Propagation of online consumer-perceived negativity: Quantifying the effect of supply chain underperformance on passenger car sales

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Abstract
The paper presents a text analytics framework that analyses online reviews to explore how consumer-perceived negativity corresponding to the supply chain propagates over time and how it affects car sales. In particular, the framework integrates aspect-level sentiment analysis using SentiWordNet, time-series decomposition, and bias-corrected least square dummy variable (LSDVc) – a panel data estimator. The framework facilitates the business community by providing a list of consumers' contemporary interests in the form of frequently discussed product attributes; quantifying consumer-perceived performance of supply chain (SC) partners and comparing the competitors; and a model assessing various firms' sales performance. The proposed framework demonstrated to the automobile supply chain using a review dataset received from a renowned car-portal in India. Our findings suggest that consumer-voiced negativity is maximum for dealers and minimum for manufacturing and assembly related features. *Firm age, GDP,* and *review volume* significantly influence car sales whereas the sentiments corresponding to SC partners do not. The proposed research framework can help the manufacturers in inspecting their SC partners; realising consumer-cited critical car sales influencers; and accurately predicting the sales, which in turn can help them in better production planning, supply chain management, marketing, and consumer relationships.

Keywords: Supply chain management, sentiment analysis, panel data modelling, online reviews, natural language processing

1. Introduction

With the emergence of Web 2.0, online text has become a primary source of consumers' product assessment and purchase decisions (Yang, Jun and Peterson, 2004; Chevalier and Mayzlin, 2006; Li *et al.*, 2019). Companies such as Yelp, Amazon.com, and CarWale.com provides online platform where existing consumers rate and share their feedback about the product and the service they use, in the form of star ratings and textual comments (Nakayama and Wan, 2019; Luo, *et al*., 2020). It helps them in attracting millions of potential consumers and generating revenue (Wu *et al.*, 2015).

Online reviews are considered explicit and implicit indicators of the product repute (Lee, Jeong and Lee, 2017). A survey by AC Nielsen suggests that online consumer reviews are second to word of mouth (WOM) from friends, which consumers trust the most (Wu *et al.*, 2015). A survey by eMarketer(1) (2014) reflects that 79 per cent of consumers go beyond the star rating and refer the review text before final purchase. Many organisations use the review text to mine consumers' contemporary interests and concerns while devising their marketing strategies (Cui, Lui and Guo, 2012; King, Racherla and Bush, 2014). The literature suggests that consumer reviews can be used as a proxy for overall WOM, which significantly influence firms' sales performance (King, Racherla and Bush, 2014).

The association between product sales and the review volume, average review length, review rating, and consumer sentiments has been under examination by extant researchers (Nikolay, Anindya and Panagiotis, 2011; Li, Wu and Mai, 2019; Zhang *et al.*, 2020). Researchers observe that negative opinions are relatively rare and contain more distinctive, sensible, and worthwhile information (Fiske, 1980; Lee, Jeong and Lee, 2017); therefore, negative texts are found to be more influential than positive ones (Cui, Lui and Guo, 2012). Negative tweets about the retailers result in 11 per cent decline in revenue (Sonnier, Mcalister and Rutz, 2011). SC glitches discussed in tweets have been reflected in significant loss in firms' stock market performance (Sonnier, Mcalister and Rutz, 2011). In a survey by eMarketer[(2)] (2011), it is revealed that 80 per cent of the consumers have changed their purchase decision after referring to the negative reviews. Chevalier and Mayzlin (2006) reported in their research that consumers are more sensitive towards the incremental negative review than an incremental positive one.

The literature suggests that the SC dimensions such as dealer loyalty, sales-services, and after-sales services are the major determinants of brand loyalty and ultimately product sales (Bloemer and Lemmink, 1992). While online text is rich in SC-related information, surprisingly little attention has been given to studying its economic impact in the extant marketing literature. Even though Swain and Cao (2019) have extracted the social media text-embedded sentiments pertaining to information sharing, collaboration, trust, and commitment and explored their association with firms' sales performance, there has been scant efforts to investigate how the consumer sentiments pertaining to the SC partners (e.g., suppliers, dealers) influence consumers' purchase decision. In their research, they have considered only the cross-sectional dimension of the data and the time-series dimension is missing.

In summary, this research studies how online review-embedded consumer-perceived negativity propagates over time and how it influences the economic/sales performance of cars in the Indian market. In particular, this research answers the following research questions:

RQ1. What are the supply chain-related car attributes which are of interest to consumers?
RQ2. How consumer-perceived SC-related negativity and its corresponding trend propagates over time?
RQ3. How do SC partner-related consumer perceptions influence car sales?

The current research proposes a novel, three-phase text analytics framework: ***Phase-I***, SC-related consumer perceptions are mined from the online reviews (Swain and Cao, 2019). ***Phase-II*** involves two steps, *first,* based on the proportion of negative SC partner-level SI (SCPLSI), manufacturers are compared using bar charts; *second*, authors record the proportion of negative SCPLSIs over time, and decompose it to extract the inherent trend (Lennox, *et al.*, 2020). The SI and corresponding trends are plotted using a line chart to study how consumer-perceived negativity propagates over time. In ***Phase III,*** authors use proportion of negative SCPLSIs and sales data over time and perform panel data regression to study the impact of consumer perceptions on future car sales (Xiaolin Li, Wu, and Mai 2019).

The contributions of the present research are fourfold. First, authors mine the automobile reviews to extract SC-related keywords, corresponding content and embedded consumer sentiments. Second, authors propose a method, which visually compares the manufacturers based on the consumer-perceived negativity with respect to the SC partners. Third, authors are the first to visualise the SC-related consumer-perceived negativity and corresponding trend over time. Fourth, to our best knowledge, it is the first attempt to integrate aspect level sentiment analysis with the LSDVc estimator to study the impact of SC-related consumer perceptions on car sales.

This research adds to the theory in many ways. It prepares a list of SC-related keywords and tags them with the appropriate SC partner. The list can be used as an asset by the research community in the domain. It provides a customised method that quantifies review-embedded SC partner-related consumer sentiments. It also proposes a method that integrates sentiment analysis, and an LSDVc estimator of panel data regression to quantify the effect of SC-related consumer perceptions on car sales in the case of a small number of participating firms. The proposed research can assist the manufacturers in inspecting their supply chain partners, comparing themselves among the competitors, and discovering review-embedded car sales influencers.

The remainder of the paper is arranged in the following manner. Section 2 presents the literature review followed by the theoretical background of the research in Section 3. Section 4 provides the application of the framework. Section 5 discusses major observations, implications and prospective extensions of the research. Section 6 presents the concluding remarks.

2. Literature review

To learn from e-WOM, organisations need to realise the hidden patterns from the textual data, which is beyond human cognition because of their large volume and amorphous structure. To overcome this difficulty and automate the pattern extraction from the textual data, sentiment analysis (SA) otherwise known as opinion mining is regarded as a useful instrument by the research community. Sentiment analysis helps the organisations in extracting peoples' opinions, sentiments, evaluations, appraisals, attitudes, and emotions regarding products and their attributes from the text documents (Lin, Wang and Zhou, 2016).

The extracted sentiments can be analysed with the tools such as regression, TOPSIS, PROMETHEE, path modelling, topic modelling, etc. to use them in decision-making (Chintagunta, Gopinath and Venkataraman, 2010; Duan *et al.*, 2016; Phillips *et al.*, 2017). Although many researchers deploy SA to use the e-WOM for sensible decision-making, consumer satisfaction analysis, sales prediction, product weakness findings, product/service rating, business performance evaluation (Ting, Davis and Pettit, 2014; Duan *et al.*, 2016; Li, Wu and Mai, 2019; Zhu, *et al.*, 2020; Chatterjee, *et al.*, 2020; Xu and Lee, 2020; Singh, Jenamani and Thakkar, 2020), its adoption in supply chain management (SCM) is relatively sluggish (Swain and Cao, 2019).

A handful of researchers deploy SA to improve the supply chain intelligence through social media text in general and Twitter in particular (Chae, 2015; Singh, Shukla and Mishra, 2018; Swain and Cao, 2019; Schmidt *et al.*, 2020). Chae (2015) used tweets and applied 1) descriptive analytics to report tweet statistics (percentage of tweets, retweets, and replies; most popular hashtags), user statistics (identified most visible and most active users), and URL analysis (discovering popular URLs); 2) content analytics to perform word analysis (representation of term frequency of popular words), cluster tweets into five topics (corporate social responsibility, risk, logistics, manufacturing, and information technology), analyse hashtags (representation of most popular hashtags), and classify the clustered tweets into neutral, weak positive/negative, and strong positive/negative classes; and 3) network analytics for topological analysis, centrality analysis (the measurement of nodes' connectedness with other nodes), and community analysis (graph density computation). They also visualise the outputs of sentiment analysis through the line and bar charts.

Swain and Cao (2019) extracted supply chain-related social media text in the form of forums, blogs, and micro-blogs from which the information related to the frequency, volume and user sentiments is mined. They clustered the textual data into four clusters, namely information sharing, collaboration, trust, and commitment and examined how sentiments corresponded to the impact on supply chain performance. Singh, Shukla and Mishra (2018) collected beef supply chain-related tweets and analysed them using content analysis (word and hashtag analysis, sentiment analysis, and hierarchical clustering). In word and hashtag analysis, most frequent keywords, hashtags, and Twitter handles are identified. In sentiment analysis, tweets are classified into positive and negative classes. Further positive and negative tweets are analysed with association rule mining and cluster analysis to identify the most closely associated words with beef or steak. They also discover the most critical issues in the beef supply chain and propose mitigation strategies.

