Master Thesis

Market Analysis of Data-Driven Value Propositions in the Automotive Industry

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Master's degree program: Production Science and Management

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STATUTORY DECLARATION

I declare that I have authored this thesis independently, that I have not used other than the declared sources / resources, and that I have explicitly marked all material which has been quoted either literally or by content from the used sources.

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Abstract

The automotive industry is undergoing substantial changes, driven by technological developments such as autonomous driving or the electrification of the powertrain. Accompanying these changes is a significant growth in generated data across all phases of the automotive value chain.

The goal of many companies is to use this available data economically. The two most important possibilities therefore are firstly the increase of sales, which includes, for example, the offering of services based on data, and secondly, the cost reduction based on the knowledge that is generated by means of existing data.

The high economic potential, which is predicted by several companies and institutions, among them McKinsey (2016c, p.7ff), is encouraging companies of various business areas to become active in the automotive data business. In addition to conventional companies in the automotive industry, such as Original Equipment Manufacturers (OEMs) and Engineering Service Providers (ESPs), new entrants, such as IT-companies and start-ups, are trying to gain a foothold in the data business of the automotive industry. This thesis aims to identify a selection of ESPs, IT-companies, and start-ups, which are of particular interest for AVL, and to analyse their market offerings regarding data-driven services, tools, platforms and other data-driven activities, such as research activities, cooperations, and takeovers. With this gathered data, various evaluations should be done including interpretation and visualization of those. The determination of relevant companies is based on rankings that identify the ESPs with the highest revenues in the automotive industry, as well as IT-companies with the highest revenues in the German automotive industry. Relevant start-ups were determined by using a start-up query from the company Innospot.

Companies of the three mentioned groups were analysed based on publicly available information. Relevant information regarding data-driven services, tools, platforms and other data-driven activities have been categorized using clusters. In this thesis, a cluster is a thematic area, for example, autonomous driving or testing.

The analysis of the data obtained, led to a multiplicity of results, which are described more detailed in chapter 4. By using the clustering method, the activity areas of the companies and those areas where no activity was detected were identified. A comparison of the activity areas of the analysed companies with those of AVL, identifies similarities between AVL and those companies. The clusters in which no activity of AVL was identified were subjected to a separate analysis to identify companies that are active in these areas.

A separate analysis identifies the phases of the automotive value chain, in which the three groups of market players are mainly active in. For ESPs these are the phases of development, validation, production and aftersales. The emphasis of IT-companies is on production and aftersales, and the analysed start-ups have their focus mainly on the aftersales phase. Another outcome of this thesis is a list of market players that are particularly active in the areas of "Advanced Driving Assistance Systems" and "Testing".

This thesis also deals with the question of whether IT-companies and ESPs are working on the same data-based topics and offer services to them, or if a clear differentiation is possible. To answer this question, a competitive landscape was created, which represents the current position of the defined ESPs, IT-companies and start-ups. Especially larger ESPs, which are active in many clusters, are increasingly engaged in IT areas.

Kurzfassung

Die Automobilindustrie erfährt aufgrund technologischer Entwicklungen, wie zum Beispiel dem autonomen Fahren oder der Elektrifizierung des Antriebsstranges, bedeutende Veränderungen. Einhergehend mit diesen Veränderungen, ist ein deutliches Wachstum generierter Daten, welche in sämtlichen Phasen der Automobilen Wertschöpfungskette erzeugt werden.

Ziel vieler Unternehmen ist es, diese zur Verfügung stehenden Daten, wirtschaftlich zu verwerten. Die zwei bedeutendsten Möglichkeiten hierfür sind die datenbasierte Umsatzsteigerung, welche beispielsweise den Verkauf von Daten oder das Angebot von datenbasierten Services, beinhaltet, und die Kostenreduktion basierend auf dem Wissen, welches mittels vorhandener Daten generiert wird. Das große ökonomische Potential, welches von diversen Unternehmungen und Institutionen, darunter auch McKinsey (2016c, p.7ff), vorhergesagt wird, ruft Unternehmen aus verschiedenen Geschäftsbereichen auf den Plan, in diesem Bereich tätig zu werden. Neben den konventionellen Unternehmen in der Automobilindustrie, wie OEMs und Entwicklungsdienstleistern, versuchen neue Marktteilnehmer wie zum Beispiel IT-Unternehmen und Start-ups, im Datengeschäft der Automobilindustrie, Fuß zu fassen.

Ziel dieser Arbeit ist es, eine Auswahl an, für die AVL relevanten, Entwicklungsdienstleistern, IT-Unternehmen und Start-ups zu identifizieren, diese auf ihr Marktangebot an datenbasierten Dienstleistungen, Produkten, Plattformen und anderen datenbasierten Aktivitäten, wie etwa Forschung, Kooperationen oder Firmenübernahmen, zu analysieren und die Ergebnisse zu interpretieren. Die Bestimmung der zu analysierenden Unternehmen basiert auf Rankings welche die umsatzstärksten Entwicklungsdienstleister in der Automobilindustrie sowie die umsatzstärksten IT-Unternehmen in der deutschen Automobilindustrie identifiziert. Relevante Start-ups wurden mit Hilfe einer Start-up Abfrage des Unternehmens Innospot bestimmt.

Unternehmen dieser drei Unternehmensgruppen wurden auf Basis der öffentlich verfügbaren Informationen analysiert. Relevante Informationen bezüglich datenbasierter Dienstleistungen, Produkte und anderer datenbasierten Aktivitäten wurden unter Verwendung von Clustern kategorisiert und mit zusätzlichen Informationen aufgenommen. In dieser Arbeit kann ein Cluster als Themengebiet verstanden werden, wie zum Beispiel „Autonomes Fahren“ oder „Testen“.

Die Auswertung der durch die Analyse gewonnen Daten, führte zu einer Vielzahl an Ergebnissen, welche in Kapitel 4 detailliert beschrieben werden. Durch die Methode des Clusterns, wurden die Aktivitätsbereiche der Unternehmen, sowie jene Bereiche, in denen keine Aktivität festgestellt wurde, ermittelt. Eine Gegenüberstellung der Aktivitätsbereiche der analysierten Unternehmen mit jenen der AVL, identifiziert Unternehmen nach ihrer Cluster-Übereinstimmung mit der AVL. Jene Cluster, in denen keine Aktivität der AVL festgestellt werden konnte, wurden einer weitern Analyse unterzogen, um Unternehmen zu identifizieren, welche in diesen Bereichen aktiv sind.

Eine separate Analyse zeigt die Aktivität der analysierten Unternehmensgruppen in den Phasen der Automobilen Wertschöpfungskette. Entwicklungsdienstleister sind in den Phasen Entwicklung, Validierung, Produktion und Aftersales aktiv. Der Schwerpunkt der IT-Unternehmen liegt im Bereich der Produktion und des Aftersales. Start-ups legen ihren Fokus hauptsächlich auf den Aftersales Bereich.

Diese Arbeit beschäftigt sich auch mit der Frage, ob Entwicklungsdienstleister und IT-Unternehmen an denselben datenbasierten Themen arbeiten oder ob eine klare Differenzierung möglich ist. Um diese Frage zu beantworten, wurde eine Competitive Landscape erstellt, welche die gegenwärtige Position von zuvor definierten Entwicklungsdienstleistern, IT-Unternehmen und Start-ups darstellt. Speziell größere Entwicklungsdienstleister, welche in vielen Clustern aktiv sind, sind vermehrt auch in IT-Bereichen tätig.

Preface

My interest in the automotive industry and new technologies, have caused me to apply for the advertised Master Thesis “Market Analysis of Data-Driven Value Propositions in the Automotive Industry”.

Mobility, with all its chances and challenges, is a topic with a high impact on our lifestyle and future. I am very grateful for the opportunity to work on this topic with AVL, the worlds-leading ESP by turnover in the automotive industry (ATZ Extra, 2016).

This thesis should be the last step required to finish my Master’s Degree Programme “Production Science and Management” at the Technical University Graz. Challenging and instructive five years at the Technical University are finally coming to an end.

Writing a thesis occupies much time, not only for the author but also for other directly or indirectly involved people. To those people, I would like to say thank you. I want to thank my supervisors DDI Michael Rachinger, from the University, and DI Michael Fruhwirth, from the Know-Center, for their excellent guidance and support. Whenever I needed help and advice, they provided their time to keep progress high. I would also like to thank DI Gerhard Schagerl, who was AVLs supervisor of this thesis, for the valuable input and guidance he gave to me in the monthly meetings at AVL.

At this point, special thanks should be expressed to my family for all kinds of support in the last five years, and to my girlfriend Nicole for always supporting, motivating and being patient with me.

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List of Abbreviations

AaaS	Analytics-as-a-Service
ADAS	Advanced Driving Assistance Systems
ADV	Advances Data Visualization
AI	Artificial Intelligence
B2B	Business to Business
B2C	Business to Consumer
CAGR	Compound Annual Growth Rate
DDBM	Data-Driven Business Model
KB	Kilobyte
MB	Megabyte
GB	Gigabyte
PB	Petabyte
ERP	Enterprise Resource Planning
ESP	Engineering Service Provider
IoT	Internet of Things
IT	Information Technology
OBD	On-board Diagnostics
OEM	Original Equipment Manufacturer
PaaS	Platform-as-a-Service
PAYD	Pay-as-you-drive
PC	Personal Computer
R&D	Research and Development
USD	United States Dollar
VaaS	Visualization-as-a-Service
VC	Value Chain
ZB	Zettabyte

1 Introduction

In this chapter, the initial situation of the thesis, the objective, the tasks, and the applied approach are described.

