Refining Personalisation in the Luxury Automotive Industry: How Customer Preferences and Perceptions Can Shape Maserati's Configuration Strategy

Irene Hsu

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Abstract

Maserati is a leading global luxury car brand. This paper aims to understand, through analysis of online car forums, the perceptions and preferences of Maserati luxury customers. The study utilises natural language processing, topic modeling and sentiment analysis to cluster profiles of luxury automotive customers, to discover their preferences and gauge their perception of personalised experience. The study also conducts a comparative analysis of Maserati's offerings distinguishing them from their top competitors and locating them within an identified topology of customer needs. In addition, this paper identifies opportunities and threats emerging from the analysis, recommending actionable configuration strategies for Maserati, and positioning Maserati more effectively in the luxury automotive market landscape.

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1 Introduction

Luxury cars feature advanced technology, premium interior/exterior materials and exceptional performance. They are designed to provide a superior driving experience, and are equipped with cutting-edge engineering and amenity features. According to Fortune Business Insight, the luxury automotive market was worth USD 1.05 trillion in 2022; still growing, it is expected to reach USD 2.55 trillion by 2027. A study conducted by Grand View Research (2023) shows Europe dominating the luxury automotive market with a 39.3% share in 2022. The research also forecasts a steady annual growth rate of more than 6.1% from 2023 to 2030 in the European market. McKinsey & Co. (2022) and Grand View Research (2023) found constant growth in the luxury automotive market to be linked with a continued increase in the number of ultra-high-net-worth and high-net-worth customers. The term “ultra-high-net-worth” refers to individuals possessing investable assets exceeding $30 million; while “high-net-worth” refers to individuals possessing investable assets ranging from $1 to $30 million, as defined by Guan, Köstring, Middleton, and Möller (2022).

As customers are the driver of growth in the luxury automotive market, it is important for luxury car brands to understand the changing needs and passions of luxury customers, along with the means of connecting products and services with such consumers. A study by McKinsey & Co. (2022) indicates that luxury customers are demanding a personalised experience during the purchasing process. Personalisation in the automotive industry is a means of helping customers outline the perfect car purchase; in other words, by factoring in customer desire as a dimension of purchasing, brands offer buyers degrees of control over what a product should be. Nowadays, increasing numbers of luxury car brands such as Maserati, Ferrari and BMW provide customers with personalisation programmes, allowing buyers to customise their car based on individual preference for interior materials, exterior design, colours and built-in technology, among other options. During the purchasing process, personalised experience is one of the key factors that could keep customers loyal to the brand, leading to a positive impact on the business. A survey conducted by Epsilon (2018) showed 80% of customers considering purchase of products when brands offer personalised experiences. McKinsey & Co. (2021) found that companies providing personalised services or products achieved a 40% increase in revenue, compared to companies offering no personalised experiences.

Well established among luxury brands in the automotive industry, Maserati is renowned for its luxurious and high-performance cars. In recent years, the launch of the Maserati Fuoriserie program has showcases the brand's commitment to addressing the desires of luxury consumers (Vega, 2023). The Fuoriserie customisation program allows customers to configure their cars with exclusive features that are not offered in other standard car models. Evidently, Maserati's objective is to engage both their established affluent customer base and those who exhibit future affordability potential. Therefore, to inform and build a best-fit configuration strategy for Maserati's luxury customers, this paper aims to understand how Maserati is positioned in the luxury landscape.

Previous research studies show that leveraging a data-driven approach, such as natural language processing (NLP), can effectively improve business strategy planning (Moloi, Marwala, 2021). In this paper, we leverage NLP techniques to analyse customers' opinions from three different car forums. By doing so, we can gain deeper insights into customer sentiment and preferences. In other words, we aim to understand how luxury customers perceive Maserati's brand and products, enabling us to refine their configuration strategy.

Purposes of this paper are *(i)* identifying the perception of Maserati as associated with luxury, (*ii*) establishing clustering of luxury-automotive customer profiles in the European market to discover customer preferences and perceptions of personalised experience, *(iii)* conducting a comparative analysis of Maserati offerings between their top competitors and within the identified topology of customer needs, and *(vi)* identifying opportunities and threats emerging from our analysis, recommending actionable configuration strategies for Maserati.

2 Literature Review

This paper starts by reviewing previous studies related to leveraging of NLP to analyse customers' opinions or sentiments towards brands or products; this attempts to understand how NLP could help in this field. We examined research by Shu, Wang, Lin, Jia, and Zhou (2022). The authors implemented an NLP technique of emotion analysis, using the Bidirectional Encoder Representations from Transformers (BERT) model—a machine learning pre-trained model for NLP (Muller, 2022)—to identify customers' sentiments towards electric vehicles, enabling businesses to adjust their marketing strategies for improved market acceptance of their electric vehicles. Hossain and Rahman (2022) conducted similar research on customer sentiment in the insurance field. The authors leveraged two unsupervised learning models: AFINN, which is a lexicon-based sentiment technique created by Finn Årup Nielsen (Nielsen, 2011), and Valence Aware Dictionary for Sentiment Reasoning (VADER), which is a lexicon and rule-based sentiment technique (Hutto and Gilbert, 2014). These models were used to extract sentiments, and machine-learning algorithms were applied to predict customer review sentiment, allowing businesses to better understand customer behaviours. Netsiri and Lhotáková (2023) employed another common NLP method, LDA Topic Modeling, to extract topics from luxury car reviews. Their findings indicated that intentions of customers to purchase pre-owned luxury cars are positively impacted by their perceived emotional, social and quality value. The authors further suggested that applying NLP in market research can be efficient and cost-effective. Abdulaziz, Alsolamy, Alabbas, and Alotaibi (2021) combined sentiment analysis with LDA Topic Modeling to conduct topic-based sentiment analysis on COVID-19-related tweets. This combination is also employed in the paper by Mok, Yu and Zihayat (2022) to understand change in the perception of sustainability in the luxury fashion industry. Topic-based sentiment analysis reveals sentiment on the topic level, providing an overarching understanding of the sentiment associated with trending topics linked to individuals 'opinions.

The studies above indicate the contribution of NLP in analysing customers' opinions and sentiments. This paper intends to utilise Topic modeling, along with topic-based sentiment analysis, to cluster luxury automotive customer profiles based on their preferences and perceptions of personalised experiences, enabling us to tailor Maserati's configuration strategy accordingly.

3 Methodology

3.1 Data Preparation

3.1.1 Data Selection

To understand how consumers perceive luxury in an automotive industry context, this study identifies textual data as the most appropriate data type. We have selected three car forums where individuals can share their thoughts and explore opinions on cars. The first is GermanCarForum, which we use to perform competitor analysis, while MaseratiLife and SportMaserati are used to understand perceptions of the Maserati brand and its offerings amongst Maserati buyers and enthusiasts.

(1) GermanCarForum

Founded in 2005, GermanCarForum is an online community for all car enthusiasts. It features various car brand sections where users can create posts, leave comments, or engage in discussions with others. Additionally, on their profile page users can choose to provide personal information, including location, age and occupation. Given the forum's extensive coverage of luxury brands such as Mercedes-Benz, Ferrari, Porsche, and the inclusion of personal details, we have selected it as a valuable data source, both for our competitor analysis and for charting the topology of needs amongst luxury automotive carmakers.

(2) MaseratiLife and SportMaserati

Tailored to Maserati enthusiasts, MaseratiLife and SportMaserati, established in 2003 and in 2010 respectively, are online forums with approximately forty thousand and four thousand members each. Both consist of a variety of sections, such as discussions around specific Maserati car models and car technical-related topics, allowing users to create posts, leave comments, and participate in discussions with other members. Additionally, users can share with others personal information such as location, age and car preferences. With abundant Maserati-specific information and user profiles, we consider these sources valuable in gaining insight to Maserati consumers, identifying their needs and points of view on multiple car- and luxury-related topics.

