BRAND HEALTH WITH SHARE OF SEARCH

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Abstract

This master thesis explores the relationship between Share of Search (SoS) and Share of Market (SoM) at the category and product levels, and the impact of pricing on this relationship. It provides insight in the validity, reliability, and method transparency. This research exploits quantitative and exploratory research methodologies, providing insight in analysing methods utilizing search data. The research method is built up around a massive dataset from the automotive industry in the Netherlands. After an in-depth correlation analysing, a moderate positive correlation was found between SoS and SoM on both the category and product levels, with a stronger correlation observed on the product level. The relation between SoS and SoM may be influenced by specific characteristics and features of different car brands, such as brand image, reputation, and customer loyalty. The study also found that including lag in time is crucial when studying the correlation between SoS and SoM. Moreover, brand search volume is a reliable indicator of brand health, and the use of SoS in understanding the dynamics of new technology growth and adoption has significant implications for businesses in terms of pricing strategies, product offerings, and marketing campaigns. Businesses and marketeers should focus on external metrics like SoS to stay ahead of the competition and meet the changing needs of consumers. The use of SoS, along with other metrics and data sources, can help identify emerging trends and adapt strategies to meet evolving consumer needs. While SoS has many advantages, there are still some limitations and directions for future research that need to be considered. Future research could investigate the relationship between SoS and consumer behaviour models, determine if SoS can be used as an indicator of attitudes, and explore ways to enhance SoS as a measurement to provide more accurate insights into brand success.

Keywords: share of search, share of market, consumer interest, brand health, correlation analysis

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Acronyms List

ESoS	Excess Share of Search
NLP	Natural Language Processing
PPC	Pay per Click
SEA	Search Engine Advertising
SEO	Search Engine Optimization
SoM	Share of Market
SoS	Share of Search

1. INTRODUCTION

With the rise of technology and the internet, the way we access and consume information has changed dramatically. Online communication has become a central part of our daily lives. One of the defining features of online communication is the ease and speed with which information can be accessed. The internet has become an information ecology, with a vast amount of information available at our fingertips. Search engines, such as Google, have become essential tools for people seeking information, helping us to navigate the vast network of data available on the internet (Van Couvering, 2011). Nowadays, Google is by far the most well-known and used search engine. It currently processes, on average, more than 40000 search queries every second, amounting to more than 3.5 billion searches daily and 1.2 trillion searches annually globally (Internet Live Stats, 2022). This emphasizes the everyday deployment of search engines in helping people find the required information they are looking for. Search engines use sophisticated algorithms to analyse and rank websites based on relevance, helping people to quickly find the information they need. This has had a profound impact on the way people access and use information and has made it easier for them to find what they are looking for. However, the impact of search engines goes beyond just providing people with access to information.

Search engines also have a powerful influence on customer purchasing behaviour. By determining which websites appear at the top of search results, search engines can determine which products and services are most likely to be seen by potential customers. This has led to the rise of marketing strategies such as search engine optimization (SEO) and search engine advertising (SEA). More recently, businesses have noticed a substantial increase in demand, which is associated with the Covid-19 pandemic (Nguyen, 2020). Brands heavily invested in pay-per-click (PPC) advertising to take advantage of this chance and used Google advertising services to increase their customer base (Lee et al., 2020). This strategy helped businesses to generate predictable levels of customer acquisition, leading to an increase in PPC expenditure and the establishment of a strong foundation for success (Lee et al., 2020). However, over the last few years, especially during the pandemic, having more customers also presented a challenge as some businesses faced a performance ceiling despite their investments in performance marketing (Kim et al., 2021). Additionally, the pandemic-induced increase in e-commerce is here to stay, but the online market has become crowded with the shift of many traditional retail stores online during the pandemic, leading to higher PPC costs and more intense competition for customers (Lee et al., 2020). To overcome this, it is important for brands to invest in the top of the funnel and the first stages of the customer experience (Al-Maghrabi et al., 2019). According to the literature, a rather simple rule of thumb is that brand identification should receive 60% of the budget, and performance marketing should receive 40% (Binet & Hankins, 2022). While brands invest in marketing strategies, such as SEO and SEA, to increase their customer base and generate predictable levels of customer acquisition, they often overlook evaluating their brand health. Which is important since it provides a clear understanding of their market position to be better prepared for uncertainty (Hauser et al., 2019). This oversight limits their ability to adapt, differentiate, and effectively engage with customers in a dynamic and competitive marketplace.

Nevertheless, when brands conduct brand tracking studies, they need to invest significant resources (Hanssens et al., 2014). Traditional brand monitoring studies need to invest a lot of time and money since they mainly rely on survey-based metrics. However, it is getting harder to get survey participants, and there are questions about how accurate self-reported opinions and actions are (Vargo & Lusch, 2016; Hanssens et al., 2014). One common method to evaluate brand health and measure consumer brand attitudes is through survey-based measures. These measures are widely embraced by marketers to assess brand performance and benchmark it against competitors (Aaker, 2019). In brand attitude surveys, respondents are usually asked to provide their opinions on various aspects of a brand, including its level of brand awareness, familiarity, consideration, and purchase intent (Vargo & Lusch, 2016). Previous studies have demonstrated that these metrics of consumer attitudes can anticipate future sales (Hanssens et al., 2014). To give a thorough insight of market demand and brand performance, in a less costly and time-consuming way additional methodologies that can supplement or replace conventional brand monitoring studies are required.

A notable development within the literature is that there appears to be a decline in studies employing customer-based performance measurements (Katsikeas et al., 2016), which suggest that there is less interest in performance measurements focusing on customer demands. This is remarkable since research also highlights the need to identify customer's demands and needs, since 66% of the consumers even want brands to understand and address their needs (Salesfore, 2020), and that customer centric companies are 60% more profitable than companies that do not focus on customers (Deloitte, 2017). Currently, the domain of financial-market indicators - as sales revenue, profit, and market share - are increasingly being used as the main performance indicators (Katsikeas et al., 2016), which indicates the rising interest in the financial performance outcomes of marketing. This might be a result from the focus on short-term profit from top management the past years (Binet & Field, 2018). The tendency to base performance evaluations on relatively short-term online measurements is harmful for long-term performance, since short-termism results in a loss of effectiveness (Binet & Field, 2013; Binet & Field, 2018). Thereby, the absence of metrics available to calculate the long-term effect of performance also contributes to the tendency of using short-term measurements (Karlíček, Chytková, Tyll & Mohelská, 2014; Feng, Morgan, & Rego, 2015). Customer centricity seems to be a key driver for growth, and measurements that indicate and define consumer interests are therefore a necessary.

Search engines like Google save anonymized search data that reveal information about potential consumers, such as the search query entered which represents their interests and needs (Google, 2022). In recent years, searches have become more detailed due to the increased availability of information online and the need for users to find the most relevant information (Sinclair & Bandyopadhyay, 2022). Previous studies have investigated the capability of Google Trends data to predict outcomes in various industries (Jun & Park, 2016; Jun, Sung & Park, 2017), with varying degrees of success (Barreira et al. 2013; Geva et al., 2017). Thereby, the lag time factor has not been considered, which is a crucial aspect since the decision-making time between an information search and the actual purchase might differ between products and categories. Furthermore, among the pile of search data, a group of brand-specific queries exists. There is, however, little research on the reasons why consumers make brand-specific queries. It is assumed that these queries represent an intermediary step in the path-to-purchase. The path-to-purchase can be explained by the consumer behaviour and adoption model. The behaviour models posit that consumers typically show interest in a product or service by conducting online research before making a purchase. Previous research found that users with positive brand attitudes are more likely to search for brand-specific queries (Dotson et al., 2017). Brand-specific queries seem to represent an intermediary step between interest and purchase, providing the ability to track consumer interest in a brand. As previously mentioned, studies have demonstrated that metrics of consumer attitudes, and aspects as the level of brand awareness, familiarity, consideration, and purchase intent (Vargo & Lusch, 2016), can anticipate future sales (Hanssens et al., 2014).

Recent research has focused on the novel metric Share of Search (SoS), which compares a brand's online visibility to that of other businesses in the same category. This is said to be a tool for businesses to assess the health of its brand since it tracks the interest in a brand. Thereby, it is proposed that the newer concept of SoS is an indicator for market share (Binet, 2021; Hankins, 2022). It assumes that, if more people are searching for a business, people are more inclined to purchase from that business.

Nevertheless, literature lacks information about validity and reliability, and method transparency to assess the relation between SoS and Share of Market (SoM). While some preliminary insights are emerging and seem encouraging, a systematic exploration is warranted. This study aims to examine how SoS is related to SoM including the lag time variable, and how SoS may be used to identify the development of consumer interest in a brand. This is captured in the following research question:

Research question: *How can Share of Search (SoS) be used to assess consumer interest and brand health?*

The terminology of consumer interest within this study is associated with the variables of brand awareness, familiarity, consideration, and purchase intent. Brand health is associated with performance of a brand, reflecting its market position, competitive advantage, and customer perception. The justification of these variables is explained within the theoretical context.

To answer the research question, it is divided into two sub-questions. The first sub-question explores the relationship between SoS and consumer interest:

Sub-question 1: *What is the relationship between Share of Search (SoS) and consumer interest in a brand?*

The second sub-question explores how SoS can be used to benchmark the performance of a brand against its competitors, and how this relates to its market position:

Sub-question 2: *How can Share of Search (SoS) be used to benchmark a brand's performance against competitors and assess its relative market position?*

In this light, this study is situated at the intersection of digital marketing and communication sciences. In today's digital age, this intersection has become increasingly important for businesses looking to succeed in the competitive digital landscape. The connection between digital marketing and communication sciences lies in the fact that digital marketing is reliant on understanding the way people interact with digital media and consume information online. A deep understanding of customer desires and needs, and how these are changing, is crucial for creating effective digital marketing strategies. The practical relevance of this study lies in determining whether SoS can be utilized by marketing strategists to assess the consumer interest in a brand on a category level and on the product level. The results of this study could contribute to the way marketeers and businesses assess the health of their brand. The examination of this novel theoretical concept has academic relevance by assessing the validity and reliability, and to provide transparency in the used method. Thereby, it contributes to existing literature on assessing consumer interest in a brand, and its implications for not only marketing, but communication sciences as well. Additionally, the systematic approach to researching by utilizing search data and exploring the SoS metric directs future researchers in their efforts. Finally, as the digital landscape continues to evolve, it will be important for researchers and businesses to continue to develop and refine consumer behaviour models to keep pace with changing consumer behaviours and preferences.

Adopting a perspective that draws upon consumer behaviour and adoption theories, the study aims to investigate the role of search data in assessing a brand’s health. This thesis is structured as follows. Prior to delving into search data, it is necessary to obtain a deeper understanding of how search engines have impacted the way in which people access and consume information online. The present study devotes the first part to exploring the influence of search engines on consumer behaviour. Subsequently, this research assesses how consumer interest is positioned within different theories of consumer behaviour and adoption, and how these models are linked to the realm of search data. Hereafter, it presents a comprehensive review of the SoS metric, and proposes hypotheses to address the research questions previously mentioned. The research design and methodology chapter define how the research questions will be answered throughout the analysis part. Hereafter, the results are presented and discussed. The study is subject to limitations and therefore directions for future research are presented in the discussion chapter as well. Some concluding remarks finalise the thesis.

2. THEORETICAL CONTEXT

This study seeks to explore the role of search data in assessing a brand's health through the consumer behaviour and adoption theories lens. The first part delves into the impact of search engines on how people access and consume information online. Hereafter, different consumer, and adoption models are discussed, and which give way to how the SoS concept is positioned within the current literature. Finally, this chapter provides working hypotheses on which this research is further built.

2.1 CONSUMER SEARCH BEHAVIOR

The role of the internet as an information ecology has been central in shaping a so-called online search culture. The amount of information that is available online has made it necessary for individuals to learn how to navigate and access the information they need efficiently.

Traditionally, search engines relied on keyword-based algorithms to match user queries with relevant web pages. The functions of a search engine entail gathering information about webpages, categorizing them, and creating an algorithm that enables users to easily find relevant webpages. A generally accepted definition, provided by Van Couvering (2008), of search engines is a "computer program that allows the user to enter a series of keywords, usually called a 'query', and that responds with a list of results from a database that match the query" (p. 1). As presented by Van Couvering (2011), the issue is not so much getting information and content to users, but rather getting users to the information and content. As a result, the 'supply chain for search engine users' was created, in which search engines serve as a link in the chain that directs users to the most relevant destination, which is usually a webpage (Van Couvering, 2011). This, however, changed when advertising-based search engines such as Google introduced pay-per-click (only pay for advertising if your ad is clicked on).