1.1 Initial Situation

The automotive industry is facing significant changes (Kuhnert et al., 2017, p.2). The automobile development and production as well as disruptive technologies, like autonomous driving or shared mobility, are producing enormous amounts of data (McKinsey&Company, 2016c, p.11; Oracle, 2015, p.2). A connected car, for example, transfers about 20 Megabytes, an autonomous car even 16 gigabytes of data per day, which may be valuable for companies, if handled in a proper way (Koehler et al., 2016, p.2).

Not only the traditional companies, like Original Equipment Manufacturers (OEMs) and Engineering Service Providers (ESPs), have perceived this potential. Also, other, mainly non-automotive companies, are now pushing into the automotive market to benefit from their capabilities in data business. These other companies include big technology players like Google and Amazon, but also smaller IT-companies and start-ups which have capabilities in data handling. Many of the mentioned companies are currently trying to work with the generated data. The aim is to utilize this data to gain a competitive advantage. (McKinsey&Company, 2016a, p.13f)

Due to those significant changes in the last few years, AVL requires information regarding data-based offerings and activities of ESPs, IT-companies and start-ups.

1.2 Objective

The objective of this thesis is to create a processed overview of market players' areas of activity, for each company and each of the three considered market player groups separately. Similarities in the field of data-driven services, tools, platforms, and other activities between ESPs, IT-companies, and start-ups should become visible.

With the information of this analysis, AVL should have a data basis that allows clear statements regarding the data-business of the considered market players and market player groups.

1.3 Tasks

The tasks of this thesis can be split into five steps:

1) Identification of the relevant market players, including ESPs, IT-companies, and start-ups. Relevant, in this context means that the company is of interest for AVL.
2) Analysis of the relevant companies and creation of clusters for the offered data-driven services, products and other data-based activities. Each information needs to be recorded in a suitable way for result preparation, interpretation, and visualization.
3) Categorization of identified data-based information by using the defined clusters.
4) Evaluation of the categorization, to identify the activity areas, in terms of clusters, for each company.
5) Interpretation and visualization of the results.

1.4 Approach

A consistent approach is a prerequisite for writing a high-quality thesis. The applied approach is shown in Figure 1.1.

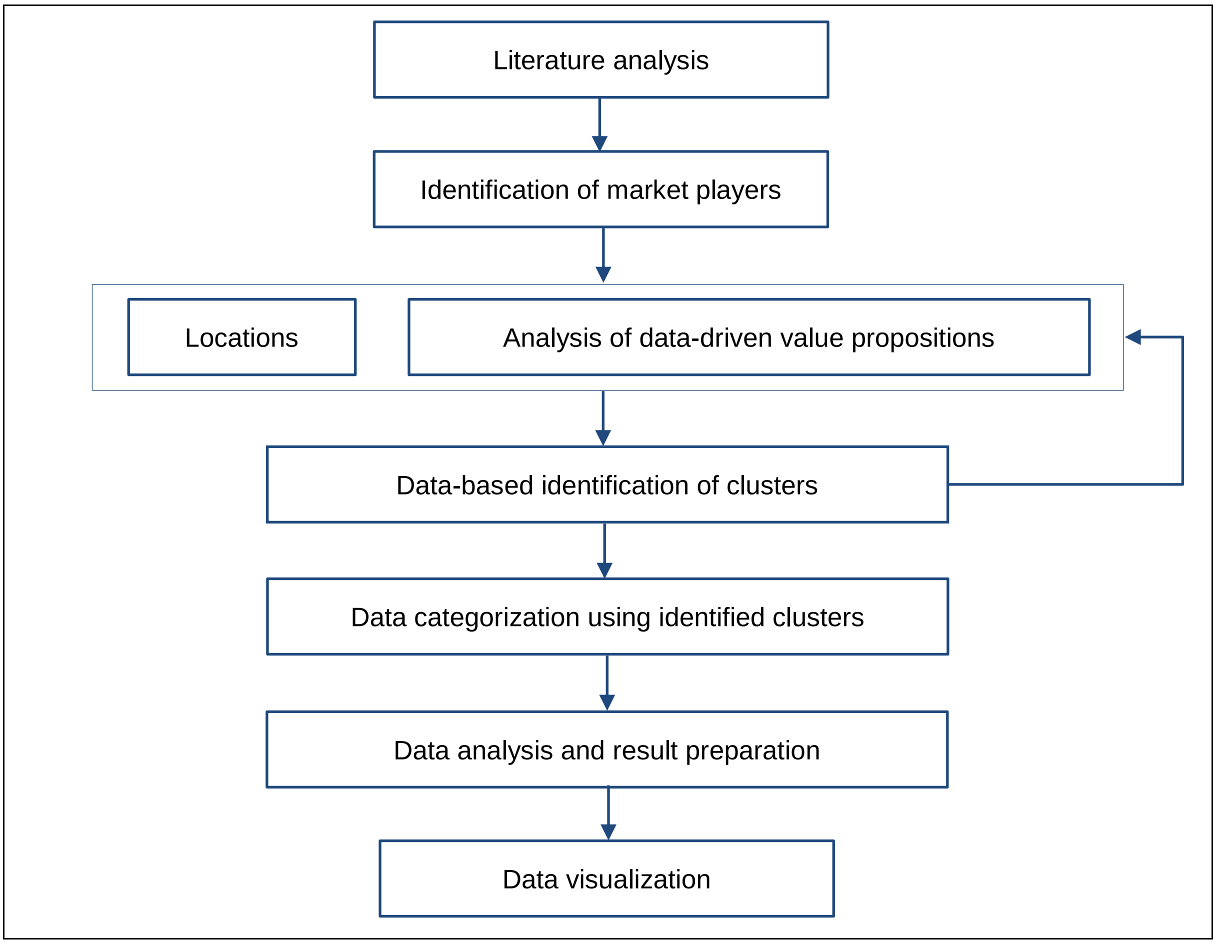


Figure 1.1: Approach

The starting point was a literature analysis that should provide the theoretical background required for writing and understanding the thesis. Chapter 2 deals with this Literature Analysis.

The first empirical part is the identification of market players that should be analysed. The focus in this thesis is on ESPs, IT-companies and start-ups. More details regarding the selection criteria and the chosen market players are provided in chapter 3.1.1. These identified market players were analysed regarding their data-driven value propositions and global locations. The scope of consideration is defined in chapter 3.1.2. More details regarding the data collection are provided in chapter 3.1.3.

The collected data then was categorized using clusters. A cluster is defined as a thematic area, for example calibration. Clusters were identified in two ways. AVL provided information regarding clusters that are of special interest and therefore highly relevant. Additionally, some clusters resulted from analysis of market players. More details regarding the data-based identification of clusters and the data categorization by using the identified clusters are provided in chapter 3.1.2 and 3.1.3. The result preparation and data visualization are the last steps required to create valuable insights from the collected data. The chapters 3.2 to 3.10 are concerned with this result preparation. The visualized results are shown in chapter 4.

2 Theoretical Background

The theoretical background consists of three main parts. The first part of this chapter deals with Big Data. Subsequently, Data Driven Business Models (DDBM) are discussed precisely. In the end, there are given insights into the automotive industry.

2.1 Big Data

The following pages are centred on big data. At the beginning, the term big data is defined. The definition of big data is followed by chapters dealing with the big data value chain and the development of big data. In the last part of this chapter, the analytics of big data is presented.

2.1.1 Definition of Big Data

The term “Big Data” describes datasets that grow extremely large which results in a difficulty of handling those data using traditional database management systems. Due to the size of these datasets, commonly used software tools and storage systems to capture, store, manage and process the data within adequate time, are no longer capable of handling those data. (Kubick, 2012, p.26)

Big data is characterized by the three main features (see Figure 2.1): volume, variety, and velocity, also called the three V´s. (Gartner, 2011)

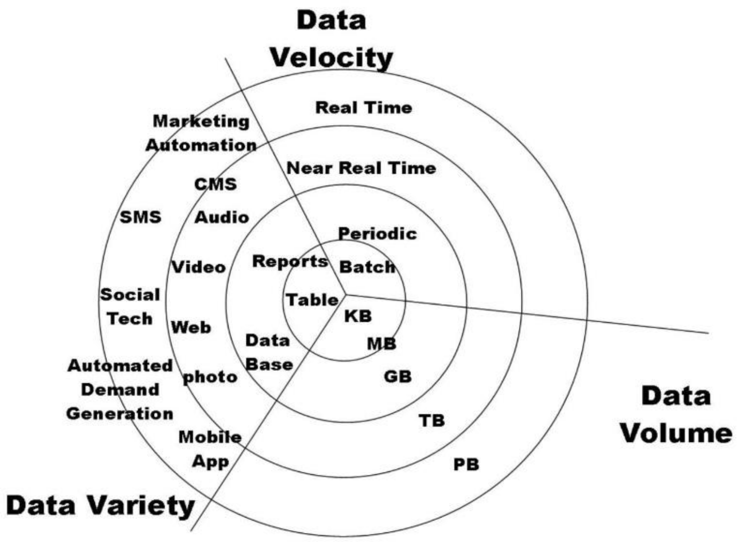


Figure 2.1: The 3 V´s (https://velvetchainsaw.com/2012/07/20/three-vs-of-big-data-as-applied-conferences/, accessed 12.02.2019)

Volume
The volume of data refers to its size (Gartner, 2011). It is the primary attribute of big data. The volume of big data can be quantified in two ways. That is by the size of the data, measured most commonly in TBs or PBs, or by the number of records, transactions, tables or files. (Elgendy & Elragal, 2014, p.216)

Variety
Another point that contributes to the volume of big data is that its variety of sources is increasing. That sources include for example logs, clickstreams, and social media. (Elgendy & Elragal, 2014, p.216) The variety considers two aspects, on the one side, the different data formats and data types, and on the other side, the different kinds of uses and ways of analysing the data (Gartner, 2011).