Su & Chen (2018) developed a text analytics framework that uses tweets to assess supplier status to improve the supplier selection process. Kinra *et al.* (2020), deploying a design science approach, proposed the methods for logistics performance assessment in global SCs. Using word frequency analysis, they discovered logistics-related keywords. Further, using the Naive Bayes classifier, they classified the corresponding text into two classes bearing positive and negative sentiments. They have also assessed the performance of global SCs. Their performance measurement is limited to the quantified value of consumer sentiments; they did not use any scientific tool for the same.

Schmidt *et al.* (2020) collected SC glitch-related data and studied if it is reflected in discussions on Twitter and whether it is reflected in tweet volume, and consumer sentiments. They also studied whether the glitch discussed in social media impacts firms' stock market performance. Chu, Park and Kremer (2020) have proposed an integrated text analytics framework that analyses the research papers and the news articles to categorise and manage global supply chain management risks. The key research papers that utilise text analytics to enhance SC intelligence are critically compared in Table 1.

The literature review on text analytics-based studies in supply chain management and subsequent gap analysis reveals the need for: a) devising methodologies to extract review-embedded consumer sentiments corresponding to various supply chain partners such as suppliers, manufacturer, service centres, etc.; b) exploring both cross-sectional and time-series dimensions of such reviews; and c) studying how consumer perception corresponding to the supply chain partners propagates over time and how it influences sales.

<Please insert Table 1 here >

3. Proposed framework

The proposed framework integrates aspect-level sentiment analysis with time series decomposition along with panel data regression to understand how text-embedded supply chain-related negativity propagates over time and how it impacts firms' sales. In particular, it a) searches SC-related attributes from online reviews, discovers corresponding content, and quantifies the inherent sentiments; b) measures the consumer-perceived negativity to evaluate the relative performance of SC partners; c) learns the patterns in the propagation of perceived negativity over time; and d) examines if the review-embedded sentiments corresponding to the SC partners impact firms' sales. Figure 1 can be referred to for a detailed description of the framework. Since this research aims to study how consumer-perceived negativity is propagated over time and how it influences car sales, we use a) an aspect-level sentiment analysis to quantify the review-embedded sentiments; b) time series decomposition to segregate the trend in negativity from the proportion of aspect-level negative sentiments; c) an LSDVc estimator of panel data regression to capture both cross-sectional and time-series dimensions of the review data while quantifying its impact on sales. For the proposed integration of sentiment analysis and panel data regression, we refer to a research document by Xiaolin Li, Wu, and Mai (2019).

3.1 *Phase I:* Sentiment extraction

3.1.1 Attribute extraction

Referring to Nikolay, Anindya, and Panagiotis (2011), and Singh, Jenamani, and Thakkar (2020), we propose to use a two-step data-driven approach for attribute extraction: first, compile the review text in a single document, and process it with an automatic keyword extraction algorithm to extract frequent noun phrases; second, with the help of domain experts, scan the extracted phrases to retain the exact SC-related attributes. Authors also propose to clean the text before compiling it for attribute extraction.

<Please insert Figure 1 here >

3.1.2 Attribute tagging with the supply chain partners

In this step, with the help of domain experts, authors need to select each individual attribute one by one and assign them to appropriate SC partners.

3.1.3 Attribute level sentiment extraction

Referring to Singh, Jenamani, and Thakkar (2020), our proposal for attribute-level sentiment extraction from the review is as follows:

i. Select the reviews one by one, split them into sentences, and record the number of attributes within them.

ii. Keep sentences with only one attribute as it is and split the sentence with more than one attribute into sub-sentences with only one attribute and corresponding text in it. Consider each sub-sentence as a individual sentence.

iii. For each individual sentence, quantify the text-embedded sentiments using sentiment lexicons, and assign the score to the attribute therein.

iv. Repeat the aforementioned steps for all the reviews. This will result in an attribute-level SI dataset consisting of the rows equal to the number of reviews and the columns equal to the SC attributes.

3.1.4 SC partner-level SI computation

Our proposal to compute the SC partner-level SI is as follows:

i. Select an SC partner, and their underlying attributes, and segregate corresponding columns from the attribute-level SI dataset.

ii. Split the dataset obtained in the previous step into two sets (positive and negative SIs separately).

iii. For each dataset, for each review, summate the SIs in all the columns and obtain SC partner-level positive and negative SIs.

iv. Repeat the aforementioned steps for all the SC partners. This will result in two datasets (positive and negative) comprising the rows equal to the number of reviews and the columns equal to the number of SC partners.

3.2 Phase II: Analysis of propagation of negativity

3.2.1 Comparing the manufacturers

Our proposal of comparing the manufacturers using the percentage negative SI is as follows:

i. Split the datasets obtained in the previous sub-section manufacturer-wise.

ii. For each manufacturer, for each SC partner, separately for positive and negative SIs, summate the SC partner-level SI (SCPLSI) for all the reviews, and compute the overall SI.

iii. For each manufacturer, for each SC partner, compute the percentage negative SCPLSI by dividing the modulus of overall negative SCPLSI by the summation of the modulus of overall positive and negative SCPLSIs, and multiplying it by 100.

iv. Using the percentage negative SCPLSI, prepare the bar chart and visually compare the manufacturers based on their SC partners' consumer-perceived performance.

3.2.2 Studying the propagation of negativity

Our proposal to study how negativity propagates over time is as follows:

i. Split the datasets obtained in the last step of Section 3.1 manufacturer-wise.
ii. For each manufacturer, split the datasets obtained in the previous step into a number of time intervals.
iii. For each time interval under each manufacturer, separately for positive and negative SIs, compute the time interval-wise SCPLSI.
iv. For each time interval under each manufacturer, compute the proportion of negative SCPLSIs on a time interval basis by dividing the modulus of time interval-wise negative SCPLSIs by the summation of modulus of time interval-wise positive and negative SCPLSIs.
v. For each SC partner and each manufacturer, compile the time interval-wise proportion of negative SCPLSIs in a time series format, and decompose it to extract the trend from it.
vi. Prepare the line charts of the time interval-wise proportion of negative SCPLSIs and their corresponding trend to visually analyse how negativity propagates over time.

3.3 Phase III: Econometric analysis

In this phase, referring to Xiaolin Li, Wu, and Mai (2019), authors examine the impact of review-embedded consumer sentiments on firms' sales performance. Similar to the SI, authors need to aggregate the sales data on the time interval basis. Including more than one manufacturer and collecting corresponding data over time, authors propose to investigate the present research issue through panel data modelling. From the literature, it is evident that the reviews influence product sales with a time lag (Nikolay, Anindya and Panagiotis, 2011). Therefore, the authors propose to compile the review-related information with a time lag to the sales. Next, the authors propose to study the data characteristic and select the most suitable panel data estimator for the analysis.

4. Application of the proposed framework and results

This section demonstrates the proposed framework with an example in the automobile domain. Surfing various automobile websites, reading documents, and consulting with the domain experts, authors discover that volatility in demand/sales is one of the major issues in the automobile sector[1]. Mostly organisations rely on the market survey and ignore the information embedded in more recently evolved assets named "online reviews", which has been found to be very important in predicting demand (Lau, Zhang and Xu, 2018; Li, Wu and Mai, 2019). Therefore, in present research, authors try to address the demand forecasting issue of the automobile industry using online reviews. There are a few studies on understanding the influence of review-embedded information on sales (Fan, Che, and Chen, 2017; and Zhang *et al*., 2019). However, to the best of our knowledge, none of them have explored the influence of SC partner-level information on sales. Building upon the literature and to fill in the research gap, the current work examines how consumer perceptions corresponding to various supply chain partners influence car sales.

The data used in present research comprises two components. First, one contains 36,558 automobile reviews corresponding to April 2006 to May 2016 from CarWale[(3)], a renowned Indian car portal. Each review contains the pros, cons, and detailed consumer comments. The second component is the Society of Indian Automobile Manufacturers' (SIAM[(4)]) report that contains monthly domestic sales and export data with respect to the passenger cars available in the Indian market. It consists of the sales figures corresponding to the micro, mini, compact, super compact, mid-size, executive, premium, and luxury segments from April 2008 to April 2016.

[1] https://www.inspirage.com/2016/07/supply-chain-challenges-automotive-industry/

4.1 Phase I: Sentiment extraction

4.1.1 Customised supply chain model for the Indian automobile industry

This sub-section reports the supply chain (SC) model customised for the Indian automobile industry. To conceptualise the car SC in India, the authors refer to Julka *et al.* (2014) and conduct an interview of two industry experts (first, the territory service manager, and second, the deputy manager of a car manufacturer). Based on their inputs, the authors customise the SC model for Indian car manufacturers as presented in Figure 2. The supply chain consists of six partners (suppliers, manufacturer, dealers, authorised service centres, and consumers). Suppliers are categorised into three categories: Tier 1, Tier 2, and Tier 3[(5)]. Tier 1 suppliers provide parts/systems directly to the manufacturers. Tier 2 suppliers do not directly supply the parts to the manufacturer rather they supply to the Tier 1 suppliers. Tier 3 suppliers provide raw or close to raw material either directly to the manufacturer or Tier 1 and Tier 2 suppliers. The manufacturers are engaged in the manufacturing, assembly, sales and marketing of cars and spare parts (Julka *et al.*, 2014). Dealers are responsible for a variety of tasks such as selling the product and spare parts, local-level marketing, service, maintenance, insurance etc. Distributers supply car accessories, spare parts, and components. Authorised service centres execute service and maintenance.

<Please insert Figure 2 here >

4.1.2 Data pre-processing

Using natural language tool kit (NLTK), authors code the rules in Python and clean the review text by eliminating HTML tags, markups, numbers, whitespaces, punctuations, and stop words. Next, authors eliminate duplicate reviews, sentences, and words. The reviews that appear more than once in the dataset, and sentences in reviews, are treated as duplicates. Two repetitive consecutive words in a sentence are assumed to be duplicates. For spelling correction of words such as Verrrrrrrrrryyyyyyyyyyy, Goooooooooooood, authors code the rules in Python, which fixes the limit of repetition of alphabet (for example the character "O" cannot consecutively appear more than twice in a word). Such rules correct the spellings to a certain extent.