The core of search business shifted from users to traffic. In other words, "the flow of visitors from one website to another" (Van Couvering, 2011, p. 10). The sophisticated algorithms search engines use to analyse and rank websites based on relevance, help people to quickly find the information they need. This has had a profound impact on the way people access and use information, since this model relies on advertising revenue, which may prioritize the interests of advertisers over users and the broader online knowledge ecosystem, leading to potential conflicts of interest and undermining trust (Crawford & Finn, 2015). Which raises questions about the responsibility of search engines in directing users to relevant and trustworthy information, as ranking algorithms can privilege certain voices and perspectives and potentially marginalize important and diverse views. Furthermore, the introduction of 'traffic' and its value led to the rise of key marketing strategies as SEO (Van Couvering, 2011) since anonymized search data and the volumes about the interaction between users and the search engine were within reach. This way not only optimalization could be performed, but manipulation as well. Search engines must filter out misinformation and promote accurate and reliable sources of information, which can be a challenging task.

But not only the core business of search engines has changed over the years. Search strategies of search engine users has also changed. Since the vast repository of digital information only became larger the past few years, users have gradually started using more precise language to filter the needed information. As a result, search queries have become considerably more complex and sophisticated over time. The queries users use when they are looking for information, consists of the main keyword, and additional words to specify the search, which are known as 'modifiers' (Rennie, Protheroe, Charron & Breatnatch, 2020). When there is more information available online, it takes more effort to find the required information. By conducting detailed searches and using (more) modifiers, more precise language, it is easier to navigate through digital information. The modifiers reveal people's thoughts and sentiments about a particular topic, and can indicate intent, which is a precursor to changes in demand (Jun & Park, 2016; Sinclair & Bandyopadhyay, 2022). In other words, modifiers are said to provide nuance and specificity to the primary topic (Sinclair & Bandyopadhyay, 2022). That search engines wield a significant impact in shaping consumer behaviour and influencing purchasing decisions is not new. According to a more recent study over 88% of consumers conduct online research before making a purchase (European E-commerce and Omni-Channel Trade Association, 2021). The study also found that search engines are the most used platform for conducting research, with 97% of consumers using them to research products and services. Previous research shows that consumer search data can be used to track these information searches (Jun et al., 2014; Jun, 2016). The rise of search engines as a primary source of information for consumers has, arguably, made them a powerful force in shaping consumer behaviour and influencing purchasing decisions. It is therefore important for businesses to understand the role of search engines in the broader information ecosystem of 'online knowledge', and to stay up to date with the latest search strategies and trends to remain competitive in the digital landscape.

We conclude that the influence of search engines on consumer behaviour is two-fold. On the one hand, search engines have become more influential in shaping users' access to information and the internet. On the other hand, search engines act as a primary source of information for consumers, which has made them a powerful force in shaping consumer behaviour and influencing purchasing decisions. As search engines become more powerful and influential, it is important to consider these potential implications to better navigate issues and ensure that informed decisions about the information encountered are made. Critical evaluation of search engines' impact on consumer behaviour from the perspective of consumer behaviour theories is warranted. Therefore, the next part assesses how different consumer behaviour and adoption theories explain consumer behaviour, and how this develops in an online environment.

2.2 CONSUMER INSIGHTS

Understanding how people search for and consume information online, and how this evolves, is crucial for businesses, marketers, and researchers alike. In this sub-chapter different theories explain consumer behaviour, and how this develops in the digital landscape. The objective of the sub-chapter is to provide a definition of consumer interest and assess how SoS and consumer interest are related in the current literature.

2.2.1 Consumer Behaviour Model

Consumer behaviour models are theories that seek to explain how consumers make decisions about what products to buy, and where to buy them. Consumer behaviour is shaped by cultural, social, and personal factors, and various models of consumer behaviour have been put forth to gain a deeper understanding of such behaviour (Kotler & Armstrong, 2021). These models have been developed by researchers in various fields, particularly, marketing, psychology, economics, and sociology, and are used to understand and predict consumer behaviour in a variety of contexts (Kotler & Armstrong, 2021). Consumer behaviour is a complex process that requires an understanding of the different stages that consumers go through before making a purchase decision. Understanding consumer models is crucial for businesses as it can help them to identify and meet consumer needs more effectively (Schiffman & Kanuk, 2016).

When the purchasing decision is included in the consumer behaviour model it describes the decision-making process consumers go through when making a purchase. Nevertheless, the process of purchasing begins before the actual purchase is made and extends well beyond it (Kotler & Armstrong, 2021). Therefore, businesses and marketers should focus on the entire purchasing process, rather than just the decision to purchase. Recent literature highlights the importance of taking a customer-centric approach to marketing and the need to consider both models to gain a comprehensive understanding of consumer behaviour and purchasing decisions. When the purchasing decision process is based on the consumer behaviour model, they buyer behaviour process comprises several stages, including problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase evaluation (Kotler & Armstrong, 2021). One of the most significant stages in the consumer behaviour model is the information search stage. This stage involves searching for relevant information that can help consumers make an informed decision before purchasing. Relying, however, solely on the information search stage to understand consumer behaviour is insufficient, and one must consider all stages of the consumer behaviour model to gain a comprehensive understanding (Kotler & Armstrong, 2021).

As discussed in the previous chapter, in most cases a purchase starts with an online information search, and the intent of these searches is, arguably, a precursor for demand. Search data may represent the information search stage, since research has shown that search volumes can predict customer behaviour and sales for both low- and high-involvement purchases, as well as buying intent (Choi and Varian 2012; Yang et al. 2015). Previous research has shown that search data has the potential to estimate near-future forecasts by analysing trends in real time. Studies in the past have explored the potential of Google Trends data to forecast results in different sectors (Jun & Park, 2016; Jun, Sung & Park, 2017), achieving mixed results (Barreira et al., 2013; Geva et al., 2017). Search data can predict changes in customer demands and interests, preceding purchases, indicating potential growth opportunities for businesses. The correlation between search activity and sales suggests that search data can be utilized as a precursor for sales. The peak in search data occurs earlier than in sales, indicating its predictive power. This aligns with consumer behaviour models that propose consumers search for information before purchasing. However, time lag varies across categories and products, and is an important factor that is often neglected in previous research. Since this research relies on consumer behaviour models, the lag time must be included when analysing the correlation between the SoS metric and sales (being SoM), because these models propose that consumers search for information before purchasing.

As most consumers start with an online search for information, and the aim of these searches acts as a forerunner to demand. This indicates that search data insights provide valuable insights in the interest search stage, as they can provide insights into customer demands and interests and how these changed and will change in the future. This is important because attracting consumers throughout the adoption process is essential for expanding market share. However, a major drawback from this model, is that the process is not a linear from awareness to adoption anymore. Consumers not only look at one business these days. They continually compare businesses with each other, to choose the best option for them. Especially, since the online environment (almost) provides unlimited opportunities. Google recognized this and introduced the messy middle model.

2.2.2 The Messy Middle Model

The "messy middle" is a concept in marketing that refers to the complex decision-making process consumers go through when making a purchase in the digital environment. It is called the "messy middle" because it is not a linear process. Instead, consumers navigate through a variety of touchpoints, research options, and may experience moments of hesitation or reconsideration. This model was thus introduced by Google, after research showed consumers were no longer taking a straightforward path to purchase. The phase of exploring all the information sources available is identified as the 'exploration phase', and the evaluation of the information and deciding where and when to purchase as the 'evaluation phase' (Rennie, Protheroe, Charron & Breatnatch, 2020). As can be expected, decisions to acquire a product or service might take time, previously introduced as the lag-time. Rennie et al. (2020) visualized this exploration and evaluation phase as a continuous process, because the customer flows through these phases until they decide on what product or service to purchase.

The difference between consumer behaviour and adoption models, and the messy middle model is that the first assume that consumers are rational decision-makers who evaluate all the available information and choose the best option. The messy middle model, on the other hand, recognizes that consumers are not always rational decision-makers. More specifically, consumers are seen to engage in complex decision-making processes that involve emotions, biases, and cognitive shortcuts. The model suggests that consumers go through three stages when making purchase decisions: initial consideration, active evaluation, and closure. In the initial consideration stage, consumers are open to considering different options. In the active evaluation stage, they engage in intense research and evaluation before deciding. In the closure stage, they make a final decision and act. Understanding the 'messy middle' is important for marketers, as it can help them to tailor their messaging and experiences to meet consumers' needs and expectations at each stage of their journey. By anticipating and addressing consumers' questions, concerns and hesitations, marketers can increase the likelihood of conversion and build long-term loyalty. In conclusion, the messy middle model highlights the complexity of the consumer decision-making process, emphasizing the importance of understanding consumers' needs and behaviours in an online environment. Which is important since this research is about the digital landscape.

2.2.3 Consumer Interest

The discussed models are built on different stages, but some overlap can be detected as well. The most important takeaway from the three models is that they all propose consumers do some kind of search for information before purchasing. Thereby, we learned that the lag time is an important factor to consider in this study, and that it is essential to remind that in a digital environment consumers engage in complex decision-making. Consumers constantly look for information, and evaluate and compare products, services, and brands to each other. The models just show how consumers make decisions, by going through the process of identifying their needs, evaluating their options, and making a final decision. In other words, the data that flows from the search for information by consumers might show something about where in the decision-making process certain information is needed or wished for. Brand-specific queries seem to represent an intermediary step between interest and purchase. This provides the ability to track consumer interest in a brand, since positive brand attitudes are more likely to search for brand-specific queries (Dotson et al., 2017). Thus, there seems to be an opportunity to track the consumer interest in a brand by analysing the branded-search queries. In respect to this study, consumer interest is the degree of a person's interest in, or desire for, a specific good, service, or brand, showing their propensity to learn more about, interact with, or even purchase it. With the novel metric SoS, which presents a brand's visibility in the digital environment, consumer interest can be measured. The next part delves into SoS as a metric, and how it is positioned within the current literature and models presented.

2.3 SEARCH INSIGHTS: SHARE OF SEARCH

SoS is a novel metric that compares a brand's online visibility to others in the same category and is said to be a measure for market share in a more accessible and cost-effective way (Binet, 2021; Hankins, 2022). SoS employs brand-specific queries that are thought to provide insight into the path-to-purchase process. As we learned from the models discussed in the previous sections, consumers indeed do some kind of search for information before purchasing or adoption, but these are complex decision-making processes that involve emotions, biases, and cognitive shortcuts. This can be seen in the queries since they have become more sophisticated and detailed. Since it is not exactly known where in the decision-making process brand-specific queries take place, SoS is positioned in the current literature as a metric for the overlapping interest, information, and evaluation stages in the previously discussed models. These stages cover the early and later phases of the decision-making process, being information and evaluation stages.

SoS is calculated by dividing a brands search for a category by the total searches for all brands of the category for the same period:

SoS = (brand searches category X) / (total searches all brands category X) * 100

All brands should be mapped for one single category to create the SoS. This way the relation of one brand against the whole category can be determined.

2.3.1 Brand Health

Understanding performance is a crucial aspect of any brand or business, as it can have a significant impact on the success of the company. In respect to this study, brand health refers to the overall well-being and strength of a brand in the market which goes by Share of Market (SoM). Within the strategic management field, the relationship between SoM and business performance have been extensively examined, and are positively correlated (Bhattacharya, Morgan, & Rego, 2021). However, there are variations in market share between areas, that are thought to reflect varying levels of market maturity (Edeling & Himme, 2018), which indicates that SoM provides insight into different phases of life cycles. SoM is defined as the percentage of a company's total sales that it generates in an industry. The company's sales for the period are divided by the total sales for the whole industry for that period to determine SoM:

SoM = (total company's sales) / (total industry sales) * 100

For 26 categories within 11 different industries, previous research examined the correlation between SoS and SoM (see Table 1; Hankins, 2021). As can be seen from Table 1, the previous examined categories differ in nature, ranging from premium make-up to cars. The 1:1 relation, SoS is an indicator for SoM, holds for all the categories. Which presents that SoS can be seen as a category wide indicator. However, as noticed before, lag-times between SoS and SoM differ across categories.

Table 1. Industries and corresponding categories in which the correlation between Share of Search and Share of Market are researched. Reprinted from Hankins (2021).

Industries	Categories
Automotive	Cars, SUVs, Motors
Fast Moving Consumer Goods (FMCG)	Breakfast cereals, Tea, Premium Make-Up, Potato snacks, Beer, Mascara, Ice-cream
E-commerce	Comparison websites, Home wear
Retail	Large retail, Discount retailers, Supermarkets
Technology	Broadband, Mobile handhelds

Education	Distance learning
Finance	Banks, Mortgages
Consumer Electronics	White goods (refrigerators etc.)
Utilities	Energy
Hospitality	Quick Service Restaurant (QSR), Restaurants, Travel
Non-Governmental Organization (NGO)	NGO

By comparing the SoM's with the SoS', they visualized the lag time, the time between searching and taking the decision to purchase a product or service. It differs per category how large the lag-time is. As previously argued, customers broadly search in proportion to the way they purchase (eCommerce Foundation, 2018), and since SoS is a metric based on search data, it is expected that SoS is a leading indicator for SoM. Within the existing body of literature, not much research focused on this concept. Consequently, the use of this measure is not widely accepted, and further assessment is necessary, and which is explored in this study by the following hypothesis:

H1: Share of Search is correlated with Share of Market.