Velocity
The third V is velocity. Velocity describes how often the data is changing or how often it is created (Gartner, 2011). When describing big data by using its velocity or speed, the focus is on the frequency of data generation or the frequency of data delivery (Russom, 2011, p.7).

Veracity
Researchers and organizations have discussed adding veracity as a fourth V. The focus of veracity is on the quality of the data. It characterizes big data quality as good, bad, or undefined due to data inconsistency, incompleteness, ambiguity, latency, deception, and approximations. (TechAmerica, 2012, p.10f)

Basically, it can be said that big data is the assemblage of infrastructure, data sources, software and skills that support the three V´s, allowing companies to undertake more relevant and timely analysis than traditional business intelligence methods (Hagen et al., 2013, p.5).

2.1.2 Big Data Value-Chain

In general, a value chain describes the value-adding activities of an organisation, allowing them to be understood and optimized. It consists of series sub-systems that are characterized by inputs, transformation processes, and outputs. (Curry, 2015, p.30f)

According to Open Data Watch (2018, p.1), the big data value chain describes the evolution of data from collection to analysis, and its final impact on decision making. Figure 2.2 illustrates the big data value chain and its phases according to Curry et al. (2014, p.1f). These phases are explained in detail in the following text.

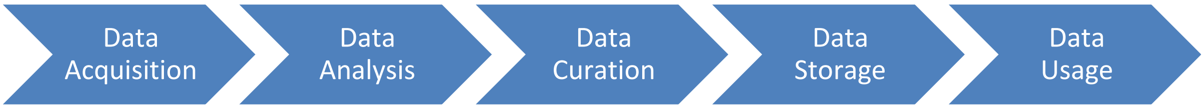


Figure 2.2: Big data value chain (Curry et al., 2014, p.1f)

Data Acquisition
Data Acquisition is the process of gathering, filtering and cleaning data before it is stored. There is no restriction to a specific type of data. Typical types of data to be acquired are:

- Structured or unstructured data
- Protocols
- Real-time data
- Others

Cleaning data means to get rid of data that was gathered but has no relevance for further considerations. Due to the characteristics of Big Data, described in chapter 2.1.1, data acquisition is one of the significant Big Data challenges in terms of infrastructure requirements. The infrastructure needs to be capable of handling data with those specific characteristics. After Data Acquisition, the data should be suitable for analysis. (Curry et al., 2014, p.4)

Data Analysis
A detailed description of the data analysis is provided in chapter 2.1.4.

Data Curation

Data Curation is the active management of data over its lifecycle. This data management aims to provide data that fulfil the quality requirements needed for an effective usage. (Pennock, 2007, p.1f) A fundamental principle of data analytics is that the quality of the analysis depends on the quality of the data analysed (Curry et al., 2014, p.62). Data quality issues can have a significant impact on business operations. Especially when it comes to data-based decision-making processes within organisations, bad data quality can have severe consequences in terms of bad or even wrong decisions. (Curry et al., 2010, p.25f)

The data curation processes can be categorised into the following activities (Curry et al., 2014, p.62):

- Content creation
- Selection
- Classification
- Transformation
- Validation
- Preservation

Data Storage

Data Storage is the management of data in a scalable way that enables applications fast access to the required data (Curry, 2014, p.97). More information regarding data storage is provided in chapter 2.1.4.2 “Big Data Storage and Management”.

Data Usage

The analysed data can be used in multiple ways. Typical data usage scenarios cover a wide range of applications. One of the core business tasks of advanced data usage is support in the decision-making process. Other use cases include automated actions like they are already applied in smart grids, where anomalies in the networks are detected, and corrective actions are executed. (Curry et al., 2014, p.136)

In addition to the mentioned use cases, the data can be utilised for (Curry et al., 2014, p.136):

- Prediction
- Visualization
- Exploration
- Modelling
- Other

2.1.3 Data Volume Development

It is assumed that the data volumes will increase sharply. Businesses around the world are intensively using data to transform themselves to become more agile, improve customer experience, introduce new business models and develop new sources of competitive advantage. Moreover, customers who are living in an increasingly digital world, are another factor influencing the growing data sphere. (Reinsel et al., 2018, p.6f)

According to Reinsel et al. (2018, p.7), it can be distinguished between three primary locations where digitization is taking place and where digital content (data) is being created. These three locations are the core, which consists of the traditional- and cloud datacentres, the edge which consists of enterprise infrastructures like cell towers and branch offices, and the endpoints, which include PCs, smartphones and IoT devices. Aggregating the data of these three primary locations results in the global data sphere. In 2018, the global data sphere amounted about 33 Zettabytes, for 2025, a data volume of about 175 zettabytes is expected. This signifies a growth rate of more than 530%. One zettabyte is equivalent to a trillion gigabytes. (Reinsel et al., 2018, p.6) Figure 2.3 shows the global data sphere from 2010 to 2025.

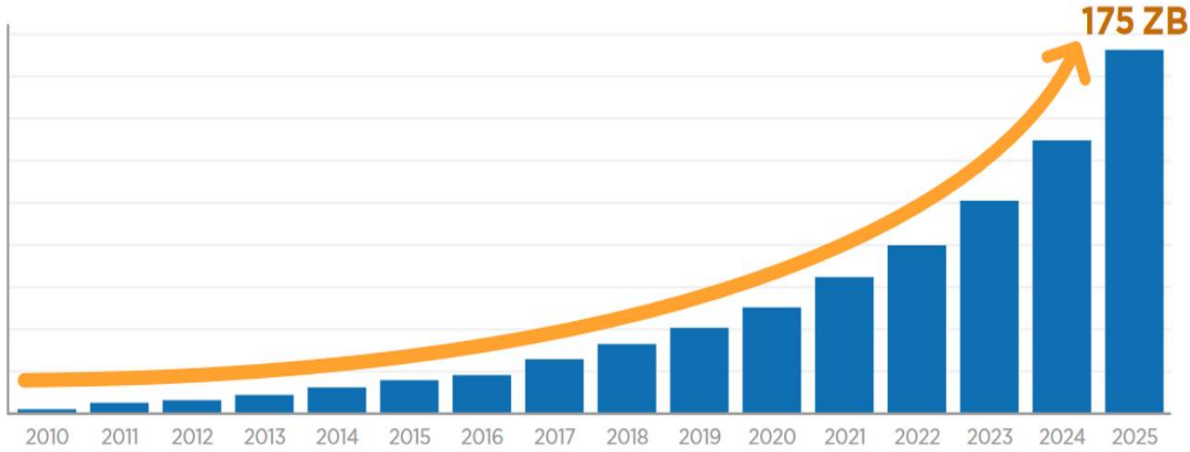


Figure 2.3: Annual size of the global data sphere (Reinsel et al., 2018, p.6)

Not only the data sphere will change rapidly in the next few years, but also the places where the data is stored will experience a significant change. For businesses and customers, the cloud is getting an increasingly attractive option to store data, driven by the characteristic of a cloud that enables fast and ubiquitous access to data. (Reinsel et al., 2018, p.10) Figure 2.4 shows the future change in storage behaviour.

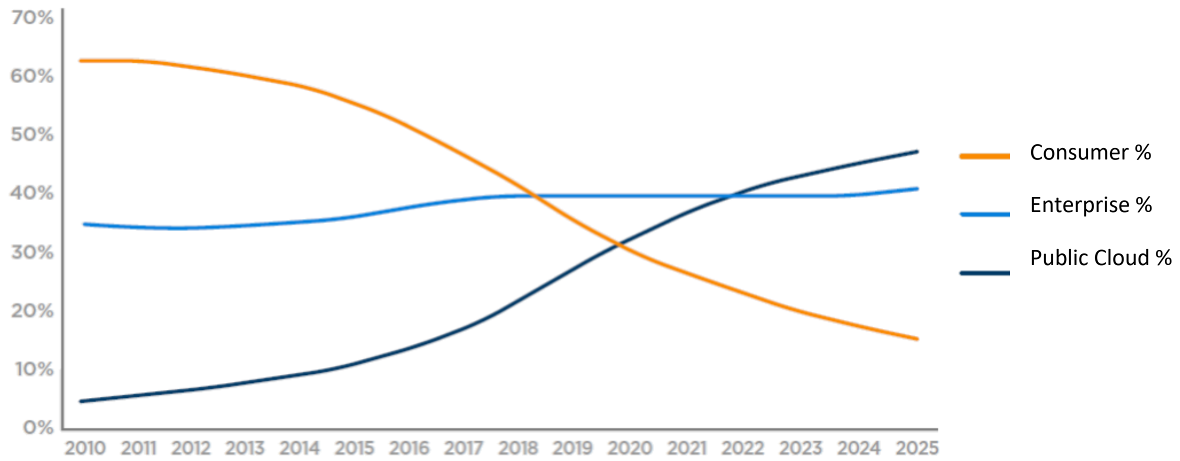


Figure 2.4: Data storage distribution (Reinsel et al., 2018, p.10)

2.1.4 Big Data Analytics

Big data analytics is the application of advanced analytics techniques on big data, which is meant to analyse data sets and gain useful information (Adams N.M., 2010, p.11f). The outcome of big data analytics is not restricted to information, it is also suitable to detect important relationships among the stored variables, as well as to extract hidden patterns from large data sets (Elgendy & Elragal, 2014, p.221). To learn from data and to gain a competitive advantage, big data analytics has become an important method for decision makers (Song & Kusiak, 2007, p.1733). Companies use advanced analytics techniques to discover unknown facts by analysing large volumes of data. In general, it can be said that the larger the data volume is, the more difficult it becomes to manage, even if advanced analytics techniques are being used. (Russom, 2011, p.5ff)