3.1.2 Data Collection

We performed web scraping utilizing a Python library: Scrapy (Hajba, 2018). Scrapy was used to extract data from the chosen forums. For each of the three resources, we excluded sub-forums which are not relevant to our study (Appendix A). Scrapy Spider was created to navigate through different sections and threads of the forum. From the main page, the Spider extracted links to sub-sections and proceeded to visit individual sub-section pages. Within sub-section pages, the Spider retrieved links to threads and iterated through thread pages, extracting post content along with relevant information such as post dates, user IDs and sub-section titles. It also parsed user profile pages, gathering details such as user demographics, engagement metrics, and car preferences. Finally, the scraped data was organised into structured dictionaries, and exported into a CSV file.

3.1.3 Data Cleaning

To ensure consistency in the textual data, we leveraged SpaCy, an open-source Python library for Natural language Processing (NLP). Because SpaCy annotates text easily and provides flexibility when creating the NLP pipeline, we can customise the pipeline and obtain the specific tokens needed for the study (Srinivasa-Desikan, 2018). SpaCy models consist of three types of pre-train models: small (sm-small), medium (md-medium) and large (lg-large) packages (Nasiboglu1 &

Gencer, 2021). The large English package "en_core_web_lg" was used in this study. Within the NLP pipeline, the texts were tokenised into individual tokens, which were lemmatised and lowercase, while excluding stopwords and punctuation. The resulting tokens underwent additional processing to extract meaningful bi-grams (two-word phrases) and tri-grams (three-word phrases) using the Gensim library, leading to better capture of idiomatic expressions.

Furthermore, duplicates were removed and date strings were transformed into a DateTime format, allowing for better data manipulation. Lastly, we created a hand-crafted dictionary to map location data to its corresponding continents, which were then appended into the newly created column, allowing us to categorise geographical information for further analysis. The description of cleaned data attributes can be found in Appendix B, Appendix C and Appendix D.

3.2 Data Analysis Methods

We relied on three methods for the study. In the first phase, to find the occurrence of car brands mentioned in the forums, we leveraged the Named Entity Recognition (NER) method used by Rau (Rau, 1991) to extract company names from financial news. Subsequently, common brands from the forums were identified to define Maserati's closest competitors. In the second phase, since our main study focuses on the European market, the data needed for 3.2.3 Topic Modeling was necessarily based on the users located in Europe. However, Figure 1 and Figure 2 show that 44% of users in MaseratiLife and 32% of those in SportMaserati do not provide their location information; consequently, text classification was carried out to filter the datasets into European datasets.

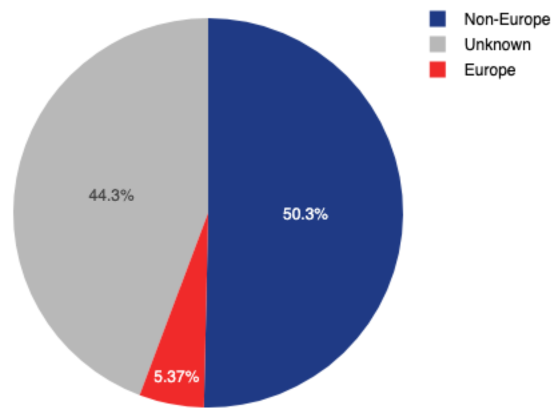

Figure 1: Distribution of User Locations in MaseratiLife

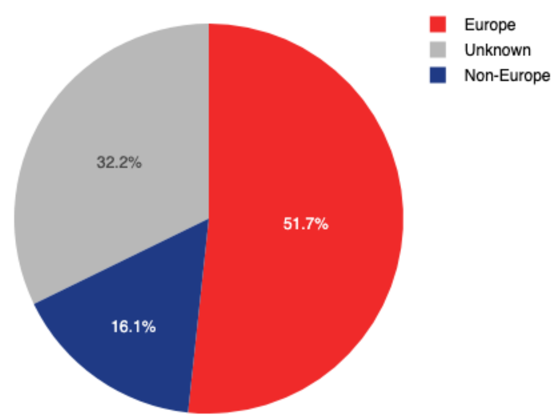

Figure 2: Distribution of User Locations in SportMaserati

We also filtered European data based on the identified competitors from our co-occurrence analysis to focus on the topology of customers' needs within the appropriate competitive landscape. The data size of three forums after filtering is shown in Appendix E. Thereafter, topic modeling was used to discover the clusters of similar words, and we compared the results to find the similarities between the three forums. In the final phase, we performed an unsupervised topic sentiment analysis to understand the sentiment of customers towards the topics.

3.2.1 Co-occurrence Analysis: NER

Given the SpaCy pre-trained model's capability to recognise various types of named entities within a large volume of documents, such as companies, locations, organisations, and products (Yadav and Bethard, 2019), we extracted tokens whose entities were identified as organisations and then calculated their occurrences. In the final phase, we carefully filtered out tokens related to car brands from the data frame and then calculated the co-occurrence of Maserati with these car brands. As shown in Figure 3, the top 6 most common car brands were selected, including Ferrari, Mercedes Benz, Porsche, BMW, Alfa Romeo and Aston Martin.