4.1.3 Attribute extraction

Referring to Singh, Jenamani and Thakkar (2020) and the steps proposed in Section 3.1, authors extract the attributes corresponding to the automobile SC partners and report them in Table A1 (Appendix available at https://drive.google.com/file/d/1eXVt9xJ91QX4px4NJZkc4W-hnLzqd3Vy/view). For attribute extraction, authors use the Rapid Automatic Keywords Extraction (RAKE) algorithm as it is relatively fast, easy to implement, and has low computational complexity. Hence, it is frequently used by researchers (Rose *et al.*, 2012; Hasan, & Ng, 2014; Thushara, Krishnapriya, & Nair, 2017; Gagliardi, & Artese, 2020). Using the RAKE, authors extract 10,000 frequent phrases as potential car attributes. The phrases are further inspected by three mechanical engineering graduates to shortlist the exact SC-related attributes. The shortlisted attributes are also validated and modified by two working professionals. For more details, readers can refer to Singh, Jenamani and Thakkar (2020). While manual scanning, authors found many misspelt words such as *mileg, milege, milleage*, *mylage*, which are replaced with the correct one through customised Python codes.

4.1.4 Attribute tagging with the supply chain partners

Referring to Singh, Jenamani and Thakkar (2020), one of the authors took the list of extracted attributes and the SC partners and consulted two mechanical engineering graduates for tagging the attributes to the appropriate SC partners. They picked attributes one by one and discussed their connectivity to the SC partners. Authors assigned a particular attribute to a SC partner if at least two or three agreed. The list of SC partners and corresponding attributes was further amended by one research scholar who has previously worked as a manager in an automobile manufacturing company in India. The output is reported in Table A1 (see Appendix).

4.1.5 Sentiment extraction and SC partner-level SI computation

Referring to Singh, Jenamani and Thakkar, (2020), a mid-sized car segment is compared in the present analysis. For segmentation, the SIAM report is referred to. Table III in Singh, Jenamani and Thakkar (2020) reports selected mid-sized car manufacturers and corresponding reviews in the dataset. Authors extract a total of 27,743 reviews corresponding to the manufacturers tabulated in the same table. Following the steps mentioned in Section 3.1, using the *sent_tokenize* module proposed by Bird, Klein and Loper (2009), authors split the reviews into sentences. The sentences containing more than one attribute were split into sub-sentences as proposed in Section 3.1. To understand how sentences are split into sub-sentences, let us consider the following example:

"The car has good interiors but bad stability, and driving control. Its mileage is wonderful and the maintenance is best in class". The review consists of the attributes ***"interiors", "stability", "suspension", "driving control" "mileage" and "maintenance".*** Referring to the first sentence one may note that the word ***"good"*** contains the opinion about the attribute ***"interiors"*** and ***"bad"*** about ***"stability" and "driving control".*** The trickiest task here is to automatically connect the attributes to the corresponding opinion-bearing words. The heuristic used here is a rule-based approach that analyses the pattern of the arrangement of attributes and the opinion-bearing words in the sentences and accordingly breaks the sentences. From the reviews, it is observed that the attributes and the opinion-bearing words are not randomly scattered in the sentences; rather, most of them follow a certain structure. Based on our observations on some reviews, authors define two rules to break the sentence into sub-sentences.

Rule 1: The opinion-bearing words appear before the attributes: Using Python codes, authors read the sentence; if the first opinion-bearing word precedes the first attribute, and two or more than two attributes co-exist, authors insert the opinion-bearing word just before them, in between each pair of attributes and break it after each attribute. Hence, the first sentence is broken into three sentences as ***"The car has good interiors." "But bad stability." and "Bad driving control."***

Rule 2: Attributes appear before the opinion-bearing words: If the first attribute precedes the first opinion-bearing word and two or more than two attributes co-exist, authors insert the opinion-bearing word just after them, in between each pair of attributes and break it after opinion-bearing words. The second example sentence is broken as ***"Its mileage is wonderful." "and the maintenance is best."***

As a result, reviews can be split into sentences containing one attribute and corresponding opinion phrase(s). Next, the sentences are split into words through the *word_tokenize* module of the *NLTK package.* Using the SentiWordNet (Baccianella, Esuli and Sebastiani, 2010) dictionary, the sentiments corresponding to the words in a sentence are quantified and assigned to the attribute therein. Based on the presence of sentiment shifters proposed by Yu *et al.* (2016), the sentiment scores are revised using the shifter effect values computed in the same research. As a result, authors record the attribute sentiment pairs for all the attributes present in the review. The process is repeated for all the reviews in the dataset. Hence, authors obtain a dataset comprised of rows equals to the number of reviews and the columns equal to the number of attributes.

4.1.6 SC partner-level SI computation

From the attribute-aspect table, authors note that in the case of supplier, distributor, dealer, and authorised service centre, many attributes are common. This may lead to the problem of multicollinearity in regression analysis. To deal with this issue, authors updated Table A1 by a) eliminating common attributes between suppliers and distributors from the distributor and keeping them with the suppliers, b) similarly, common attributes between the supplier and dealer were dropped from the dealer and kept with the supplier, c) common attributes between suppliers and authorised service centre were dropped from the authorised service centre. In the updated table the distributor does not have even a single attribute unique to it, therefore it was dropped from further analysis. Next, authors note the dealer and the authorised service centre still have some common attributes. Authors further updated the table by preparing a list of attributes common to the dealer and the service centre and unique to them. The updated list can be found in Table A1 (Appendix). Here, authors note that there is no unique attribute with the service centre. Hence, authors select four dimensions, which are attributes under suppliers, manufacturing and assembly, unique to dealers and common to the dealer and service centre, for further analysis. Finally, selecting aforementioned four dimensions and the attributes corresponding to them (Table A1), and following the steps mentioned in Section 3.1 (SC partner-level SI computation), authors compute positive and negative SC partner-level sentiment SIs.

4.2 Phase II: Analysis of propagation of negativity

For further analysis, authors select eight manufacturers with a condition that it must have both reviews and sales data for at least 16 quarters.

4.2.1 Comparing the manufacturers

Referring to the steps mentioned in Section 3.2, authors compute the manufacturer-wise percentage of overall negative SCPLSIs and develop a bar chart as reported in Figure 3 to visually compare the manufacturers. To compute the overall percentage of negative SCPLSIs, the authors propose a two-step approach:

Step 1: For each manufacturer and SC partner, compute the overall SC partner-level sentiment index (SCPSI) as:

$$OvSCPLPSI_{ij} = \sum_{k=1}^{l} \mathrm{Re}\, vSCPLPSI_{ijk}$$

(1)

$$OvSCPLNSI_{ij} = \sum_{k=1}^{l} \mathrm{Re}\, vSCPLNSI_{ijk}$$

(2)

Where, $OvSCPLPSI_{ij}$ and $OvSCPLNSI_{ij}$ represent overall positive and negative SCPLSIs for i^{th} manufacturer j^{th} SC partner; l represents the total number of reviews represented; $\mathrm{Re}\,vSCPLPSI_{ijk}$ and $\mathrm{Re}\,vSCPLNSI_{ijk}$ represent the review-wise SCPLSI.

Step 2: For each manufacturer and SC partner, compute the percentage of overall negative SCPLSIs as:

$$\mathrm{Pr}\,OvSCPLNSI_{ij} = 100 * \frac{|OvSCPLNSI_{ij}|}{|OvSCPLPSI_{ij}| + |OvSCPLNSI_{ij}|} \tag{3}$$

<Please insert Figure 3 here >

4.2.2 Studying the propagation of negativity

Referring to the steps mentioned in Section 3.2, we compute the proportion of quarterly SCPLSIs for each SC partner and manufacturer. This is a two-step approach:

Step 1: For each quarter under each manufacturer, and each SC partner, compute the quarterly SCPLSI as:

$$QSCPLPSI_{ijt} = \sum_{k=1}^{m} \mathrm{Re}\,vSCPLPSI_{ijtk}$$

(4)

$$QSCPLNSI_{ijt} = \sum_{k=1}^{m} \mathrm{Re}\,vSCPLNSI_{ijtk}$$

(5)

Where $QSCPLPSI_{ijt}$ and $QSCPLNSI_{ijt}$ represent quarterly SC partner-level positive and negative sentiment indices for i^{th} manufacturer, j^{th} SC partner, and t^{th} quarter; m represents the total number of reviews representing i^{th} manufacturer in t^{th} quarter.

Step 2: For each quarter under each manufacturer’s SC partner, compute the proportion of negative SCPLSIs on a quarterly basis as:

$$PQSCPLNS_{ijt} = \frac{|QSCPLNSI_{ijt}|}{|QSCPLPSI_{ijt}| + |QSCPLNSI_{ijt}|} \tag{6}$$

Arranging the obtained proportion of the negative SCPLSI data in a time series format, we tested the stationarity of the data using the augmented Dickey–Fuller test (ADF) test (see Table 2). In present research, we have gone for a 99 per cent confidence level. Therefore, the time series with p-value less than or equal to 0.01 is considered to be stationary otherwise non-stationary (Burdekin, and Tao, 2021). From Table 2, it is apparent that in some cases the data is stationary and in others, it is not. This provokes the need to analyse the data in detail to see if it needs further attention.

<Please insert Table 2 here >

To investigate the data in more detail, we visualise the negativity and the trend in it using a line chart (see Figure 4). Here, one may note that an organisation may be interested in identifying its current consumer-perceived negativity, which may be an indicator to compare current and past performance. If the trend in perceived negativity (orange line in Figure 2) corresponding to an SC partner is going up as compared to its past data points, this may indicate that the consumers are not happy with the features associated with the specified SC partner and the system needs immediate attention. From Figure 4, one may note that the trend in perceived negativity is going up with respect to the supplier of Manufacturer M3. This indicates immediate attention is needed for this supplier. To extract the trend from the data, we decompose the data using the *seasonal_decompose* module coded in Python. Figure 4 only reports charts corresponding to the manufacturer M3 because of the space limitation in the manuscript. Details for this can be found in Figure A1 (see Appendix).