Based on the increase in storage capabilities and data collection methods, large amounts of data are no rarity anymore. Additionally, the costs of data storing, and analysing have become lower, which results in a growing number of enterprises implementing big data analytics. To extract value from big amounts of data, the data needs to be stored and analysed. (Elgendy & Elragal, 2014, p.214)

2.1.4.1 Big Data Analytics Framework

Due to the increasing amount of data, traditional data management and analysis techniques are no longer able to analyse those complex data sets. Therefore, a need for faster and more efficient ways to store, manage, and analyse that data, arises. To handle all those requirements, Elgendy & Elragal (2016, p.1073), proposed the Big-Data, Analytics, and Decision (B-DAD) framework. This framework integrates the data analytics tools and methods in the decision-making process. It also assigns the different big data tools and methods, including storage, management and processing tools, analytics tools and methods, as well as visualization tools and methods, to the different phases of the decision-making process. The changes associated with big data analytics can be reflected in the areas of big data storage and management, big data analytics processing, and big data analyses. (Elgendy & Elragal, 2014, p.216)

2.1.4.2 Big Data Storage and Management

The starting point when dealing with big data is managing where and how to store the data after it has been acquired. Traditional ways of storing and retrieving structured data include relational databases, data warehouses, and data marts. The data uploading from an operational store to the storage is done with Extract, Transform, Load, or Extract, Load, Transform tools. These tools have three main functions which are extracting the data from outside sources, transforming the data to fit operational needs and loading the data into the data storage. (Elgendy & Elragal, 2014, p.217) This approach ensures that the uploaded data is cleaned, transformed and catalogued before it is available for analytics (Bakshi, 2012, p.1).

A usual enterprise data warehouse environment differs from a big data environment in many aspects, which calls for magnetic, agile and deep analysis skills. One major difference is that traditional enterprise data warehouse approaches discourage the integration of new data sources until they are cleaned. On the contrary, big data environments are attracting all the data sources, regardless of the data quality. (Cohen et al., 2009, p.1481f) Based on the growing number of data sources, big data storage should allow data analysts to produce and adapt data in an efficient way. Therefore, an agile database is required. (Herodotou et al., 2011, p.261)

2.1.4.3 Advanced Analytics Methods

After big data is stored, managed and processed, the data is ready to get analysed by performing big data analyses (He et al., 2011, p.1199f). The most common advanced data analytics methods are association rules, clustering, classification, decision trees, and regression (Elgendy & Elragal, 2014, p.220f). As the application of Artificial Intelligence (AI) and Machine Learning plays an important role in the analysis of big data (Kibria et al., 2018, p.4), both technologies are described in the following.

Most advanced analytics methods are based on the application of AI and Machine Learning. Both tools are powerful solutions for handling and analysing large amounts of data to extract valuable information from it. (Kibria et al., 2018, p.4) To gain a better understanding of the term AI, the definition of this term is presented in the following. Literature provides dozens of AI-definitions, three common ones are:

> “AI is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment” (Nilsson, 2009, p.13)
>
> AI is a “collective term for computer systems that can sense their environment, think, learn, and take action in response to what they are sensing and their objectives” (Rao, 2017, p.2)
>
> “AI is intelligence exhibited by machines and systems, with machines mimicking functions typically associated with human cognition” (McKinsey&Company, 2018, p.13)

AI is seen as the extended perception of machines becoming capable of carrying out tasks on their own. Compared to Machine Learning, AI is not restricted to predictive solutions. It allows performing prescriptive analytics which are characterized by giving advice for future actions, based on historical data. (Kibria et al., 2018, p.4)

Machine Learning is often defined as an application of AI, based around the basic concept that machines can learn for themselves by providing them access to large amounts of data (Kibria et al., 2018, p.4). It refers to any type of computer program that can learn by historical data, without the requirement to be programmed by a human (Wehle, 2017, p.2). Machine Learning solutions are suitable for predicting future occurrences based on large amounts of historical data (Jiang et al., 2017, p.98). In Figure 2.5 the maturity and productivity of analytics methods, among them Machine Learning solutions, are shown.

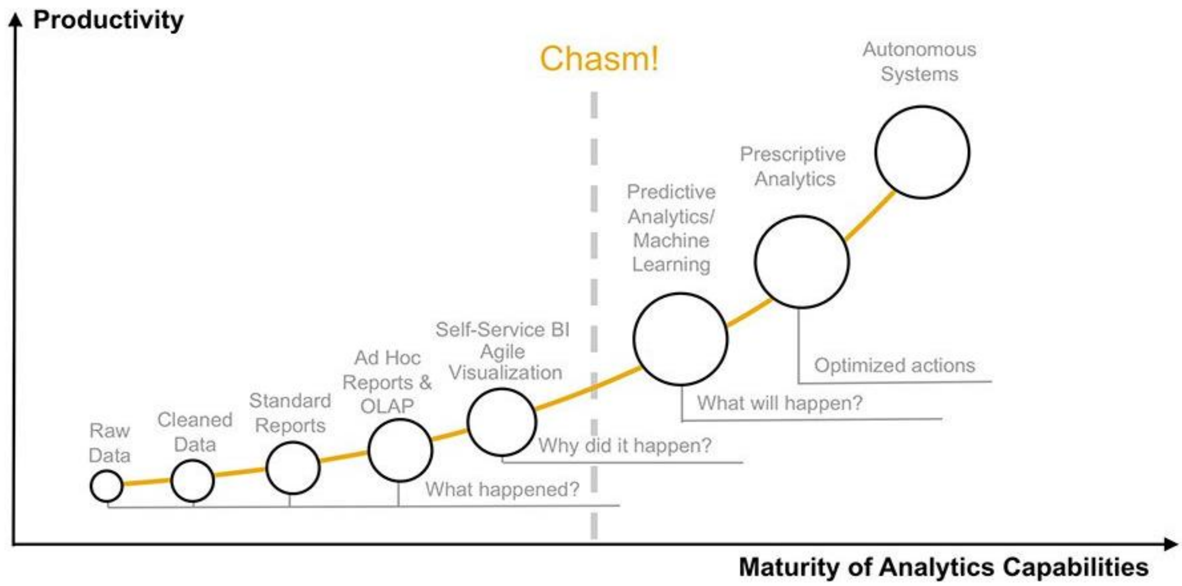


Figure 2.5: Analytics maturity (Elliott, 2018)

The left side of the chart consists of descriptive and diagnostic analytics, called the “traditional analytics”. The collection of raw data and the preparation of reports or visualizations are carried out by humans. The responsible persons are then able to make decisions based on this prepared data. The characteristic of the left side of the graph is that humans prepare the data and humans make the decisions. (Elliott, 2018)

An example for the steps on the left side of the graph is Advanced Data Visualization (ADV) (Russom, 2011, p.24). ADV is a combination of data analysis methods and data visualization to enable comprehensive data exploration. The ADV approach fits well in situations where the analysts have only a little knowledge about the considered data. (Shen et al., 2012, p.64) Visualizing big data in a way that allows decision makers to analyse the data and to base decisions on it, is the key challenge of ADV (Manyika et al., 2011, p.33). The increasing volume and complexity of generated data has led to an increasing demand for ADV solutions (Zhang et al., 2012, p.181). One significant advantage is that most ADV tools support interfaces to leading sources. This enables analysts to explore data across a variety of sources and additionally in real-time. (Russom, 2011, p.26)

The right side of the chart consists of predictive and prescriptive analytics which are powered by math for processes. The required approach is very different compared to the left side of the graph. (Elliott, 2018) Further information regarding predictive and prescriptive analytics is provided in chapter 2.2.3.

2.2 Data-Driven Business Models and Innovation

The importance of data-driven businesses in today's world can be illustrated by comparing the market-values of the world's top five data businesses (Apple, Alphabet, Microsoft, Amazon, and Facebook) with other branches or for example with the entire DAX (German Stock Index). The market capitalization of the mentioned data businesses amounted 3,347.20 billion USD in October 2017, while the market capitalization of the entire DAX companies amounted 1,236.00 billion USD (Nasdaq, 2018). This comparison indicates that the world's five leading tech companies are 2.7-times more valuable than leading companies of Germany, considering that Germany is the world's fourth-largest economy. (Seibert & Gründinger, 2018, p.9f)

In 2007, eight in ten of the biggest companies were from the financial or energy sector. In the Top 10 ranking of 2017, only two of these eight companies were still represented in this ranking. These two companies are Microsoft and Exxon Mobil. In 2017, seven out of the ten leading companies were tech players that have embraced data-driven business models. (Bloomberg, 2017)

This chapter describes the types of data-driven innovations, followed by the definition and framework of data-driven business models. In the last part of this chapter, archetypes of Analytics-as-a-Service Business Models are described.

2.2.1 Types of Data-Driven Innovation

According to Seibert & Gründinger (2018, p.6f), data as a key resource, which is further developed by applying additional defining characteristics, can result into the three different data-driven innovations: data-driven product innovation, data-driven process innovation, and data-driven business model innovation.

Data-Driven Product Innovation
The data-driven product innovation consists of the three sub-categories product enhancement, product augmentation, and data as a product (Seibert & Gründinger, 2018, p.6f).