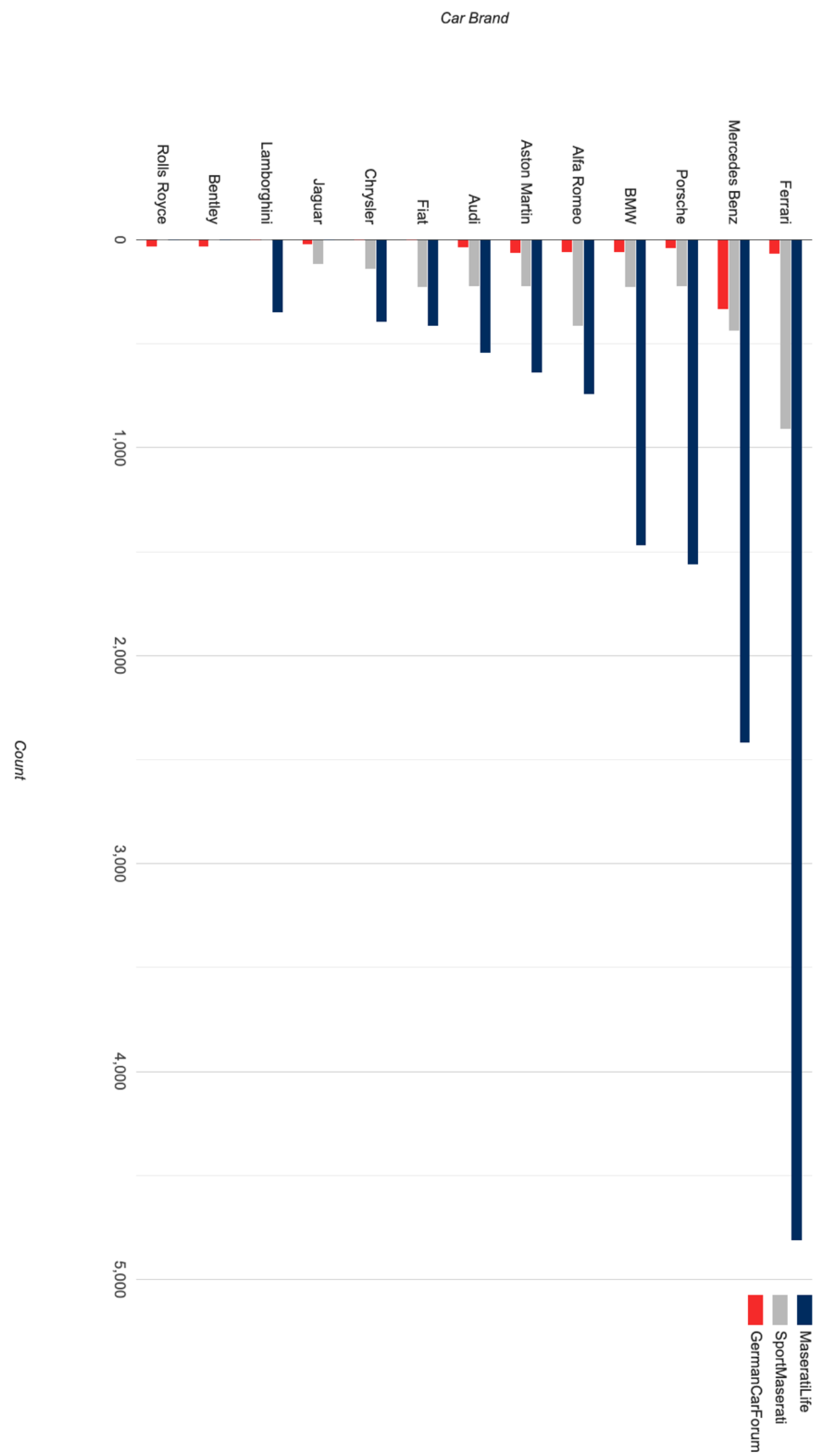

Figure 3: Co-occurrence Analysis: Maserati and Top Competitors

3.2.2 Text Classification

The process of text classification begins with combining MaseratiLife with SportMaserati labelled datasets, as both datasets are associated with Maserati buyers and enthusiasts. Figure 1 and Figure 2 show that both MaseratiLife and SportMaserati data are imbalanced, negatively impacting the classification model's accuracy when the classifier was trained on the imbalanced dataset (He & Garcia, 2009). Hence, combination can balance the training data, as shown in Figure 4. Thereafter, combined data was split into training and test datasets. Since machine learning and deep learning classifiers require numerical values as inputs to make predictions (Srinivasa-Desikan, 2018), textual data was transformed into vectors. Two common text vectorisation techniques which are widely used in text classification tasks were carried out in the analysis: Term Frequency-inverse document frequency (Scikit-learn library) and Word2Vec (Gensim library).

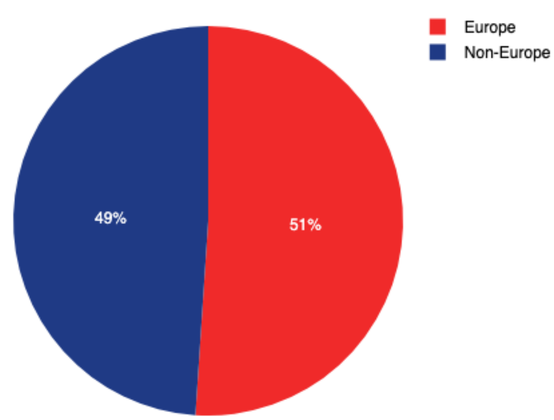

Figure 4: Distribution of User Locations in Combined Dataset

TF-IDF is used in this study to reflect the significance of rare words. This calculates the number of appearances these specific words make in a document, along with the frequency of appearances measured against the total words in the document (Arora, Mittal and Aggarwal, 2021). Word2Vec is employed to capture both the semantic and syntactic connections among words. This technique produces word embeddings, where a word's vector tends to resemble the vectors of the surrounding words in the text. In other words, it considers the association between words and the order of words in a sentence (Arora, et al., 2021).

The resulting word vectors were utilized as the classification features. This study leverages Logistic Regression, Naïve Bayes, Ridge regression and a simple dense neural network as classification methods. These methods are widely used in the field of text classification (Thangaraj & Sivakami, 2018). Machine learning models were built using Scikit-learn library, while the deep learning model was built using Tensorflow library. The simple dense neural network consists of a dense layer with ReLU activation to overcome vanishing gradients (Cui, Qiu, Jiang, Pei & Lu, 2017), a dropout layer to prevent overfitting (Srivastava, Hinton, Krizhevsky, Sutskever & Salakhutdinov, 2014) and a final dense layer (output layer) with Sigmoid activation as our task is a binary classification. The architecture of the model is in Appendix F. A comparative analysis of the results obtained from several classifiers was carried out and it was found that Ridge regression performed better than other classifiers for TF-IDF, as shown in Table 1. Hence, TF-IDF with Ridge regression was chosen to classify the unlabelled data into Europe and Non-Europe classes.

Text Vectorisation	Classifier	Test accuracy	F1 score	AUC
TF-IDF	Naïve Bayes	0.719	0.719	0.80
TF-IDF	Logistic Regression	0.726	0.725	0.80
TF-IDF	Ridge Regression	0.730	0.728	0.81
Word2Vec	Logistic Regression	0.676	0.676	0.73
Word2Vec	Ridge Regression	0.677	0.676	0.72
Word2Vec	Simple Dense Neural Network	0.692	0.720	0.69

Table 1: Text Classification Model Performance Comparison

3.2.3 Topic Modeling

Topic modeling is an unsupervised machine learning technique to classify documents into discovered topics. It can also uncover hidden topics in the corpus. Latent Dirichlet allocation (LDA) is one of the common methods in this field; LDA is a means of finding the representative words for a topic and of calculating the probability that those words may belong to the topic (Jelodar, Wang, Yuan, Feng, Jiang, Li & Zhao, 2018). We carried out LDA using the Gensim library on the three forums, and evaluated models based on the coherence metric "c_v" to gauge how interpretable the topic is. C_v measure has been widely used in several studies including works by Mifrah and Benlahmar (2018) and Röder, Both and Hinnebur (2015). We chose the number of topics based on the highest coherence score (Syed & Spruit, 2017).

3.2.4 Unsupervised Topic-based Sentiment Analysis

Since the data was unlabelled as regards sentiment, Vader-lexicon was used in the study for sentiment analysis. An unsupervised pre-trained model in the NLTK library, Vader-lexicon has been used in research including works by Abdulaziz et al. (2021) and Hossain et al. (2022) to analyse sentiment within social media and customer reviews. After obtaining topics from SportMaserati, we labelled each thread with the topic number to which it belonged. Vader-lexicon was used to glean the sentiment for each thread. Table 2 displays the average polarity scores for each topic. Polarity scores are numeric values, representing the sentiment of the sentence, with positive and negative scores ranging from 0 to 1. A higher value indicates a stronger sentiment.

Topic Number	Negative Polarity Score	Positive Polarity Score	Sentiment
0	4.23%	11.35%	Positive
1	7%	3.5%	Negative
2	0.97%	1.97%	Positive
3	5.48%	7.79%	Positive
4	2.42%	4.68%	Positive
5	4.78%	6.93%	Positive

Table 2: Polarity Score: SportMaserati

3.2.5 Limitations

In this study, social media was not chosen as a data source because accessing data from most social media platforms requires payment for their APIs. Although certain platforms, such as Twitter, offer free plans allowing users to access their data, these plans come with limitations on the amount and timeframe of accessible data. Furthermore, due to the insufficiency of information on user age, we were not able to apply age-based text classification to understand the perception of luxury amongst customers in different age groups. Moreover, the choices of classifiers used for filtering the datasets into European datasets were limited due to the high computation cost and limited time scope of the project.

4 Results and Discussions

Topic Modeling visualisations of three car forums are shown in Appendix G, Appendix H and Appenxdix I. There are 6 and 25 topics extracted from SportMaserati and MaseratiLife, with the coherence score of 0.41 (Figure 5) and 0.52 respectively (Figure 6) respectively, while 7 topics were extracted from GermanCarForum with the coherence score of 0.47 (Figure 7).