<Please insert Figure 4 here >

4.3 Phase III: The econometric analysis

4.3.1 Data preparation

To see if SC-related consumer perception influences the product sales (referring to Section 3.3) we compile the sales and SI data corresponding to the eight manufacturers. Next, referring to the literature and based on our intuition, authors prepare a list of controls: review *rating* (Li, Wu and Mai, 2019), *product variety* (Brynjolfsson, Hu and Smith, 2003), *review volume* (Li, Wu and Mai, 2019), *average review length* (Nikolay, Anindya and Panagiotis, 2011), *service centre frequency, search volume* (Nikolay, Anindya and Panagiotis, 2011), *product price* (Nikolay, Anindya and Panagiotis, 2011), *firm age* (Li, Wu and Mai, 2019) and *per capita gross domestic product (GDP)*. But authors could collect the data only for *product variety, review volume, average review length, search volume, firm age* and *GDP*.

4.3.2 Empirical model and analysis

In sales prediction studies, where both cross-sectional and time series data are available, researchers frequently use panel data regression. Researchers such as Nikolay, Anindya, and Panagiotis (2011), Li, Wu and Mai (2019) and Xiaolin Li, Wu, and Mai (2019) have integrated text analytics with panel data regression to discover product sales influencers from online text. In the same line, referring to Li, Wu and Mai (2019), authors use the dynamic panel data (DPD) model as presented in Equation 7:

$$y_{it} = \alpha y_{i,t-1} + \beta x_{it} + \gamma c_{it} + \mu_i + \varsigma_{it} \tag{7}$$

Where y_{it} , x_{it}, c_{it} represent the sales, review related variables, and controls for i^{th} manufacturer and t^{th} quarter respectively; u_i represents the individual specific effect; ς_{it} represents the error term; and $\beta, \text{ and } \gamma$ represent the estimates. The inclusion of the lagged dependent variable in the equation allows the partial adjustment mechanism that handles the endogeneity arising from the fact that review-embedded consumer sentiments are influenced by products' past sales. The parameter α indicates the persistence.

Researchers (e.g. Arellano and Bond, 1991; Blundell and Bond, 1998) frequently use estimators in DPD modelling, which become biased in the case of a small number of individuals (N) (Perić, 2019). In small N-cases, the bias-corrected least squares dummy variables (LSDVc) estimator proposed by Kiviet (1995) and upgraded by Bruno (2005a, 2005b) for the unbalanced case is widely used. Perić (2019) in his Monte Carlo experimentation proved that the LSDVc performs better in terms of the bias when compared to Arellano-Bond (1991) and Blundell-Bond (1998), estimators in case of ten individuals and 30 time periods. Since our setup (with eight manufacturers and 32 time periods) is similar to them, authors use the LSDVc.

The LSDVc estimator assumes strict exogeneity. To test it, authors perform the strict exogeneity test proposed by Wooldridge (2002). Results are reported in Table 3. The variable search volume is endogenous, therefore dropped from further analysis.

<Please insert Table 3 here >

The variables used in the final model are defined in Table 4. It also reports the descriptive statistics for SC partner-level sentiment.

<Please insert Table 4 here >

Next, authors test the multicollinearity (see Table 5). No significant multicollinearity is found in the model. Authors also test for autocorrelation and heteroscedasticity. Since, the *p-value* in the Wooldridge test (F (1, 7) = 9.157, p = 0.0192) for autocorrelation is greater than the threshold (0.01) value for 99 per cent confidence interval, no autocorrelation is discovered in the model (El-Massah, Bacheer & Al Sayed, 2019). But if the *p-value* for the heteroscedasticity test (χ^2 (17) = 63.94, p = 0.00) is less than 0.01, it indicates the problem of heteroscedasticity (El-Massah, Bacheer, & Al Sayed, 2019). Present research uses bootstrapping to overcome this concern.

<Please insert Table 5 here >

Referring to Bruno (2005b), the following Stata command is used:

xtlsdvc Dependent_Variable Independent_Variables Time_Dummies, initial(estimator) bias (#) vcov(#)

Here, the initial (estimator) requires Arellano and Bond (AB), Blundell and Bond (BB) or Anderson and Hsiao (AH) estimators to initialise the bias correction. In present experimental settings, Baltagi (2005) suggests the AB estimator. To cross-verify the superiority of the estimator, authors deploy all of them one by one and report the results in Table A2 (Appendix). It also advocates the AB estimator as it has the least error components. Option *bias (#)* needs the input for the order of the bias correction. The available options are the order of O(1/T), O(1/NT), and O(1/NT^2). Authors test the suitability of these options; the results advocate the correction of order O(1/NT) (see Table A2 in Appendix). The vcov(#) represents the bootstrap to compute the variance-covariance matrix. The present research uses bootstrapping with 100 repetitions.

Finally, using the AB estimator for bias correction initialisation and correction of order O(1/NT), authors analyse the data and check if the consumer perceptions corresponding to the SC partners influence the car sales. Table 6 reports the regression results. Model 1 reports the results with actual variables, whereas Model 2 reports the same with the Z-transformed [2] variables. Referring to the results reported in Model 1, one may note that the coefficients of variables are not comparable and vary a lot. Z-transformation overcomes this issue.

From the table, one may note that using Z-transformed variables does not alter the confidence level (refer to the P-values in parentheses), and brings the coefficients to the same scale. Authors also test for overidentification and the joint significance of the textual information along with the controls. Sargan test results (χ^2(182) = 162.5721, p=0.8465) alleviate the concern of overidentification and the Wald test (χ^2(7) = 11100.24, p=0.0000) confirms the joint significance of the textual information.

<Please insert Table 6 here >

5. Discussion

[2] The Z-transformation standardizes the data with zero mean and one standard deviation

The present research aims to quantify the consumer perceptions on SC partners, compare them based on their relative performance, and study how SC-related perceptions influence car sales. Figure 3 compares the consumer-perceived performance of the SC partners. From the figure, one may note that consumer-voiced negativity is at a maximum with the unique features of dealers whereas it is at a minimum with the manufacturing and assembly-related features regardless of the manufacturer. It indicates that i) the manufacturers' internal systems associated with manufacturing and assembly operate well in the case of all the manufacturers selected in the present research. The plausible reason behind it may be automobile manufacturers invest the majority of their resources in the latest technologies and have well-managed core activities such as manufacturing and assembly; ii) the consumer-perceived negativity is at a maximum with respect to the features associated with the dealers. The plausible reason behind it may be dealers are not under direct control of manufacturers; hence, not as organised as manufacturers are.

From Figure 4, it is apparent that the trend goes up for the features connected to suppliers, manufacturing and assembly, commonly to the service centres and dealers. It indicates that consumer-perceived negativity has an upward trend, which is not a positive indication for Manufacturer M3. The manufacturers need to retrospect their system with respect to these SC partners and fix the issues to avoid probable losses in their brand image and the market value.

Table 6 reports the regression results. From the table, it can be noted that the lag of sales significantly impacts the economic performance of the SC, which validates the model to be dynamic. Factors such as the ***firm's age, GDP*** and ***review volume*** significantly influence the sales. The sign of the coefficient indicates that the firm's age negatively influences sales; this implies that the sales of cars decrease as the manufacturing firm grows older. The plausible explanations are as follows: a) new manufacturers usually come with relatively attractive appearance, low cost and vibrant marketing tactics (i.e. free service, warranty, price discount, exchange offers, etc.); b) the estimator used in the present research uses the Arellano-Bond estimator that works on the first differencing for estimate computation (which means it works on the change in the variable value with respect to its previous value); c) in the Indian market, for the years 2007 to 2016, the percentage change in the vehicle sales has dropped several times. Our finding differs from Li, Wu and Mai (2019), maybe because authors study the different category of products, which may exhibit different sales patterns.

The GDP influences the sales positively, which is in line with Sivak (2013). The ***review volume*** also positively influences the sales. It may be because the ***review volume*** is considered as the symbol of product popularity (Li *et al.*, 2016) and quality (Hellofs and Jacobson, 1999). The findings are consistent with Nikolay, Anindya and Panagiotis (2011); Li *et al.* (2016); Chong *et al.* (2017) and Li, Wu and Mai (2019). The findings are also consistent with ***"classical models of risk aversion",*** which indicates that if the consumers have the option of two products with similar features, they prefer the highly reviewed product (Nikolay, Anindya and Panagiotis, 2011). Nikolay, Anindya and Panagiotis (2011) claim that review length has a positive influence on digital camera sales. Our findings differ from them, indicating that review length does not significantly impact sales in the case of passenger cars. The possible reason may be that the products considered and the dimensions studied in our studies are different. The most important observation from this research is that the consumer perceptions corresponding to the SC partners have no significant effect on the economic performance of automobile SCs. This indicates that while purchasing cars, consumers do not pay much attention to the SC partners such as the dealer and service providers, and peers' experiences with them.