In product enhancement, data is used to enhance or personalize an existing product or to optimize the customer experience. As an example, Nike with NIKEiD can be mentioned. (Seibert & Gründinger, 2018, p.6f) The basic idea of product augmentation is to differentiate a product from similar competitors' products (Abratt & Bendixen, 2009, p.3). This differentiation comes in form of added features or services (Investopedia, 2019b). The data-driven product augmentation is a process where data is used to make a product smart. Examples for product augmentation are connected cars, smartphones, and wearable devices (Mühlhauser, 2007, p.158ff). In the third type of data-driven product innovation, data becomes the product itself. Examples for data as a product are advertising, location-based services, and recommendation systems. (Seibert & Gründinger, 2018, p.6f)

Data-Driven Process Innovation
The data-driven process innovation consists of the two sub-categories enterprise process innovation and customer process innovation (Seibert & Gründinger, 2018, p.7).

Enterprise process innovation is about using data to optimize an internal process. As a result of this optimization, the costs are being reduced. A typical example of this type of data-driven process innovation are car manufacturers who optimize their design and production processes based on the usage of data. The customer process innovation uses data to optimize delivery or service processes with direct impact on customer experience. Two potential outcomes of customer process innovation are cost effects and enhanced customer satisfaction with possible indirect margin and revenue contributions. An example is Tesla´s over-the-air-update process. (Seibert & Gründinger, 2018, p.7)

Data-Driven Business Model Innovation

Data-driven business model innovation is about designing an entirely new business model based on data. It does not have to be disruptive, but it must result in a significant improvement of firm's value propositions caused by a change in the value creation, value appropriation, or value delivery (Sorescu, 2017, p.692). This leads to changes in how a company creates value to customers. Theoretically, a distinction can be made between two basic forms of data-driven business model innovation. In practice, it is fairly common that these two basic forms merge into one another. These forms are the value model innovation and the monetization model innovation. (Seibert & Gründinger, 2018, p.7)

The value model innovation uses data to provide new methods of value generation for the customer. An example is the Google search feature which uses advanced algorithms to retrieve suitable information. In this case, the value model is meant to provide access to global information at any given time. The monetization model innovation is characterized by using data to offer innovative ways of value recording for companies. And again, an example therefore is the Google search engine. The usage of this feature is free for the customer if he or she allows Google to show advertisements. This converts a user into a marketing product. Google is offering the user of the search engine as a potential customer to the advertising companies. (Seibert & Gründinger, 2018, p.7)

2.2.2 Definition of Data-Driven Business Models

The characteristic of a data-driven business model is data as a key resource (Hartmann et al., 2014, p.6). It is a blueprint that describes the way a company uses data to deliver value to their customers and to convert this value into revenue and/or profit. This conversion can be in form of direct or indirect monetization. Data-driven business models utilize advanced technologies. These technologies require dynamic capabilities to fully master the leverage of diverse big data sources. (Seibert & Gründinger, 2018, p.8)

2.2.3 Data-Driven Business Model Framework

This chapter describes a data-driven business model framework. The dimensions of the data-driven business model framework were identified by systematically analysing existing static business models of start-ups. There is no general agreement in literature about the absolute number and types of business model dimensions (Hartmann et al., 2016, p.2f), but the six key dimensions: value proposition, key resource, key activity, market/customer segment, revenue stream, and cost structure, are commonly found among various authors. These authors include Chesbrough & Rosenbloom (2002) and Johnson et al. (2008).

Dimension 1: Key Resources

According to Wernefelt (1984), a resource is a prerequisite, a company needs to create value. All assets, capabilities, organisational processes, firm attributes, information and knowledge, controlled by the firm, are firm resources (Barney, 1991, p.101).

A key resource, a DDBM has to have, is data. Additionally to data, the business model may also have other key resources. Data can occur in different forms from different sources. A prerequisite when creating the DDBM framework is to understand the data and its sources used by companies. (Hartmann et al., 2016, p.3)

In the broadest sense, data sources can be divided into internal data sources and external data sources. According to Hartmann et al. (2016, p.8), internal data sources can be further broken down into existing data and self-generated data. The existing data is data that can be drawn from IT systems, but there is currently no application for it. An example of existing data is Enterprise Resource Planning (ERP) data. The self-generated data can be further divided into data for a specific purpose, through tracking (e.g. sensor data), or crowd sourced data which is created by contributors over the web or social collaboration techniques (Gartner, 2013). The external data can be divided into acquired data, customer-provided data and freely available data (Hartmann et al., 2016, p.8).

Dimension 2: Key activities

To produce and deliver products and/or services, a company has to perform different activities. In a DDBM, these key activities have to be related to the key resource data. (Hartmann et al., 2016, p.8)

The following identified key activities in a DDBM framework, result from integrating different perspectives from literature research along the steps of the “virtual value chain”, which consist of gathering, organising, selecting, synthesising and finally distributing (Rayport & Sviokla, 1995, p.76). The identified key activities, considering the data value chain, are data generation, data acquisition, processing, aggregation, analytics, visualization and finally distribution (Hartmann et al., 2016, p.18).

Data generation can be made internally by crawling internal sources, tracking sensors or using crowdsourcing. In the case of external data generation, data can be acquired from external sources, it can be customer provided, or it can be freely available. When the data is fully available, it may be further processed (transformed or cleaned), or it may be aggregated (organising and selecting) from different data sources. If the data is available in the required form and quality, data analytics can provide valuable insight (Hartmann et al., 2016, p.8).

According to Delen & Demirkan (2013, p.361), these data analytics can be further divided into three sub-categories: descriptive analytics, predictive analytics, and prescriptive analytics.

- **Descriptive Analytics**
  The focus of descriptive analytics is on historical data and the analysis of this data to identify problems or opportunities. Descriptive analytics is all about finding an answer to the question “What has happened?”. (Delen & Demirkan, 2013, p.361)

- **Predictive Analytics**
  The purpose of predictive analytics is to identify patterns and future trends based on past and current data. Typical means used are data mining and advanced analytics tools. Predictive analytics is typically associated with other techniques such as machine learning and regression analysis (Watson, 2014, p.7). Predictive analytics is meant to assist finding answers to the following questions “What will happen and/or why will it happen?”. (Delen & Demirkan, 2013, p.361)

- **Prescriptive Analytics**
  The purpose of prescriptive analytics is to improve business performance by determining a set of “alternative courses-of-actions or decisions given a complex set of objectives, requirements, and constraints”. The questions someone tries to answer with prescriptive analytics are “What should I do?” and “Why should I do it?”. The methods and tools used are mathematical modelling, optimization models, simulation models, expert systems and decision modelling tools. (Delen & Demirkan, 2013, p.361)

The analysed data might be visualized for a better understanding. Finally, the data might be distributed to customers. (Hartmann et al., 2016, p.8)

Dimension 3: Offering/ Value Proposition

The central dimension of all business model frameworks is the offering (Hartmann et al., 2016, p.9). The offering is also well known as the value proposition (Chesbrough and Rosenbloom, 2002, p.7). The value proposition is defined as the value created for customers through the offering. According to the definition of knowledge discovery in databases, the offering of a company can be divided into two groups. On the one side, data which is just a set of facts, also called raw data without meaning, and on the other side information and/or knowledge. Analysed data becomes information/knowledge due to the attached meaning (Fayyad et al., 1996, p.37f). For companies who provide a non-virtual offering, a third dimension, called non-data products or services is added to the offering possibilities. (Hartmann et al., 2016, p.9)

Dimension 4: Target Customer Segment

One dimension of the DDBM framework is the target customer segment. Each company offers their products and/or services to a specific group called target customers. A possibility to subdivide the entire group of target customers is to differentiate businesses (B2B) from individual customers (B2C). (Morris et al., 2005, p.731) The companies are not limited to either B2B or B2C customers, they can also supply both (Hartmann et al., 2016, p.10).

Dimension 5: Revenue Model

In a long-term perspective, it is crucial for a company, to have at least one revenue stream (Hartmann et al., 2016, p.10). The literature identifies nine different main revenue streams. These revenue streams are:

- **Asset sale**
  Asset sale brings a change in the ownership rights of a physical product. It is the most widely understood revenue stream. (Osterwalder et al., 2010, p.31)

- **Lending/renting/leasing**
  This lending/renting/leasing revenue stream is created by granting someone the right to use a certain asset. The usage is time-limited and chargeable. (Osterwalder et al., 2010, p.31)

- **Licensing**
  Permitting customers to use protected intellectual property (e.g. patent) in exchange for a fee. (Osterwalder et al., 2010, p.31)

- **Usage fee**
  In this revenue model, the customer pays on a per-use basis. The fee depends on how much the service is used by the customer. (Schüritz et al., 2017, p.5352) An example for this type of revenue stream is a telecom operator who charges the customer for the number of messages sent (Osterwalder et al., 2010, p.31).

- **Subscription fee**
  Giving customers continuous access to a service in exchange for a subscription fee (Osterwalder et al., 2010, p.31). The customer perceives value during the period of service usage (Schüritz et al., 2017, p.5355). A major benefit of the subscription model is that companies that offer their services based on this model can gather data from the customers and use this data to improve their offered service (Schüritz et al., 2017, p.5352).

- **Brokerage fee**
  The brokerage fee is charged for the use of an intermediate service (Osterwalder et al., 2010, p.32).