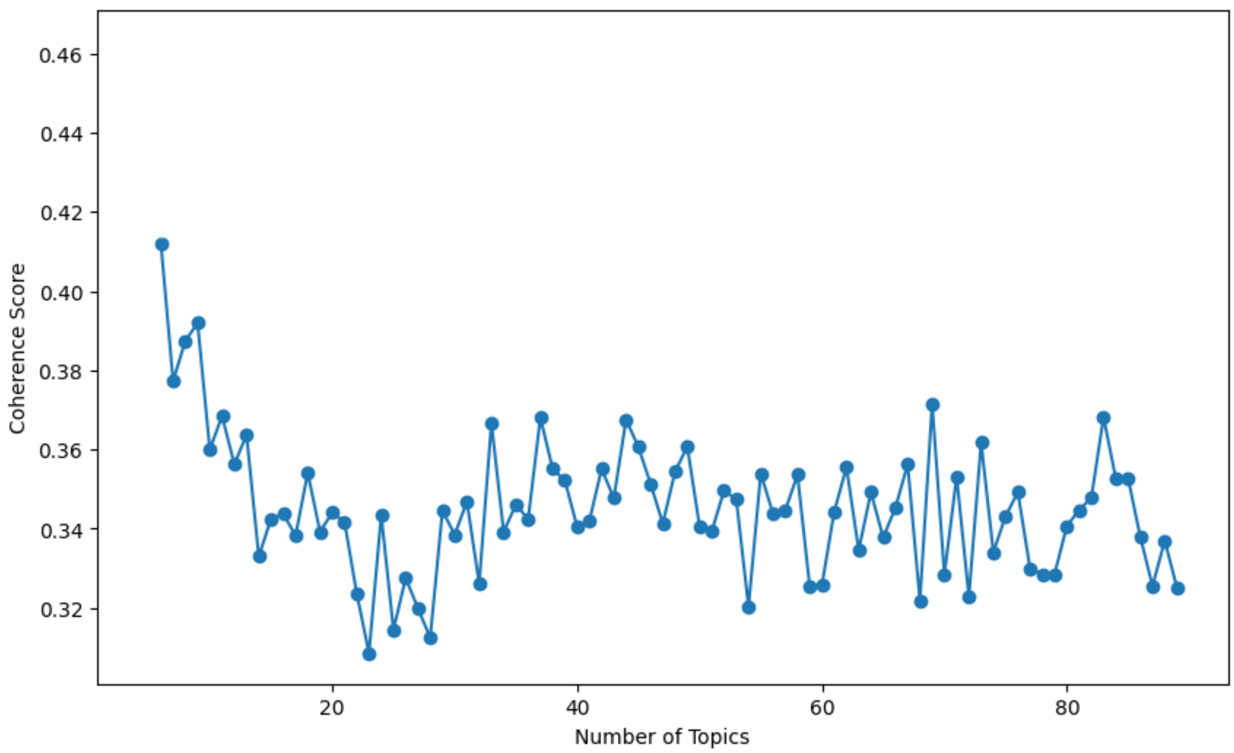

Figure 5: SportMaserati Topic Coherence Score versus Number of Topics

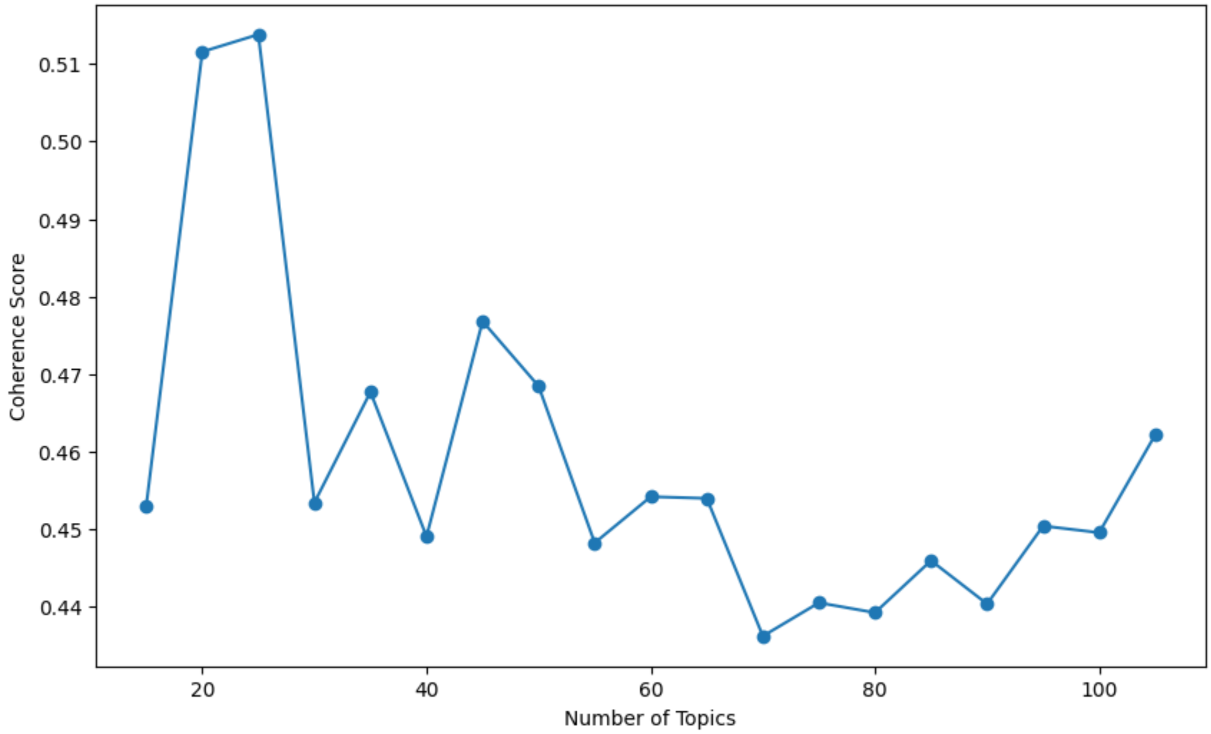

Figure 6: MaseratiLife Topic Coherence Score versus Number of Topics

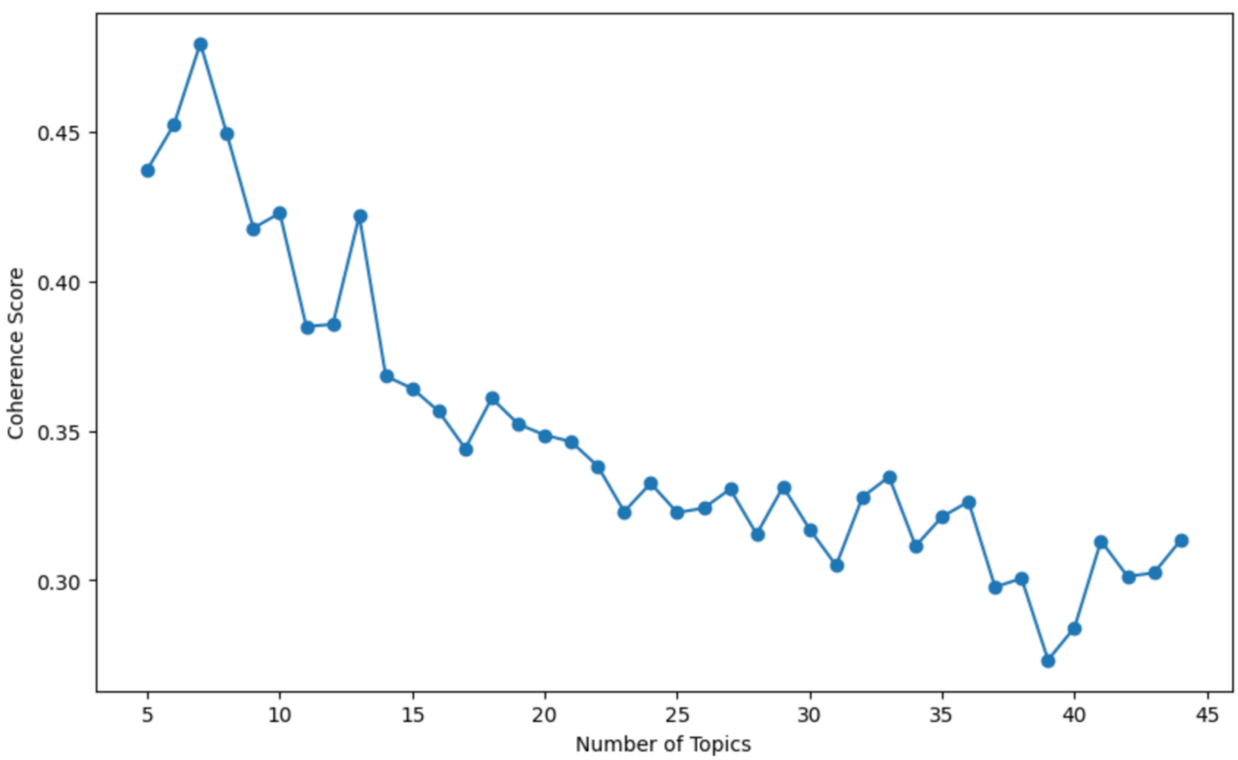

Figure 7: GermanCarForum Topic Coherence Score versus Number of Topics

Topics from MaseratiLife and GermanCarForum were prioritised according to objectives of this paper (Table 3 and Table 4); the same topic-prioritisation was apllied to SportMaserati, the dataset for this forum also allowing us to provide sentiment results (Table 5).

Topic Number	Topic Name	Keywords
4	Maintenance Service	Issue, Service, Replace, Cost, Warranty, Fix
6	Interior & Exterior Design	Leather, Interior, Colour, Black, Red, Blue, Finish, Carbon
5	Engine Performance	Engine, Sound, Power, Speed, RPM
7	Track & Technical Performance	Handle, Sporty, Torque, Test-drive

Note. Only the topics related to the objectives of this paper were selected

Table 3: Topic Modeling: MaseratiLife

Topic Number	Topic Name	Keywords	Description
5	Exterior / Interior Design	Design, Interior, Rear, Grille, Wheel, Door, Headlight, LED	Discussing 1. car design (interior and exterior features) 2. lighting technology (e.g., LED)
6	Technical Performance	Engine, Speed, Suspension, HP, Control, Steering, Torque, Mode	Discussing 1. engine power (e.g., horsepower and torque) 2. drivability (e.g., steering and suspension) 3. driving modes
7	Customisation & Technological Innovations	Display, Digital, Assist, Standard, Package, Available, Function	Discussing 1. customisation packages options 2. advanced safety systems (e.g., driver assistance) 3. infotainment and digital display systems (e.g., navigation & entertainment)

Note. Only the topics related to the objectives of this paper were selected

Table 4: Topic Modeling: GermanCarForum

Topic Number	Topic Name	Keywords	Sentiment
2	Maintenance Service	Service, Problem, Check, Cost	Negative
3	Interior / Exterior Design & Brand Image	Luxury, Colour, Design, Quality, Trident, Leather, Paint	Positive
4	Track & Technical Performance	Track, Performance, Speed, GTS, Race, mph, Clutch, Speed	Positive
6	Engine Performance	Engine, Exhaust, Power, Oil, Litre, Fuel	Positive

Note. Only the topics related to the objectives of this paper were selected

Table 5: Topic Modeling & Sentiment Analysis: SportMaserati

This paper begins by analysing similarities between SportMaserati and MaseratiLife (Table 6), and conducts a comparative analysis to compare Maserati's offering with results from GermanCarForum, which is related to user perceptions of competitors.

Topic Number	Topic Name	Description	Sentiment
SP(3) / ML(4)	Design, Personalisation & Brand Image	Discussing: 1. Materials (e.g., leather, carbon) 2. Exterior & interior finishes (e.g., paint, colour, body) 3. Brand image (e.g., luxury, trident)	Positive
SP(6) / ML(6)	Engine Performance	Discussing: 1. measures of engine performance (e.g., horsepower, revolutions per minute and torque) 2. Fuel efficiency and exhaust system	Positive
SP(4) / ML(7)	Track & Technical Performance	Discussing: 1. car performance capabilities (e.g., acceleration, top speed and handling) on tracks 2. GTS models sporty attributes and performance	Positive