5.1 Theoretical contributions

The contributions of the present research to the existing knowledge are fivefold: *First,* it proposes a semi-automatic approach for extracting car supply chain-related features from automobile reviews. Using feature extraction methods, it extracts the probable supply chain attributes, which are manually scanned by the domain experts to create a shortlist of exact car features. It further assigns the shortlisted attributes to the corresponding supply chain partners with the help of the expert practitioners. The systemisation of output of feature extraction algorithms and the inputs from the domain experts results in a list of SC partners and corresponding features. The list is considered an asset for researchers and the business community as it saves their time in searching the features from the text. *Second,* it provides a customised method that automatically quantifies the review-embedded consumer perceptions corresponding to various SC features extracted in previous steps. It searches the SC-related features and corresponding content from the reviews and using a rule-based approach it quantifies the inherent sentiments. The present research not only determines the polarity of the review text but also captures the strengths of the expressed sentiments. To understand the strength, let us take the example of *"good"* and *"best"* where both are positive words but the intensity of their sentiment scores are different: the intensity of the positivity of the word *"best"* is higher than *"good"*. SentiWordNet, the dictionary used in present research captures it, the score of *"best is = + 0.75"* and the same for *"good is = + 0.625"*. The proposed sentiment quantification method is generic and can be applied by the researchers/firms in new domains with little customisation. *Third,* it proposes a technique that uses the quantified perceptions to visually compare the manufacturers and the SC partners. It not only helps the manufactures in comparing their consumer-perceived performance as compared to their competitors but also in evaluating their SC partners. *Fourth,* it develops a method that extracts SC-related consumer-perceived negativity, corresponding to the trend from the review text and studies how it propagates over time. It can be used as an early warning system; in case the SC partner is discovered to have uncontrolled perceived negativity. *Fifth,* it is the first text analytics-based sales performance evaluation study that studies how SC-related consumer perceptions influence car sales.

5.2 Implications for practice

The proposed framework can assist the manufacturers in decision-making in many ways: *First,* they can use it to inspect their SC partners using the bar chart and the line chart reported in Figures 3 and 4. The bar charts not only help them in identifying the consumer-perceived performance of their SC partners but also in comparing them with the partners of their competitors. *Second,* they can use the text analytics enabled line charts as a visual inspection of propagation of negativity over time and discover if their SC partners need immediate attention (in case an upward trend is recorded in the line charts, see Figure 4). *Third,* they can use the framework in devising the supply chain (SC) improvement strategies to emphasise weak components. For instance, let us consider the example presented in this research; when the consumer-perceived performance of the dealer is worst, manufacturers may divert their resources to emphasise strategies to improve their performance. Fourth, they can use the proposed econometric analysis to discover the consumer-cited critical car sales influencers. It can assist the manufacturers with more effective sales forecasting, thereby enabling them with improved production planning, efficient supply chain management and consumer relationships (Ivert *et al.*, 2014; Mascle and Gosse, 2014). Here it is noted that car sales decrease with the increase in the firm's age. The reason behind this may be that the existing consumers get attracted with the design or the aggressive marketing strategies of the new manufacturers. Authors recommend the manufacturers adopt dynamic marketing strategies and product design. They can consider launching new models frequently to attract more and more consumers. Present research discovers that the review volume positively influences car sales; this can help marketing people in encouraging consumers to share their experiences online. They can have various discussion forums and, with some dynamic tactics, they can keep the discussion alive all the time. The SC partners such as suppliers, dealers and service providers can use the proposed framework to scrutinise their consumer-perceived performance and compare it with their competitors using the bar chart and the line chart in Figures 3 and 4. They can also search the potential consumers (manufacturers), in case they discover their competitors are underperforming. They can also use it in setting the benchmarks among their competitors and learning from them, if they feel some of their competitors perform better than them.

5.3 Limitations and future research directions

The limitations and the future research directions of the present research are as follows: a) reviews in the present study come only from CarWale; hence, research may be subject to single-source bias, and self-selection bias (Podsakoff and Organ, 1986; Rozin and Royzman, 2001). In future, researchers can randomly select multiple sources (i.e., CarDekho, AutoCarIndia etc.) and collect online reviews from each. This will eliminate the single-source and self-selection bias; b) To improve the applicability of the proposed framework, the attribute extraction and sentiment quantification algorithms used in the present research need to be improved in terms of the Precession, Recall, and F-measure in future. Moreover, authors use only the SentiWordNet dictionary for sentiment quantification. Future researchers may compare the effectiveness of this dictionary with other options such as SenticNet-3, SentiStrength, OpinionFinder (Thelwall, Buckley and Paltoglou, 2012; Cambria, Olsher and Rajagopal, 2014), etc. and use the best one; c) human errors in attribute extraction and attribute-aspect tagging are possible and there is always room for improvement. To reduce human errors, a number of experts involved in shortlisting attributes and tagging them with the supply chain partners can be increased; d) future researchers may also apply the proposed framework in other domains such as the hotel industry or home appliances as well.

6. Conclusion

The present research proposes an integrated text analytics framework that uses aspect-level sentiment analysis to mine the car reviews to extract the supply chain related consumer perceptions. Our main research questions included: ‘How is consumer-perceived SC-related negativity, and its corresponding trend, propagated over time? ‘How do SC partner-related consumer perceptions influence car sales? The proposed research is unique as it offers the visualisation of SC-related consumer perceptions through bar and line charts with which the manufacturing and operations community is acquainted with. Moreover, it is the first research of its kind that considers both time series as well as cross-sectional dimensions of the SC-related consumer sentiments extracted from consumer reviews, and deploys panel data regression to study its influence on car sales. The results obtained from the example included suggest that consumer perception is the best with the manufacturing and assembly, whereas it tends to be worst with dealers; the firm's age negatively influences car sales indicating that car sales decrease with the age of a particular manufacturing firm; GDP positively influences sales, which indicates that people with increased income invest in luxuries like cars; the review volume positively influences the sales, which indicates that a higher number of online reviews give a positive indication to potential consumers which increases the sales.

References

Abrahams, A. S., Jiao, J., Wang, G. A., & Fan, W. (2012) 'Vehicle defect discovery from social media', Decision Support Systems, 54(1), 87–97. doi: 10.1016/j.dss.2012.04.005.

Abrahams, A. S. et al. (2015) 'An Integrated Text Analytic Framework for Product Defect Discovery', Production and Operations Management. Wiley/Blackwell (10.1111), 24(6), 975–990. doi: 10.1111/poms.12303.

Archak, N., Ghose, A. and Ipeirotis, P. G. (2011) 'Deriving the Pricing Power of Product Features by Mining Consumer Reviews', Management Science, 57(8), 1485–1509. doi: 10.1287/mnsc.1110.1370.

Arellano, M. and Bond, S. (1991) 'Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations', The Review of Economic Studies, 58(2), 277. doi: 10.2307/2297968.

Baccianella, S., Esuli, A. and Sebastiani, F. (2010) 'SENTIWORDNET 3.0: An enhanced lexical resource for sentiment analysis and opinion mining', Proceedings of the 7th International Conference on Language Resources and Evaluation, LREC 2010, 2200–2204. Available at: https://esuli.it/publications/LREC2010.pdf (Accessed: 20 November 2018).

Baltagi, B. (2005) Econometric analysis of panel data, Vasa.

Bird, S., Klein, E. and Loper, E. (2009) 'Natural Language Processing with Python', Journal of Endodontics. doi: 10.1097/00004770-200204000-00018.

Bloemer, J. M. M. and Lemmink, J. G. A. M. (1992) 'The importance of customer satisfaction in explaining brand and dealer loyalty', Journal of Marketing Management, 8(4), 351–364. doi: 10.1080/0267257X.1992.9964204.

Blundell, R. and Bond, S. (1998) 'Initial conditions and moment restrictions in dynamic panel data models', Journal of Econometrics, 87(1), 115–143. doi: 10.1016/S0304-4076(98)00009-8.

Bruno, G. S. F. (2005a) 'Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models', Economics Letters, 87(3), 361–366. doi: 10.1016/j.econlet.2005.01.005.

Bruno, G. S. F. (2005b) 'Estimation and inference in dynamic unbalanced panel-data models with a small number of individuals', Stata Journal, 5(4), 473–500. doi: 10.1177/1536867x0500500401.

Brynjolfsson, E., Hu, Y. J. and Smith, M. D. (2003) ‘Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers’, Management Science, 49(11), 1580–1596. doi: 10.1287/mnsc.49.11.1580.20580.
Burdekin, R. C., & Tao, R. (2021) 'From Shanghai to Sydney: Chinese stock market influences on Australia', Finance Research Letters, 38, 101502. https://doi.org/10.1016/j.frl.2020.101502
Cambria, E., Olsher, D. and Rajagopal, D. (2014) ‘SenticNet 3: A common and common-sense knowledge base for cognition-driven sentiment analysis’, in Proceedings of the National Conference on Artificial Intelligence, 1515–1521.
Chae, B. (2015) ‘Insights from hashtag #supplychain and Twitter analytics: Considering Twitter and Twitter data for supply chain practice and research’, International Journal of Production Economics, 165, 247–259. doi: 10.1016/j.ijpe.2014.12.037.
Chatterjee, S., Goyal, D., Prakash, A., and Sharma, J. (2020) 'Exploring healthcare/health-product ecommerce satisfaction: A text mining and machine learning application', Journal of Business Research. doi: 10.1016/j.jbusres.2020.10.043.
Chevalier, J. A. and Mayzlin, D. (2006) ‘The effect of word of mouth on sales: Online book reviews’, Journal of Marketing Research, 345–354. doi: 10.1509/jmkr.43.3.345.
Chintagunta, P. K., Gopinath, S. and Venkataraman, S. (2010) ‘The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets’, Marketing Science, 29(5), 944–957. doi: 10.1287/mksc.1100.0572.
Chong, A. Y. L. et al. (2016) ‘Predicting online product sales via online reviews, sentiments, and promotion strategies’, International Journal of Operations & Production Management, 36(4), 358–383. doi: 10.1108/IJOPM-03-2015-0151.
Chong, A. Y. L. et al. (2017) ‘Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews’, International Journal of Production Research, 55(17), 5142–5156. doi: 10.1080/00207543.2015.1066519.
Chu, C. Y., Park, K. and Kremer, G. E. (2020) ‘A global supply chain risk management framework: An application of text-mining to identify region-specific supply chain risks’, Advanced Engineering Informatics, 45. doi: 10.1016/j.aei.2020.101053.
Cui, G., Lui, H. K. and Guo, X. (2012) ‘The effect of online consumer reviews on new product sales’, International Journal of Electronic Commerce, 17(1), 39–58. doi: 10.2753/JEC1086-4415170102.
Duan, W. et al. (2016) ‘Exploring the Impact of Social Media on Hotel Service Performance: A Sentimental Analysis Approach’, Cornell Hospitality Quarterly, 57(3), 282–296. doi: 10.1177/1938965515620483.
El-Massah, S., Bacheer, S. M., and Al Sayed, O. (2019) 'Liquidity Risk in the Mena Region Banking Sector: Does Bank Type Make a Difference?', The Journal of Developing Areas, 53(1).
Fan, Z. P., Che, Y. J., & Chen, Z. Y. (2017) “Product sales forecasting using online reviews and historical sales data: A method combining the Bass model and sentiment analysis.’ Journal of Business Research, 74, 90-100.
Fiske, S. T. (1980) ‘Attention and weight in person perception: The impact of negative and extreme behavior’, Journal of Personality and Social Psychology, 38(6), 889–906. doi: 10.1037/0022-3514.38.6.889.
Gagliardi, I., & Artese, M. T. (2020) 'Semantic Unsupervised Automatic Keyphrases

