer perception, from which a manufacturer could find its perceived performance in the market. In *Phase-III*, we use control charts, the *U*-chart at the aspect level, and the *P*-chart at the attribute level, to discover the reasons for performance degradation. This discovery gives the manufacturer an opportunity to identify the reasons for consumer dissatisfaction and take action accordingly. We apply the framework to a review dataset from a car portal in India, compare the manufacturers within a car segment, and identify the worst-performing manufacturer. In addition, we delve into the data to find the reasons for performance degradation.

The contributions of this research are as follows. *First*, we have proposed a passenger car aspect ontology consisting of 16 aspects at the system level and 15 at the subsystem level. *Second*, a heuristic for attribute-level sentiment index generation has been proposed, which differs from contemporary approaches such as (Hu & Liu, 2004; Moghaddam & M Ester, 2010), in the way opinion-bearing words are connected to the exact target attribute. Specifically, the proposed heuristic splits the sentences with

more than one attribute into a number of sub-sentences, each containing one attribute and corresponding sentiment phrases. The proposed heuristic has also been vetted using human annotators. *Third*, to our best knowledge, we are the first to integrate text analytics with the traditional tools of quality control, providing a new avenue for a company to visualize consumer perception of its product. *Fourth*, we extend TOPSIS, a well-accepted method for prioritizing alternatives based on expert views, to apply to consumer views for ranking automobile manufacturers. While the traditional approach can synthesize the opinions from a handful of expert comments, which may include their biases, the views synthesized from a large number of online reviews in our novel approach are likely to be more precise, following the law of large numbers. *Sixth*, we collect the data from CarWale¹ and processed it for automobile attribute extraction and attribute-level sentiment index generation. We have also tested the proposed framework using this data.

The rest of the paper is organized as follows. Section 2 reports the related research works on SA and its applications, especially on product defect identification. We report the proposed framework in Section 3, followed by its application in Section 4. Section 5 reports the evaluation measures of the algorithm/heuristic used. We discuss the results and the implications of the present research in Section 6. Section 7 concludes the research followed by the limitations and the potential future research directions in Section 8.

2. Background

Sentiment analysis (SA) captures peoples' opinions, sentiments, evaluations, appraisals, attitudes, and emotions regarding products and their attributes (Lin et al., 2016). It can be performed at a) document level, b) sentence level, and c) attribute level. In the first case, the complete document is classified, whereas in the second case, individual sentences are analysed (Lyu, Foster, & Graham, 2020; Araújo, Pereira, & Benevenuto, 2020; Singh, Jenamani & Thakkar 2020). In the third case, the specific attribute is targeted and the corresponding context is analysed to capture consumer sentiments. Technique wise SA can be broadly categorised into two categories, dictionary-based and machine learning-based approach. In the dictionary-based approach, sentiment dictionaries such as SentiWordNet (Baccianella,

¹ https://www.carwale.com/

Esuli, & Sebastiani, 2010), SentiStrength (Thelwall, M., Buckley, K., Paltoglou, 2012), SenticNet-3 (Cambria, Olsher, & Rajagopal,2014), etc., are used to quantify the text. Unlike the dictionary-based approach, the machine learning-based method is data-dependent. This approach learns many of the parameters from the available text only. It is categorised into two categories, supervised and unsupervised approaches. In the first approach, the classifier is trained through the annotated data, based on which it predicts the polarity of the new text. The second approach is frequently used, as it does not require manual annotation. Researchers use dependency parsing (Fernández-Gavilanes et al., 2016), semantic orientation of the phrases (Turney, 2002), and probabilistic modelling (Rustamov, Mustafayev, & Clements, 2013), to name a few as the unsupervised-learning approach for text classification.

In some cases supervised learning approaches are preferred over dictionary-based ones to extract user sentiments, the latter are more appropriate in the new area (Bhatia et al., 2015). Machine learning approaches require data labeling and training and testing data from the same domain, which is expensive and time-consuming (Gamon et al., 2005). As an alternative, lexicon-based approaches have been found effective in cross-domain applications (Kouloumpis et al., 2011; Mudinas et al., 2012a, 2012b). Moreover, such approaches are useful for aspect-level analysis because they provide more structured, readable results with aspect-oriented explanation and justification (Mudinas et al., 2012a). These approaches also use rules for *sentiment shifters* and *and/but clauses* (Lin et al., 2016).

As per Mankad et al., (2016), contributions to the literature in SA lie in two categories, a) *methodological literature* and b) *managerial literature*, which we connected. The first category focuses on either evolving new algorithms or amending the existing ones. It fundamentally add value to the way sentiments are extracted by extending the numbers of features, enhancing the computational efficiency, and improving accuracy (Baccianella et al., 2009; Ray, & Chakrabarti, 2020). The key contributions to this category in the automobile domain have focused on designing algorithms to extract product attributes(Schouten & Frasincar, 2016). The second category, managerial literature, focuses on applications. In managerial literature well-established methods have been applied in different domains to draw specific insights such as weakness identification (Law et al., 2017; Y. Liu et al., 2018; Wang & Wang, 2014), predicting recalls (X. Zhang et al., 2015), predicting sales (Chong et al., 2017; Hou et

al., 2017), assisting the businesses in mining consumer requirements (Qi et al., 2016), analysing social media influence (Chang, 2019). As research in the *methodological literature* has progressed, more applications have evolved.

Text analytics-based product ranking, automatic product-weakness detection and product-recall prediction have attracted numerous researchers in recent years. A few classic examples include product and service evaluation (Guo et al., 2018; Peng et al., 2014) product weakness finder (Wang & Wang, 2014; W. Zhang et al., 2012; Singh, Jenamani, Thakkar, 2020), automated product-defect discovery (Abrahams et al., 2012, 2015; Law et al., 2017; Y. Liu et al., 2018), product recall prediction (Bhat & Culotta, 2017; X. Zhang et al., 2015) and product-improvement strategy development (Qi et al., 2016). Wang & Wang (2014) have proposed a text analytics-based method for weakness detection in digital camera domain. They found their method to be outperforming over baseline methods. Abrahams et al. (2015) have proposed a method that uses the smoke words to detect the defects of automobile and consumer electronics products. Law et al. (2017) have introduced unigram, bigram, and trigram smoke words and walidated their applicability in detecting the defects in home appliance products. A few attempts at product defect discovery in the automobile industry were made (Abrahams et al., 2012, 2015; Singh et al., 2020). For example, Abrahams et al. (2012) proposed a learning-based text-mining method that analyzes consumer sentiments inherent in social media to detect vehicle defects automatically. They have identified that negative sentiments are not correlated with the defects. Abrahams et al. (2015) proposed an integrated text-analytics method to automatically discover product defects using textual information. To detect product defects, they used the frequent keywords mined from vehicle complaints. Singh et al. (2020), used pareto analysis and analysed the consumer sentiments to discover product weakness from the reviews.

Table 1 critically summarizes a few key studies that served as the basis of our research; we position our work in their context. The tables provide the Text analytics applications on product-defect discovery and recall prediction. As evident from the table, we position our research in a domain that combines algorithmic research and its application. Most of these attempts were at the product level and have not tried to integrate the traditional tools of quality control. By contrast, our work focused on the manufacturer level and integrated tools of statistical quality control with ASLSA.

Table 1:	Literature on	defect/weakne	ss detection			
Author	Contril	bution Type	Appr	oach	Remarks	Tools Used
	Decision Making	Algorithmic	Learning- Based	Lexicon Based	Data Sources, Area, and Findings	
(Abraha ms et al., 2012)	~	x	✓	~	 Area: Automobile industry Data source: Complaint documents, Online discussion threads Contributions: They tested the usefulness of auto enthusiast discussion forums in discovering defects. Prepared a list of automotive smoke words for defect discovery. They found that negative sentiment is not positively correlated with defects. 	OpinionFinder, Harvard General Inquirer, Automotive smoke words, Text Analytics, Logistic regression
(Wang & Wang, 2014)	\checkmark	x	\checkmark	\checkmark	 Area: Digital Camera Data source: Online reviews Contributions: They proposed a sentiment mining supported weakness finder, which was found outperforming over other methods. 	Authority score, and Sentiment analysis
(Abraha ms et al., 2015)	~	x	~	\checkmark	 Area: Automobile industry and consumer electronics Data source: NHTSA complaint documents, automotive and consumer electronics discussion forums Contributions: They identified that selection of distinctive terms, product features, and semantic factors were found to be the predictors of the defect. Smoke words were found very useful in defect detection. 	Sentiment analysis, Harvard General Inquirer H4, Laswell LVD lexicon, PCA, Multivariate logistic regression, Learning based classifiers
(Zhang et al., 2015)	\checkmark	×	\checkmark	\checkmark	 Area: Automobile industry Data source: Online vehicle discussion threads, NHTSA complaint documents Contributions: They developed a vehicle recall prediction model. They also claimed that K-Nearest Neighbour (KNN) classifier performs better as compared to Naïve-Bayes and decision tree in predicting vehicle recalls. 	Content analysis, KNN, Naive-Bayes and Decision tree, Smoke words, Chi- squared feature selection
(Singh et al., 2020)	✓ 	x	✓ 	✓	 Area: Automobile industry Data source: CarWale, SIAM Contributions: An integrated framework that integrates sentiment analysis with quality function deployment (QFD) to evaluate the manufacturers and pareto analysis to discover the weakness. 	Sentiment analysis QFD, TOPSIS, Pareto- chart, Fishbone diagram dictionaries. Harvard general inquirer dictionary
Present research	✓	✓	x	✓	 Area: Automobile industry Data source: Consumer reviews from CarWale.com and brochure of the Volkswagen Ameo Maruti Suzuki Alto and Mahindra Bolero Contributions: We proposed a quality analytics framework that integrates multi-criteria decision making and tools of quality control with aspect level sentiment analysis to evaluate the manufacturers' and discover perceived weaknesses. 	TOPSIS, U-chart, P-chart, Text analytics, ATLSA, SentiWordNet dictionary, RAKE