SP(2) / ML(7)	Maintenance & Longevity	Concern about: 1. maintenance, repairs, service costs and warranty claims	Negative

Note. SP refers to SportMaserati; ML refers to MaseratiLife

Table 6: Topic Modeling: Similarities Between SportMaserati and MaseratiLife

4.1 Similarities Between SportMaserati and MaseratiLife

4.1.1 Design, Personalisation and Brand Image

Discussions about design and personalisation reveal a positive sentiment within the Maserati community. Materials and exterior and interior finishes are highlighted in this topic, with customers mentioning materials such as leather and carbon, indicating their appreciation for the luxurious elements that define Maserati vehicles. Moreover, exterior and interior finishes such as paint, colour variations, and body aesthetics, reflect customer enjoyment of a personalised and visually appealing experience. Customers perceived the trident symbol as a significant representation of luxury, indicating brand image plays an important role in their preferences.

4.1.2 Engine Performance

Discussions about engine performance, including horsepower (HP), revolutions per minute (RPM), torque, and fuel efficiency, are associated with a positive sentiment. This suggests that Maserati is perceived favourably in terms of its engine capabilities. Additionally, the inclusion of conversations regarding fuel efficiency and exhaust systems showcases customers ’environmental consciousness.

4.1.3 Track and Technical Performance

Conversations regarding the cars' performance on tracks, and on technical aspects including attributes such as acceleration, top speed, and handling, have a positive sentiment. Specifically, GTS models are highlighted for their sporty attributes and strong performance. This indicates that Maserati is perceived favourably in terms of its drivability, and GTS models equipped with sporty modes can satisfy customers seeking a more advanced driving experience.

4.1.4 Maintenance and Longevity

Topics related to maintenance, repairs, service costs, and warranty claims are met with negative sentiment. These are areas where Maserati can potentially make improvements.

4.2 Comparative Analysis of Maserati Offerings and Top Competitors

The similarities between Maserati's offerings and those of competitors are consistent. Both groups of customers focus on engine and technical performance, seeking the more advanced driving experience that luxury cars can provide to fulfil their needs. Exterior and Interior design is also discussed regularly in both Maserati's and their Competitors 'forums, underlining the appreciation among luxury customers for the aesthetic appearance and interior design that luxury cars exclusively feature.

In terms of personalisation, Maserati's and their competitors 'customers share different views. The former discusses more technological innovations such as in-car entertainment, display screens, and navigation systems, as well as safety systems, while the latter focuses more on the use of luxurious materials and brand image, indicating diversity in the preferences of luxury customers. The identified preference for technological innovations among competitors' customers could be an opportunity for Maserati to enhance its technology offerings.