IPA research (2021) has shown that the SoM and SoS changes are best linked through Excess SoS (ESoS). Where ESoS is determined by subtracting the SoM for year X minus 1 from the SoS for year X.

$$ESoS = SoS(X) - SoM(X-1)$$

Previous research indicated that when the ESoS is positive, it is a signal that SoM will rise, and if the ESoS is negative, it is a signal that SoM might decrease (Binet, 2021; Hankins, 2022). This way ESoS can be utilized to monitor the movements of SoS and the implications it has for SoM. Consequently, it provides the opportunity to predict future category and product development.

2.3.2 Influence of Price

When taking price into consideration, it seems to influence the correlation since luxury products and brands attract a lot of attention, but only a select few people choose to purchase them (Jun, Park & Yeom, 2014). Therefore, it is likely that an increase in searching for luxury products and brands by 'fans' does not translate into an increase in purchases. This is explored in the following hypothesis:

H2: The higher the average price of a brand, the weaker the correlation between Share of Search and Share of Market.

2.3.3 Influence of Lag Times

The previous working hypotheses are formulated based on the assumption that they are explored and analysed for a category level. However, this research wants to provide insights on the product level as well. Previous research mentioned that analysis at the product level is still difficult, but further refinement of keyword selection may help (Schaer, Kourentzes & Fildes, 2019). As mentioned in Chapter 1, changes in search strategies of users show that searches become more sophisticated and detailed. The modifiers in the searches provide specificity to the primary topic, which indicates that consumers interest can be observed by the different modifiers at the product level.

Following the fundaments of consumer behaviour and adoption models that the interest and information need converts into a purchase; it is expected that consumers who are searching for a brand and product combination are further along in the decision-making process. To illustrate, consider a potential consumer who might research a product online before making a purchase, say a car. If the potential consumer has a low level of knowledge on what kind of car to purchase, she will probably first search for information about cars in general, or brands she knows. The objective is to purchase a car, but the decision-making time can be rather long since the potential consumer first needs more information. Once she has done more research, she probably will search for the car brand and model she would like to purchase since she already did her research. In other words, it seems that the way the potential customer is searching, shows the stage of the decision-making process the potential customer is in. It is expected that more detailed searches at a product level will have a smaller lag time before purchasing, and the SoS and the SoM will be more strongly correlated than on a category level. This translates into the following hypotheses:

> H3: The Share of Search and the Share of Market are correlated on the product level with a smaller lag time than on the category level.

> H4: The Share of Search and the Share of Market are more strongly correlated on the product level than on the category level.

2.3.4 Exploring SoS

There will probably be differences in customer interest levels between newer and older products when assessing the SoS on the product level. In other words, when it comes to newer product models compared to older ones, consumers may display different searches and degrees of engagement. When a new product enters the market, it frequently arouses interest and curiosity among consumers. greater search volumes and a greater SoS compared to prior product models from the same brand may reflect the increasing interest in the new product. Customers may be actively seeking out details, opinions, or comparisons about the new product, demonstrating a higher level of involvement and possible purchase intent. On the other hand, as fresh models are introduced, older product models could see a reduction in consumer interest over time. As buyers turn their focus to more recent goods, the SoS for these older models may decline. This drop in SoS may be a sign that consumers are less interested in or searching for information on older products less actively. Marketers and companies benefit from knowing how the SoS of newer and older products differ. It offers information about consumer preferences, the dynamics of the product lifespan, and potential business prospects. Marketers may spot patterns, assess the success of their product range, and make well-informed decisions about product development, marketing tactics, and resource allocation by monitoring and evaluating the SoS of various product models. It's crucial to keep in mind that the precise SoS discrepancies between newer and older products may differ based on the sector, market conditions, and consumer behaviour. Nevertheless, the following hypothesis was stated:

> H5: On the product level there will be a difference in how the Share of Search is correlated with the Share of Market between newer and older products.

2.4 RESEARCH MODEL

This research investigates how SoS can be used to assess consumer interest and brand health. Figure 1 illustrates the research model of this study and helps visualizing the objective of measuring the relationship between consumer interest and brand health. Additionally, the research model (Figure 1) indicates the interaction effect (moderating) of lag times and price.

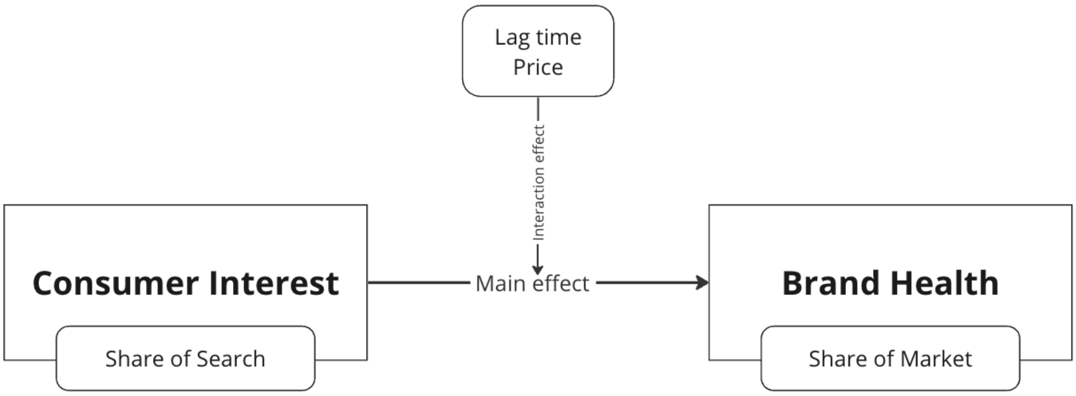

Figure 1. Conceptual Research Model

3. RESEARCH DESIGN AND METHODOLOGY

The first part of this chapter delves into the analytical approach of the research. Hereafter, the data collection process is described. Finally, it is presented how data is going to be analysed for the results section. The research design and methodology used in this research are explained with the aim to ensure that data is gathered and analysed in a systematic and reliable manner.

3.1 ANALYTICAL APPROACH

To answer the research question stated in the introduction, the research design of this study is divided into two phases. The objective in the initial phase of the research design is to assess the first four hypotheses. The aim of the second phase is to explore the fifth hypothesis.

This study utilizes both quantitative and exploratory research methodologies. A quantitative research design is used, which involves the collection and analysis of numerical data. This provides a clear understanding of the relationships between the SoS and SoM variables and enables statistical analysis to be conducted (Creswell & Creswell, 2017). A case study approach is used to obtain comprehensive information on the relationship between SoS and SoM (Yin, 2018). In this research, quantitative data is collected and analysed from a case using statistical methods to identify patterns and relationships. By using a case study in quantitative research, researchers can gather in-depth data and insights that may not be possible through other research methods (Yin, 2018). Additionally, a case study can help to provide context and nuance to quantitative findings and generate hypotheses for future research. The second part of the research has an exploratory research design since it explores how SoS can be utilized to provide insights in the development of customer interest for new products. This approach allows for a flexible and open-ended exploration of the concept, which can generate new ideas and hypotheses for future research.

Overall, the combination of quantitative and exploratory research methodologies used in this study can provide a comprehensive and nuanced understanding of the relationship between SoS and SoM. The use of case studies and statistical analysis can provide detailed insights into the phenomenon, while the exploratory research design can generate new ideas for future research. Due to the limited scope of the study and the time-consuming nature of data collection and analysis, the focus is on thoroughly examining one case study, namely the automotive industry with a focus on cars. The automotive industry is a major contributor to the economy of the Netherlands, which makes it a topic of interest for research since data on sales numbers is largely available. The SoS data for the research part is provided by the graduation firm: Trendata. In the following sub-chapter, Trendata and its way of working are introduced.

3.1.1 Graduation firm: Trendata

This study is conducted in collaboration with Trendata which is a real-time market and customer insights company that aims to assist businesses in making informed decisions about customer value, product innovation, brand engagement, and future-proof business strategies (Trendata, n.d.). In other words, its search insights offer businesses the opportunity to formulate demand-driven strategies. Trendata's working method approach is to search, capture, classify, analyse, and visualize data. This methodological approach helps to ensure that the data is gathered and analysed in a consistent and reproducible manner as previously discussed. This means that the data should be able to be collected again in the future using the same methods and produce similar results. This is important because it allows businesses to track changes in consumer behaviour over time and make informed decisions about future marketing efforts. The different stages of the methodological approach are shortly discussed below.

The first stage of Trendata's process is searching for data, which is solely obtained by scraping Google. It is feasible to obtain search results from different engines if clients wish that. However, as Google is one of the most widely used search engines worldwide, this supports arguments for generalizability. It is important to note that the relative search volume provided by Google is not an absolute number of searches. Instead, it is a comparison of the search volume for a particular keyword or topic in a specific time frame and location. This normalization process ensures that places with the most search volume would not always be ranked highest, making it easier to compare the relative popularity of different keywords or topics (Google, n.d.). For example, a search query for 'pizza' may show a higher search volume in Amsterdam compared to a smaller town like Enschede, but both locations may have the same search interest in pizza. Previous studies relied on absolute volumes, like the total number of hits, and as a result, they did not consider environmental elements that affect consumer exposure, including an overall rise in the number of web pages (Jun, 2012). So, Google only provides relative search volume per month, which is the query share of the searched term. The query share is calculated by dividing the query volume of the searched term by the total number of searches in the specified region and time frame (Google, n.d.). Once the query share is calculated, the month with the highest relative search volume is normalized to 100. This means that the score of 100 represents a different query share and the absolute number of searches for every model, depending on what the monthly maximum of searches was. For example, if the month with the highest search volume for a particular query was August 2022, then the score of 100 represents the highest query share for that query in August 2022 (Choi & Varian, 2012).

The next stage in the Trendata methodology is capturing the data by extracting it from the source and preparing it for analysis. Natural Language Processing (NLP) is used to capture all relevant queries over the past four years. Some research may argue that four years of data may not be enough to make reliable predictions or inform decisions accurately. However, in today's fast-changing environment, four years of historical data can be a significant advantage. Businesses need to stay ahead of the curve and adapt quickly to new trends to remain competitive. Thus, relying on data from a few years ago may not be relevant anymore. Moreover, older data may not reflect current market conditions or consumer behaviour. As people's preferences change, their search behaviour changes too. For instance, research related to remote work or online learning has significantly increased in the past two years due to the COVID-19 pandemic. A trend that was not as relevant before the pandemic. Therefore, using historical data from before the pandemic may not provide insights into current market conditions. Yet, four years of data can provide firms with a comprehensive picture of patterns across time. It enables businesses to monitor adjustments and spot trends in consumer behaviour as seasonal patterns and demand peaks.

Trendata relies heavily on NLP to capture relevant queries. While NLP is a powerful tool, it is not fool proof and may miss some critical data. Therefore, it is essential to have human oversight to ensure the accuracy and completeness of the data. Therefore, this stage is supervised by a data analyst of Trendata. After the NLP stage, the data analyst proceeds to classify the data into different categories or groups in the third stage. The classification of data into different categories or groups is beneficial, as it helps to organize the data and make it easier to understand and analyse. The fourth stage is analysing the data to extract valuable insights. Finally, the data is visualized to make it easier to understand and communicate the findings. In conclusion, the way of working of Trendata typically involves a methodical approach of searching, capturing, classifying, analysing, and visualizing data. By breaking down the process into these different stages, it can help to ensure that the data is gathered and analysed in a systematic and reliable manner. This approach allows for the extraction of valuable insights.

Trendata's approach to data collection and analysis appears to be thorough and rigorous, which is essential for generating reliable insights. Nevertheless, the question arises whether using Google Trends directly is not more effective than the Trendata approach since most data is scraped from the Google search engine. As noticed in Chapter 1, search engines are becoming more powerful these days. Therefore, it is not a surprise that search data tools have become increasingly popular for analysing trends in consumer behaviour. Google Trends is a particularly powerful and popular tool that allows users to track the popularity of specific keywords and phrases over time. In other words, it allows for nearly real-time trend analysis. Multiple research designs utilized the insights provided by Google Trends to guide their studies. However, there are limitations to using Google Trends, which demonstrate the usefulness of Trendata.