3. Proposed research framework and methodologies

The proposed framework integrates sentiment analysis (SA) with a multi-criteria decision-making technique (TOPSIS) and two kinds of control charts (*U*-chart and *P*-chart) that aims discover their weaknesses. In particular, the framework a) compares the automobile manufacturers operating in a segment and computes their perceived ranks, b) discovers the perceived weak aspects responsible for performance degradation, and c) identifies the attributes responsible for the perceived weakness. As presented in Figure 1, the framework comprised three phases. In *Phase I*, automobile reviews are processed to extract aspect level sentiment indices (ASLSIs). In Phase **II**, extracted indices are analyzed to carry out intra-segment comparison of manufacturers. The methodology employed here is TOPSIS, with modification to incorporate sentiment indices (SIs) instead of expert inputs as the decision matrix. In Phase **III**, control charts are developed to discover aspects and corresponding attributes responsible for consumer-perceived product weaknesses. The proposed method is detailed below:



Figure 1: Proposed research proposal flow chart for performance assessment and weakness detection

3.1 Phase I: Sentiment index generation

3.1.1 Car aspects ontology preparation

To develop a passenger car aspect ontology, we refer to brochures for the Volkswagen Ameo, the Maruti Suzuki Alto, and the Mahindra Bolero and prepare a list of car systems and subsystems, defined as *"aspects"* in the present research. The three brochures coming from different segments are used to generalize the ontology. The list is further refined and validated in consultation with the *deputy general manager of production* of a car manufacturing company situated in eastern India. The final list consists of 16 aspects at the system level and 15 at the subsystem level. To highlight which aspect is selected from which brochure, we have tabulated the aspects with a tick mark if they are present in the particular car brochure (Table A1 in appendix). From the table, one may note that 16 out of 26 aspects (61.5%) are common in all three models. Based on the list, we prepare the passenger car aspect ontology as shown in Figure 2.



Figure 2: Passenger car aspect ontology

3.1.2 Data pre-processing

3.1.3 Attribute identification and aspect tagging

We define an attribute as a word or a phrase representing an automobile component, feature, or service it provides. Identifying the target attributes is one of the core tasks in ASLSA. Among the various existing approaches, such as supervised and unsupervised machine learning, syntax-based, and frequency-based the latter option has been accepted as a straightforward and powerful tool for this task (Schouten & Frasincar, 2016). Despite their proven usefulness, however, frequency-based approaches possess certain shortcomings. First, they ignore less-frequent attribute phrases; second, they extract many phrases which do not represent actual product attributes (Hu & Liu, 2004; Schouten & Frasincar, 2016). To partially overcome these drawbacks, we use a frequency-based semi-automatic approach used in Singh et al. (2020). It is a three-step, semiautomatic approach comprising a) extraction of frequently used nouns and noun phrases, b) manual scanning of extracted attribute phrases, and c) tagging with appropriate car aspects. *Aspect* here has been defined as a group of similar automobile attributes two are manual. Manual intervention is essential to select the right noun phrases to represent given attributes and connect them to the passenger car ontology presented in Figure 2.

3.1.4 Attribute-level sentiment extraction

Here, we have extracted consumer sentiments from the reviews and mapped them with the appropriate automobile attributes. We have proposed a rule-based heuristic for pairing sentiment phrases with their target attributes that breaks the sentence into sub-sentences in such a way that each sub-sentence comprises only one *AttributePhrase* and the corresponding *SentimentPhrase(s)*. We have defined an *AttributePhrase* as a (set of) word(s) representing an automobile attribute identified by the procedure mentioned in the last section. Similarly, a *SentimentPhrase* is defined as a set of consecutive words available in the sentiment dictionary or in the list of sentiment shifters reported by Yu et al., (2016). The heuristic shown in Figure 3 requires four inputs: *Pre-processed review data set* (D), *List of target automobile attribute phrases* (A), *Sentiment dictionary* (S), and *List of sentiment shifters* (F). The heuristic has five steps as detailed below. We have used two reviews as running examples to demonstrate the proposed heuristic.

Review 1: The car has good mileage but bad comfort, style and driving control. It has very good pickup

and best class suspension.

Review 2: The look and interiors of the car are excellent whereas the boot space and air conditioning are troubling. Its driving is not so smooth.

Step 1. Tokenizing reviews to sentences

A review typically comprises multiple sentences. Lines 5–7 in the heuristic (Figure 3) split the reviews into sentences and stored in *SentenceList*. The result of this step appear in Figure 4 (step 1).

1 SubSentenceGeneration:
2 Input: Pre-processed review data set: D, list of target automobile attribute phrases: A, Opinionated Words (Sentiment
Dictionary): S, List of Sentiment Shifter:F
3 Output: Sub sentences with only one attribute and corresponding Opinionated Words and Sentiment Shifters
4 begin
// Tokenising reviews to sentences
5 for each review in D:
6 tokenize the reviews into sentences
7 store the sentences in <i>SentenceList</i>
// Creating pseudowords for attribute phrases and sentiment shifters
8 MakeWord (A,F) //Search for the phrases in A and F and treat as words
// Conjunction partitioning at "but" and "however"
9 for each sentence in SentenceList
10 if but word is in the sentence,
11 break the sentence at but
12 create two sentences and put back in SentenceList
// Word tagging and SentimentPhrase creation
13 for each sentence in SentenceList:
14 tokenise sentence into words
15 for each word in the sentence:
16 If word in A
17 Tag word as AttributePhrase and add in list L
18 If word in S
Tag word as OpinionatedWord and add in list L
20 If word in F
20 Tag word as SantimantShiftar and add in list I
22 for all works in <i>I</i>
22 In an words in <i>D</i>
25 economic consecutive optimization works and securities in between two
24 restors the sequence of AttributePhysics and ContinentPhysics in list 11
24 resolution of Automatic mases and Semiment mases in the Li
25 Store I Les a sentence in NeuSentence List
2.5 Survey and Attribute Drass and Sentiment Phrase combination
7/ Other and such sentences in Naw Sentenceal ist
20 In cach schence in rewschence list
// AttributeDhyose First Dule
// Attributer infaster first Kute
2/ If the sentence starts with Sentiment Prase
28 If two or more consecutive Ainthouter process is the consecutive Ainthouter Process
29 insert the first second attribute Phrase before the consecutive AuributePhrases in
20 between each pair of AirPouter masses
30 break the sentence atter each AttributePhrases
3) Create a sub-sentence for each AttributePhrases and SentimentPhrases pair store in SubSentenceList
32 If no two consecutive AttributePhrases
3.5 break the <i>sentence</i> atter each <i>AttributePhrases</i>
34 Create a <i>sub-sentence</i> for each <i>AttributePhrases</i> and <i>SentimentPhrases</i> pair store in <i>SubSentenceList</i>
// AttributePhrase-Second Rule
35 if the sentence starts with AttributePhrase
36 If two or more consecutive AttributePhrases
37 insert the first SentimentPhrases after the consecutive AttributePhrases in
between each pair of <i>AttributePhrases</i> .
38 break the sentence before each AttributePhrases
39 Create a sub-sentence for each AttributePhrases and SentimentPhrases pair store in SubSentenceList
40 If no two consecutive AttributePhrases
41 break the sentence before each AttributePhrases
42 Create a sub-sentence for each AttributePhrases and SentimentPhrases pair store in SubSentenceList
43 end
44 return SubSentenceLists

Figure 3: Heuristic for attribute-sentiment pair generation



Figure 4: Process diagram (the example of sub-sentence generation heuristic)

Step 2. Creating pseudo words for attribute phrases and sentiment shifters

Certain attributes and sentiment shifters contain more than one word (refer to Table A4 in appendix). However, the words in the sentence are the target of our sentiment extraction algorithm. Therefore, we have searched for such group of words and combined them to create single pseudo-words (Line 8 in Figure 3). In Review 1, "*driving control*", and in Review 2, "*boot space*", "*air conditioning*", and "*not so*", are examples of such pseudo words, as demonstrated in Figure 4 (output of step 2).

Step 3. Conjunction partitioning

It is accepted in the literature that the polarity of the context represented by a text content gets typically reversed at conjunctions such as "but" and "however" (Shelke et al., 2017). To accommodate this effect, we broke a given sentence at each conjunction (i.e., but, yet, however, etc.). We have restored the broken sentences as individual entities in the *SentenceList* (Line 9–12, Figure 3). For our running examples, the revised sentence list appears in Figure 4 (output of step 3). It may be noted from the figure that two input sentences in review 1 became three because of the partitioning at "but" in the first sentence, whereas this step did not affect review 2.

Step 4. Word tagging and SentimentPhrase creation

In ASLSA, we identify the sentiment phrases and map them with the corresponding attributes (Schouten & Frasincar, 2016). Since sentiment shifters alter the polarity of texts (Polanyi & Zaenen, 2006; Xia et al., 2016), we need to locate them as well. To do so, the proposed heuristic first tags the words within these sentences with three categories: attribute phrases (A), sentiment words (S), and sentiment shifters (F) (Lines 13–21, Figure 3). The results of this step for the running examples appear in Figure 4 (output of step 4[a]). Next, all consecutive opinion bearing words and sentiment shifters are grouped and represented as what we termed a *SentimentPhrase* (Lines 22–25, Figure 3). The remaining words in a sentence are ignored. This step for both of the running examples appears in Figure 4 (step 4[b]), where the tags A, S, and F have been attached appropriately.

Step 5. Generating sub-sentences using AttributePhrase and SentimentPhrase combination:

In some sentences, more than one automobile attribute may be the target of a single sentiment phrase. For example, in Review 1, the string "bad comfort, style and driving control" indicate that the sentiment word "bad" is associated with three attributes: "comfort", "style", and "driving control". The logical approach here is to pair the sentiment word with each of the attributes. Two widely discussed approaches in this regard are: a) parse syntactic dependencies (Popescu & Etzioni, 2007) and b) grammatical relations (Heemskerk et al., 2011; Zhuang et al., 2006). Either approach would require defining the set of relations between the phrases. Defining a specific set of relations would create the problem of high precision but low recall, while a more general set of rules would result in low precision and high recall (Schouten & Frasincar, 2016). The proposed heuristic has partially addressed such concerns. We have first searched for all sentiment and attribute phrases in a sentence and then utilized the sentence structure to map them appropriately using a rule-based approach. The rules have been created based on our observation of a few sample reviews. We have noted that the *SentimentPhrases* are not randomly scattered in the sentence; rather, most of them follow one of the two structures appearing either before or after the target attribute. We designed two specific rules to address these structures separately.