5 Recommendation

The findings of this paper reveal a positive sentiment toward the Maserati Fuoriserie program, with particular emphasis on both the exterior and interior. These aspects suggest that Maserati's customers are satisfied with the personalised options currently provided by their car maker. Options include exterior finishes such as paints, liveries and dreamlines, as well as interior features such as dashboard, trim and lighting. We recommend that Maserati keep and reinforce their current customisation offerings. While the competitor's customer perception emphasises technological innovation such as infotainment systems, Maserati's in-car technology options place a greater emphasis on safety features such as driving systems, and on comfort elements such as heated seats and climate control. Although Maserati vehicles are also equipped with infotainment systems, this particular aspect is not frequently highlighted by their customers. Therefore, the comparative analysis findings indicate that luxury customers are also inclined to seek more advanced in-car technology, an area that Maserati could further improve upon. In addition to custom options tailored to drivers' infotainment needs, Maserati can attempt to enhance infotainment interactions with passengers, offering more personalised entertainment options tailored to passengers (Sen and Sener, 2020).

Furthermore, the findings of this paper reveal a positive sentiment toward the Maserati car engine and track performance, for which Maserati has been renowned. Besides discussing performance, customers mentioned fuel efficiency, reflecting their environmental consciousness. According to research (Kunz, May and J. Schmidt, 2020), there is an increasing trend in demand for sustainable luxury products; Millennials and Gen-Z customers in particular consider sustainability when buying luxury products (Devic, 2023). Moreover, Kunz et al. state that combining sustainability and environmental friendliness with luxury can help businesses achieve long-term success.

In recent years, Maserati has launched a series of eco-friendly car models such as the "Ghibli Hybrid" and "Grecale Folgore", showcasing their consciousness of environment-related concerns (Judge, 2020). Regarding customisations, to cater to environmentally aware luxury customers, Maserati could provide more options for sustainable, recycled, and natural materials, or fuel-saving technologies for luxury customers to choose from.

Contrasting with these positives, the findings of this paper reveal a negative sentiment toward Maserati maintenance. Maserati has been implementing a pre-paid maintenance programme for their customers, utilising a service indicator system to periodically remind customers when it is time for vehicle maintenance involving Maserati's skilled technicians. The preventive maintenance approach Maserati is leveraging today is a common strategy in the automotive industry. According to a report by Plant Engineering Maintenance (2019), 78% of businesses operated a preventive maintenance strategy in 2019.

While preventive maintenance follows a pre-planned schedule of servicing, the timing for car maintenance is contingent upon both the vehicle's condition and driver's behaviour. If drivers use their cars infrequently, the pre-planned service schedule might seem premature; conversely, if the car is driven extensively, the scheduled maintenance could appear delayed. This might cause an increase in over-maintenance and no-fault-found events, leading to cost inefficiency for car companies and customers. Finding an optimal time for vehicle maintenance can be challenging. To address that issue, this paper proposes a predictive maintenance approach for Maserati.

Accompanying the rise of Big Data and AI technology, an increasing number of automotive businesses have embraced the predictive maintenance approach. Research by Fortune Business Insight (2023) shows that the automotive industry's predictive maintenance market is forecast to reach a worth of USD $100 billion by 2032, indicating a steady Compound Annual Growth Rate

(CAGR) of 18.6% between 2022 and 2032. Predictive maintenance is a data-driven approach to predict future failures related to the vehicle, allowing the maintenance team to act before the actual problem arises. By gathering historical and real-time data from past service records and in-vehicle sensors, a data analytics team can use Machine Learning or Deep Learning techniques to conduct predictive analysis to forecast potential failures and send real-time notifications to both the customer and maintenance team about servicing or replacement of a component or system as and when it is required (Figure 8).

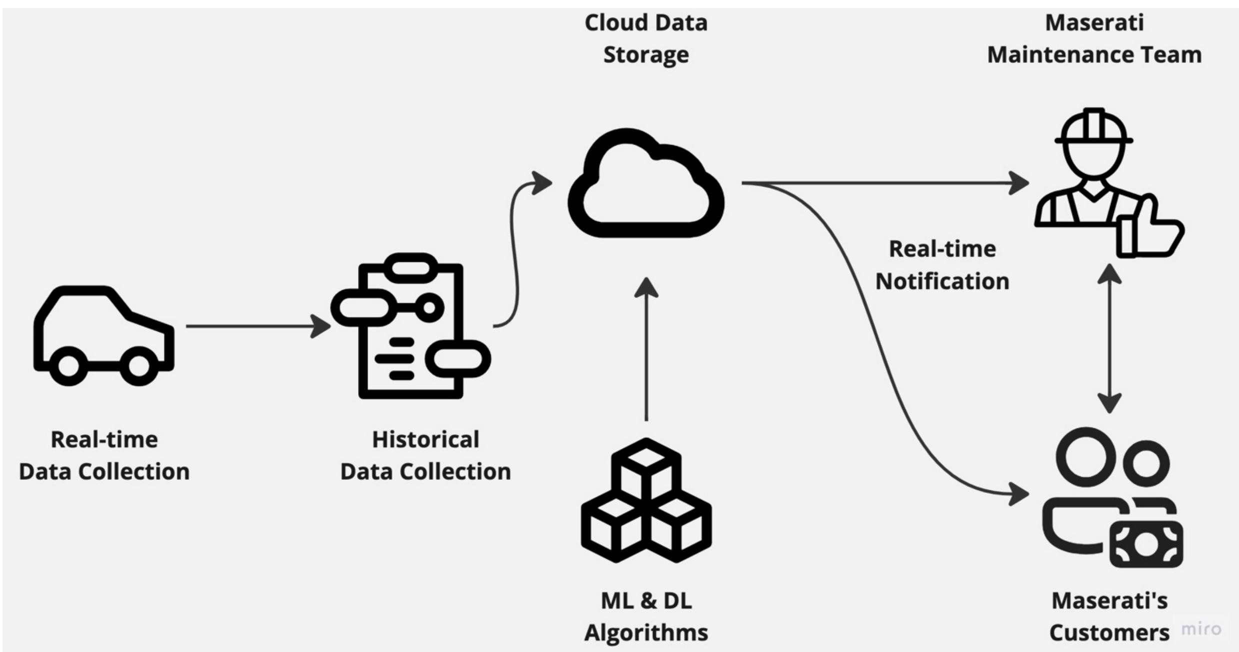

Figure 8: Flowchart of Predictive Maintenance Approach

Predictive maintenance is beneficial for both customers and car companies; it can reduce unnecessary visits for customers, leading to a decrease in their car repair costs. Moreover, it can reduce downtime and extend the car's longevity. Benefits extend to car companies, giving more effective control over their maintenance costs, allowing for provision of tailored maintenance services ahead of time, and leading to reduced warranty claims from customers. As the findings of this paper show, luxury customers care about maintenance services and want their luxury cars to be kept in good condition; consequently, Maserati could incorporate predictive maintenance into their configuration strategy.

6 Conclusion

In conclusion, this study delved into the perceptions and preferences of luxury automotive customers, particularly those of Maserati, through the analysis of online forums. The findings underscore the positive sentiment towards Maserati's personalised offerings, engine performance, and track capabilities, while also highlighting areas for improvement in maintenance services. By comparing Maserati's standing with competitors' perceptions, the study has revealed opportunities to enhance technological innovation and sustainability in alignment with customer desire. The proposed incorporation of predictive maintenance as part of the configuration strategy addresses the customer concerns surrounding maintenance. Through these insights, this paper provides valuable recommendations for Maserati to refine their approach to customisation, technology, sustainability, and maintenance, positioning themselves more effectively in the dynamic luxury automotive market landscape.