Extraction by Integrating Word Embedding with Clustering Methods', Multimodal Technologies and Interaction, 4(2), 30.
Geva, T. et al. (2013) ‘Using Forum and Search Data for Sales Prediction of High-Involvement Products’, Ssrn. doi: 10.2139/ssrn.2294609.
Hasan, K. S., & Ng, V. (2014) 'Automatic keyphrase extraction: A survey of the state of the art', In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 1262-1273).
Hellofs, L. L. and Jacobson, R. (1999) ‘Market share and customers’ perceptions of quality: When can firms grow their way to higher versus lower quality?’, Journal of Marketing, 63(1), 16–25. doi: 10.2307/1251998.
Hou, F., Li, B., Chong, A. Y. L., Yannopoulou, N., & Liu, M. J. (2017) ‘Understanding and predicting what influence online product sales? A neural network approach’, Production Planning and Control, 28(11–12), 964–975. doi: 10.1080/09537287.2017.1336791.
Ivert, L. K. et al. (2014) ‘Sales and operations planning: Responding to the needs of industrial food producers’, Production Planning and Control, 26(4), 280–295. doi: 10.1080/09537287.2014.897769.
Julka, D. T., Subodh, S. J., & Lamba, A. S. (2014) ‘Supply Chain and Logistics Management Innovations at Maruti Suzuki India Limited’, International Journal of Management and Social Sciences Research, 3(3), 41–46.
King, R. A., Racherla, P. and Bush, V. D. (2014) ‘What we know and don’t know about online word-of-mouth: A review and synthesis of the literature’, Journal of Interactive Marketing, 28(3), 167–183. doi: 10.1016/j.intmar.2014.02.001.
Kinra, A., Hald, K. S., Mukkamala, R. R., & Vatrapu, R. (2020) ‘An unstructured big data approach for country logistics performance assessment in global supply chains’, International Journal of Operations and Production Management, 40(4), 439–458. doi: 10.1108/IJOPM-07-2019-0544.
Kiviet, J. F. (1995) ‘On bias, inconsistency, and efficiency of various estimators in dynamic panel data models’, Journal of Econometrics, 68(1), 53–78. doi: 10.1016/0304-4076(94)01643-E.
Lau, R. Y. K., Zhang, W. and Xu, W. (2018) ‘Parallel Aspect-Oriented Sentiment Analysis for Sales Forecasting with Big Data’, Production and Operations Management, 27(10), 1775–1794. doi: 10.1111/poms.12737.
Law, D., Gruss, R. and Abrahams, A. S. (2017) ‘Automated defect discovery for dishwasher appliances from online consumer reviews’, Expert Systems with Applications, 67, 84–94. doi: 10.1016/j.eswa.2016.08.069.
Lennox, R. J., Veríssimo, D., Twardek, W. M., Davis, C. R., & Jarić, I. (2020) 'Sentiment analysis as a measure of conservation culture in scientific literature', Conservation Biology, 34(2), 462-471.
Lee, M., Jeong, M. and Lee, J. (2017) ‘Roles of negative emotions in customers’ perceived helpfulness of hotel reviews on a user-generated review website: A text mining approach’, International Journal of Contemporary Hospitality Management, 29(2), 762–783. doi: 10.1108/IJCHM-10-2015-0626.
Li, B., Ch’ng, E., Chong, A. Y. L., & Bao, H. (2016) ‘Predicting online e-marketplace sales performances: A big data approach’, Computers and Industrial Engineering, 101, 565–571. doi:

10.1016/j.cie.2016.08.009.
Li, X., Wu, C. and Mai, F. (2019) ‘The effect of online reviews on product sales: A joint sentiment-topic analysis’, Information and Management, 56(2), 172–184. doi: 10.1016/j.im.2018.04.007.
Li, Y., Li, G., Tayi, G. K., & Cheng, T. C. E. (2019) ‘Omni-channel retailing: Do offline retailers benefit from online reviews?’, International Journal of Production Economics, 218, 43–61. doi: 10.1016/j.ijpe.2019.05.002.
Li, Xiaolin, Chaojiang Wu, and Feng Mai. (2019). 'The Effect of Online Reviews on Product Sales: A Joint Sentiment-Topic Analysis', Information and Management 56 (2), 172–184. doi:10.1016/j.im.2018.04.007.
Lin, Y., Wang, X. and Zhou, A. (2016) ‘Opinion spam detection’, Opinion Analysis for Online Reviews, 5(1), 79–94. doi: 10.1142/9789813100459_0007.
Luo, Y., Tang, L., Kim, E., & Wang, X. (2020) 'Finding the reviews on yelp that actually matter to me: Innovative approach of improving recommender systems', International Journal of Hospitality Management, 91, 102697.
Mascle, C. and Gosse, J. (2014) ‘Inventory management maximization based on sales forecast: Case study’, Production Planning and Control, 25(12), 1039–1057. doi: 10.1080/09537287.2013.805343.
Nakayama, M., & Wan, Y. (2019) 'The cultural impact on social commerce: A sentiment analysis on Yelp ethnic restaurant reviews', Information & Management, 56(2), 271-279.
Nikolay, A., Anindya, G. and Panagiotis, G. I. (2011) ‘Deriving the pricing power of product features by mining consumer reviews’, Management Science, 57(8), 1485–1509. doi: 10.1287/mnsc.1110.1370.
Perić, B. Š. (2019) ‘Do the most frequently used dynamic panel data estimators have the best performance in a small sample? A Monte Carlo comparison’, Croatian Operational Research Review, 10(1), 45–54. doi: 10.17535/crorr.2019.0005.
Phillips, P., Barnes, S., Zigan, K., & Schegg, R. (2017). (2017) ‘Understanding the Impact of Online Reviews on Hotel Performance: An Empirical Analysis’, Journal of Travel Research, 56(2), 235–249. doi: 10.1177/0047287516636481.
Podsakoff, P. M. and Organ, D. W. (1986) ‘Self-Reports in Organizational Research: Problems and Prospects’, Journal of Management, 12(4), 531–544. doi: 10.1177/014920638601200408.
Rose, S. J. et al. (2012) ‘Rapid automatic keyword extraction for information retrieval and analysis’, U.S. Patent 8,131,735. Available at: https://patents.google.com/patent/US8131735B2/en.
Rozin, P. and Royzman, E. B. (2001) ‘Negativity bias, negativity dominance, and contagion’, Personality and Social Psychology Review, 5(4), 296–320. doi: 10.1207/S15327957PSPR0504_2.
Schmidt, C. G. et al. (2020) ‘Does social media elevate supply chain importance? An empirical examination of supply chain glitches, Twitter reactions, and stock market returns’, Journal of Operations Management. doi: 10.1002/joom.1087.
Singh, A., Jenaman, M. and Thakkar, J. (2020) ‘Do online consumer reviews help to evaluate the performance of automobile manufacturers?’, Journal of Enterprise Information Management. doi: https://doi.org/10.1108/JEIM-09-2019-0292.
Singh, A., Shukla, N. and Mishra, N. (2018) ‘Social media data analytics to improve supply

chain management in food industries', Transportation Research Part E: Logistics and Transportation Review, 114, 398–415. doi: 10.1016/j.tre.2017.05.008.
Sivak, M. (2013) 'Predicting Vehicle Sales From GDP in 48 Countries : 2005-2011', in Transportation Research Institute., 2005–2011.
Sonnier, G. P., Mcalister, L. and Rutz, O. J. (2011) 'A dynamic model of the effect of online communications on firm sales', Marketing Science, 30(4), 702–716. doi: 10.1287/mksc.1110.0642.
Swain, A. K. and Cao, R. Q. (2019) 'Using sentiment analysis to improve supply chain intelligence', Information Systems Frontiers, 469–484. doi: 10.1007/s10796-017-9762-2.
Thelwall, M., Buckley, K. and Paltoglou, G. (2012) 'Sentiment strength detection for the social web', Journal of the American Society for Information Science and Technology, 63(1), 163–173. doi: 10.1002/asi.21662.
Thushara, M. G., Krishnapriya, M. S., & Nair, S. S. (2017), 'A model for auto-tagging of research papers based on keyphrase extraction methods', In 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 1695-1700). IEEE.
Ting, T., Davis, J. and Pettit, F. (2014) 'Online marketing research utilizing sentiment analysis and tunable demographics analysis', US Patent 8,694,357.
Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data, Booksgooglecom. MIT press. Cambridge, MA,. doi: 10.1515/humr.2003.021.
Wu, C., Che, H., Chan, T. Y., & Lu, X. (2015) 'The economic value of online reviews', Marketing Science, 739–754. doi: 10.1287/mksc.2015.0926.
Xu, X. and Lee, C. (2020) 'Utilizing the platform economy effect through EWOM: Does the platform matter?', International Journal of Production Economics, 227. DoI: 10.1016/j.ijpe.2020.107663.
Yang, Z., Jun, M. and Peterson, R. T. (2004). Measuring customer perceived online service quality: Scale development and managerial implications. International Journal of Operations and Production Management, 24(11), 1149–1174. doi: 10.1108/01443570410563278.
Yu, H., Shang, J., Hsu, M., Castellanos, M., & Han, J. (2016) 'Data-driven contextual valence shifter quantification for multi-theme sentiment analysis', in International Conference on Information and Knowledge Management, Proceedings, 939–948. doi: 10.1145/2983323.2983793.
Zhang, C., Tian, Y. X., Fan, Z. P., Liu, Y., & Fan, L. W. (2020) 'Product sales forecasting using macroeconomic indicators and online reviews: a method combining prospect theory and sentiment analysis.' Soft Computing, 24(9), 6213-6226.
Zhu, J. J., Chang, Y. C., Ku, C. H., Li, S. Y., & Chen, C. J. (2020) 'Online critical review classification in response strategy and service provider rating: Algorithms from heuristic processing, sentiment analysis to deep learning.' Journal of Business Research, DoI: 10.1016/j.jbusres.2020.11.007