Rule 1: SentimentPhrase precedes AttributePhrase: If the sentence in NewSentenceList starts with a SentimentPhrase and more than one AttributePhrase co-exist, insert the last SentimentPhrase just before them, in between each pair of AttributePhrases; break the sentence after each AttributePhrase.

Otherwise, if the sentence starts with a *SentimentPhrase* and no two *AttributePhrases* co-exist, simply break the sentence after each *AttributePhrase*. Lines 27–34 in Figure 3 describe the rule.

Rule 2: *AttributePhrase* **precedes** *SentimentPhrase*: If the sentence in *NewSentenceList* starts with an *AttributePhrase* and two or more *AttributePhrases* co-exist, insert the first *SentimentPhrase* just after them, in between each pair of *AttributePhrases*, and break the sentence before each *AttributePhrase*. Otherwise, if the sentence starts with an *AttributePhrase* and no two attributes co-exist, simply break the sentence before each *AttributePhrase*. Lines 35–42 in Figure 3 describes the rule. The results of the applications of these rules for the running examples appear in Figure 4 (output of step 5). (Review 1: First Rule and Review 2: Second Rule)

Each *SubSentence* generated in the previous section contains only one attribute and corresponding *SentimentPhrase*. Following a dictionary-based approach, we propose to compute the sentiment index (SI) of each *SubSentence* and assign it to the attribute therein to determine the attribute-level sentiment indices (ATLSIs) for each review in the dataset.

3.1.5 Aspect-level index generation

The automobile aspects contain more than one attribute (refer to Table A4 in appendix). Therefore, we need to add up the attribute level sentiment index (ATLSI) values corresponding to each aspect to compute the ASLSIs. Here, we have followed the weighted summation method, and used term-frequency (TF) of attributes as their weight (Abualigah et al., 2017). The intuition behind using TF rating is- *"the more the discussion about the attribute in the text the higher will be its corresponding weight"*.

3.2 Phase II: Manufacturers' performance evaluation

Traditionally, in TOPSIS (Gong, 2017; Yoon & Hwang, 1981), experts evaluate various *alternatives* based on predefined *evaluation criteria* to create the input *decision matrix*. The matrix is used to prioritize the alternatives. We have proposed to modify TOPSIS by regarding reviewers as experts, manufacturers as *alternatives*, and automobile aspects as *evaluation criteria*. For a detailed description of the steps involved in modified TOPSIS, refer to Appendix. Our proposal for creating the decision matrix to be used as the input for TOPSIS is as follows:

• Divide the available time-span into a number of equal time intervals.

- For the target manufacturers, segregate the aspect-level sentiment indices (ASLSIs) according to time interval.
- Select the inspection criteria (aspects).
- For each manufacturer, for each inspection criterion and for each time interval, calculate the *consumer-perceived performance rating* as

$$x_{ijt} = \frac{\sum_{k=1}^{l} P_{ijtk}}{\sum_{k=1}^{l} P_{ijtk} - \sum_{k=1}^{l} N_{ijtk}}$$
(1)

Where x_{ijt} represents the consumer-perceived performance rating of i^{th} manufacturer with respect to j^{th} aspect for t^{th} time interval; l denotes the number of reviewers in the same time-interval; P_{ijtk} and N_{ijtk} represent the positive and negative sentiment index (SI) with respect to i^{th} manufacturer, j^{th} aspect, t^{th} time interval, and k^{th} reviewer respectively. Hence, a m * n decision matrix is obtained as

$$X_t = \begin{pmatrix} x_{11t} & \cdots & x_{1nt} \\ \vdots & \ddots & \vdots \\ x_{m1t} & \cdots & x_{mnt} \end{pmatrix}$$

Where n and m represent the number of evaluation criterion (automobile aspects) and the number of manufacturers in the segment, respectively, for t^{th} time interval.

This decision matrix is used as the input for TOPSIS to compute manufacturers' relative performance indices. Based on these index values, manufacturers are ranked in the segment.

3.3 Phase III: Weakness detection and root cause analysis

Degradation in performance, if any, for a specific manufacturer calls for further analysis of the data to identify the root cause. We propose to statistically examine the products' perceived underperformance over the time, the literature suggest the use of statistical quality control tools (*i.e.*, *P*-chart, *U*-chart) for the same (Chukhrova, & Johannssen, 2019). Accordingly, we propose to use two categories of control chart, *U*-chart and *P*-chart (Laney, 2002), at the aspect and attribute level, respectively. Since an aspect has more than one attribute and can have more than one weakness/defect per unit (in case customers are dissatisfied with respect to more than one attributes corresponding to an aspect), using *U*-chart is appropriate. Whereas an attribute represents only one feature, proportion of nonconformity makes sense here, therefore we propose to use *P*-chart at attribute level. While

developing control charts, we have defined the nonconformity in accordance with our problem as discussed below.

3.3.1 Weakness detection at aspect level using U-chart

Considering each time-interval as an inspection sample, we have recorded number of nonconformities and the sample size for each aspect. In our context, we have defined the number of nonconformities as the *number of attributes bearing negative SI* per review. Based on the recorded data, we have developed separate *U*-charts for all aspects. If the data point with respect to the interval of analysis interest crosses the *Upper Control Limit (UCL)*, it indicates consumer-perceived weakness. Such incidences with respect to each of the aspects require analysis at the attribute level as discussed below.

3.3.2 Root cause analysis at attribute level using *P*-chart

Once weak aspects are identified, we need to process the SIs to record the time-interval-wise nonconformities and sample size for each individual underlying attribute. We define a nonconformity as an *attribute bearing negative sentiment*. Separate *P*-charts are need to be developed for individual attributes. If the data point with respect to the interval of interest deviate from UCL, the attribute is considered to be weak. This analysis provides a list of underperforming attributes, which would be of interest to manufacturers.

4. Application of the framework

We have applied the proposed framework to a dataset containing 36,558 automobile reviews received from Carwale.com, a well-known car portal in India. The dataset comprises consumer reviews for 53 different car manufacturers for 2006 to 2016.

4.1 Phase I: Sentiment index generation

In the data set we found 315 duplicate reviews, which are deleted. Remaining reviews are preprocessed to eliminate HTML tags, mark-ups, stop words, and duplicate reviews. In addition, we have eliminated duplicate sentences and words from the text.

4.1.1 Attribute identification and aspect tagging

Referring to Singh et al. (2020), the pre-processed dataset is processed with the RAKE algorithm. We have extracted 10,000 frequent noun phrases, which are manually checked by three engineering graduates, to create a short list of car attributes. Though the manual intervention is both expensive and time consuming but is necessary to a) eliminate phrases that are not intended to identify car attributes, and b) simplify the task of researchers and practitioners associated with aspect level sentiment analysis in automobile industry as the prepared list of frequent car attributes can easily be reused. Such practices have been adopted widely in ASLSA (Schouten & Frasincar, 2016). During manual scanning, we note that many attributes are represented by their synonyms or by different, misspelled words. For instance, the word *maintenance* is present in 21 forms, such as *maintainace, maintained, maitanance*, etc. We have fixed the issue by devising rules (in form of python codes) to replacing them with the correct, most standard word. In this phase 260 car attribute phrases are shortlisted and tagged with the respective aspects, following the car ontology we have prepared (Figure 2). A particular attribute could belong to one or more listed aspects. To tag the attributes-aspect pair, we have circulated the list of all shortlisted attribute phrases, along with the list of target aspects, to a group of three undergraduate students. We have collected their responses and opted for a voting-based approach to prepare the list of car aspects and corresponding underlying attributes. The list is further amended by two automobile experts. Their amendments are tabulated in Table A3 in appendix. The able A3 comprising three columns: first, the aspects; second, the common attributes in both lists; third, the uncommon attributes in both lists. Table A3 is then shared with the third expert (deputy general manager of production of an automobile manufacturer) with a request to reallocate/include/exclude the attributes as needed. From the list amended by the third expert, we note that many similar attributes are represented with different words; we have replaced all such words with the standard AttributePhrase. The final list is compiled as Table A4 (appendix). From Table A4, it is apparent that few attributes are present with more than one aspect. Such ambiguous terms are made bold and italic in the list. The final list has 252 attributes tagged with 26 aspects.

4.1.2 Aspect-level index generation

Among the various car segments in our dataset, we have selected the mid-size segment for performance evaluation. We have carried out the intra-segment comparison of manufacturers based on the suggestion of the deputy general manager of *a car manufacturer*. To demonstrate the framework, we have compared the manufacturers from mid-sized segment. For segmentation, we have referred to

the Society of Indian Automobile Manufacturers (SIAM) report. For the list of mid-sized car manufacturers in India and corresponding reviews (irrespective of their models) in the dataset readers are referred to Table III in Singh et al. (2020). From the dataset, it is apparent that very small number of reviews pertained to certain manufacturers, which are supposed to have scope of a huge margin of error. Therefore, we have computed maximum possible margin of errors for each manufacturer and tabulated the results in Table A2 (appendix). The computation is based on the average number of reviews per quarter and total vehicles sold in the last quarter by the particular manufacturer (for details readers are referred to Singh et al., 2020). To demonstrate the proposed framework, we have selected the five manufacturers with the smallest margin of error from the list and renamed them(M_1, M_2, \ldots, M_5). We have purposefully given pseudonyms to the manufacturers to avoid any kind of market confusion. For further analysis, we have separated 21,852 reviews corresponding to the five abovementioned manufacturers from our dataset.