First, the accuracy of information provided by Google Trends may be affected by changes made by Google in the way it collects and processes data (Li, 2016). Sample instability is one such problem that may arise from Google Trends, making research replication more challenging. As learned from the previous chapters, collecting data from search engines is a valuable way for businesses to understand consumer behaviour and make informed strategical decisions. However, it is important to ensure that the data being collected is consistent and reproducible to draw accurate conclusions (Lazer, Kennedy, King & Vespignani, 2014). One way to ensure data consistency is to use a standardized method for collecting data from search engines. This may involve using a specific tool or software to extract the data. By using a consistent method, it ensures that the data being collected is comparable across different time periods or different search engines. To address this issue, Trendata employs a standardized method to increase data consistency and enhance the reliability of research findings.

Additionally, selecting relevant and specific keywords is crucial when collecting search traffic information (Goel et al., 2010). Keyword selection is an important consideration when collecting data from search engines, as it can have a significant impact on the accuracy and relevance of the data. By choosing the right keywords it can be ensured that the collected data is relevant and will provide valuable insights. One way to select keywords when collecting search engine data is to use a keyword research tool. These tools allow businesses to identify the most popular and relevant keywords for their industry, as well as to understand the search behaviour of their target audience. This can be particularly useful for identifying long-tail keywords, which are more specific and less competitive, but may still be relevant to the business. Another important consideration when selecting keywords is to ensure that they are as specific as possible. Broad, generic keywords may result in a large volume of data, but it may not be as relevant or useful to the business. By using more specific keywords it can be ensured that data is collected that is more closely aligned with the products or services. The Google Trends tool only permits users to track specific keywords or phrases, necessitating the need for careful keyword selection. Although Google Trends provides the option to search in ‘Categories’ to filter out irrelevant results, it is unclear how these categories are created and what matching techniques are used. Trendata solves this problem by categorizing or grouping the keywords using an AI tool. However, selection bias is a common limitation in the use of AI tools, which can be mitigated by regularly evaluating AI models. As previously noted, the Trendata approach involves the oversight of a data analyst at this stage to address these biases.

In conclusion, while search engine data can provide valuable insights for businesses, it is important to ensure that the data being collected is consistent, reproducible, and relevant. By choosing the right keywords and using standardized methods for data collection, businesses can make more informed decisions about their marketing strategies. However, it is important to use caution and validate the results with other sources of information. In summary, ensuring data consistency in collecting data from search engines involves using a standardized method, which may include utilizing a specific tool or software for data extraction. The current research utilizes a tool provided by Trendata for data extraction.

3.2 DATA COLLECTION

As previously mentioned, this research focuses on one case study, being the automotive industry. It is attempted to obtain a deeper understanding of the challenges and opportunities facing the industry by studying this case. One of the challenges when conducting a case study is working with large datasets. The automotive industry generates a significant amount of data. In the sales figures, but even more the search volume figures.

Search volume datasets for this research were provided by the graduation firm, Trendata. The datasets consist of millions of search queries from within the Netherlands. These descriptive, quantitative data give insights on how consumer needs and trends are evolving over the past four years (Trendata, n.d.). The required data was gathered for all brands and models within the automotive industry with the focus on cars over a period ranging from January 2019 until November 2022. Multiple spellings and expressions that a user might use when mentioning a car or car model were taken into consideration. Resulting in a dataset that provides the relevant search data. Once all the required data was acquired during the data collecting step, the datasets needed to be cleaned. To effectively analyse this data, it was necessary to split it into smaller, more manageable chunks. To reduce biases, significant attention was taken during the data collection process. The collected datasets were therefore imported into R Studio, where they were cleaned and transformed. Two distinct datasets were created from the search data. The first dataset categorized all search data per car brand and can be found in Appendix 1. The second dataset categorized the search volume per car model and can be found in Appendix 2. were categorized and later analysed. The models were identified by searching for the product name within the branded searches. For this sample, a selection was made since it was not feasible to analyse them all because of conflicting names like 'Seat Leon' and 'Cupra Leon' or 'Byd Han' and 'Byd Handrem'. All search volumes were later translated into SoS volumes (see formula in Chapter 2).

Sales numbers of cars are obtained via third party BOVAG, the Dutch Federation of Automotive Dealers and Garage Holders, which is a trade association of more than 8000 entrepreneurs involved in mobility. They provide sales numbers of cars over the past years by brand per model per month. The source website is https://www.bovag.nl/pers/cijfers/personenauto/verkoopcijfers-personenauto-s-naar-merk-model-per (accessed December 2022). These sales numbers were later translated into SoM volumes (see formula in Chapter 2). As sales numbers were not available for all searched car brands, and the focus of this research is on the relationship between SoS and SoM, only the car brands and models with corresponding sales numbers were included in the analysis.

To account for the impact of prices on correlation, average prices per car brand and car model were included in the analysis. Prices were sourced from https://www.autoweek.nl/carbase (accessed January 2023), and brand averages were computed from the included models. An overview can be found in Appendix 3.

Furthermore, the dates when different car models were revealed are also accounted for. These dates were found on multiple different websites and news articles. As previously noted, it is expected that on the product level there will be a difference between newer and older product models. Besides, this research delves into how SoS can be utilized to provide insight in early development. Therefore, on the product level the sample group was divided into newer and older product models of certain brands. The newer models contain models that are either electric or hybrid car models. An overview of this division can be found in Appendix 3.

3.3 DATA ANALYSIS

The tool used to conduct the quantitative case study is R Studio, which is a widely used software for data analysis and visualization. After the collected datasets were imported into R Studio, and were cleaned and transformed, they were analysed. In Table 2, the formulas can be found to determine the SoS, SoM, and ESoS.

Table 2. Formulas used.

Concept	Abbreviation	Formula
Share of Search	SoS	SoS = (brand searches category X) / (total searches all brands category X) * 100
Share of Market	SoM	SoM = (total brand sales) / (total industry sales) * 100
Excess Share of Search	ESoS	ESoS = (SoS(X)) - (SoM(X-1))

The hypotheses were examined using correlation analysis. The degree and direction of the linear link between two parameters are both considered in correlation analysis (Cohen, 2013). The intensity and importance of a relationship between them are indicated by the degree of correlation. To examine the relation between SoS and SoM, the Pearson correlation is utilized. With the Pearson correlation the intensity and direction of the relation between two variables is expressed as a number between -1 and 1. If there is a correlation, both variables change in the same way when one of them is changed. The correlation is defined as moderate correlation when it is higher than 0.40 (or lower than –0.40). When the correlation is 0.70 or higher (or -0.70 or lower), then the correlation is defined as strong to very strong correlation (Schober, Boer & Schwarte, 2018). Nevertheless, a correlation coefficient that is nearly 0 does not prove that the variables are not correlated. First, a correlation coefficient only measures the linear relationship between two variables. If the relationship between the variables is non-linear, a correlation coefficient of 0 may still indicate a strong relationship between the variables. For example, two variables that have a curved relationship may still be strongly related, even if their correlation coefficient is close to 0. Second, a correlation coefficient can be affected by outliers. Outliers are extreme values that are far away from the other values in the data set. If there are outliers in the data set, they can weaken the relationship between the variables and reduce the correlation coefficient. Therefore, if the correlation coefficient is close to 0, it is important to check for outliers that may be affecting the relationship between the variables. Finally, the sample size can also affect the correlation coefficient. If the sample size is small, the correlation coefficient may not accurately reflect the relationship between the variables. This is because a small sample size may not provide enough data points to accurately capture the relationship between the variables. Therefore, if the correlation coefficient is close to 0, it is important to check the sample size and ensure that it is large enough to accurately reflect the relationship between the variables. Because very low correlation coefficients might have statistical significance when applied to large datasets (Schober, Boer & Schwarte, 2018). To address these challenges, plotting data should be considered as a crucial first step prior to conducting any numerical analysis (Schober, Boer & Schwarte, 2018). Therefore, this research did not only rely on the correlation coefficient but also visually examined the relationship by plotting the data.

Furthermore, previous research has shown that there is often a delay between the time when potential customers begin searching for a product (SoS) and when they ultimately make a purchase (SoM). In the automotive industry, studies have found that 60% of car buyers take between one and six months to move from contemplating buying a new car to making the purchase, while 16% make the purchase within a month. Only 9% of buyers require more than a year to decide (Putsis & Srinivasan, 1994). Recent research by Binet (2021) and Hankins (2022) has revealed that in the automotive industry, the time lag between SoS and SoM is up to twelve months. As a result, the time lag will be tested for up to twelve months in the current study.

In the second part of the research, the exploratory part, it is examined how SoS can be used to assess how interest in a brand develops for new products. As mentioned, the dates when different car models were revealed are also accounted for, but this research works with data that goes back to the start of 2019, which indicates that not all data for all products is known from when they were first revealed. The assessment is made by analyzing the SoS/SoM ratio (SoS divided by the SoM), to assess whether one is relatively higher, and if one is relatively higher in a certain period segment, then the question is when. The ratios where thus divided in different segments, based on when the new car models were announced. This way the difference between older and newer products is created. To account for the lag time present in the first part of the research, the results present the outcomes for the data with no lag time, and the lag time that came out of the research in the first part.

4. RESULTS

In the previous chapter it is discussed how the research is conducted. In this chapter, the results are presented. Initially, the relation between SoS and SoM was examined at the category level, being car brands. Subsequently, the analysis is conducted at a product level. The final part of this chapter investigates how SoS can be used to assess consumer interest in a brand developing for new products.

4.1 CATEGORY LEVEL

A summary of the results of the correlation analysis for SoS and SoM can be found in Table 3.

Table 3. Correlation Analysis for averages of variables with Share of Market.

Variable	**R**	**R2**	**Significance**
SoS Car Brands	0.253	0.096	0.252

By running a correlation analysis for Share of Search and Share of Market per car brand, the averages did reveal a not significant but positive correlation of rather low strength, 0.253. However, consumer behaviour may differ depending on the type of car a person wants to purchase, therefore later in the analysis the analysis is performed on the car model level. Furthermore, consumer behaviour may differ depending on the decision-making time a customer needs before purchasing. Therefore, although no significant correlation is found on this general level, it is possible that the ratio serves as a predictor for market share when including lag times. This was accomplished by using a cross-correlation function of R Studio. The strongest correlation of SoS with SoM for time lags (positive or negative) of less than or equal to 12 months was determined for each car brand. Table 4 provides a summary of the average results when a lag in time was included.

Table 4. Optimal time lags and Pearson's correlation for averages of variables with Share of Market

Variable	**Time lag in months**	**R**	**R2**	**Significance**
SoS Car Brands	6.058	0.416	0.197	0.044*

As can be seen, the average time lag is approximately six months, with a correlation of 0.416, significant at $p < 0.05$ level, and a R^2 value of 0.197. This means that about 19,7% of all variances can be calculated using this variable. Including the time lags when performing the correlation analysis revealed a significant and positive moderate correlation. Out of the 52 car brands, 40 car brands showed a significant correlation when including a time lag.

The 52 car brands were also divided into two pricing ranges. The higher price class included all cars with starting prices greater than €30.000,- (27 brands), while the lower price class included all cars with starting prices less than or equal to €30.000,- (25 brands). The Autoweek website (https://www.autoweek.nl/carbase/ accessed January 25th, 2023) was used to retrieve the starting prices per car model. The averages of the models included in this study were taken as the average price per brand. The relationships shown are then compared in an independent t-test per group (high- and low-priced cars). Since a t-test requires the variables to be normally distributed, the Shapiro-Wilk test for normality was performed for each group (each correlation divided into high priced cars and lower priced cars). It revealed that the p-value of the Shapiro-Wilk Test is greater than 0.05, which indicates that the data is normally distributed. Furthermore, Levene's test showed insignificant results, so it seems that equal variances between the high- and low-priced group exist. Table 5 displays the average findings from the t-Test (Two-Sample Assuming Equal Variances). The mean correlation for higher priced cars SoS with SoM is 0.427, and for lower priced cars SoS is 0.405. This leads to a mean difference of 0.023. Thereby, no significant difference is present (p-value > 0.05).

Table 5. Influence of price on correlation: t-tests for higher and lower priced car brands' correlations with Share of Market.

Variable	**Mean difference**	**Significance**
SoS Car Brands	0.023	0.608

4.2 PRODUCT LEVEL

Like the analysis on the category level, the analyses were also performed on a product level. For the analysis at the product level, a sample of 102 different car models were extracted from the original dataset. Within the dataset, 44 out of 102 analysed car models are electric or hybrid car models. A summary of the results of the linear regression analysis for SoS and SoM can be found in Table 6.

Table 6. Correlation Analysis for averages of variables with Share of Market.

Variable	**R**	**R2**	**Significance**
SoS Car Brands Models	0.325	0.158	0.210

By running a correlation analysis for Share of Search and Share of Market per car model, the averages did reveal a significant, positive correlation of rather low strength, 0.325. Since the ratio serves as a predictor for SoM when including lag times on a category level, the lag times are included in this analysis as well. This was accomplished by using a cross-correlation function of R Studio. The strongest correlation of SoS with SoM for time lags (positive or negative) of less than or equal to 12 months was determined for each car model. Table 7 provides a summary of the average results when a lag in time was included.