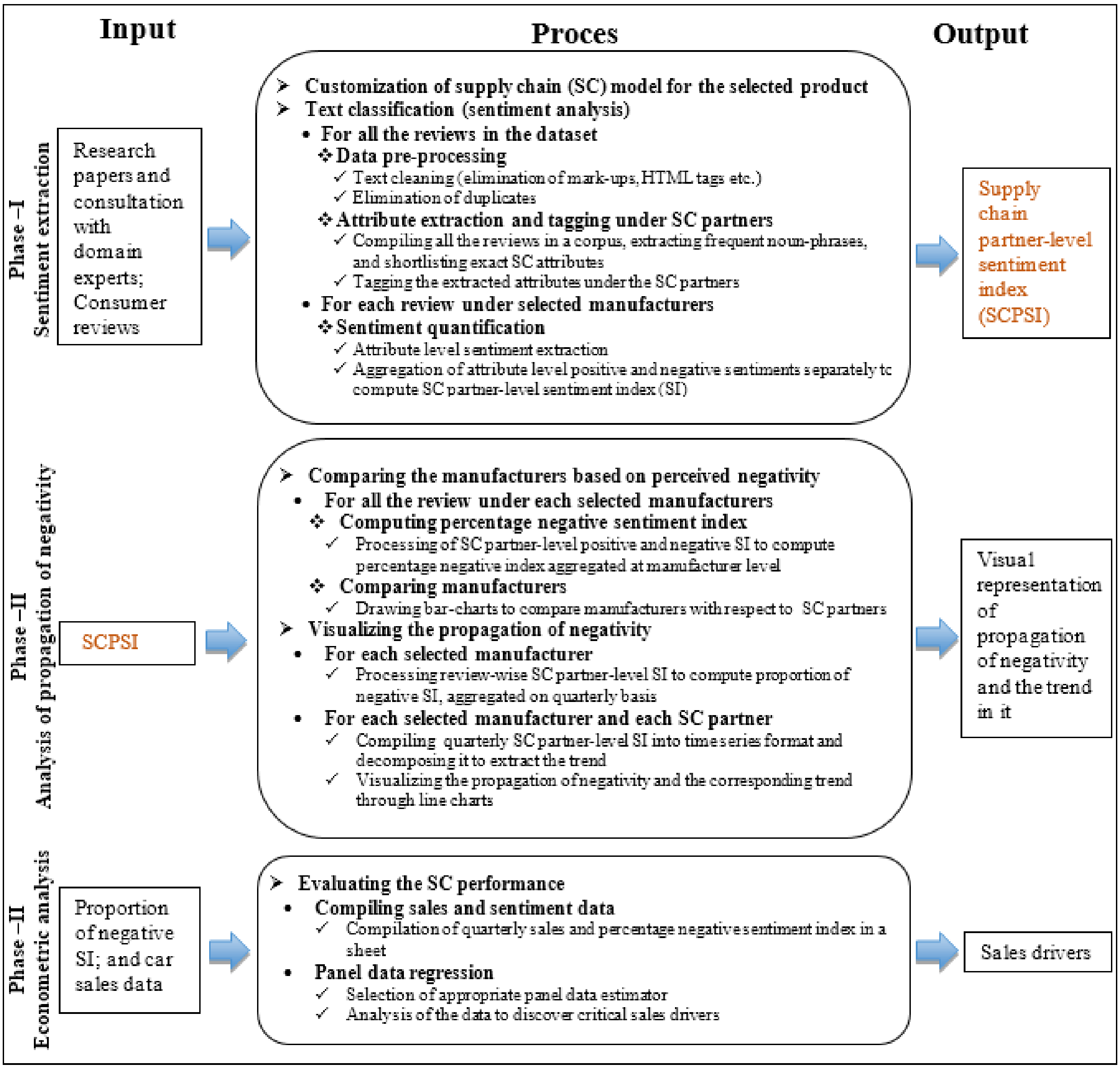

Figure 1: Proposed research proposal flowchart

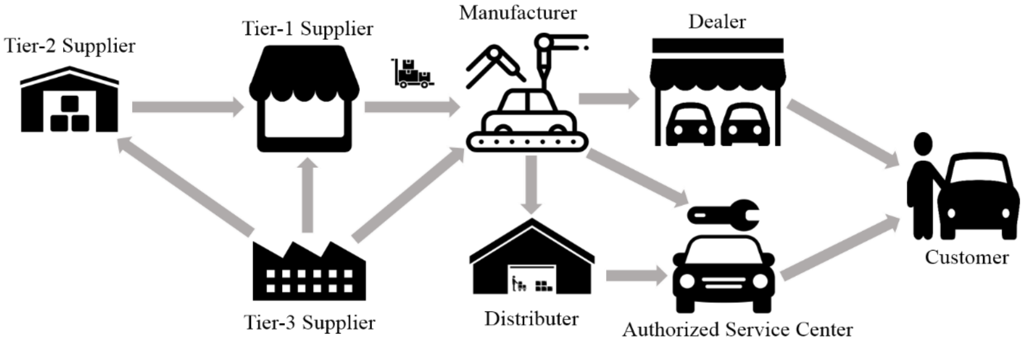

Figure 2: Customized supply chain model for Indian car manufacturers

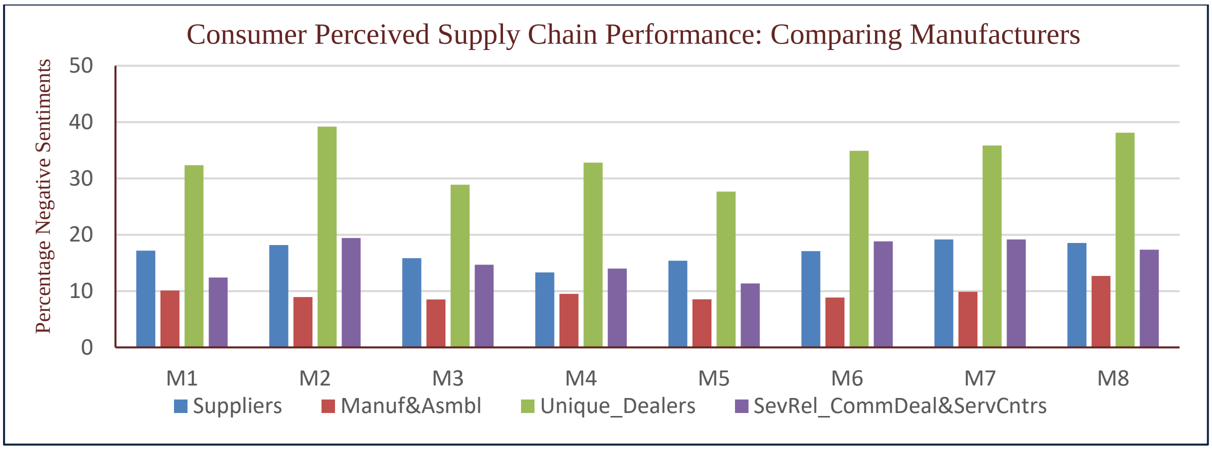

Figure 3: Comparison of manufacturers based on the Proportion of Negativity

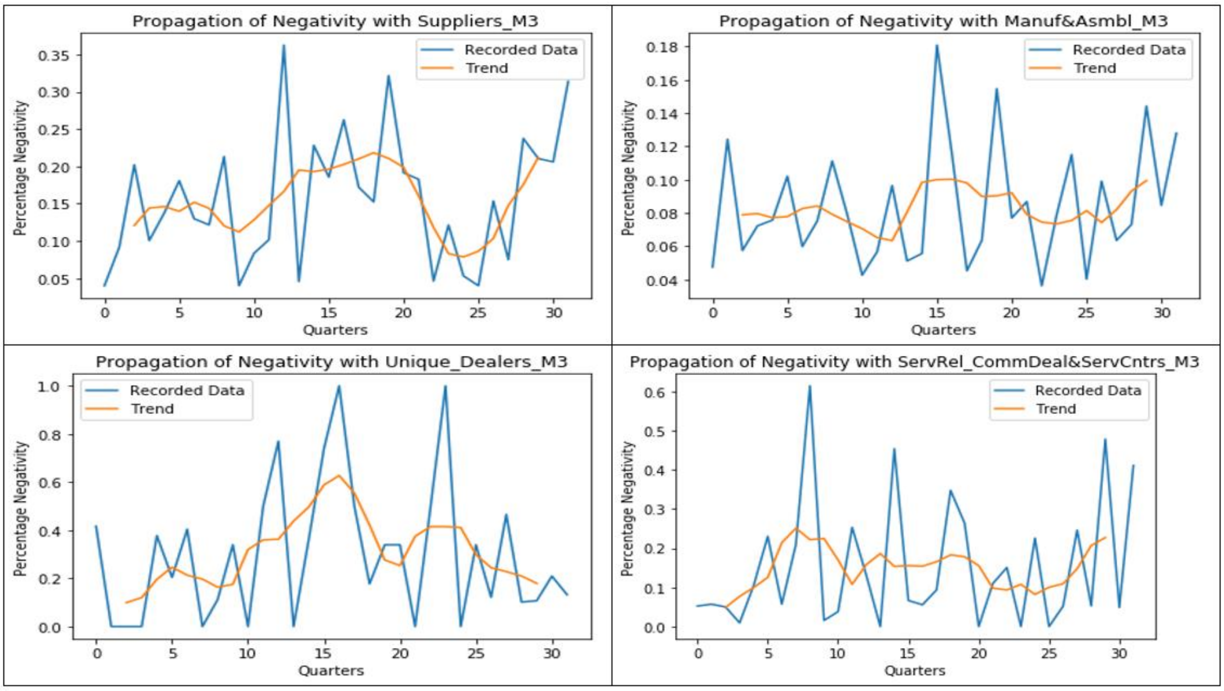

Figure 4: Negativity propagation

Table 1: Literature review on text analytics bases supply chain research

Author	Category of contribution				Remarks	Tools Used
	Application oriented	**Algorithm-oriented**	**Learning -Based**	**Lexicon -Based**	**Domain, Data Sources, and Contributions**	
(Chae, 2015)	✓	✓	✓	✗	**Domain:** Supply chain **Data source:** Twitter **Contributions:** They mine tweets and extract supply chain related information. They also categorized the tweets into five clusters, corporate social responsibility, risk, logistics, manufacturing, and information technology and presented the descriptive stats of the tweets ranging from -3 to 3 scale of sentiment intensity.	Text analytics, Descriptive analytics, Content analytics, and Network analytics
(Swain and Cao, 2019)	✓	✗	✓	✗	**Domain:** Supply chain **Data source:** Board reader; Google Blog Search; Twitter **Contributions:** They extracted user sentiments with respect to SCM dimensions (information sharing, collaboration, trust, and commitment) from the eWOM data present in form of forum, blogs, and micro-blogs and tested their impact along with the text frequency and volume on the supply chain performance.	Text analytics, Naïve Bayes classifier, Multiple linear regression, F-measure
(Singh, Shukla and Mishra, 2018)	✓	✗	✓	✓	**Domain:** Food supply chain **Data source:** Twitter **Contributions:** They collected beef/steak supply chain related tweets processed them to discover most frequently discussed issues such as bad flavor, hard texture, extra fat, discoloration of beef products, and presence of horsemeat in beef products. They also proposed mitigation strategies for these issues.	Text analytics, Support vector machine, Multi-scale bootstrap resampling, Five-fold cross validation (CV) accuracy
(Schmidt *et al.*, 2020)	✓	✗	✓	✗	**Domain:** Supply chain **Data source:** Twitter, Thomson Reuters, Wall Street Journal and the Dow Jones Newswire **Contributions:** They studied how supply chain (SC) glitches are reflected in stock market and the twitter. In their study it is discovered that 1) firms experience negative stock market return when a SC-glitch is noted; 2) tweet volume significantly increases with the occurrence of glitch; 3) twitter sentiments get negative on the occurrence of glitch; 4) cumulative tweet volume and negative sentiments have significant negative impact on stock market return	Text analytics, Event study method, t-test, Random effects regression, F-statistic, Adjusted R-squared test, Chi-square test
(Kinra *et al.*, 2020)	✓	✗	✓	✗	**Domain:** Country logistics **Data source:** Logistics related text from various sources	Text analytics, Design science approach, Word frequency analysis, Collocation analysis,

					Contributions: They proposed a text analytics framework that searches important SC-related keywords, computes their frequency, and quantifies the corresponding sentiments to measure the performance of the country logistics	Naıve Bayes classifier, keyword analysis
(Chu, Park and Kremer, 2020)	✓	×	×	✓	**Domain:** Supply chain risk management **Data source:** Scopus, Google News **Contributions:** Using the text in form of research papers and the news articles, they proposed a text analytics framework that automatically categorizes supply chain risks. They have also studied the variations of supply chain risks over time.	Text analytics, Feature selection, Term frequency, Correlation, Bi-gram analysis, Topic modelling