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Appendix A - Excluded Sub-forums within Forums

GermanCarForum	**SportMaserati**	**MaseratiLife**
Buysell	Announcements	Asia
In the News	Australia	CARiD.com
Off Topic	Events	DashLynx.com
Resource Discussion	Humour, Jokes and Other Topics	Do It Yourself (DYI)
	USA	EBC Brakes
		Loudoun County Exotics
		Maserati Market
		Maserati Events
		Middle East
		Maserati Registry
		North America
		Vintage Maserati
		Vendor Deals
		4X4 Shop Canada

Table 7: Excluded Sub-forums within Forums

Appendix B - GermanCarForum Description of Data Attributes

Field Name	Data Type	Field Size	Example
section_name	object	198502	Aston Martin
thread_title	object	198502	Aston Martin Zagato concept revealed
post_ID	object	198502	518615
post_date	datetime64[ns]	198502	2011-05-26
post_username	object	194275	330CIZHP
post_text	object	183810	This look gorgerous.
post_order	int64	198502	9
replier_post_ID	object	54275	518615
user_location	object	1154	Paris
user_gender	object	831	Male
user_occupation	object	458	Engineer
user_messages_count	float64	2899	270
user_reaction_score	float64	2899	543
user_car	object	475	BMW 330 CI ZHP 6 speed manual
user_birthday	datetime64[ns]	108	1980-05-26
user_about	object	190	Automotive History,1989 Porsche 930 - M48 - G64/51
user_member_type	object	25	Staff member
user_country	object	1154	France
user_continent	object	1154	Europe
occupation_group	object	407	Technicians and associate professional
user_age	float64	108	43

Table 8: GermanCarForum Description of Data Attributes

Appendix C - SportMaserati Description of Data Attributes

Field Name	Data Type	Field Size	Example
Section	object	391608	MC
Title	object	391608	MC20 no likey
Comment	object	391608	This smarts a bit and shatters a dream
User	object	391608	conaero
Forum Owner	object	391608	conaero
Date	datetime64[ns]	391608	2023-05-28 13:40:25+01:00
ParentUser	object	106368	conaero
ParentComment	object	106368	Captain slow me be
ParentID	float64	106368	3
Location	object	265469	United Kingdom
Age	float64	47834	54
Message Counts	float64	97835	270
Reaction Score	float64	195425	543
Points	float64	97835	222
ID	int64	391608	1

Table 9: SportMaserati Description of Data Attributes

Appendix D - MaseratiLife Description of Data Attributes

Field Name	Data Type	Field Size	Example
section_name	object	291887	Formula Dynamics
sub_section_name	object	268408	MC20 no likey
thread_title	object	291887	Thanks to Cyril for great support
thread_id	int64	291887	17217
thread_views_count	int64	291887	4078
thread_reply_count	int64	291887	2
thread_participants_count	int64	291887	1
sender_name	object	290572	Spectrum
sender_post_id	int64	291887	158130
receiver_post_id	float64	75423	43840
receiver_name	object	75097	j01270
date	object	291887	Jul 26, 2012
time	object	291887	12:54 AM
content	object	288928	What year is the QP?
order	int64	291887	1
datetime	datetime64[ns]	291887	26/07/12 0:54
user_name	object	283926	cessna_2100
user_location	object	165065	Dubai, UAE
user_replies	float64	285241	179
user_discussions_created	float64	285241	17
user_reaction_score	float64	285241	133
user_points	float64	285241	63

Field Name	Data Type	Field Size	Example
user_additional_info	object	136780	2011 Quattroporte Sport GT S
user_country	object	164720	USA
user_continent	object	163350	North America