- **Advertising**
  Earning money with advertising is based on charging fees for advertising a certain product, service, or brand. (Osterwalder et al., 2010, p.32)

- **Gain sharing**
  In the gain sharing revenue model, the provider is paid based on the success of the offered service. Usually, the provider earns a certain percentage of the generated value at the customer end. The gain sharing model is suitable if the data-driven service is measurable and quantifiable. (Schüritz et al., 2017, p.5353)

- **Pay-with-data**
  In the pay-with-data revenue model, customers pay for using a data-driven service with granting access to personal data. The service providers can collect and analyse this data and offer it to interested customer groups. (Schüritz et al., 2017, p.5354)

Dimension 6: Cost structure
One goal of a company is to create and deliver value to customers. An effect of value creation are different types of expenditures like costs for labour or costs for material. In DDBM, the specific cost advantage regarding data use is far more important than the company´s cost structure. If the data used in the product or service are created independently of the specific offering, the company would have a cost advantage. A car manufacturer who uses data which is automatically created and stored in the car´s electronics would be an example for a company that faces a cost advantage. The car manufacturer can use the data without additional effort. In contrast, a company like the start-up Automatic, which is offering car-data analytics to its customers, has to gather the data through specific hardware. (Hartmann et al., 2016, p.10)

The result of bringing together the dimensions 1 to 6, including all their sub-dimensions, is shown in Figure 2.6, the framework of a DDBM.

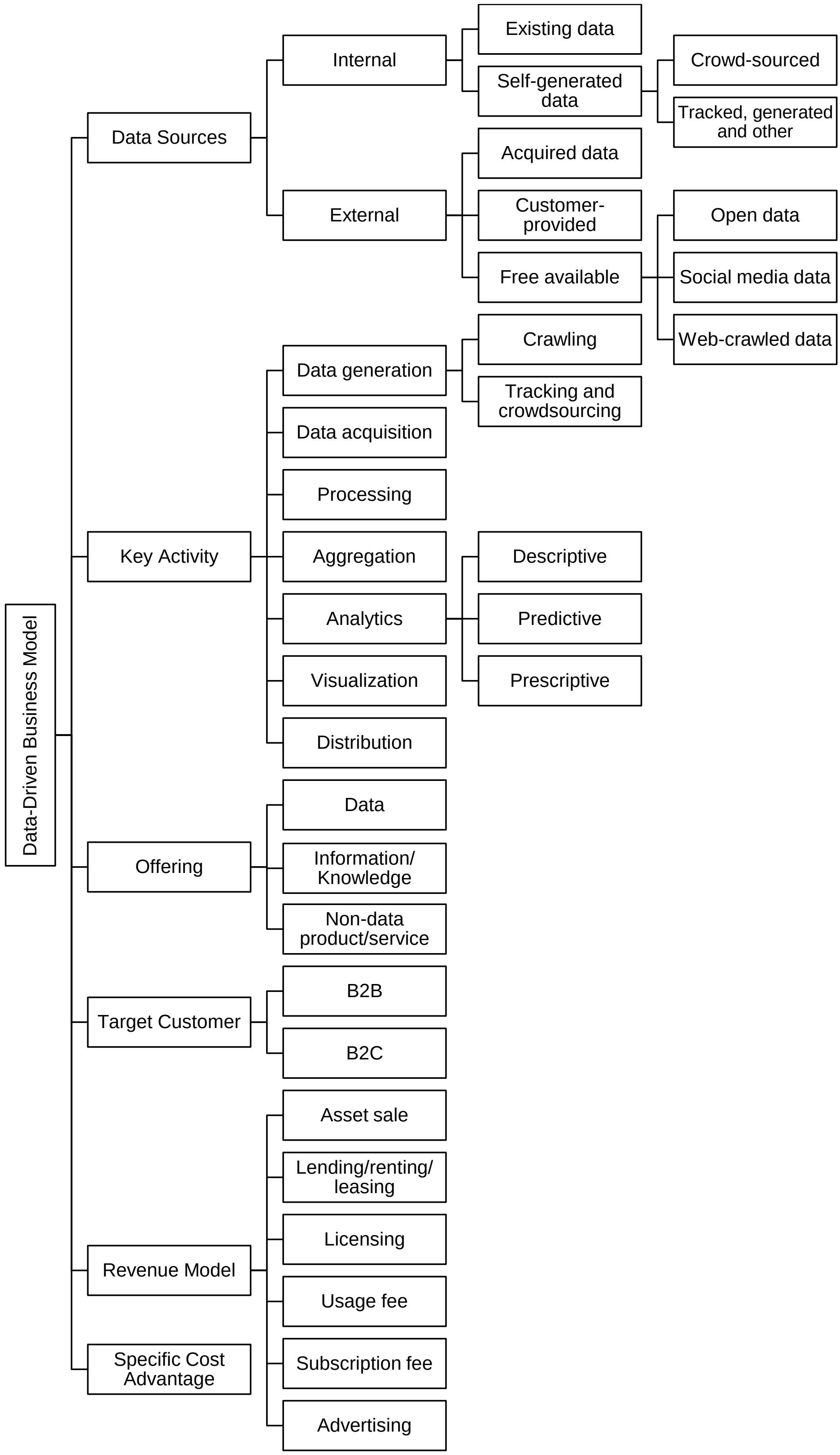


Figure 2.6: Framework DDBM (Hartmann et al., 2016, p.11)

2.2.4 Archetypes of Analytics-as-a-Service Business Models

According to Hartman et al. (2014, p.6) the key resource of a DDBM is data. In many cases, the data needs to be analysed to make it suitable for further utilization. Various business models exist, which allow such an analysis. What all of them have in common, is the goal to maximise business value by leveraging and analysing data (Chen et al., 2011, p.16).

According to a case study research from Naous et al. (2017, p.491ff), 5 different Analytics-as-a-Service (AaaS) archetypes exist. These five archetypes are derived from identified business model patterns of 21 vendors with 28 offerings. The case study research is the preferred approach to study cloud-based business models to thoroughly analyse the value creation logic (Boillat and Legner, 2013, p.5f). The identified AaaS-archetypes are:

Visualization-as-a-Service (VaaS)
This archetype provides visualization like charts, graphics, plots, and basic data discovery capabilities (Naous et al., 2017, p.496). Visualization makes it easy to identify patterns and trends in data compared to data in tables (Barbulescu, 2016, p.1). Additionally, also a basic form of data reporting may be included in VaaS business models. It does not provide analytic algorithms or models. The integration and visualization of data from different applications, even with the possibility of live connection to cloud data sources, is possible in this AaaS type. It allows the sharing of results among teams. (Naous et al., 2017, p.496)

Self-service Analytic-as-a-Service (Self-service AaaS)
This AaaS-type offers self-service analytics for business users, business analysts and data scientists who are able to access data from different sources. It should support responsible persons in making the right decisions (Zaghaloul, 2013, p.41). With this archetype, descriptive and basic predictive analytical jobs can be performed. These jobs include multidimensional reporting and statistical modelling. (Naous et al., 2017, p.496)

Analytics Platform-as-a-Service (Analytics PaaS)
This archetype offers a set of software and development tools for advanced analytics to its users. The required infrastructure, especially the server where the tools are working on, are hosted by the provider. (Kulkarni et al., 2011, p.116)

An Analytics PaaS provides a development environment for its users where they can build specialized analytics applications with advanced capabilities. The customer segments are data scientists, developers, and IT architects. (Naous et al., 2017, p.496f)

Big data Analytics-as-a-Service (Big data AaaS)
This archetype provides big data infrastructure and data management resources to its users. The provided resources can be used for taming and big data processing. The customer segments of Big data AaaS are business analysts, data scientists, developers, and IT architects. Big data AaaS provides data management solutions and comprehensive platform capabilities for big data sources as well as advanced analytics capabilities. These advanced analytics capabilities include for example advanced data mining, advanced text mining, and machine learning algorithms for big data applications. The mentioned offerings are provided in the form of cloud services. (Naous et al., 2017, p.497)

Edge Analytics-as-a-Service (Edge AaaS)
This archetype provides advanced analytics capabilities for the data on IoT platforms. This data derives from the so-called Edge, which are with sensors equipped devices. Since the number of these

devices is growing exponentially, Edge AaaS solutions are gaining in significance. (Xu et al., 2017, p.349)

The Edge AaaS provides the required infrastructure for data storage and real-time data processing to make the analysis of this produced data possible. It also supports prescriptive analytic functions for data modelling and application development on the cloud platform. The customer segments of Edge AaaS are business users, data scientists, and developers. (Naous et al., 2017, p.497) Typical examples for these IoT data sources are connected cars (Satyanarayanan et al., 2015, p.1).

2.3 Trends and Data Business in the Automotive Industry

This chapter deals with the global macrotrends in the automotive industry, the automotive data value chain, the possibilities to monetize car data, the different types of car data, and the changing competitive landscape in the automotive industry. Since AI, which is a fundamental part of big data analytics, is expected to release the next wave of digital disruption in the automotive industry (McKinsey Global Institute, 2017, p.4), it is considered more detailed in this chapter.

2.3.1 Global Macrotrends

The automotive industry is facing significant systemic and technological changes (Hungerland et al., 2015, p.39). These changes become visible in form of four global macrotrends: powertrain electrification, shared mobility, car connectivity, and autonomous vehicles. (McKinsey&Company, 2016c, p.10)

Powertrain electrification
Powertrain Electrification can occur in different ways by using different technologies. Electrified vehicles can be hybrid, plug-in, battery electric, and fuel cell cars. The growing electrification is driven by many factors, including stricter emission regulations, research successes that make the technology affordable, the provided infrastructure as well as increased customer satisfaction (McKinsey&Company, 2016c, p.10). But without a connected infrastructure that helps people locate free charging stations, battery electric cars will not become practicable in everyday life (Hungerland et al., 2015, p.45).