Table 7. Optimal time lags and Pearson's correlation for averages of variables with Share of Market

Variable	**Time lag in months**	**R**	**R2**	**Significance**
SoS Car Brands Models	4.810	0.502	0.290	0.033*

As can be seen, the average time lag is approximately 5 months, with a correlation of 0.502, significant at $p < 0.05$ level, and a R^2 value of 0.290. This means that about 29% of all variances can be calculated using this variable. Including the time lags when performing the correlation analysis revealed a significant and positive moderate correlation.

The method to define the influence of price on the correlation is the same as before. This time it revealed that the p-value of the Shapiro-Wilk Test is greater than 0.05, which indicates that the data is normally distributed. Furthermore, Levene's test showed insignificant results, so it seems that equal variances between the high- and low-priced group exist. Table 9 displays the average findings from the t-Test (Two-Sample Assuming Equal Variances).

Table 8. Influence of price on correlation: t-tests for higher and lower priced car brands' correlations with Share of Market.

Variable	Mean difference	Significance
SoS Car Brands Models	0.064	0.320

The mean correlation for higher priced car models SoS with market share is 0.525, and for lower priced car models SoS is 0.461. This leads to a mean difference of 0.064. Thereby, no significant difference is present (p-value > 0.05).

4.3 BRANDED SEARCHES FOR NEW PRODUCTS

To assess how consumer interest in a brand develops for newer products, three different segments of products – car models – are analysed and compared. Segment 1 consists of 29 analysed car models, ranging from 2019 until 2023. In this segment, 21 of the 29 cars are either hybrid or electric cars. The second segment consists of 34 car models, which reveal dates range from 2010 until 2019, where 14 from the 34 cars are electric or hybrid models. The third segment consists of 37 car models which reveal dates range from the early 1960s to 2010, where only 9 out of 37 car models were electric or hybrid models. It was chosen to divide the segments in approximately similar number of car models, where the first segment had no reveal dates earlier than 2019. Table 9 presents the SoS/SoM of the different segments for three different time lags. It was chosen to include the time lags that were found in the previous chapters on the category and product level, and no time lag at all.

The SoS/SoM ratio is used to examine whether SoS or SoM is relatively stronger than one another analysed over different segments. The first statistic that becomes clear from Table 9, is the lower SoS/SoM ratio for segment 1. In all the time lag scenarios analysed, the SoS/SoM ratio is substantial lower in segment 1 than in the other segments. The standard deviation is slightly lower but compared to the other segments not considerably different. This difference can possibly be explained by looking at the maximum value per segment. The maximum SoS/SoM ratio is, for both segment 2 and 3, higher than segment 1. Since the difference between these maximum observations and the mean is rather large, it can pose a possible solution for the slightly higher standard deviation. Thereby, all categories have more or less the same number of samples.

Table 9. SoS/SoM ratio, different segments, different lag times.

		Mean	Std dev	Count	Max	Min
Segment 1	*No lag*	0,95	1,15	29	5,31	0,03
	5m lag	0,85	1,29	29	5,20	0,00
	6m lag	0,82	1,21	29	4,87	0,00
Segment 2	*No lag*	1,90	2,77	34	13,15	0,03
	5m lag	2,26	3,49	34	13,84	0,03
	6m lag	2,41	3,86	34	15,80	0,03
Segment 3	*No lag*	1,58	2,45	37	13,35	0,09
	5m lag	1,69	2,79	37	15,73	0,10
	6m lag	1,74	2,85	37	15,88	0,10

The fact that the SoM is always lower for segment 1 than the SoS can be explained by that the SoS is low, the SoM is high, or a combination of both. It is only possible to see what lowers the SoS/SoM ratio when we know the absolute numbers within the segments. Therefore, Table 10 divides the average

SoS of one segment by the SoS of another segment and Table 11 does the same, but then for SoM. When we look at the factors in the tables, we see that the SoS of segment 3 is 5,34 times as high as segment 1, while the SoM is 3,59 as high. Overall, in all the cases the older and more established car models have a higher SoS relative to their SoM. Thus, it is found that even though the SoM is also higher for older cars, the SoS outperforms the SoM and therefore it can be concluded that the main reason that the SoS/SoM ratio is higher for segment 2 and 3, is due to the SoS in these segments.

Table 10. SoS/SoS ratio, different segments.

	SoS Segment 1	**SoS Segment 2**	**SoS Segment 3**
SoS Segment 1	1	0,34276136	0,187281918
SoS Segment 2	2,91748173	1	0,546391575
SoS Segment 3	5,33954378	1,83018928	1

Table 11. SoM/SoM ratio, different segments.

	SoM Segment 1	**SoM Segment 2**	**SoM Segment 3**
SoM Segment 1	1	0,48894885	0,278475165
SoM Segment 2	2,04520372	1	0,569538443
SoM Segment 3	3,5909845	1,75580773	1

5. DISCUSSION

In this Chapter, the findings presented earlier are discussed. Hereafter, limitations are critically examined, and potential avenues for future research are suggested. Finally, the theoretical and practical implications are discussed.

5.1 DISCUSSION OF THE FINDINGS

5.1.1 Similarities and Differences

With regards to the first hypothesis, the study found a moderate positive correlation (R = 0.253) between SoS and SoM on a category level. This is consistent with previous research. An even stronger positive correlation was found on the product level (R = 0.325). The two correlations exhibited statistical significance when considering the entire dataset. However, upon restricting the analysis to only the brand data, significance was not observed due to the small sample size of the datasets. Nevertheless, since significance was found when considering all the data, and with a relative strong Pearson correlation, H1 was accepted. In other words, SoS seems to be correlated with SoM on the category level, as well as the product level. The difference is correlation can be found in the fact that the current study considered the lag in time when examining the correlation between SoS and SoM, which is an important factor that may affect consumer behaviour and market share as found in literature. This finding suggests that including lag in time is crucial when studying the correlation between SoS and SoM. This was shown in the difference in lag time between the category (6.1 months) and product (4.8 months) level. Since the correlation has smaller lag time on the product level, H3 is accepted. Furthermore, the Pearson correlation was more strongly correlated on the product level (R = 0.502), than on the category level (R = 0.416). Thus, the acceptance of H4 is warranted. However, given the minimal discrepancy, further investigation is required to determine whether this divergence is specific to this sample or whether it represents a statistically significant difference. In this research, the correlation seems stronger on the product level (R = 0.502), than the category level (R = 0.416). Previously it was stated that more positive brand attitudes do more branded searches **(**Dotson et al., 2017; Vargo & Lusch, 2016).

Since the correlation is stronger on the product level, it seems likely to say that those people indeed have a positive attitude to the brand. However, this should be further examined in future research. Thus, one significant question that needs to be addressed in future research is the role of attitudes in shaping the decision-making process, and the impact this has on the SoS metric. The research started with a theory section on the role of search engines on customer behaviour. The statement highlighted the increasing role of search engines in shaping consumer behaviour and emphasized the need to critically evaluate the impact of search engines on consumer behaviour from the perspective of consumer behaviour theories (Jun & Park, 2016; Sinclair & Bandyopadhyay, 2022). This includes considering how search engines affect consumer decision-making processes, and how they shape consumer attitudes and perceptions towards products and brands. Consumer attitudes are closely linked to consumer behaviour models because they play a crucial role in shaping the way consumers make decisions. Consumer attitudes can influence each of these stages by shaping consumers' perceptions of the products, services, or brands they are considering. For example, if a consumer has a positive attitude towards a particular brand, they may be more likely to consider that brand when making a purchasing decision. This is based on the Theory of Planned Action (Ajzen, 1991), which states that the attitude toward an activity is the degree of acceptance or rejection of that behaviour. In this sense, attitudes influence how information is digested, altered, utilised, or rejected (Urala & Lähteenmäki, 2003). In other words, the data that flows from the search for information by consumers might show something about where in the decision-making process certain information is needed or wished for, but it is important to remember that consumer attitudes influence how the information is processed and further utilized. As mentioned before, positive brand attitudes are more likely to search for brand-specific queries (Dotson et al., 2017). Brand-specific queries seem to represent an intermediary step between interest and purchase, providing the ability to track consumer interest in a brand. Thereby, positive brand attitudes are more likely to result in brand-specific queries. It is important to know the role of attitudes in shaping the decision-making process because attitudes can significantly impact a consumer's behaviour and purchasing decisions. Understanding a consumer's attitudes can provide insight into their preferences, values, and beliefs, which can ultimately influence their likelihood to search for and purchase certain products or services. Additionally, attitudes can impact a consumer's perceived value of a product or service, which can influence their willingness to pay and the likelihood of repeat purchases. By understanding the role of attitudes in shaping the decision-making process, and its impact on the SoS metric, businesses would be able to predict consumer behaviour more accurately.

5.1.2 The Absence of Significant Correlation of Price

Even though the study found that the correlation between SoS and SoM varies depending on the type of car brand a customer wishes to purchase, the study did not find a significant difference in the correlation between high- and low-priced cars on the category and product level. This finding implies that the relationship between SoS and SoM is similar for both high- and low-priced cars, indicating that the pricing range may not play a significant role in affecting the correlation between SoS and SoM. Therefore, H2 is rejected. This is in contrast with our literature findings, since price seems to influence the correlation since luxury products and brands attract a lot of attention, but only a select few people choose to purchase them (Jun, Park & Yeom, 2014). Nevertheless, the finding in the current research needs to be interpreted with caution since the sample size for each group is relatively small, and there may be other factors, such as product features and marketing strategies, that influence the correlation between SoS and SoM for high- and low-priced cars.

5.1.3 SoS as a Metric for New Products

The second part of the research exploratively delved into how SoS can be utilized to provide insight in how consumer interest is developing for new products.

In all the time lag scenarios analysed, the SoS/SoM ratio is substantial lower in segment 1 than in the other segments. When examining the ratio further, it was found that even though the SoM is higher for cars in the higher segments, the SoS outperforms the SoM. Therefore, it can be concluded that the main reason that the SoS/SoM ratio is higher for segment 2 and 3, is due to the SoS in these segments. Possible explanations for the higher searches might be the popularity of well-known and market established cars. Even though, the segment 3 cars need more searches for selling a car, the SoM is also higher. So, people look more for a well-known car than for a car that is new to the market. Another explanation might be the survivorship bias, which posits that cars that were not popular in terms of searches may be less likely to end up in segment 3 and leave the market early. This causes that only popular cars end up in segment 3.

Furthermore, in segment 1, 21 out of 29 car models where either electric or hybrid models. Coming down to more than 70%. In segment 2, a little bit over 40% was either hybrid or electric, and in segment 3 only 24% was either electric or hybrid. While the growth in SoS of electric car models is undoubtedly a positive development, it is important to acknowledge that it is still in the early stages of development, and that other factors might influence the growth rate after this phase. There are still several challenges that might need to be addressed before electric cars can become a mainstream alternative to traditional cars. For instance, one of the biggest challenges is the development of infrastructure, including charging stations and battery technology. It is interesting to follow the next growth phase, to assess whether these other factors indeed impact the growth rate, and thus if the relationship between SoS and SoM still holds. Another challenge is the high cost of electric cars compared to traditional cars, which makes them inaccessible to many consumers. Furthermore, it is important to note that the growth in SoS of electric car models might not be uniform across all regions and countries. The growth in SoS of electric car models is primarily driven by demand in developed countries (Agusdinata, Liu, Eakin & Romero, 2018). In contrast, developing countries are still heavily reliant on traditional gasoline-powered cars.

On the product level, there seems to be a difference in SoS development between newer and older product models. This disparity can provide valuable insights into a product's competitive advantage in the market. In this context, if the SoS of a newer model consistently outperforms its older counterpart and competitors, it may signal a superior product. This could be due to factors such as better features, more effective marketing, or a stronger brand image. SoS for a new product is likely to be low or non-existent at the start of the product launch. However, as consumers become aware of the product and start searching for information online, the SoS is likely to increase. The rate of increase in SoS will depend on various factors such as the level of brand awareness, advertising, and other marketing activities. As mentioned earlier, SoS has been suggested as a leading indicator for SoM. This means that a higher SoS for a brand can indicate a higher SoM in the future. However, it is important to note that SoS is not the only variable that influences SoM. Other factors such as product quality, pricing, and availability also play a significant role. Furthermore, one of the key drivers of adoption of new ideas or innovations is the Diffusion of Innovation Theory. Adoption can occur because of both internal and external influences, and agents who are externally influenced are known as innovators, whereas imitators are influenced by both external influences and the system's social pressures generated by other agents who have previously adopted the innovation. Therefore, it is essential to understand the social system in which the innovation will be introduced to anticipate and mitigate resistance to change. Future research can assess how the social system influences the introduction of new products.