We have tokenized the review into sentences using the *sent_tokenize* module of *NLTK package in Python* (Bird et al., 2009) and applied the *SubSentenceGeneration heuristic* (Figure 3) to split them into sub-sentences containing "only one attribute and corresponding opinionated phrase(s)". These sub-sentences are further tokenized into words with the *word_tokenise* (Bird et al., 2009) module. Next, we have lemmatized each word using *WordNetLemmatizer* and compared the word and its lemma with the same in *SentiWordNet*, a general-purpose lexicon. We have created an updated list of sentences by keeping either the original word or its lemma, whichever is present in *SentiWordNet*. These updated sentences are processed to compute sentence-level *SI* by aggregating the sentiment scores of individual words. Next, the sentence is modified referring to Yu et al., (2016), and Singh et al. (2020). The sentiment score is assigned to the attribute present in sub-sentence. The sentiment quantification is done for all the sentences in a review and all the reviews in the dataset.

Finally, referring to the Table A4 (appendix), we have aggregated the SIs of all attributes within a particular aspect to generate ASLSI for all 26 aspects. We have used a weighted summation method to compute the aspect level index. As discussed in Section 3, the TF rating of the attribute determined from the entire corpus is used as the weight. We have generated such aspect-level indices for the

individual reviews of all five manufacturers involved in present analysis. With these indices, we have generated a table comprising 21,852 rows and 26 columns, where the rows indicate the reviews and the columns refer to the aspects. The table turns out to be sparse because many aspects are not discussed frequently in this set of reviews. Based on the frequency of occurrence of the aspects in the review dataset, we have selected 12 most frequent aspects for further analysis (for frequency table refer to Table A5 appendix). The selected aspects are, ACCESSORIES (C_1), PASSENGER AND DRIVER COMFORT (C_2), SAFETY (C_3), EXTERIORS AND APPEARANCE (C_4), INTERIORS (C_5), MILEAGE (C_6), DRIVE SYSTEM (C_7), DRIVING & CONTROL (C_8), STORAGE CAPACITY (C_9), ENGINE ASSEMBLY (C_{10}), TRANSMISSION ASSEMBLY (C_{11}), and SPARE PARTS (C_{12}).

4.2 Phase II: Manufacturers' performance evaluation

The abovementioned aspects are used as the evaluation criteria in modified TOPSIS (Deng et al., 2000) to compare manufacturers' performance. Our dataset includes reviews from June 2006 to May 2016 (41 quarters). The dataset is incomplete for the second quarters of the years 2006 and 2016; therefore, we have excluded those quarters from the analysis. From the remaining data, for demonstration purposes, we have selected the last five consecutive quarters for analysis in this phase. As discussed in Section 3, the TOPSIS input decision matrices for the selected quarters are prepared using Equation 1. The resulting matrix appears in Table A6 (appendix). It is further normalized with Equation 2 (appendix) to obtain positive and negative ideal solutions using Equations 4 and 5 (appendix) for all five quarters (refer to Table 2). The intermediate results can be found in Table A7 in appendix. The criterion weights are also obtained from the decision matrix (Table A6 in appendix) by computing row-wise standard deviation (SD). Table 3 shows the criteria-wise weights for each quarter.

Table 2: Ideal solutions

							Crit	erion					
Quarters	Ideal												
	Solution	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Q1	Positive	0.2381	0.2069	0.2240	0.2034	0.2031	0.2355	0.2389	0.2654	0.2069	0.2358	0.2434	0.2539
	Negative	0.1186	0.1841	0.1530	0.1964	0.1924	0.1609	0.0956	0.1056	0.1781	0.1067	0.1664	0.1274
Q2	Positive	0.2206	0.2134	0.2778	0.2076	0.2211	0.2111	0.2197	0.2536	0.2325	0.2191	0.2185	0.2110
	Negative	0.1689	0.1569	0.0937	0.1928	0.1753	0.1820	0.1698	0.1155	0.1347	0.1715	0.1644	0.1792
Q3	Positive	0.2268	0.2040	0.2260	0.2036	0.2046	0.2130	0.2356	0.2177	0.2026	0.2350	0.2192	0.2193
	Negative	0.1591	0.1920	0.1707	0.1967	0.1940	0.1674	0.1598	0.1561	0.1977	0.1594	0.1580	0.1717
Q4	Positive	0.2404	0.2159	0.2152	0.2092	0.2175	0.2261	0.2199	0.2417	0.2364	0.2202	0.2157	0.2206
	Negative	0.1097	0.1758	0.1848	0.1932	0.1834	0.1687	0.1484	0.1298	0.1444	0.1485	0.1813	0.1787
Q5	Positive	0.2481	0.2060	0.2615	0.2082	0.2118	0.2750	0.2214	0.2314	0.2117	0.2217	0.2717	0.2361
	Negative	0.1396	0.1858	0.0922	0.1885	0.1832	0.0630	0.1477	0.1597	0.1795	0.1480	0.1254	0.1189

Where: accessories (C_1), passenger and driver comfort (C_2), safety (C_3), exteriors and appearance (C_4), interiors (C_5), mileage (C_6), drive system (C_7), driving & control (C_8), storage capacity (C_9), engine assembly (C_{10}), transmission assembly (C_{11}), and spare parts (C_{12}),

Table 3: Criterion weights

						Crite	erion					
Quarters	C1	C2	C3	C4	C5	C6	C7	C8	С9	C10	C11	C12
Q1	0.1197	0.0225	0.0785	0.0075	0.0109	0.0676	0.1458	0.1881	0.0303	0.1307	0.0740	0.1245
Q2	0.0691	0.0741	0.2058	0.0214	0.0510	0.0404	0.0656	0.1677	0.1226	0.0630	0.0788	0.0405
Q3	0.1183	0.0229	0.1224	0.0129	0.0209	0.0882	0.1311	0.1195	0.0114	0.1305	0.1255	0.0965
Q4	0.1690	0.0468	0.0441	0.0199	0.0459	0.0749	0.0940	0.1666	0.1358	0.0937	0.0502	0.0591
Q5	0.0944	0.0184	0.1592	0.0238	0.0262	0.1829	0.0698	0.0659	0.0313	0.0700	0.1459	0.1121

Where: accessories (C_1), passenger and driver comfort (C_2), safety (C_3), exteriors and appearance (C_4), interiors (C_5), mileage (C_6), drive system (C_7), driving & control (C_8), storage capacity (C_9), engine assembly (C_{10}), transmission assembly (C_{11}), and spare parts (C_{12}),

Finally, the relative performance indices for each quarter are computed using Equations 6–8 (appendix). The relative performance indices, along with the corresponding ranks of the manufacturers, appear in Table 4. In analysing the results presented in Table 4, it is observed that M3 is the worst-performing manufacturer in the last quarter and its performance is continuously deteriorating over the previous three quarters. Next, we have considered this particular case to explain the weakness detection phase of the proposed approach.

					Qua	rter				
	Q	Q1 Q2			Q3		Q4		Q5	
Manufacturer	Index	Rank	Index	Rank	Index	Rank	Index	Rank	Index	Rank
M1	0.5088	4	0.5536	4	0.7464	1	0.8661	1	0.6862	2
M2	0.6785	2	0.4517	5	0.2591	5	0.6405	3	0.6161	4
M3	0.5251	3	0.6344	3	0.7430	2	0.5299	4	0.2363	5
M4	0.5007	5	0.6565	1	0.6067	3	0.3901	5	0.6578	3
M5	0.7917	1	0.6351	2	0.5868	4	0.6491	2	0.8123	1

 Table 4: Manufacturers' relative performance index and ranks

4.3 Phase III: Weakness detection

To analyze the root cause of performance degradation of the manufacturer M3, we have performed two tasks. First, we have identified the weak aspects using the *U*-chart. Second, we have explored their attribute-level details and discovered the weak attributes using the *P*-chart. The control charts are prepared using Minitab 17. Traditionally, the control charts have used actual defects as the input. As discussed in Section 3 and shown below, we have used SIs as inputs. Since the weakness are encountered within the last few quarters, the perceived performance degradation might have begun at an earlier time and the manufacturer have failed to adopt remedial measures. Therefore, in the analysis presented below, we have used the data from all past quarters beginning in 2006. All together, we have 39 data points.

4.3.1 Weakness detection at aspect level using U-chart

Treating each quarter as an individual inspection sample, number of reviews as the sample size, and *number of attributes* bearing negative SIs corresponding to a particular aspect as the nonconformities, we have prepared separate *U*-charts for each of the 12 aspects as presented in Figure 5 (a-1). We have analyzed the charts in Figure 5 for the last three quarters because the manufacturer's performance was continuously degrading for those quarters. It is noted that the second last-quarter data point for the

aspect *DRIVING* & *CONTROL* has crossed the UCL, indicating that manufacturer M3 to be underperforming with respect to this particular aspect. As discussed in Section 3, each aspect is represented by a set of attributes. Therefore, attributes pertaining to the aspect *DRIVING* & *CONTROL* must be analyzed to detect the underperforming attributes.

4.3.2 Root cause analysis at attribute level using *P*-chart

We have used *P*-chart for attribute-level weakness detection. This chart plots the proportion of nonconformity over time. We have treated a negative perception about an automobile attribute as equivalent to non-conformity. Therefore, the proportion of negative reviews to total reviews in a specific quarter is considered while constructing the *P*-chart. In the last section, we have observed that *DRIVING* & *CONTROL* is an especially weak aspect. This aspect contains many attributes; however, only a few attributes contain negative sentiments. The attributes bearing negative SI are: *grip, control, ground clearance, parking, ride handling, steering, suspension,* and *touch screen.* We have prepared separate *P*-charts for these attributes, as presented in Figure 6. Interpreting these charts, it is noted that the second last-quarter data point crossed the UCL in Figure 6 (f). This indicates underperformance with respect to the attribute *[Steering]* under *DRIVING* & *CONTROL*.