Shared mobility
Shared mobility is a major change, the automotive industry has to deal with. This trend occurs mainly in cities. Many people are willing to forego owning a car, instead they want to use one when they need it. This phenomenon can be seen especially by young people living in cities. In contrast, older generations prefer owning a car. (McKinsey&Company, 2016c, p.10) The perception of values is changing. The car is experiencing a slow loss of value as a status symbol. This change in mobility is the reason why flexible usage models are becoming more important than ownership in some areas. (Hungerland et al., 2015, p.44)

As a result of these changes, the traditional business model of car sales will be complemented by a range of diverse on-demand mobility solutions. This will especially occur in urban environments that proactively discourage private car use. (McKinsey&Company, 2016a, p.8)

Future business models of OEMs will change to a significant extent. They will consist more of providing mobility services and less of selling vehicles. In other words, a traditional, mainly product market, will evolve more and more into a service market. For car makers, this will lead to a shift in how they generate revenues. While earnings from selling new cars tend to decrease, a new area of after-sales activities will grow. (McKinsey&Company, 2016a, p.8)

Car connectivity
Cars that are getting more and more connected to each other and the infrastructure, will allow new functionalities and features to be offered to drivers and passengers. Car connectivity will also play a significant role in the functionality and effectiveness of advanced driving assistance systems. (McKinsey&Company, 2016c, p.10)

Figure 2.7 shows how the number of cars and light commercial vehicles is expected to develop in Europe. Additionally, information regarding the proportion of not connected and connected vehicles is provided. Two possibilities to grant connectivity exists. On the one hand, the car can have the technology as standard or on the other hand, car connectivity can be provided by retrofitting (Caruso, 2017, p.5).

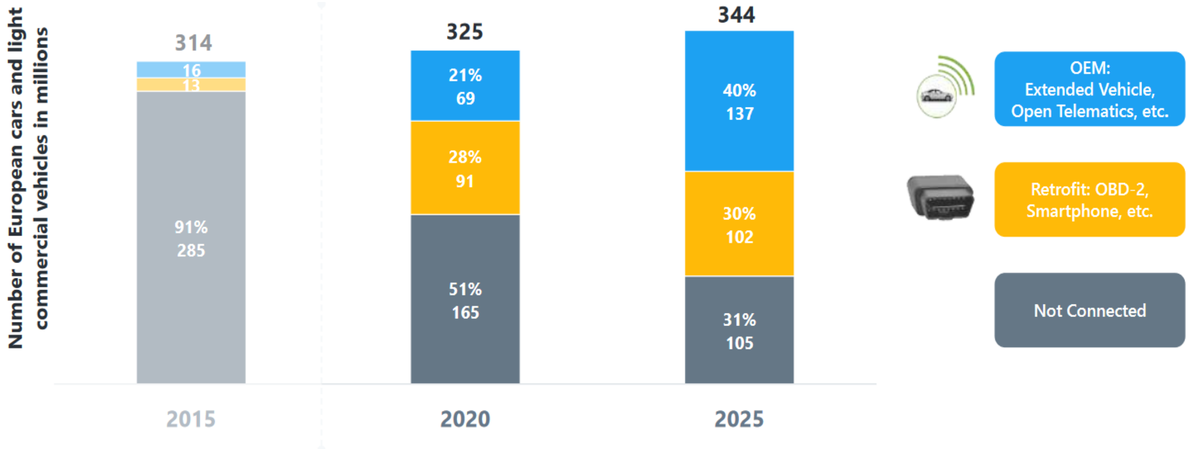


Figure 2.7: Connected vehicle development (https://blog.iese.fraunhofer.de/wp-content/uploads/2018/03/2018-03-13-Bitkom-AK-Plattformen-Caruso.pdf, p.5, accessed: 17.02.2019)

Autonomous vehicles

Driverless cars will completely change the mobility market situation (Roland Berger, 2014, p.3). Autonomous vehicles will result from the ultimate manifestation of ADAS. According to a progressive adoption scenario, in 2030 about 15% of new passenger vehicles sold could be fully autonomous. (McKinsey&Company, 2016c, p.10)

Significant differences depending on different markets might occur, due to many factors like legislation. (McKinsey&Company, 2016c, p.10)

Changes in automotive industry due to these market trends

The described global macrotrends: powertrain electrification, shared mobility, car connectivity, and autonomous driving, will lead to new mobility models and data-driven services. These trends will radically change the mobility industry. Two outcomes are (McKinsey&Company, 2016c, p.10f):

Shifting market and revenue pools

Due to on-demand mobility services and data-driven services, the automotive revenue pool will grow and diversify. In 2015, the traditional automotive revenues amounted about 3,500 billion USD. The revenues consist of the one-time vehicle sales, the aftermarket revenues, and the recurring revenues. The most significant part of these revenues are the one-time vehicle sales. In 2030, the revenues are expected to reach 6,700 billion USD. Like today, also in 2030, the majority of revenues will attribute to direct vehicle sales, but the recurring revenues will increase above average. (McKinsey&Company, 2016a, p.6)

Detailed information about the revenues, the areas where they are generated, and the influencing factors, are shown in Figure 2.8.

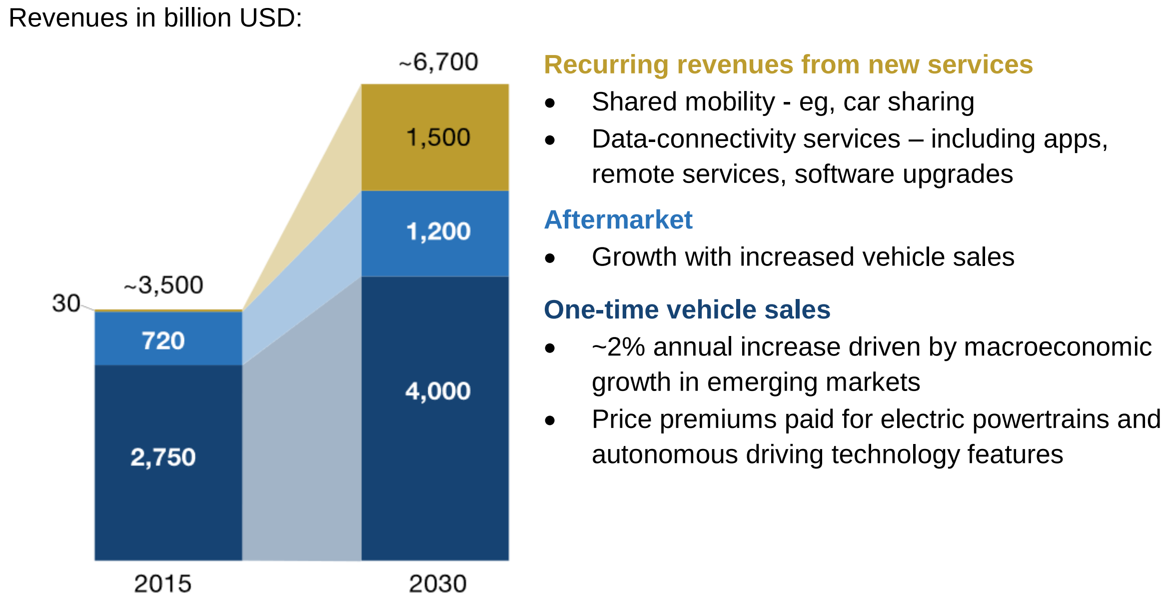


Figure 2.8: Development of automotive revenues (adapted McKinsey&Company, 2016a, p.6)

The automotive revenue is expected to reach about 6,700 billion USD in 2030. While the revenues from vehicle sales and the aftermarket are expected to grow at a moderate level, the recurring revenues are supposed to be fifty times higher than 2015. Data-driven services will be jointly responsible for the significant growth of these recurring revenues. (McKinsey&Company, 2016a, p.6) In 2050, OEMs will generate 50% of their revenue from data-driven services. They will have very different operating models compared to current times. (Seibert & Gründinger, 2018, p.44)

New Competition

The automotive industry itself, as well as its competitive landscape, is changing substantially. In the past, the OEMs had to compete against other car manufacturers. Based on new mobility solutions and data-based services, the future, and this future has already started, brings an increase in the complexity of the industry´s competitive landscape. (McKinsey&Company, 2016a, p.13) Currently, new competitors who are mainly from the digital world, are pushing into the mobility sector (Hungerland et al., 2015, p.39). Figure 2.9 shows how the competitive landscape will change in the next years.

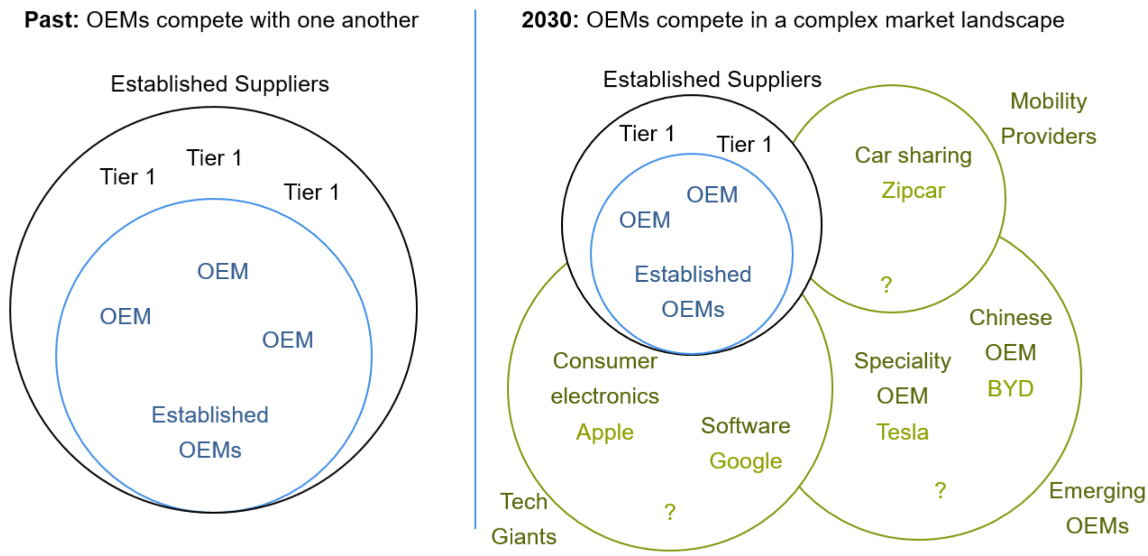


Figure 2.9: Competitive landscape (adapted McKinsey&Company, 2016a, p.13)

According McKinsey&Company, (2016a, p.13), the potential market players in the future will be:

- **Established OEMs**
  The established OEMs sell cars, provide aftersales and in most cases also financial services. Often, they sell features and service packages from service developers, start-ups and suppliers.