Finally, SoS is a crucial metric in analysing the success of a new product launch, since SoS is different correlated to SoM at the product level. Therefore, H5 is accepted. At the initial stage of the product launch, SoS is likely to be low or even absent, but it is expected to increase as consumers become aware of the product and start searching for information online. The rate of increase in SoS is contingent on multiple factors such as the brand awareness level, advertising, and other marketing activities. Thus, continuous monitoring of SoS seems to be necessary to detect any potential hindrances to its growth. SoS has been posited as a leading indicator for SoM, signifying that a higher SoS for a brand can indicate a higher SoM in the future. However, it is crucial to note that other factors, including product quality, and availability, also might affect SoM. Thus, an accurate prediction of the potential SoM of a new product entail analysing SoS in conjunction with other metrics.

Table 12. Hypotheses acceptance or rejection.

Hypotheses	Hypotheses acceptation or rejection
H1: Share of Search is correlated with Share of Market.	Accepted
H2: The higher the average price of a brand, the weaker the correlation between Share of Search and Share of Market.	Rejected
H3: The Share of Search and the Share of Market are correlated on the product level with a smaller lag time than on the category level.	Accepted
H4: The Share of Search and the Share of Market are more strongly correlated on the product level than on the category level.	Accepted

H5: On the product level there will be a difference in how the Share of Search is correlated with the Share of Market between newer and older products.	Accepted

5.2 LIMITATIONS OF THE STUDY

The focus on the automobile industry and the use of only correlation analysis are two of the many limitations that should be considered when evaluating the validity of this study. The findings' generalizability and comprehensiveness are constrained by these limitations, which also point to potential directions for future investigation to strengthen the study's validity.

Firstly, the study's focus on the automotive industry limits the generalizability of the findings to other industries. Different industries may display distinctive traits and customer behaviours that can affect how SoS and SoM are related. To corroborate the found correlations and develop a deeper knowledge of the relationship between SoS and SoM, comparable studies must be carried out in various industries. When looking at the automotive industry, future research should assess whether the growth in SoS of electric and hybrid car models is primarily driven by the increasing awareness and demand for sustainable energy sources. Electric cars offer a more sustainable alternative to traditional gasoline-powered cars, which have been associated with environmental damage and pollution. This might have resulted in an increased interest in electric cars, and a corresponding increase in their SoS. Additionally, the increase in the number of electric car models available in the market might have contributed to the growth in SoS. As more models become available, consumers have more choices, which leads to increased competition and innovation in the industry. However, despite the growth in SoS of electric car models, the development of electric cars has been more fluctuating than that of other car models (International Energy Agency, 2021). This might be because the production and development of electric cars is more complex and expensive than that of traditional cars. Electric cars require a more extensive and specialized supply chain, and the infrastructure needed to support their operation is still in the early stages of development. Nevertheless, the growth in SoS for electric car models has significant implications for the automobile industry. It represents a shift in consumer preferences and demands towards more sustainable and eco-friendly alternatives. This shift has already resulted in increased competition and innovation in the industry, which has led to more efficient and advanced electric car models. Furthermore, it might encourage traditional car manufacturers to invest in electric car development and production, which contributes to the growth of the electric car market.

Second, while correlation analysis is useful for revealing the connections between variables, it is not without drawbacks. Without taking into consideration other relevant causes, correlation analysis assesses the direction and strength of the association between two variables. In this study, other factors that could affect market share, such as product quality, pricing, advertising expenditures, and competition, were not considered while analysing the association between SoS and SoM. Therefore, by enabling the inclusion of more independent variables and enabling a more thorough investigation of the factors impacting SoM, the use of linear regression analysis for example could improve the research. Linear regression analysis can provide a more robust statistical model that incorporates multiple variables simultaneously. By employing linear regression, the study could control for confounding variables and assess the individual and combined effects of various factors on SoM. A regression model, for instance, would make it possible to assess the impact of variables more precisely like consumer attributes, marketing spending, brand reputation, and brand characteristics on the relationship between SoS and SoM. By taking a wider range of factors that affect market share into account, this would improve the accuracy and dependability of the conclusions. Additionally, the predictive ability of the independent factors on the dependent variable can be evaluated using linear regression analysis. By examining the significance and magnitude of the regression coefficients, the study could identify the most influential factors in driving SoM. This information would provide actionable insights for marketers and businesses to develop effective strategies to improve market performance based on the identified key drivers. Additionally, using linear regression analysis would make it possible to investigate potential moderating or mediating effects. For instance, the study could look at whether certain product attributes, pricing scenarios, or market circumstances have an impact on how SoS and SoM are related to one another. Such analyses would offer insightful information about the context-dependent influences on the relation between SoS and SoM, enabling the development of more tailored marketing initiatives and strategies.

Another limitation is that it is important to acknowledge that SoS may not be suitable for all brands or product names. Conflicting product names, such as ‘Seat Leon’ and ‘Cupra Leon’, or ‘Byd Han’ and ‘Byd Handrem’ make it difficult to accurately track SoS within all branded searches. This limitation highlights the need for further optimization of AI tools to enhance their effectiveness in tracking SoS. It also emphasizes the importance of human thinking and checking to ensure accurate data interpretation.

5.3 IMPLICATIONS

Although, this study was able to a substantial moderate strong relationship between SoS and SoM, validation remains an aspect for future research.

Regarding the theoretical implications, this study gives academics important knowledge for future research on this subject, especially on the validation part. This study makes the assumption that the variable SoS and consumer interest are related, and hence, future studies should examine this relationship in the framework of this research methodology. Furthermore, the theoretical implications of this research include improving our comprehension of how SoS is related to consumer interest and its implications for brand health.

In relation to practical implications, the results imply that SoS can be a useful technique for determining customer interest at both the category and product levels. Marketers can acquire insights into variations in customer attention and pinpoint the main selling factors that pique consumer interest by measuring the SoS of various product models over time. To effectively meet consumer demands, this information can guide product development, marketing plans, and resource allocation. The study also emphasizes how crucial it is to consider the lag in time when analysing the relationship between SoS and SoM. According to the findings, there is a stronger relation at the product level than at the category level based on the time gap between SoS and SoM. This shows that for a more precise knowledge of customer behaviour and market dynamics, taking time into account during the analysis is essential. This study also sheds light on how SoS may function as a criterion for gauging the success of new product launches. The results imply that SoS monitoring can offer useful cues on a product's potential market performance. Businesses are able to determine the potential market share of a new product and allocate resources wisely by monitoring the rise of SoS and examining its relationship with other indicators. Overall, the findings of this study have significant implications for businesses in terms of brand tracking. Instead of relying on complex and expensive data collection methods, SoS can be utilized as a metric to track consumer interest.

Finally, while SoS has been shown to be a strong measure that provides rapid, economical, and comprehensive solutions for a range of brand tracking concerns, future research is necessary.

6. CONCLUSION

This study provides insights into the relationship between SoS and SoM at both the category and product levels, and the impact of pricing on this relationship. The first research question was defined in the introduction as:

Research question: *How can Share of Search (SoS) be used to assess consumer interest and brand health?*

Sub-question 1: *What is the relationship between Share of Search (SoS) and consumer interest in a brand?*

Sub-question 2: *How can Share of Search (SoS) be used to benchmark a brand's performance against competitors and assess its relative market position?*

The study found that SoS can be used to assess consumer interest and brand health by tracking the relative search volume of a brand compared to its competitors, providing insights into consumer preferences and market trends. Thereby, the relationship between SoS and consumer interest in a brand is indicated by a positive correlation, suggesting that higher levels of consumer interest are associated with a larger SoS queries. Finally, SoS can be used to benchmark a brand's performance against competitors and assess its relative market position by comparing the SoS with other brands in the same industry, indicating the brand's level of visibility and consumer interest compared to its competitors.

As businesses and marketers face new challenges in the upcoming years, they will need to find new ways to navigate the ever-changing landscape of consumer behaviour. To increase their chances of success, they can leverage external data and invest in their brand, rather than relying solely on internal metrics. This means breaking free from entrenched habits and thought patterns and focusing on external metrics such as SoS. The use of SoS can provide valuable insights into consumer interest in a brand. By analysing online search patterns and consumer behaviour, businesses can identify emerging trends and adapt their strategies to meet changing consumer needs. This is especially important in fast-paced industries driven by innovation and competition. Moreover, SoS can bridge the gap between communication sciences and business administration by providing a more comprehensive approach to understanding consumer behaviour. SoS can provide valuable insights into consumer behaviour, which is essential for both communication sciences and business administration. By analysing branded queries, researchers and businesses can understand what consumers are searching for, what language they use, and what their interests are. This can help communication scientists and businesses to better understand how people consume and process information, and what their demands and needs are and how these develop. Furthermore, branded search data can provide insights into the effectiveness of brand messaging and communication strategies. By analysing SoS, researchers and businesses can see how consumers are searching for their brand, which can provide insights into the effectiveness of their branding and messaging. This information can help communication scientists to better understand how people perceive and engage with brands, while businesses can use it to improve their branding and communication strategies. Overall, the use of SoS provides a more comprehensive approach to understanding consumer behaviour, bridging the gap between communication sciences and business administration. In terms of analysing and using the benefits of the collaboration between communication sciences and business administration bring to both fields are major. By working together, researchers and practitioners from both fields can combine their expertise and knowledge to develop new methods and approaches for analysing and using search data. This can lead to new insights and strategies that benefit both fields.

7. REFERENCES

Aaker, D. A. (2012). Building strong brands. Simon and Schuster.

Abdelnour, A., Daniels, B., Parikh, N., & Redaelli, S. (2022). Category management's next horizon: How distributors can outperform. McKinsey & Company.

Agusdinata, D. B., Liu, W., Eakin, H., & Romero, H. (2018). Socio-environmental impacts of lithium mineral extraction: towards a research agenda. *Environmental Research Letters*, *13*(12), 123001.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. International Journal of Production Economics, 182, 113-131.

Barreira, N., Godinho, P., and Melo, P. 2013. "Nowcasting unemployment rate and new car sales in southwestern Europe with Google Trends," NETNOMICS: Economic Research and Electronic Networking (14:3), Springer, pp. 129–165.

Bass, F. M. (1969). A new product growth for model consumer durables. Management science, 15(5), 215-227.

Bhattacharya, A., Morgan, N. A., & Rego, L. L. (2021). Examining why and when market share drives profit. Journal of Marketing.

Binet, L., & Field, P. (2018). Effectiveness in context: A manual for brand building. Institute of Practitioners in Advertising. Retrieved from https://ipa.co.uk/knowledge/publications-reports/effectiveness-in-context

Binet, L. (2021). Share of Search as a Predictive measure. Retrieved from https://ipa.co.uk/effworks/effworksglobal-2020/share-of-search-as-a-predictive-measure

Bovag. (2022). Dutch Federation of Automotive Dealers and Garage Holders. *VERKOOPCIJFERS PERSONENAUTO'S NAAR MERK/MODEL PER MAAND*. Retrieved December, 2022 from https://www.bovag.nl/pers/cijfers/personenauto/verkoopcijfers-personenauto-s-naar-merk-model-per

Brdulak, A., Chaberek, G., & Jagodziński, J. (2021). BASS Model Analysis in "Crossing the Chasm" in E-Cars Innovation Diffusion Scenarios. Energies, 14(11), 3216. Chicago.

Cattani, G., Porac, J. F., and Thomas, H. 2017. "Categories and competition," Strategic Management Journal (38:1), Wiley Online Library, pp. 64–92.

Choi, H. (2018). Technology-push and demand-pull factors in emerging sectors: evidence from the electric vehicle market. Industry and Innovation, 25(7), 655-674.

Choi, H., and Varian, H. 2012. “Predicting the present with Google Trends,” Economic Record (88:special issue SI), pp. 2–9.

Crawford, K., & Finn, M. (2015). The limits of crisis data: analytical and ethical challenges of using social and mobile data to understand disasters. *GeoJournal*, *80*, 491-502.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage publications.

Cohen, L. (2013). Research methods in education (7th ed.). London: Routledge Falmer.

D’Amuri, F., & Marcucci, J. (2017). The predictive power of Google searches in forecasting US unemployment. International Journal of Forecasting, 33(4), 801-816.

Day, G. S. (2011). Closing the marketing capabilities gap. Journal of marketing, 75(4), 183-195.

Deloitte. (2017). Wealth Management im digitalen Zeitalter. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/de/Documents/WM%20Digitalisierung.pdf

Dotson, J. P., Fan, R. R., Feit, E. M., Oldham, J. D., & Yeh, Y. H. (2017). Brand attitudes and search engine queries. *Journal of Interactive Marketing*, *37*(1), 105-116.

Edeling, A., & Himme, A. (2018). When does market share matter? New empirical generalizations from a meta-analysis of the market share–performance relationship. Journal of Marketing, 82(3), 1-24.