Figure 5: U-charts for Accessories (a), Passenger and Driver Comfort (b), Safety (c), Exteriors and Appearance (d), Interiors (e) Mileage (F), Drive System (g), Driving & Control (h), Storage Capacity (i), Engine Assembly (j) Transmission Assembly (k), and Spare Parts (l)



Figure 6: P-charts for Grip (a), Control (b), Ground Clearance (c), Parking (d), ride handling (e) Steering (f), Suspension (g), and Touchscreen

5. Evaluation measures

The correctness of the analysis depends on the quantitative performance of attribute extraction ans sentiment quantification algorithm. Researchers measure them separately using precision, recall, accuracy, and F_1 measures (Lu et al., 2011; Yanyan Zhao, Bing Qin, Shen Hu, 2011; J. Yu et al., 2011). In order to measure the performance of the algorithm adopted in the present research, we have randomly selected 500 reviews for manual annotation and made two copies of the reviews. One copy is distributed among five mechanical engineering undergraduate students (100 reviews each). We requested them to

i) tag the automobile attributes present in the review and ii) detect the polarity of the text corresponding to each specific attribute. The polarity indicates whether a text possesses a positive or negative sentiment (Kar, & Dwivedi, 2020). The second copy of reviews is annotated by the research lead. We have received 200 mutually annotated reviews with a total of 1,416 attributes tagged. In several cases, conflicting annotations between the research lead and the other annotators are noted, which we resolved by preferring the annotation of the research lead.

Finally, based on the annotators' responses, we separately measured the performance for attribute extraction and sentiment index generation. During the attribute annotation, annotators have detected 1,416 attributes, whereas the algorithm proposed in the present research could detect only 1,266 attributes, out of which only 1,206 are correctly detected. Based on these numerical values, we have computed the performance evaluation metrics and compiled the results in Table 6. The metrics used in the computation appear in the tables itself: where, N is the total number of reviews; C_1 is the number of actual attributes in review I; E_I is the number of attributes extracted by the algorithm from review I; EC_I is the number of correctly extracted attributes from review I. From the table, we have noted that the values for Precision, Recall, and F1-Measure are 95.62%, 85.16%, and 89.93%, respectively. Precision value shows that out of total attributes extracted by the algorithm, 95.62% were correctly identified. Recall value shows that out of total attributes present in the reviews 85.16% were correctly identified by the algorithm. Whereas F1-Measure represents the geometric mean of Precision, and Recall. For sentiment index generation, based on the responses from annotators and the heuristic, we prepared a confusion matrix as presented in Table 5, wherein the number rue positive (TP), true negative (TN), false positive (FP), and false negative (FN) instances are found to be 671, 119, 113, and 115, respectively. Based on these values, we computed the performance matrices as presented in Table 6. The values for Precision, Recall, and F1-Measure, were 85.59%, 85.37%, and 85.48%, respectively. This algorithm is also used by Singh, Jenamani, & Thakkar, J. (2020). Precession score here indicates that out of the total positive sentiments identified by the algorithm, 85.59% were correctly captured. Whereas the *Recall* score suggests that out of total exact positive sentiment scores in the reviews, the algorithm could only discover 85.37%. Here one may note total correctly identified attributes were

1206, whereas in confusion matrix total attributes are 1018, the difference is because 188 out of 1206 reviews bear neutral sentiment index.

N=1206	Predicted as negative	Predicted as positive	
Annotated as negative	TN = 119	FP = 113	232
Annotated as positive	FN = 115	TP = 671	786
	234	784	

Table 5: The confusion matrix for sentiment index generation heuristic

	Table 6: A	Algorithm eva	luation measures
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Evaluation	Attribute extraction al	ribute extraction algorithm Sentiment index				
measures			heuristic			
	Metric (Liu et al.,	Values	Metric (Tripathy et al.,	Value		
	2005)		2016)	S		
Precession	$P = \sum_{I=1}^{N} EC_{I} / \sum_{I=1}^{N} E_{I}$	0.9526	P TP	0.855		
	<i>I</i> =1 <i>/ I</i> =1		$F = \frac{1}{TP + FP}$	9		
Decell	$R = \sum_{n=1}^{N} EC_{n} / \sum_{n=1}^{N} C_{n}$		$R = \frac{TP}{TP}$	00.85		
Recall	$\sum_{I=1}^{I} \sum_{I=1}^{I} \sum_{I$	0.8516	TP + FN	37		
	$2 \times P \times R$		$2 \times P \times R$	0.854		
F ₁ -Measure	$F_1 = \frac{P + R}{P + R}$		$F_1 = \frac{P + R}{P + R}$			
		0.8993		8		
			TP + TN	0.776		
Accuracy	NA	NA	$A = \frac{1}{TP + TN + FP + FN}$	0		
				3		

6. Discussion

In this research we have proposed and tested a text analytics framework that not only ranks the manufacturers among the competitors but also discovers their consumer perceived weaknesses. We have selected five manufacturers from the mid-sized segment in India, compared them based on the consumers' perceptions with respect to the features, ACCESSORIES, PASSENGER AND DRIVER COMFORT, SAFETY, EXTERIORS AND APPEARANCE, INTERIORS, MILEAGE, DRIVE SYSTEM, DRIVING & CONTROL, STORAGE CAPACITY, ENGINE ASSEMBLY,

TRANSMISSION ASSEMBLY, AND SPARE PARTS, and found M3 to be the least performing. We have also discovered the reason for the underperformance and found that customers were not happy with the feature driving and control. Probably because of customers' dissatisfaction with the aforementioned aspect/feature, the manufacturer performed weak.

6.1 Theoretical Implications

The present research makes several contributions to the existing body of knowledge. *First*, it has proposed a customized aspect level sentiment quantification algorithm. *Second*, it has also proposed a sub-sentence generation heuristic that deals with the sentences with more than one attributes. *Third*, it has proposed a replacement of expert inputs in TOPSIS through the sentiments extracted from reviews. *Fourth*, it has seamlessly integrated the aspect level sentiment analysis with P- and U- charts to statistically discover the consumer perceived weaknesses of the manufacturers.

6.2 Managerial implications

The proposed framework can be used as decision support by customers, manufacturers, and component suppliers. A customer can rank the manufacturers to identify the best option in a specific product line and compare the performance of various cars at an individual system or subsystem level. The proposed framework can also help manufacturers in- i) keeping track of consumers' current interests by extracting most frequently discussed features from the online discussions; ii) comparing their performance with their competitors using the method proposed in the Phase II of the framework; discovering the performance, weaknesses, and strengths of their competitors using the last phase of the framework. A manufacturer can use the proposed framework to monitor its consumer-perceived market performance over time to facilitate informed decision making for improvement. If degradation in ranking occurs, the manufacturer can identify the origin of the problem at the aspect level and the root cause at the attribute level. This retrospective analysis may help them with continuous improvement. If the manufacturers are informed by their customers through online reviews that they have mistaken somewhere which may lead to hazardous events in the long run, they may initiate product recalls. In a typical automobile manufacturing setup, many subsystems and components are sourced from various suppliers. The proposed framework can facilitate early warning for such component suppliers regarding the weaknesses encountered in the components they provide, which would help not only in building a

better relationship with the manufacturer by enabling the suppliers to correct their weaknesses promptly, but also in discovering new business prospects by identifying the weaknesses of competitors.

7. Concluding remarks

This research represents an attempt to connect aspect-level consumer sentiment extracted from online reviews with statistical tools for quality control to summarize the reviews in form of controlcharts which are easily comprehensible by the operations management community. The proposed threephase framework integrates sentiment analysis to mine aspect-level consumer sentiments and analyze them for i) manufacturers' market performance evaluation, using TOPSIS, ii) weakness detection at the aspect level, using a *U*-chart, and iii) root cause analysis at the attribute level using a *P*-chart. To demonstrate the proposed framework, we have selected five manufacturers from the mid-size car segment, identified the weakest-performing one, and discovered its weaknesses at the aspect and attribute levels. The proposed semi-automatic approach for aspect identification was validated with human annotators. Our major contributions include an ontology for passenger cars, a semi-automatic method for aspect identification and sentiment index generation, use of TOPSIS with inputs as a sentiment index, and corroborating control charts as visualization tools for aggregating the perceived market sentiment.

8. Limitations and future work

The present research possesses certain limitations-

- U-charts and P-charts are usually developed on the assumption that the random sample is selected from a large population, which is violated in the case of online reviews. Moreover, in the present analysis, the sample size (the number of reviews per quarter) was not large enough, leaving a margin of error from 9% to 14%. Therefore, the results drawn from these charts cannot directly be used as representatives of consumer-perceived weakness; rather, they can only be treated as indicators requiring further investigation.
- Based on a random sample of 100 reviews, we observe that 33.46% of the text was expressed non-emotively which was found to be useful by research community. The present study did not account for it.

- We collected reviews from Carwale the present study may be subject to self-selection bias.
- We do not use the reviews that compare products since the proposed approach is not appropriate for multi-product aspect extraction.
- Our research focuses towards consumer review-based quality analytics framework which extracts qualitative patterns from automobile reviews. Since, our focus was on application of sentiment analysis, we did not compare the performance of the proposed sentiment extraction algorithm with the other sentiment dictionaries (i.e. SenticNet-3 (Cambria et al., 2014) (Cambria et al.2014), Opinionfinder (Wilson et al., 2005) etc.). Hence, leaving a scope for the future researchers to compare such dictionaries.
- We have adopted a dictionary-based approach due to the scarcity of annotated data in the automobile industry. Future researchers may consider manual annotation and apply machine learning approaches to investigate the same issue.
- *The F1-Measure* for the algorithm used in the present research is only 89.93%, for attribute extraction and 85.48%, for sentiment index generation. Hence, leaving a scope for the future researchers to improve it.
- In present the scenario, managing with the Misinformation is an issue (Song, Lau, Kwok, Mirkovski, & Dou, 2017; Aswani, Kar, & Ilavarasan 2018; Aswani, Kar, & Ilavarasan, 2019). In case of online reviews, it is noted that sometimes organizations manage fake positive reviews for themselves and negative reviews for their competitors. Present research did not account for detecting and eliminating them. Researchers may extend it in future.

Keeping such biases and assumptions in mind, we recommend supplementing the findings of the present research with other diagnostic tools available in the domain of quality assessment and market research.