Table 10: MaseratiLife Description of Data Attributes

Appendix E - Data Size of Three Forums

Forum	Data Size
GermanCarForum	146025
SportMaserati	25790
MaseratiLife	5201

Table 11: Data Size of Three Forums

Appendix F – Architecture of Simple Dense Neural Network

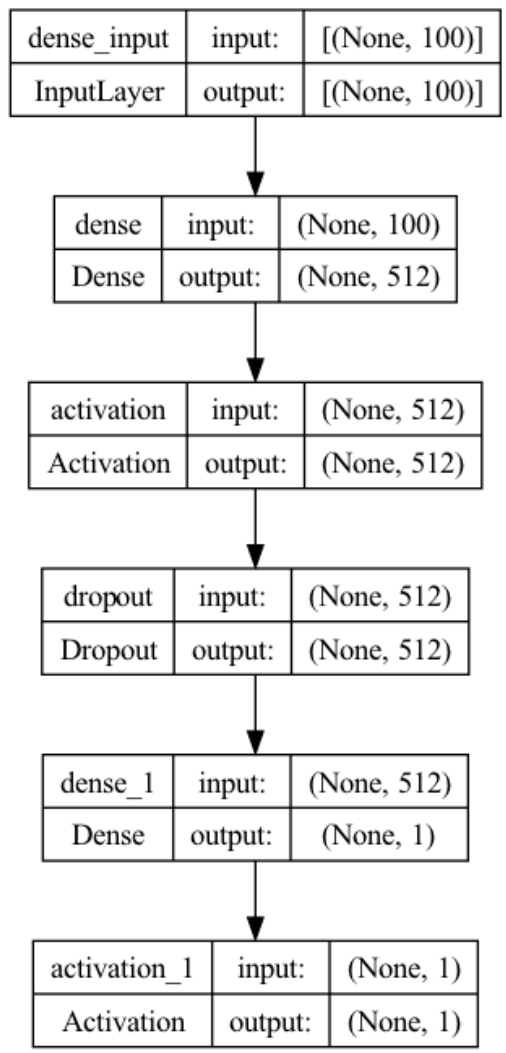

Figure 9: Architecture of Simple Dense Neural Network

Appendix G - Topic Modeling visualisations: GermanCarForum

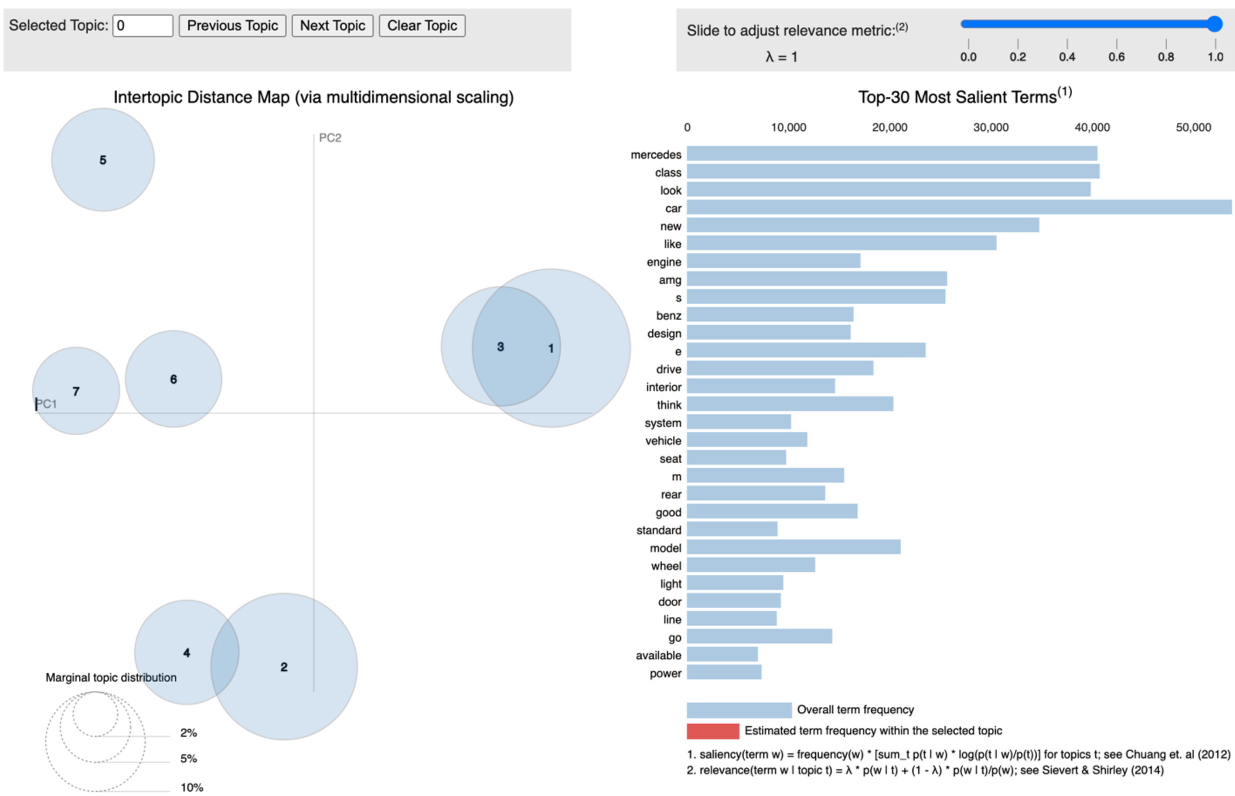

Figure 10: Topic Modeling visualisations: GermanCarForum

Appendix H - Topic Modeling visualisations: SportMaserati

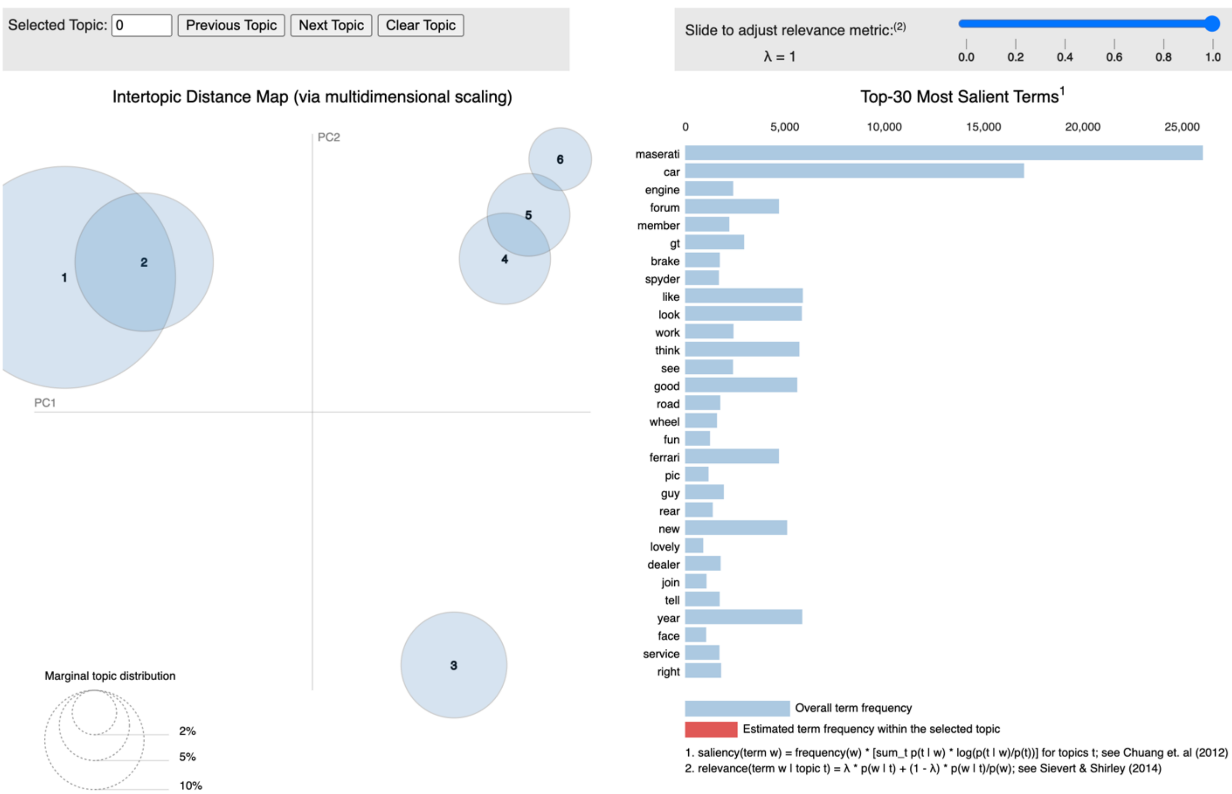

Figure 11: Topic Modeling visualisations: SportMaserati

Appendix I - Topic Modeling visualisations: MaseratiLife

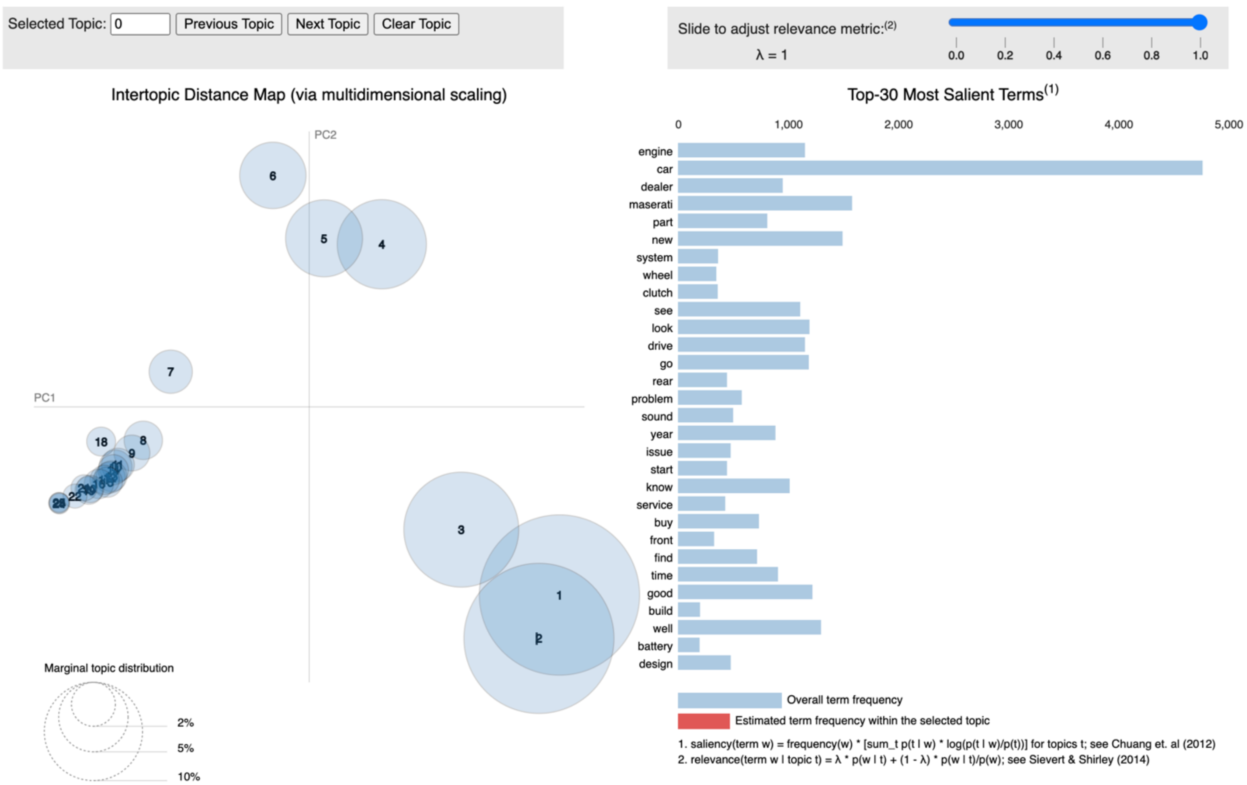

Figure 12: Topic Modeling visualisations: MaseratiLife