European E-commerce and Omni-Channel Trade Association. (2021). European E-commerce Report 2021: The European E-commerce Market in 2020-2021. Retrieved from https://ecommerce-europe.eu/wp-content/uploads/2021/09/2021-European-E-commerce-Report-LIGHT-VERSION.pdf

Feng, H., Morgan, N. A., & Rego, L. L. (2015). Marketing Department Power and Firm Performance. Journal of Marketing, 79(5), 1–20. https://doi.org/10.1509/jm.13.0522

Folan, P., Browne, J., & Jagdev, H. (2007). Performance: Its meaning and content for today's business research. Computers in industry, 58(7), 605-620.

Funta, R. (2021). Data, their relevance to competition and search engines. Masaryk UJL & Tech., 15, 119.

Geva, T., Oestreicher-Singer, G., Efron, N., and Shimshoni, Y. 2017. “Using Forum and Search Data for Sales Prediction of High-Involvement Products,” Management Information Systems Quarterly (41:1), pp. 65–82.

Google. (2022). Privacy Policy – Terms of Service. Retrieved from https://support.google.com/websearch/answer/6096136?hl=en&co=GENIE.Platform%3DAndroid

Grewal, D., Roggeveen, A. L., & Nordfält, J. (2021). The future of retailing. Journal of Retailing, 97(1), 1-7.

Hankins, J. (2021). Intro to Share of Search and how to use it. Retrieved from https://www.youtube.com/watch?v=N80_cRH_cno

Hanssens, D. M., Pauwels, K. H., Srinivasan, S., Vanhuele, M., & Yildirim, G. (2014). Consumer attitude metrics for guiding marketing mix decisions. Marketing Science, 33(4), 534-550.

Hsiao, K.-L., Chen, Y.-L., & Yang, Y.-C. (2018). Understanding smartphone adoption in Taiwan: An extension of the unified theory of acceptance and use of technology model. Telecommunications Policy, 42(4), 264-277. doi: 10.1016/j.telpol.2018.01.003

Hauser, J., Tellis, G. J., & Griffin, A. (2006). Research on innovation: A review and agenda for marketing science. Marketing science, 25(6), 687-717.

Inan, G. G., & Kop, A. E. (2018). Marketing Capability Development in Micro Manufacturing Enterprises. American Journal of Industrial and Business Management, 8(01), 1.

International Energy Agency. (2021). Global EV outlook 2021: Trends and developments in electric vehicle markets. https://www.iea.org/reports/global-ev-outlook-2021/trends-and developments-in-electric-vehicle-markets

Internet Live Stats. (2022). Retrieved from https://www.internetlivestats.com/google-search statistics/

Internet World Stats. (2022). Internet usage statistics. Retrieved from https://www.internetworldstats.com/stats.htm

Jun, S. P. (2012). An empirical study of users' hype cycle based on search traffic: the case study on hybrid cars. *Scientometrics*, *91*(1), 81-99.

Jun, S. P., Park, D. H., & Yeom, J. (2014). The possibility of using search traffic information to explore consumer product attitudes and forecast consumer preference. Technological Forecasting and Social Change, 86, 237-253.

Jun, S. P., Yeom, J., & Son, J. K. (2014). A study of the method using search traffic to analyze new technology adoption. Technological Forecasting and Social Change, 81, 82-95.

Jun, S. P., & Park, D. H. (2016). Consumer information search bahviour and purchasing decisions: Empirical evidence from Korea. Technological Forecasting and Social Change, 107, 97-111.

Jun, S. P., Sung, T. E., & Park, H. W. (2017). Forecasting by analogy using the web search traffic. Technological Forecasting and Social Change, 115, 37-51.

Karlíček, M., Chytková, Z., Tyll, L., & Mohelská, H. (2014). Barriers of marketing effectiveness and efficiency within companies: a qualitative study. Economics and Management.

Katsikeas, C. S., Morgan, N. A., Leonidou, L. C., & Hult, G. T. M. (2016). Assessing Performance Outcomes in Marketing. Journal of Marketing, 80(2), 1–20. https://doi.org/10.1509/jm.15.0287

Kotler, P., & Keller, K. L. (2008). Marketing Management,(Vol. 13th international ed.).

Kotler, P. J. 1994. Marketing management : analysis, planning, implementation, and control (8th ed.), Englewood Cliffs, N.J.: Prentice Hall.

Kumar, V., Choi, J. B., & Greene, M. (2017). Synergistic effects of social media and traditional marketing on brand sales: Capturing the time-varying effects. Journal of the Academy of marketing Science, 45(2), 268-288.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Wasserman, W. (2004). *Applied linear regression models* (Vol. 4, pp. 563-568). New York: McGraw-Hill/Irwin.

Lazer, D., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: traps in big data analysis. *science*, *343*(6176), 1203-1205.

Liang, X., Li, G., Zhang, H., Nolan, E., & Chen, F. (2022). Firm performance and marketing analytics in the Chinese context: A contingency model. Journal of Business Research, 141, 589-599.

Maria, S., Pusriadi, T., & Darma, D. C. (2020). Marketing intelligence: Benefits and implementation of its business. Problems of Management in the 21st Century, 15(2), 92-99.

Mu, J., Bao, Y., Sekhon, T., Qi, J., & Love, E. (2018). Outside-in marketing capability and firm performance. Industrial Marketing Management, 75, 37-54.

Overall, J., & Wise, S. (2015). An S-curve model of the start-up life cycle through the lens of customer development. The Journal of Private Equity, 18(2), 23-34. Performance. (n.d.). In *Cambridge English Dictionary*. Retrieved from https://dictionary.cambridge.org/dictionary/english/performance

Performance. (n.d.). In *Oxford Dictionary*. Retrieved from https://www.oxfordlearnersdictionaries.com/definition/american_english/performance

Putsis, W. P., and Srinivasan, N. 1994. "Buying or just browsing? The duration of purchase deliberation," Journal of Marketing Research (31:3), US: American Marketing Association, pp. 393–402 (doi: 10.2307/3152226).

Rao, A. R., & Sieben, W. A. (1992). The effect of prior knowledge on price acceptability and the type of information examined. Journal of consumer research, 19(2), 256-270.

Rennie, A., Protheroe, J., Charron, C., & Breatnatch, G. (2020). Decoding Decisions: Making Sense of the Messy Middle (Think with Google). Google, UK.

Rogers, E. (2003). Diffusion of innovations, reviewed by Greg Orr (2003). Retrieved September, 27, 2022.

Sahin, A., & Robinson, R. (2015). Mobile banking adoption in Turkey: An extended TAM with trust and innovativeness. Electronic Commerce Research and Applications, 14(5), 380-392. doi: 10.1016/j.elerap.2015.04.001

Salesfore. (2020). State of the Connected Customer. Retrieved from https://www.salesforce.com/resources/research-reports/state-of-the-connected-customer/

Schaer, O., Kourentzes, N., & Fildes, R. (2019). Demand forecasting with user-generated online information. International Journal of Forecasting, 35(1), 197-212.

Schiffman, L. G., & Kanuk, L. L. (2016). Consumer behavior (11th ed.). Pearson.

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: appropriate use and interpretation. Anesthesia & Analgesia, 126(5), 1763-1768.

Sinclair, L. & Bandyopadhyay, D. (2022). Think with Google. Spot intent in searches to increase ROI. Retrieved February 14, 2023, from shttps://www.thinkwithgoogle.com/intl/en-154/marketing-strategies/search/spot-intent-in-searches/

Stevens, J. P. (2012). *Applied multivariate statistics for the social sciences*. Routledge.

Trendata. (n.d.). Trendata Methodology. Retrieved from https://www.trendata.nl/technology/

Urala, N., & Lähteenmäki, L. (2003). Reasons behind consumers' functional food choices. *Nutrition & Food Science*, *33*(4), 148-158.

Van Couvering, E. (2008). Search Engines. The International Encyclopedia of Communication.

Van Couvering, E. (2010). Search engine bias: the structuration of traffic on the World-Wide Web (Doctoral dissertation, London School of Economics and Political Science).

Van Couvering, E. (2011). Navigational media: The political economy of online traffic. The Political Economics of Media: The Transformation of the Global Media Industries. London: Bloomsbury Academic, 183-200.

Varadarajan, R. (2020). Customer information resources advantage, marketing strategy and business performance: A market resources based view. Industrial Marketing Management, 89, 89-97.

Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: an extension and update of service dominant logic. Journal of the Academy of marketing Science, 44, 5-23.

Venkatraman, N., & Ramanujam, V. (1986). Measurement of Business Performance in Strategy Research : A Comparison of Approaches. The Academy of Management Review, 11(4), 801–814. Retrieved from http://www.jstor.org/stable/258398

Walker, M. J., Burton, B., & Cantara, M. (2017). Hype cycle for emerging technologies, 2017. *Gartner*, 1-68.

Yang, X., Pan, B., Evans, J. A., and Lv, B. F. 2015. "Forecasting Chinese tourist volume with search engine data," Tourism Management (46), pp. 386–397 (doi: 10.1016/j.tourman.2014.07.019).

Yin, R. K. (2018). *Case study research and applications*. Sage.

Yue, X., Wang, H., Jin, D., Li, M., & Jiang, W. (2016). Healthcare data gateways: found healthcare intelligence on blockchain with novel privacy risk control. Journal of medical systems, 40, 1-8.

APPENDICES

APPENDIX 1

Brand / Model	(Average) price in Euro
aiways	€ 39.083,00
alfa romeo	€ 43.391,83
alpine	€ 67.690,00
aston martin	€ 734.497,43
audi	€ 91.429,82
bentley	€ 264.853,50
bmw	€ 73.281,03
byd	€ 62.286,00
citroen	€ 25.667,65
cupra	€ 43.775,00
dacia	€ 16.151,43
ds	€ 38.870,00
ferrari	€ 339.910,89
fiat	€ 19.656,20
ford	€ 65.039,48
honda	€ 31.417,00
hyundai	€ 33.088,73
infiniti	€ 39.868,33
jaguar	€ 73.195,14
jac	€ 29.900,00
jeep	€ 59.460,20
kia	€ 31.412,33
lamborghini	€ 347.696,67
land rover	€ 82.315,25
lexus	€ 66.874,67
lotus	€ 91.777,00
lucid	€ 222.000,00
lynk and co	€ 44.882,00
maserati	€ 152.197,20
mazda	€ 31.247,78
mercedes	€ 71.756,00
mg	€ 35.450,00
mini	€ 29.913,33
mitsubishi	€ 24.758,00
morgan	€ 87.399,67
nio	€ 70.485,50
nissan	€ 36.270,18
opel	€ 27.134,80
polestar	€ 102.600,00
peugeot	€ 28.887,14

porsche	€ 108.348,14
renault	€ 28.104,39
rolls-royce	€ 454.783,00
seat	€ 27.543,57
skoda	€ 25.993,00
smart	€ 24.059,00
ssangyong	€ 30.320,33
subaru	€ 43.795,50
suzuki	€ 23.959,89
tesla	€ 75.490,00
toyota	€ 39.326,63
volkswagen	€ 37.826,41
volvo	€ 48.336,30
xpeng	€ 46.500,00