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Appendix

The modified TOPSIS

We used the modified TOPSIS because of its capabilities in (a) depicting the relative performance of manufacturers' operations based on cumulated evaluation criteria in simplified mathematical terms, (b) adopting the data-driven approach to assign weights to the evaluation criteria, and (c) prioritizing alternatives based on their distance from the positive as well as the negative ideal solutions. The prioritization of manufacturers was accomplished as follows (Deng, Yeh, and Willis, 2000; Yoon and Hawang, 1981):

Representation of performance matrix:

Traditionally, in TOPSIS a questionnaire is prepared where experts are asked to assess various *alternatives* based on predefined *evaluation criteria* to create the input *decision matrix*. TOPSIS uses this *decision matrix* to prioritize the alternatives. We have proposed to modify TOPSIS by regarding reviewers as experts. Treating manufacturers as *alternatives* and automobile aspects as *evaluation criteria*, our proposal for creating the decision matrix to be used as the input for TOPSIS was as follows:

- Divide the available time-span into a number of equal time intervals.
- For the target manufacturers, segregate the ASLSIs time-interval-wise.
- Select the inspection criteria (aspects).
- For each manufacturer, for each inspection criterion and for each time interval, calculate the *consumer-perceived performance rating* as

$$x_{ijt} = \frac{\sum_{k=1}^{l} P_{ijtk}}{\sum_{k=1}^{l} P_{ijtk} - \sum_{k=1}^{l} N_{ijtk}}$$
(1)

Where x_{ijt} represents the consumer-perceived performance rating of i^{th} manufacturer with respect to j^{th} aspect for t^{th} time interval; l represents the number of reviewers in the same time interval; P_{ijtk} and N_{ijtk} represent the sentiment index (SI) with respect to i^{th} manufacturer, j^{th} aspect, t^{th} time interval, and k^{th} reviewer if it is positive and negative, respectively. Hence, a m * n decision matrix is obtained as

$$X_t = \begin{pmatrix} x_{11t} & \cdots & x_{1nt} \\ \vdots & \ddots & \vdots \\ x_{m1t} & \cdots & x_{mnt} \end{pmatrix}$$

Where n and m represent the number of evaluation criteria (automobile aspects) and the number of manufacturers in the segment for t^{th} time interval. This decision matrix is used as the input to TOPSIS to compute manufacturers' relative performance indices. Based on the index values, manufactures are ranked in the segment. The steps involved are as follows:

Normalization of decision matrix: Normalization of the decision matrix is obtained as

$$P_{ijt} = \frac{X_{ijt}}{\sum_{i=1}^{n} X_{ijt}}$$
(2)

Weight calculation for the criteria: The more divergent the performance ratings, the higher the corresponding criteria weight. Consequently, use the standard deviation of the performance rating to calculate the criteria weight. Calculate the criteria weight in accordance with (Deng, Yeh, and Willis, 2000), as

$$W_{jt} = \frac{\sigma_{jt}}{\sum_{j=1}^{m} \sigma_{jt}}$$
(3)

Where σ_{jt} is the standard deviation of the performance ratings of the j^{th} criterion for t^{th} time interval.

Calculation of overall performance index: Calculation of the overall performance index requires positive and negative ideal solutions.

Positive ideal solution:

$$A^{+}_{t} = \left(\left(\max_{i} P_{i1t} \right), \left(\max_{i} P_{i2t} \right), \dots \left(\max_{i} P_{imt} \right) \right) = \left(p_{1t}^{+}, p_{2t}^{+}, \dots p_{mt}^{+} \right)$$
(4)

Similarly, negative ideal solution:

$$A^{-}_{t} = \left(\left(\min_{i} P_{i1t} \right), \left(\min_{i} P_{i2t} \right), \dots \left(\min_{i} P_{imt} \right) \right) = \left(p_{1t}^{-}, p_{2t}^{-}, \dots p_{mt}^{-} \right)$$
(5)

Weighted Euclidean distances are used in calculations for aggregation. These are calculated as:

$$d_{it}^{+} = \left[\sum_{p=1}^{m} w_{jt} (d_{ijt}^{+})^2\right]^{1/2}$$
(6)

$$d_{it}^{-} = \left[\sum_{p=1}^{m} w_{jt} (d_{ijt}^{-})^2\right]^{1/2}$$
(7)

Where
$$d_{ijt}^+ = p_{jt}^+ - p_{ijt}$$
 and $d_{ijt}^- = p_{ijt} - p_{jt}^-$, $i = 1, 2, ..., n, j = 1, 2, ..., m$ and $t = 1, 2, ..., T$

The overall performance index of an alternative is calculated by:

$$P_{it} = \frac{d_{it}^{+}}{d_{it}^{+} + d_{it}^{-}}$$
(8)

The higher the index value, the better the alternative performance is. Based on the value of relative performance index, an underperforming manufacturer may be identified.

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Table A1:

List of passenger car aspects and then representative prochure	List of	passenger	car aspect	s and their	[•] representative	brochures
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System	Sub-systems	Volkswagen Ameo brochure	Maruti Suzuki Alto brochure	Mahindra Bolero brochure
TECHNOLOGY	DAS (DRIVER ASSISTANCE SYSTEM)	\checkmark	\checkmark	\checkmark
	INFOTAINMENT SYSTEM	\checkmark	\checkmark	\checkmark
ACCESSORIES		\checkmark	\checkmark	\checkmark
COMFORT	PASSENGER AND DRIVER COMFORT	\checkmark	\checkmark	\checkmark
	VIBRATION			\checkmark
SAFETY		\checkmark	\checkmark	
EXTERIORS AND APPEARANCE		\checkmark	\checkmark	\checkmark
INTERIORS		\checkmark	\checkmark	\checkmark
MILEAGE		\checkmark	\checkmark	\checkmark
DRIVE SYSTEM		\checkmark	\checkmark	\checkmark
DRIVING & CONTROL		\checkmark	\checkmark	\checkmark
CAPACITY	STORAGE CAPACITY	\checkmark	\checkmark	\checkmark

	POWER/TORQUE CAPACITY	\checkmark	\checkmark	\checkmark
	SEATING CAPACITY			\checkmark
	FUEL TANK CAPACITY	\checkmark		
ASSEMBLY	BRAKE ASSEMBLY	\checkmark	\checkmark	\checkmark
	ENGINE ASSEMBLY	\checkmark	\checkmark	\checkmark
	TRANSMISSION ASSEMBLY	\checkmark	\checkmark	\checkmark
	CLUTCH ASSEMBLY			\checkmark
	WHEEL ASSEMBLY	\checkmark	\checkmark	\checkmark
SALES AND MARKETING		\checkmark	\checkmark	
AFTER SALES SUPPORT	SERVICE SUPPORT & MAINTENANCE	\checkmark	\checkmark	
	SPARE PARTS	\checkmark		\checkmark
BRAND RELIABILITY				\checkmark
COOLING				
SYSTEM				\checkmark
SUSPENSION		\checkmark	\checkmark	\checkmark

Table A2:Manufacturers in the mid-size car segment

Manufacturer	Margin of error	Manufacturer	Margin of error
BMW India Pvt Ltd	38%	Mahindra Renault Pvt Ltd	49%
Fiat India Automobiles Pvt Ltd	18%	Maruti Suzuki India Ltd	7%
Ford India Pvt Ltd	14%	Nissan Motor India Pvt Ltd	25%
General Motors India Pvt Ltd	44%	Renault India Pvt Ltd	18%
Hindustan Motors Ltd	40%	SkodaAuto India Pvt Ltd	19%
Honda Siel Cars India Ltd	12%	Tata Motors Ltd	11%
Hyundai Motor India Ltd	9%	Volkswagen India Pvt Ltd	22%

Table A3:

List of automobile aspects and corresponding attributes (compiled first and second expert)

System	Sub-systems	Target attribute phrases	Target attribute
		(Common)	phrases (Non common)
TECHNOLOGY	DAS (DRIVER ASSISTANCE SYSTEM)	driving information system, navigation, gps, touch screen, sensor, parking sensor, thermal sensor, cruise control, camera, rear camera, front camera	around view camera, speed sensing power steering, speedometer, hill launch assist, fish eye camera, tyre pressure monitoring, TPMS, tachometer, digital odo, cluster, steering controls, hill hold, hill descent, push button start, peps, stereo jack, voice assist, regenerative braking, EPB, electric parking brake, adaptive cruise control, glare-free high beam, adaptive light control: swivelling curve lights. automatic parking, night vision, blind spot monitor, lane assistance, automatic emergency braking,
	NT SYSTEM	infotainment, dynamic player, entertainment, media player, stereo, stereo, android auto, audio, audio system, audio	phonebook sync, radio

player, head phone, ear phone, music system, music, bluetooth, CD player, CD, dynamic player, sound, sound system, speakers, USB, touch screen, android sync, iPhone sync,

ACCESSORIES

mat, seat cover, car cover, tool kit, car care kit, mirror, steering wheel, display, steering cover, sunshades,

COMFORT

PASSENGER AND DRIVER COMFORT

air conditioning, comfort, inner space, legroom, luxury, passenger comfort, seat quality, seat adjustment, seat space, space, storage capacity, driver comfort, driving comfort, driving information system, driving seat, ride quality, headroom, maneuverability plate, waste bag, air filter, dust filter, air purifier, tyre, mobile holder, air freshener, driver utility set, luggage box, safety triangle, umbrella holder, hydraulic jack, first-aid kit, sun shield, spare wheel space, driving information system, maneuverability, boot space, climatronic, seat design, , shock absorber, steering adjustment space. suspension, ergonomics, ambient mood lighting, adjustable seat, sunroof, ventilated seats, temperature control, tiltable steering, power window, foldable seat, power outlets, keyless entry, tyre pressure monitoring (tpms), bucket seats, lumber support, bolster support, adjusting seatbelts, tilt & telescopic, foldable seats, 50:50, 60:40, cabin cooling, ride comfort, anti-pinch, cigarette lighter, 12v, reclining seats, shimmy, steering vibrations, judder, pedal vibration, road load, tyre noise, pass-by noise, crash test, n-cap rating, pedestrian safety, front hood, gas springs, srs,

carpet, armrest, seat, seat

cover, cup holder, bottle

holder, lamp, gadgets, scuff

VIBRATION engine vibration, body noise, cabin noise, vibration, engine

SAFETY

noise, noise, sound, jerk,

abs, ebd, antilock brake

lock, bearing, body, body

quality, body strength, bonnet, braking system, breakdown, car material, control, disc, disc brakes, driving control, fog lamp, grip, handbrake, hill climb control, power brakes, rear