Present research	✓	×	×	✓	**Domain:** Automotive supply chain **Data source:** CarWale.com, Society of Indian Automobile Manufacturers (SIAM) **Contributions:** Proposal of an integrated text analytics framework that extracts SC related information from automobile reviews analyses them to 1) evaluate the supply chain partners, 2) compare the manufacturers based on the consumer perceived negativity with respect to various SC partners, 3) study how consumer perceived negativity propagates over time, and 4) examine if the consumer sentiment corresponding to the supply chain units influence the car sales	Aspect based sentiment analysis, Bias-corrected least square dummy variable estimator, Text analytics, SentiWordNet dictionary, RAKE, Line chart, Bar chart

Table 2: Stationary test (Dickey Fuller Test)

Manufacturer	Suppliers		Manufacturing and Assembly		Unique Attributes of Dealers		Service Related (Common with Dealers and Service Centres)	
	Test-statistic	P-value	Test-statistic	P-value	Test-statistic	P-value	Test-statistic	P-value
M1	-4.832904	0.000047	-1.325007	0.617655	-5.063811	0.000017	-4.983926	0.000024
M2	-4.501343	0.000196	-1.605256	0.480953	0.650547	0.988797	-5.381630	0.000004
M3	-3.327891	0.013677	-5.324939	0.000005	-4.800209	0.000054	-6.676296	0.000000004
M4	-5.326016	0.000005	-4.698826	0.000085	-0.920185	0.781253	-6.501037	0.00000001
M5	-4.515201	0.000185	-4.372451	0.000332	-5.897157	0.00000028	-7.035684	0.0000000006
M6	-4.884404	0.000037	1.485684	0.997471	-5.036754	0.000019	-4.740646	0.000071
M7	-3.599322	0.005774	-5.197596	0.000009	-2.312496	0.167969	-5.536883	0.000002
M8	-0.000000	0.085144	-0.166631	0.942384	-4.231262	0.000583	-1.093978	0.717467

Table 3: Strict exogeneity test

Variables	P-value	Variables	P-value
Variety	0.061	Rev_Vol	0.675
Firmage	0.877	Suppliers	0.477
GDP	0.053	Manuf&Asmbl	0.834
Avg_RevL	0.455	Unique_Dealers	0.732
Search_Vol	0.003	ServRel_CommDeal&ServCntrs	0.280

Table 4: Definition of the variable used in supply chain performance evaluation model

Variable	Acronyms	Definition	Minimum	Maximum	Mean	Standard Deviation
Sales	Sales	Number of cars sold in the specified time period				
Variety of products	Variety	Number of models provided by the particular manufacturer in specified time period				
Firm age	Firmage	Number of years from the date specific manufacturer started functioning in Indian market				
Gross domestic product	GDP	Gross domestic product of India during the specified time period				
Average review length	Avg_RevL	Average number of words per review				
Product search volume	Search_Vol	Number of times the manufacturer is searched online (obtained from Google trends) in specified time period				
Review volume	Rev_Vol	Number of review in the same period				
Suppliers	Suppliers	Extracted SI with respect to the aspect suppliers	0.02	0.48	0.17	0.08
Manufacturing and Assembly	Manuf&Asmbl	Extracted SI with respect to the aspect manufacturing and assembly	0.01	0.51	0.10	0.05
Unique Attributes of Dealers	Unique_Dealers	Extracted SI with respect to the aspect unique attributes of dealers	0.00	1.00	0.34	0.28

Service Related Attributes (Common with Dealers and Service Centres)	ServRel_CommDeal&ServCntrs	Extracted SI with respect to the aspect service related attributes (common with dealers and service centres)	0.00	0.69	0.16	0.12

Table 5: Correlation results

	Variety	GDP	Firmage	Avg_RevL	Rev_Vol	Suppliers	Manuf&Asmbl	Unique_Dealers	ServRel_CommDeal
Variety	1								
GDP	-0.0845	1							
Firmage	0.4955	0.0333	1						
Avg_RevL	-0.1137	0.1652	-0.2149	1					
Rev_Vol	-0.1137	-0.3284	0.2618	-0.3643	1				
Suppliers	0.0622	-0.0095	0.1051	0.0666	-0.0366	1			
Manuf&Asmbl	-0.0106	0.0843	0.0104	0.2167	-0.0848	0.4071	1		
Unique_Dealers	0.0312	-0.0257	-0.0177	-0.0101	-0.0773	0.1194	0.1423	1	
ServRel_CommDeal&ServCntrs	0.0181	0.1352	0.0389	0.0623	-0.1376	0.2009	0.248	0.066	1

Table 6: Regression results (actual and Z-transformed variable)

Variables	Model 1 (Actual Variables)	Model 2 (Z-transformed (standardized) Variables)
L.Zsales	0.7170***	0.7170***
	(0.000)	(0.000)
Variety	1,051.4595	0.1267
	(0.202)	(0.202)
Firmage	-1,764.4194*	-4.1765*
	(0.079)	(0.079)
GDP	0.2115*	0.5353*
	(0.058)	(0.058)
Avg_RevL	-4.1281	-0.0332
	(0.539)	(0.538)
Rev_Vol	29.3857*	0.1145*
	(0.069)	(0.068)
Suppliers	-940.9284	-0.0096
	(0.846)	(0.846)
Manuf&Asmbl	5,484.3980	0.0355
	(0.523)	(0.523)
Unique_Dealers	-1,146.8709	-0.0416
	(0.363)	(0.363)
ServRel_CommDeal&ServCntrs	-1,525.1857	-0.0246
	(0.624)	(0.624)

Note: p-value in parentheses
*** p<0.01, ** p<0.05, * p<0.10