APPENDIX 2

Brand / Model	Electric / Hybrid	Announce date (first model)	Segmentation of release dates	Price in Euro
aiways u5	Electric	01/01/2020	1	€ 39.083,00
alfa romeo giulia	Other	27/06/1962	3	€ 45.390,00
alfa romeo giulietta	Other	01/03/2010	3	€ 23.950,00
alfa romeo 4c	Other	01/03/2011	2	€ 68.141,00
alfa romeo mito	Other	01/01/2008	3	€ 16.645,00
alfa romeo stelvio	Other	16/11/2016	2	€ 63.905,00
alfa romeo tonale	Other	01/02/2022	1	€ 42.320,00
byd atto 3	Electric	19/02/2022	1	€ 42.998,00
byd tang	Electric	01/06/2014	2	€ 72.335,00
cupra born	Electric	01/05/2021	1	€ 39.925,00
cupra formentor	Electric	01/03/2020	1	€ 44.985,00
dacia dokker	Other	10/05/2012	2	€ 15.690,00
dacia duster	Other	01/03/2010	3	€ 21.230,00
dacia jogger	Other	01/08/2021	1	€ 18.835,00
dacia lodgy	Other	01/11/2011	2	€ 15.990,00
dacia logan	Other	01/01/2005	3	€ 8.495,00
dacia sandero	Other	01/03/2008	3	€ 14.535,00
dacia spring	Electric	01/03/2021	1	€ 18.285,00
ford ecosport	Other	01/09/2013	2	€ 21.635,00
ford puma	Other	01/01/1997	3	€ 24.680,00
ford kuga	Other	01/09/2007	3	€ 30.095,00
ford explorer	Other	01/01/1991	3	€ 86.995,00
ford explorer phev	Other	21/03/2023	1	€ 86.995,00
ford fiesta	Other	01/01/1967	3	€ 19.870,00
ford focus	Other	01/07/1998	3	€ 28.500,00
ford galaxy	Other	01/06/1995	3	€ 45.760,00
ford mondeo	Other	23/11/1992	3	€ 34.300,00
ford mustang	Other	17/01/1964	3	€ 24.890,00
ford ka+	Other	01/06/2016	2	€ 13.125,00
jac iev7s	Electric	27/10/2017	2	€ 29.900,00
lotus elise	Electric	09/02/2021	1	€ 42.134,00
lotus evora	Electric	22/09/2008	3	€ 82.849,00
lotus exige	Electric	09/12/2015	2	€ 92.711,00
mg ehs	Hybrid	07/12/2020	1	€ 35.590,00
mg marvel r	Electric	01/10/2021	1	€ 45.990,00
mg zs	Electric	24/03/2020	1	€ 32.590,00
nio et7	Electric	09/01/2021	1	€ 83.471,00
rolls-royce cullinan	Other	13/02/2018	2	€ 432.485,00
rolls-royce dawn	Other	01/03/2015	2	€ 462.300,00
rolls-royce ghost	Other	24/01/2019	1	€ 400.939,00

rolls-royce wraith	Other	01/01/2013	2	€ 420.211,00
rolls-royce phantom	Other	27/09/2017	2	€ 557.980,00
seat alhambra	Other	01/01/1995	3	€ 42.930,00
seat arona	Other	01/01/2017	2	€ 20.600,00
seat ateca	Other	01/03/2016	2	€ 32.360,00
seat ibiza	Other	01/01/1984	3	€ 21.065,00
seat mii	Other	01/01/2011	2	€ 9.925,00
seat tarraco	Hybrid	19/02/2018	2	€ 37.510,00
skoda citigo	Electric	01/10/2011	2	€ 10.890,00
skoda enyaq	Electric	01/09/2020	1	€ 47.710,00
skoda fabia	Other	01/09/1999	3	€ 21.575,00
skoda kamiq	Other	01/02/2019	1	€ 23.055,00
skoda karoq	Other	01/02/2017	2	€ 29.155,00
skoda kodiaq	Other	01/02/2017	2	€ 30.365,00
skoda rapid	Other	20/10/2012	2	€ 14.190,00
skoda octavia	Hybrid	01/11/1996	3	€ 28.940,00
skoda scala	Other	06/12/2018	2	€ 19.140,00
skoda superb	Other	01/01/2001	3	€ 34.910,00
smart fortwo	Electric	01/03/1998	3	€ 24.926,00
smart forfour	Electric	01/03/2004	3	€ 23.192,00
suzuki across	Hybrid	01/07/2020	1	€ 56.320,00
suzuki baleno	Other	01/07/2016	2	€ 14.705,00
suzuki celerio	Other	1-1-2-14	1	€ 10.244,00
suzuki ignis	Other	01/01/2000	3	€ 19.205,00
suzuki jimny	Other	01/09/1975	3	€ 28.279,00
suzuki swace	Hybrid	01/10/2022	1	€ 31.449,00
suzuki swift	Hybrid	01/09/2004	3	€ 15.994,00
suzuki vitara	Hybrid	01/08/1991	3	€ 20.744,00
tesla model 3	Electric	16/09/2014	2	€ 44.990,00
tesla model s	Electric	22/06/2012	2	€ 99.990,00
tesla model x	Electric	29/09/2015	2	€ 109.990,00
tesla model y	Electric	14/03/2019	1	€ 46.990,00
vw arteon	Hybrid	06/03/2017	2	€ 36.665,00
vw caddy	Other	01/01/1979	3	€ 12.550,00
vw california	Other	09/12/2021	1	€ 74.181,00
vw crafter	Other	01/01/2006	3	€ 25.050,00
vw golf	Other	01/03/1974	3	€ 26.760,00
vw golf sportsvan	Other	04/09/2012	2	€ 26.180,00
vw id.3	Electric	09/09/2019	1	€ 31.085,00
vw id.4	Electric	01/11/2021	1	€ 42.540,00
vw id.5	Electric	29/04/2021	1	€ 51.830,00
vw id.buzz	Electric	01/01/2017	2	€ 70.160,00
vw multivan	Other	01/01/1985	3	€ 54.630,00
vw passat	Other	01/01/1973	3	€ 38.915,00
vw polo	Other	01/01/1975	3	€ 21.000,00

vw sharan	Other	01/01/1995	3	€ 48.685,00
vw taigo	Other	28/09/2021	1	€ 27.890,00
vw tiguan	Hybrid	01/01/2006	3	€ 41.925,00
vw touareg	Other	23/02/2018	2	€ 80.840,00
vw touran	Other	01/08/2002	3	€ 29.605,00
volvo c40	Electric	02/03/2021	1	€ 47.330,00
volvo s60	Hybrid	01/01/2000	3	€ 44.385,00
volvo s80	Other	01/01/1999	3	€ 35.995,00
volvo s90	Hybrid	01/01/2016	2	€ 55.775,00
volvo v40	Other	01/01/2012	2	€ 26.195,00
volvo v60	Hybrid	01/10/2010	3	€ 39.875,00
volvo v90	Hybrid	01/01/2016	2	€ 58.775,00
volvo xc40	Hybrid	21/09/2017	2	€ 44.385,00
volvo xc60	Hybrid	01/02/2013	2	€ 51.875,00
volvo xc90	Hybrid	01/05/2012	2	€ 78.773,00
xpeng p5	Electric	14/04/2021	1	€ 48.000,00
xpeng p7	Electric	30/11/2019	1	€ 45.000,00

APPENDIX 3

Brand / Model	Electric / Hybrid	Release date (first model)	Segmentation of release dates	(Average) price in Euro
aiways u5	Electric	01/01/2020	1	€ 39.083,00
alfa romeo 4c	Other	01/03/2011	2	€ 68.141,00
alfa romeo giulia	Other	27/06/1962	3	€ 45.390,00
alfa romeo giulietta	Other	01/03/2010	3	€ 23.950,00
alfa romeo mito	Other	01/01/2008	3	€ 16.645,00
alfa romeo stelvio	Other	16/11/2016	2	€ 63.905,00
alfa romeo tonale	Other	01/02/2022	1	€ 42.320,00
byd atto 3	Electric	19/02/2022	1	€ 42.998,00
byd tang	Electric	01/06/2014	2	€ 72.335,00
cupra born	Electric	01/05/2021	1	€ 39.925,00
cupra formentor	Electric	01/03/2020	1	€ 44.985,00
dacia dokker	Other	10/05/2012	2	€ 15.690,00
dacia duster	Other	01/03/2010	3	€ 21.230,00
dacia jogger	Other	01/08/2021	1	€ 18.835,00
dacia lodgy	Other	01/11/2011	2	€ 15.990,00
dacia logan	Other	01/01/2005	3	€ 8.495,00
dacia sandero	Other	01/03/2008	3	€ 14.535,00
dacia spring	Electric	01/03/2021	1	€ 18.285,00
ford ecosport	Other	01/09/2013	2	€ 21.635,00
ford explorer	Other	01/01/1991	3	€ 86.995,00
ford explorer phev	Other	21/03/2023	1	€ 86.995,00
ford fiesta	Other	01/01/1967	3	€ 19.870,00
ford focus	Other	01/07/1998	3	€ 28.500,00
ford galaxy	Other	01/06/1995	3	€ 45.760,00
ford ka+	Other	01/06/2016	2	€ 13.125,00
ford kuga	Other	01/09/2007	3	€ 30.095,00
ford mondeo	Other	23/11/1992	3	€ 34.300,00
ford mustang	Other	17/01/1964	3	€ 24.890,00
ford puma	Other	01/01/1997	3	€ 24.680,00
jac iev7s	Electric	27/10/2017	2	€ 29.900,00
lotus elise	Electric	09/02/2021	1	€ 42.134,00
lotus evora	Electric	22/09/2008	3	€ 82.849,00
lotus exige	Electric	09/12/2015	2	€ 92.711,00
mg ehs	Hybrid	07/12/2020	1	€ 35.590,00
mg marvel r	Electric	01/10/2021	1	€ 45.990,00
mg zs	Electric	24/03/2020	1	€ 32.590,00
nio et7	Electric	09/01/2021	1	€ 83.471,00
rolls-royce cullinan	Other	13/02/2018	2	€ 432.485,00
rolls-royce dawn	Other	01/03/2015	2	€ 462.300,00
rolls-royce ghost	Other	24/01/2019	1	€ 400.939,00

rolls-royce phantom	Other	27/09/2017	2	€ 557.980,00
rolls-royce wraith	Other	01/01/2013	2	€ 420.211,00
seat alhambra	Other	01/01/1995	3	€ 42.930,00
seat arona	Other	01/01/2017	2	€ 20.600,00
seat ateca	Other	01/03/2016	2	€ 32.360,00
seat ibiza	Other	01/01/1984	3	€ 21.065,00
seat mii	Other	01/01/2011	2	€ 9.925,00
seat tarraco	Hybrid	19/02/2018	2	€ 37.510,00
skoda citigo	Electric	01/10/2011	2	€ 10.890,00
skoda enyaq	Electric	01/09/2020	1	€ 47.710,00
skoda fabia	Other	01/09/1999	3	€ 21.575,00
skoda kamiq	Other	01/02/2019	1	€ 23.055,00
skoda karoq	Other	01/02/2017	2	€ 29.155,00
skoda kodiaq	Other	01/02/2017	2	€ 30.365,00
skoda octavia	Hybrid	01/11/1996	3	€ 28.940,00
skoda rapid	Other	20/10/2012	2	€ 14.190,00
skoda scala	Other	06/12/2018	2	€ 19.140,00
skoda superb	Other	01/01/2001	3	€ 34.910,00
smart forfour	Electric	01/03/2004	3	€ 23.192,00
smart fortwo	Electric	01/03/1998	3	€ 24.926,00
suzuki across	Hybrid	01/07/2020	1	€ 56.320,00
suzuki baleno	Other	01/07/2016	2	€ 14.705,00
suzuki celerio	Other	01/01/2014	2	€ 10.244,00
suzuki ignis	Other	01/01/2000	3	€ 19.205,00
suzuki jimny	Other	01/09/1975	3	€ 28.279,00
suzuki swace	Hybrid	01/10/2022	1	€ 31.449,00
suzuki swift	Hybrid	01/09/2004	3	€ 15.994,00
suzuki vitara	Hybrid	01/08/1991	3	€ 20.744,00
tesla model 3	Electric	16/09/2014	2	€ 44.990,00
tesla model s	Electric	22/06/2012	2	€ 99.990,00
tesla model x	Electric	29/09/2015	2	€ 109.990,00
tesla model y	Electric	14/03/2019	1	€ 46.990,00
volvo c40	Electric	02/03/2021	1	€ 47.330,00
volvo s60	Hybrid	01/01/2000	3	€ 44.385,00
volvo s80	Other	01/01/1999	3	€ 35.995,00
volvo s90	Hybrid	01/01/2016	2	€ 55.775,00
volvo v40	Other	01/01/2012	2	€ 26.195,00
volvo v60	Hybrid	01/10/2010	3	€ 39.875,00
volvo v90	Hybrid	01/01/2016	2	€ 58.775,00
volvo xc40	Hybrid	21/09/2017	2	€ 44.385,00
volvo xc60	Hybrid	01/02/2013	2	€ 51.875,00
volvo xc90	Hybrid	01/05/2012	2	€ 78.773,00
vw arteon	Hybrid	06/03/2017	2	€ 36.665,00
vw caddy	Other	01/01/1979	3	€ 12.550,00

vw california	Other	09/12/2021	1	€ 74.181,00
vw crafter	Other	01/01/2006	3	€ 25.050,00
vw golf	Other	01/03/1974	3	€ 26.760,00
vw golf sportsvan	Other	04/09/2012	2	€ 26.180,00
vw id.3	Electric	09/09/2019	1	€ 31.085,00
vw id.4	Electric	01/11/2021	1	€ 42.540,00
vw id.5	Electric	29/04/2021	1	€ 51.830,00
vw id.buzz	Electric	01/01/2017	2	€ 70.160,00
vw multivan	Other	01/01/1985	3	€ 54.630,00
vw passat	Other	01/01/1973	3	€ 38.915,00
vw polo	Other	01/01/1975	3	€ 21.000,00
vw sharan	Other	01/01/1995	3	€ 48.685,00
vw taigo	Other	28/09/2021	1	€ 27.890,00
vw tiguan	Hybrid	01/01/2006	3	€ 41.925,00
vw touareg	Other	23/02/2018	2	€ 80.840,00
vw touran	Other	01/08/2002	3	€ 29.605,00
xpeng p5	Electric	14/04/2021	1	€ 48.000,00
xpeng p7	Electric	30/11/2019	1	€ 45.000,00