system, accident, airbag, door

EXTERIORS AND APPEARANCE

INTERIORS

MILEAGE

DRIVE SYSTEM camera, safety, scratch, seatbelt, security, sensor, shock absorber, stability, steering control, traction control, wheel assembly. wheel material, electronic stability program, esp, rollover protection, central door locking, immobilizer, stability control, side impact protection, park assist, parking aid, aerodynamics, appearance, body, body shape, bonnet, bumper, contour, design, door, door design, door handles, exterior, exterior design, external appearance, front view, head lamp, head light, look, mirror, paint, rear look, rear style, rear view, rim design, style, tyre, wheel assembly, wheel design, wiper, window glass, guards, mud flaps steering, boot space, bottle holder, cabin, carpet, compartment, cup holder, dashboard, footrest, inner space, inside lamps, interior, interior design, interior look, interior material, leather, mat, seat, seat design, seat material, seat quality, space, steering, steering cover, seat cover, sunshades, touchscreen, AC vent, roof lining, vanity mirror, dual tone dashboard, upholstery, ORVM, IRVM, hand brake lever, HMI, mood lighting, arm rest, utility box, sunglass holder, automatic retracting ORVM, electrically adjusted ORVM, shark-fin antenna, back seat AC vent, last row controller, sun roof, moonlight roof, follow-mehome headlamps mileage, average, fuel economy,

shaft, crank shaft, transmission system, flywheel, gear box, crdi shaft, side light, indicators, roof rails, foot rails, rub rail, chrome, chrome painted, cornering light, height adjusting lights,

temperature display,

kmpl, km/ltr, kilometer per liter, km/liter, gallon per miles engine, cvti, semi-hybrid, hybrid, automatic transmission, amt, bearing differential,

DRIVING & CONTROL		acceleration, brake, braking system, power, break horsepower, bhp, clutch, control, dashboard, driving information system, driving system, gear, gear shift, gps, grip, handbrake, jerk, legroom, maneuverability, navigation, parking, parking sensor, parking quality, pickup, power brakes, rear camera, remote locking, rpm, speedometer, stability, steering, steering control, torque, traction, traction control	ground clearance, touchscreen, jerk, legroom, side toss, head toss, body roll, handling, ride & handling, multi link suspension, stabiliser, road grip, vehicle pull, cornering, understeer, oversteer, firm ride, plush ride, steering on-centre feel, parking assist, parking effort, returnability, e-pas, h-pas, turning radius, cornering radius, ground clearance, approach angle, departure,
CAPACITY	STORAGE	boot space, space, storage capacity	
	CAPACITY		
	POWER/TORQ	power, torque, traction, break horsepower, bhp	break force distribution,
	UE CAPACITY		
	SEATING	sitting capacity, seats	
	CAPACITY		
	FUEL TANK CAPACITY	fuel tank, tank capacity	
ASSEMBLY	BRAKE ASSEMBLY	brake, disc, disc brake, brake holder, braking system, handbrake, power brakes	shoe, spring, adjuster
	ENGINE ASSEMBLY	cylinder, engine, engine parts, engine valve, injection system, intercooler, multijet cylinder, turbocharger	crank shaft, cam shaft, exhaust valve, flywheel, head, head cover, fuel injector, spark plug, piston, piston rings, gasket, tcic
	TRANSMISSIO N ASSEMBLY	gear box, gear box gasket, transmission, transmission system, transmission assembly, gear.	gear shaft lever, gear box bearing, counter shaft, main shaft, transmission case,
	CLUTCH ASSEMBLY	clutch, clutch housing, clutch plate,	clutch disc, clutch cover, pressure plate, flywheel
	WHEEL ASSEMBLY	tyre, tyre material, wheel assembly, wheel material, rim, wheel bearing.	wheel, wheel caps
SALES AND MARKETING		dealer, dealer support, delivery experience, sales, sales executive, sales support, showroom, advertisement,	exchange benefit, customer loyalty
AFTER SALES SUPPORT	SERVICE SUPPORT & MAINTENANC	maintenance, maintenance cost, repair, repair cost, workshop, service center,	overhauling, reseller, flagship

BRAND RELIABILITY	E SPARE PARTS	service cost, service issues, service manager, service personnel, service providers, service quality, service support, post sales services, customer care service, bonnet, brake holder, clutch, clutch housing, clutch plate, crankshaft, crdi shaft, disc, engine parts, engine valve, flywheel, gear box, gear box bearing, gear box gasket, head, injection system, spares, spare parts, spares quality, tyre, wheel bearing, wheel assembly, wiper,	brake, bumper, compressor, rim, shock absorbers, steering wheel, filter, ignition system, wheel caps, suspensions, oil filter, filter, wiper blades, spark plug, fan belt, pressure plate, radiator, light, mirror, spare wheel, clutch wire, shaft, steering, steering assembly, grease, mobil oil, lube oil,
BRAND		brand, car quality, car	breakdown,
KELIABILITY		reliability, resale	
COOLING		intercooler, radiator, cooling	
SYSTEM		system, neat, temperature	
SUSPENSION		suspension, shock absorber, shocker, spring	

Table A4:Final list of automobile aspects and corresponding attributes

SVSTEM	SUB_SVSTEMS	Target attributes
SISIEM	SUD-SISIENIS	
	DAS (DRIVER	camera, cruise control, display, driver utility set,
TECHNOLOGY	ASSISTANCE	driving information system, EPB, GPS, hill climb
	SYSTEM)	assist, lane assistance, navigation, night vision, parking
		assist. PEPS, push button start, sensor, speedometer.
		stereo jack, tachometer, <i>touch screen</i> , tyre pressure
		monitoring system voice assist FBD auto dimming
		montoring system, voice assist, EDD , auto unining
		minor, automatic ram sensing wiper
	INFOTAINME	infotainment system, bluetooth, ear phone,
	NT SYSTEM	entertainment, iPhone sync, phonebook sync, radio,
		USB, android auto, car play
ACCESSORIES		air purifier, <i>bottle holder</i> , car care kit, car cover, <i>cup</i>
		holder. driver utility set. first-aid kit. gadgets.
		hydraulic iack. luggage box, mat, mirror, mobile
		holder scuff plate seat cover seat spare wheel
		starting cover our chield gunghadag tool kit ture
		sieering cover, suit silieid, sunsnades, tool kit, tyre,
		waste bag
COMFORT	PASSENGER	adjustable seat, <i>air conditioning</i> , <i>boot space</i> ,
	AND DRIVER	climatronic, comfort, driver comfort, ergonomics,
	COMFORT	foldable seat, headroom, inner space, keyless entry,
		legroom, lumber support, luxury, manoeuvrability.
		passenger comfort, ride comfort, ride quality, seat

		adjustment, <i>seat quality</i> , seat space, <i>shock absorber</i> , <i>space</i> , tillable steering, <i>sunroof</i> , <i>suspension</i> , temperature control, ventilated seats, <i>cup holder</i> , <i>bottle</i> <i>holder</i>
SAFETY	VIBRATION	jerk, judder, noise, vibration ABS, accident, airbag, body, <i>bonnet, brake</i> , <i>breakdown, camera</i> , car material, central door locking, crash test, door lock, driving control, <i>EBD</i> , ESP, fog lamp, front hood, <i>grip</i> , <i>handbrake</i> , <i>hill climb assist</i> , immobilizer, <i>parking assist</i> , rollover protection, safety, seatbelt, security, <i>sensor</i> , <i>shock absorber</i> , side impact protection, <i>spring</i> , SRS, stability, traction control, <i>wheel assembly</i> , NCAP, child lock
EXTERIORS		aerodynamics, appearance, <i>bonnet</i> , bumper, contour,
AND APPEARANCE		<i>lighting system</i> , look, <i>mirror</i> , ORVM, mud flaps, paint,
INTERIORS		rails, rear view, style, window glass, <i>wiper</i> armrest, <i>boot space</i> , <i>bottle holder</i> , cabin, compartment, <i>cup holder</i> , dashboard, foot rest, interior design, interior material, interior, IRVM, leather, <i>lighting</i>
		system, mat, roof lining, seat cover, seat material, seat quality, seat, space, steering cover, sunroof, sunshades, display, touch screen, upholstery
MILEAGE DRIVE SYSTEM		Mileage crank shaft, crdi shaft, differential, engine, flywheel, gear box bearing, shaft, transmission
DRIVING & CONTROL		<i>grip</i> , ground clearance, head toss, oversteer, <i>parking assist</i> , parking, plush ride, ride handling, stabiliser, <i>steering</i> , <i>suspension</i> , <i>touch screen</i> , understeer, control
CAPACITY	STORAGE CAPACITY	boot space, space
	POWER/TORQ UE CAPACITY	BHP, power, torque, traction
	SEATING CAPACITY FUEL TANK	seats, sitting capacity, seating capacity
	CAPACITY	fuel tank, tank capacity
ASSEMBLY	BRAKE ASSEMBLY	adjuster, brake, handbrake, shoe, spring
	ENGINE ASSEMBLY	cam shaft, <i>crank shaft</i> , cylinder, <i>engine parts</i> , <i>engine</i> , <i>flywheel</i> , <i>fuel injector</i> , gasket, head cover, head, <i>injection system</i> , intercooler, piston assembly, <i>spark plug</i> , turbocharger
	TRANSMISSIO	counter shaft, gear box bearing, gear box gasket, gear
	N ASSEMBLY	box, gear, main shaft, transmission case, transmission
	ASSEMBLY	ciaich assembly, pressure plate
	WHEEL ASSEMBLY	tyre, rim, wheel assembly, wheel

SALES AND MARKETING		advertisement, customer loyalty, dealer support, delivery experience, exchange benefit, sales support, showroom
AFTER SALES SUPPORT	SERVICE SUPPORT & MAINTENANC E	customer care service, flagship, maintenance, overhauling, post sales services, reseller, service support, workshop
	SPARE PARTS	bonnet, brake holder, brake, bumper, clutch assembly, compressor, crank shaft, crdi shaft, disc, engine parts, fan belt, filter, flywheel, fuel injector, gear box bearing, gear box gasket, gear box, grease, ignition system, injection system, lighting system, lube oil, mirror, mobil oil, oil filter, pressure plate, radiator, rim, shaft, shock absorber, spare parts, spark plug, steering, suspension, tyre, wheel assembly, wiper blades, wiper
BRAND RELIABILITY COOLING SYSTEM SUSPENSION		brand, <i>breakdown</i> , car performance, car quality, reliability, satisfaction, resale <i>cooling system</i> , heat, <i>radiator</i> , temperature <i>air</i> <i>conditioning</i> <i>shock absorber</i> , shocker, <i>spring</i> , <i>suspension</i>

Table A5: Frequency table of aspects

Aspect	Frequency	Aspect	Frequency
driver assistance system	854	seating capacity	2193
infotainment system	1489	fuel tank capacity	3
accessories	4099	brake assembly	613
passenger and driver comfort	9473	engine assembly	6687
vibration	1024	transmission assembly	4113
Safety	4354	clutch assembly	2
exteriors and appearance	10915	wheel assembly	1099
interiors	8740	sales and marketing	1285
mileage	7699	service support & maintenance	2463
drive system	6537	spare parts	5641
driving & control	3202	brand reliability	2118
storage capacity	4279	cooling system	2010
power/torque capacity	1798	Suspension	875

Table A6:Decision matrices

			Criteria										
Quarters	Manufacturer	C1	C2	C3	C4	C5	C6	C7	C8	С9	C10	C11	C12
Q1	M1	0.6986	0.9689	1.0000	1.0000	0.9759	0.6742	0.8947	0.4813	1.0000	0.8947	0.7913	0.7637
	M2	0.7973	0.8678	0.9765	0.9926	0.9669	0.8114	1.0000	1.0000	1.0000	1.0000	0.6836	0.4904
	M3	0.8670	0.9500	0.8044	0.9653	0.9619	0.8969	0.9879	0.3981	0.9804	0.9879	0.7471	0.6891
	M4	0.4321	0.9754	1.0000	0.9884	0.9757	0.9867	0.4000	0.9300	0.9915	0.4526	1.0000	0.9774
	M5	0.8465	0.9518	0.6829	0.9693	0.9242	0.8207	0.9027	0.9591	0.8607	0.9052	0.8870	0.9290
Q2	M1	0.7654	0.7063	1.0000	1.0000	0.7565	0.8540	1.0000	0.4554	0.5711	1.0000	1.0000	1.0000
	M2	1.0000	0.9559	0.3371	0.9286	0.8532	0.9371	0.9244	0.9626	0.9855	0.9245	0.9976	0.9606
	M3	0.8412	0.9278	0.7867	0.9679	0.9541	0.9505	0.8548	0.7604	0.9458	0.8569	0.7522	0.8490
	M4	1.0000	0.9503	0.6881	0.9285	0.8948	0.9407	1.0000	1.0000	0.7984	1.0000	1.0000	1.0000
	M5	0.9259	0.9607	0.7876	0.9909	0.8576	0.8194	0.7729	0.7648	0.9383	0.7828	0.8262	0.9286
Q3	M1	0.9000	0.9956	0.9689	0.9648	0.9957	0.9686	1.0000	0.9041	0.9775	1.0000	0.8058	0.8201
	M2	0.6811	0.9724	0.7637	0.9868	0.9445	0.7614	0.6781	0.9694	1.0000	0.6781	0.6768	0.7574
	M2	0.6811	0.9724	0.7637	0.9868	0.9445	0.7614	0.6781	0.9694	1.0000	0.6781	0.6768	0.7

	M3	0.8425	0.9824	0.9214	0.9703	0.9576	0.9183	0.9056	0.9880	0.9824	0.9070	0.9363	0.9671
	M4	0.9710	0.9962	0.7509	0.9848	0.9893	0.9680	0.8135	0.9680	0.9757	0.8187	0.9388	0.9581
	M5	0.8867	0.9380	0.9944	0.9985	0.9803	0.9315	0.8471	0.7083	1.0000	0.8509	0.9252	0.9078
Q4	M1	0.9470	0.9833	0.9223	0.9591	0.9736	0.8321	0.9482	0.9685	0.9311	0.9493	0.8405	0.8976
	M2	0.8280	0.8007	0.9572	0.9474	0.8775	1.0000	0.9269	0.9265	0.5689	0.9269	1.0000	0.8827
	M3	0.9564	0.9288	0.8218	0.9156	0.9971	0.8696	0.6397	0.5200	0.9208	0.6400	0.9258	0.7545
	M4	0.4364	0.9266	0.8257	0.9917	0.8405	0.9741	0.8724	0.6320	0.8716	0.8739	1.0000	0.7269
	M5	0.8114	0.9157	0.9199	0.9268	0.8951	0.7461	0.9245	0.9600	0.6460	0.9203	0.8691	0.8065
Q5	M1	0.9182	0.9558	0.9587	0.9972	0.9352	0.6620	0.8887	0.9726	0.9516	0.8824	0.6527	0.6769
	M2	1.0000	0.9470	0.9501	0.9990	0.9914	0.7250	0.6674	0.6904	0.9662	0.6675	0.4350	0.8404
	M3	0.7943	0.8622	0.3381	0.9047	1.0000	0.2012	1.0000	1.0000	0.9750	1.0000	0.5363	0.4302
	M4	0.5624	0.9334	0.6415	0.9932	0.8650	0.7293	0.9756	0.8231	0.8264	0.9760	0.9023	0.8168
	M5	0.7550	0.9412	0.7771	0.9047	0.9305	0.8789	0.9854	0.8361	0.8859	0.9851	0.9424	0.8545

Where: accessories (C_1), passenger and driver comfort (C_2), safety (C_3), exteriors and appearance (C_4), interiors (C_5), mileage (C_6), drive system (C_7), driving & control (C_8), storage capacity (C_9), engine assembly (C_{10}), transmission assembly (C_{11}), and spare parts (C_{12}),

Table A7: Normalized decision matrices

							Crite	ria					
Quarters	Manufacturer	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Q1	M1	0.1918	0.2055	0.2240	0.2034	0.2031	0.1609	0.2138	0.1277	0.2069	0.2110	0.1926	0.1984
	M2	0.2189	0.1841	0.2188	0.2019	0.2012	0.1937	0.2389	0.2654	0.2069	0.2358	0.1664	0.1274
	M3	0.2381	0.2015	0.1802	0.1964	0.2002	0.2141	0.2360	0.1056	0.2029	0.2330	0.1818	0.1790
	M4	0.1186	0.2069	0.2240	0.2011	0.2031	0.2355	0.0956	0.2468	0.2052	0.1067	0.2434	0.2539
	M5	0.2325	0.2019	0.1530	0.1972	0.1924	0.1959	0.2157	0.2545	0.1781	0.2135	0.2159	0.2413
Q2	M1	0.1689	0.1569	0.2778	0.2076	0.1753	0.1897	0.2197	0.1155	0.1347	0.2191	0.2185	0.2110
	M2	0.2206	0.2124	0.0937	0.1928	0.1977	0.2082	0.2031	0.2441	0.2325	0.2025	0.2180	0.2027
	M3	0.1856	0.2061	0.2186	0.2010	0.2211	0.2111	0.1878	0.1928	0.2231	0.1877	0.1644	0.1792
	M4	0.2206	0.2111	0.1912	0.1928	0.2073	0.2090	0.2197	0.2536	0.1883	0.2191	0.2185	0.2110
	M5	0.2043	0.2134	0.2188	0.2058	0.1987	0.1820	0.1698	0.1940	0.2213	0.1715	0.1805	0.1960
Q3	M1	0.2102	0.2038	0.2202	0.1967	0.2046	0.2130	0.2356	0.1992	0.1980	0.2350	0.1881	0.1859
	M2	0.1591	0.1991	0.1736	0.2012	0.1940	0.1674	0.1598	0.2136	0.2026	0.1594	0.1580	0.1717
	M3	0.1968	0.2011	0.2094	0.1978	0.1967	0.2019	0.2134	0.2177	0.1990	0.2132	0.2186	0.2193
	M4	0.2268	0.2040	0.1707	0.2008	0.2032	0.2129	0.1917	0.2133	0.1977	0.1924	0.2192	0.2172
	M5	0.2071	0.1920	0.2260	0.2036	0.2014	0.2048	0.1996	0.1561	0.2026	0.2000	0.2160	0.2058
Q4	M1	0.2380	0.2159	0.2074	0.2023	0.2124	0.1882	0.2199	0.2417	0.2364	0.2202	0.1813	0.2206
	M2	0.2081	0.1758	0.2152	0.1998	0.1914	0.2261	0.2150	0.2312	0.1444	0.2150	0.2157	0.2170
	M3	0.2404	0.2039	0.1848	0.1932	0.2175	0.1967	0.1484	0.1298	0.2338	0.1485	0.1997	0.1855
	M4	0.1097	0.2034	0.1857	0.2092	0.1834	0.2203	0.2023	0.1577	0.2213	0.2027	0.2157	0.1787
	M5	0.2039	0.2010	0.2069	0.1955	0.1953	0.1687	0.2144	0.2396	0.1640	0.2135	0.1875	0.1982
Q5	M1	0.2278	0.2060	0.2615	0.2078	0.1981	0.2071	0.1967	0.2250	0.2066	0.1956	0.1882	0.1870
	M2	0.2481	0.2041	0.2592	0.2082	0.2100	0.2268	0.1477	0.1597	0.2098	0.1480	0.1254	0.2322
	M3	0.1971	0.1858	0.0922	0.1885	0.2118	0.0630	0.2214	0.2314	0.2117	0.2217	0.1546	0.1189
	M4	0.1396	0.2012	0.1750	0.2070	0.1832	0.2282	0.2160	0.1904	0.1795	0.2164	0.2601	0.2257
	M5	0.1874	0.2029	0.2120	0.1885	0.1970	0.2750	0.2182	0.1934	0.1924	0.2184	0.2717	0.2361

Where: accessories (C_1), passenger and driver comfort (C_2), safety (C_3), exteriors and appearance (C_4), interiors (C_5), mileage (C_6), drive system (C_7), driving & control (C_8), storage capacity (C_9), engine assembly (C_{10}), transmission assembly (C_{11}), and spare parts (C_{12}),