- **Established suppliers**
  The suppliers provide software and hardware parts, as well as features and applications. In many cases, they perform and sell car data analytics.

- **Tech giants but also smaller IT-companies**
  The focus mainly is on analysing and selling data from different sources, which may include car-related data, but also data from the infrastructure.

- **Mobility service providers**
  They offer car sharing and rental services.

- **Emerging OEMs**
  Emerging OEMs are for example OEMs with a high specialization in a certain area. As examples, Tesla and the Chinese OEM BYD can be named.

2.3.2 Artificial Intelligence in the Automotive Industry

Experts agree that Artificial Intelligence (AI) is poised to release the next wave of digital disruption in the automotive industry (McKinsey Global Institute, 2017, p.4). It has the potential to fundamentally disrupt the market through the creation of innovative new services and entirely new business models based on data (Rao, 2017, p.23). Common definitions of AI are provided in chapter 2.1.4.3.

AI has the power to change the automotive industry in a significant way. It is a key technology for the four global macrotrends, autonomous driving, powertrain electrification, shared mobility and car connectivity, described in chapter 2.3.1. Regarding autonomous driving, AI is a prerequisite because it is the only technology that enables a real-time recognition of objects in the vehicle surrounding. The other three global macrotrends will benefit from AI in the form of cost reductions, for example in R&D, and the possibility to create new revenue streams. For shared mobility services, AI will additionally provide an improvement in fleet management and maintenance scheduling. (McKinsey&Company, 2018, p.6)

This enormous potential of AI has triggered massive investments in advanced analytics and AI. Especially the tech companies are trying to exploit the full potential. This becomes visible when looking at the five companies with the highest R&D spends worldwide. In 2016, Volkswagen led the ranking with total R&D spends of 13.2 billion USD. Samsung took the second place of this ranking with total R&D spends of 12.7 billion USD. Amazon was the third-placed company which has spent 12.5 billion USD on R&D. In 2017, the situation changed. Amazon became the new leader in R&D spending with 16.1 billion USD. The second and third places were occupied by Alphabet and Intel. Volkswagen has slipped on rank 5 with 12.1 billion USD. (Strategy+Business, 2017) The mentioned rankings are shown in Figure 2.10.

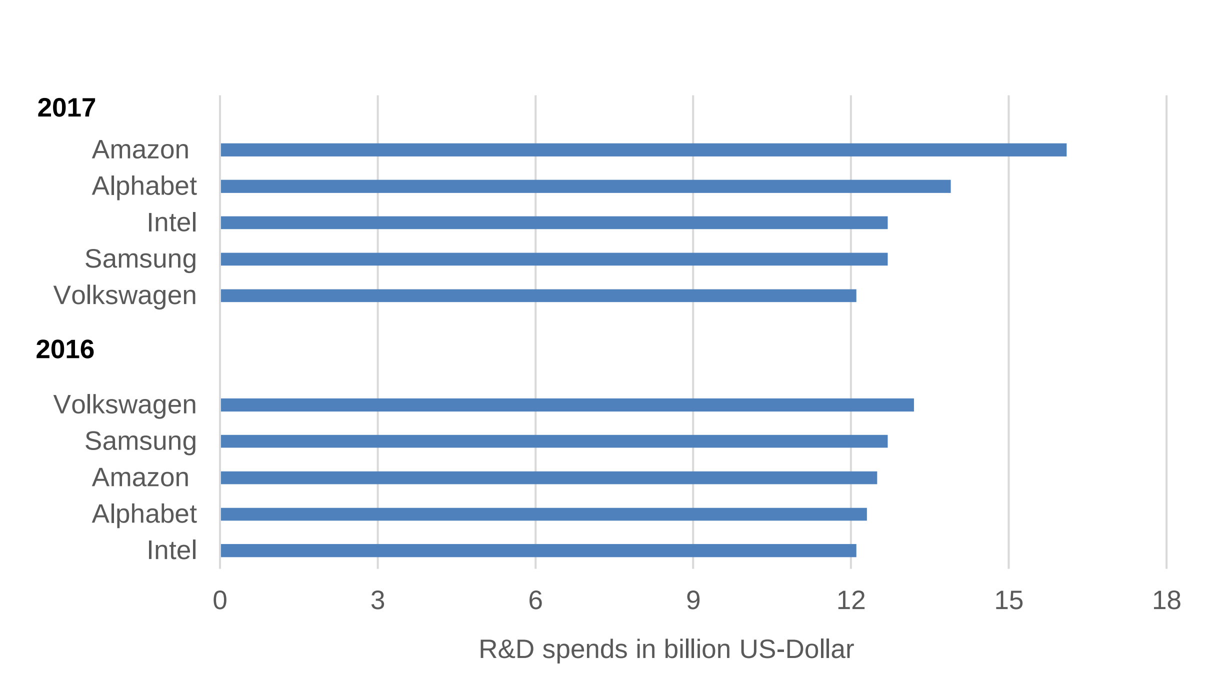


Figure 2.10: Top 5 companies regarding R&D spends in 2016 and 2017 (Strategy+Business, 2017)

R&D in the area of AI is the key driver behind these significant changes in the ranking (Strategy+Business, 2017).

AI comes in different forms with different tasks and goals. According to Rao (2017, p.2), the most common ones used today are:

- **Automated intelligence**
  Automated intelligence is the automation of routine or non-routine tasks that can either be manual or cognitive. Automated Intelligence does not involve new solutions, new ways of doing things. It just automates existing tasks.

- **Assisted intelligence**
  Assisted intelligence is an AI system that aims to assist humans in making decisions or taking actions. These systems do not learn from their interactions.

- **Augmented intelligence**
  Augmented intelligence is an AI system that augments human decision making. In contrast to assisted intelligence, these systems continuously learn from their interactions with humans and the environment.

- **Autonomous intelligence**
  Autonomous intelligence is an AI system that can adapt to different situations and can act autonomously. Those systems do not need human assistance.

2.3.3 Automotive Data Value Chain

According to Koehler et al. (2016, p.7f), the automotive data value chain describes the steps from data generation, in the form of raw data, to an application of data in the form of a service. The value chain consists of six value creation steps and two platforms. In the creation steps, an activity is carried out, in the two platforms, data and services are made available to stakeholders. In the automotive data value chain, each processing step increases the value of the processed data. Figure 2.11 shows the automotive data value chain.

Figure 2.11: Automotive data value chain (Koehler et al., 2016, p.7)

1) Data generation

The first processing step in the automotive data value chain is the data generation. Different types of sensors are used to generate raw data. In this step, a sensor internal processing of the data is done (e.g. deriving object information from raw optical data). (Koehler et al., 2016, p.7ff)

2) On-board processing

In the second step, the data is transmitted to a central controller for further on-board processing. It is the first level of data aggregation/interpretation/analysis. (Koehler et al., 2016, p.7ff) The goal of this first data-processing is to identify the potentially valuable data, which should be processed further in the next steps (Schweppe, 2010, p.81).

3) Data transmission

In the process step data transmission, the generated data gets transmitted from the physical vehicle system to a central processing and storing entity (Koehler et al., 2016, p.7ff). Technologies for data transmission can be separated into wired and wireless solutions. Since the data transmission should take place while the car is driving, the wireless solution is the most common one. Wireless technologies are for example Bluetooth, Wi-Fi, and Ultra-Wide Band (UWB). (Nolte, 2005, p.7)

4) Off-board processing

Off-board processing is the second level data aggregation/interpretation/analysis. It is a key step in the value chain for value creation out of vehicle-related data. In this step, also other data sources from within and without the automotive eco-system can be considered, such as infrastructure data. The vehicle-related data can be enriched with data from other sources which allows more powerful data analytics. (Koehler et al., 2016, p.7ff)

5) Data Access Platform

A data access platform is a marketplace where data, from sources in the automotive system, is made available. Potentially every customer can buy those data. Data can also be monetized along the other steps of the automotive data value chain, but the central market place is the data access platform. (Koehler et al., 2016, p.7ff)

OEMs and some third parties, like suppliers or digital players, run platforms (e.g. BMWs CarData Platform) that collect data and provide this to downstream processes. Platforms from OEMs offer selected data from a single OEM, the BMW CarData platform for example offers only data from BMW cars. In contrast, data platforms from third parties can collect data from a wider range of sources, not limited to a single OEM. The concept of the data access platform is shown in Figure 2.12. The data generators produce vehicle-related data. According to the automotive data value chain, this data gets processed on-board, transmitted to a central storage system, and processed off-board. In the off-board processing, the data may get enriched with data from other platforms and afterwards analysed. On the market place (data access platform), the data gets offered and service developers, but also other parties, can buy data based on a contract. (Koehler et al., 2016, p.7ff)

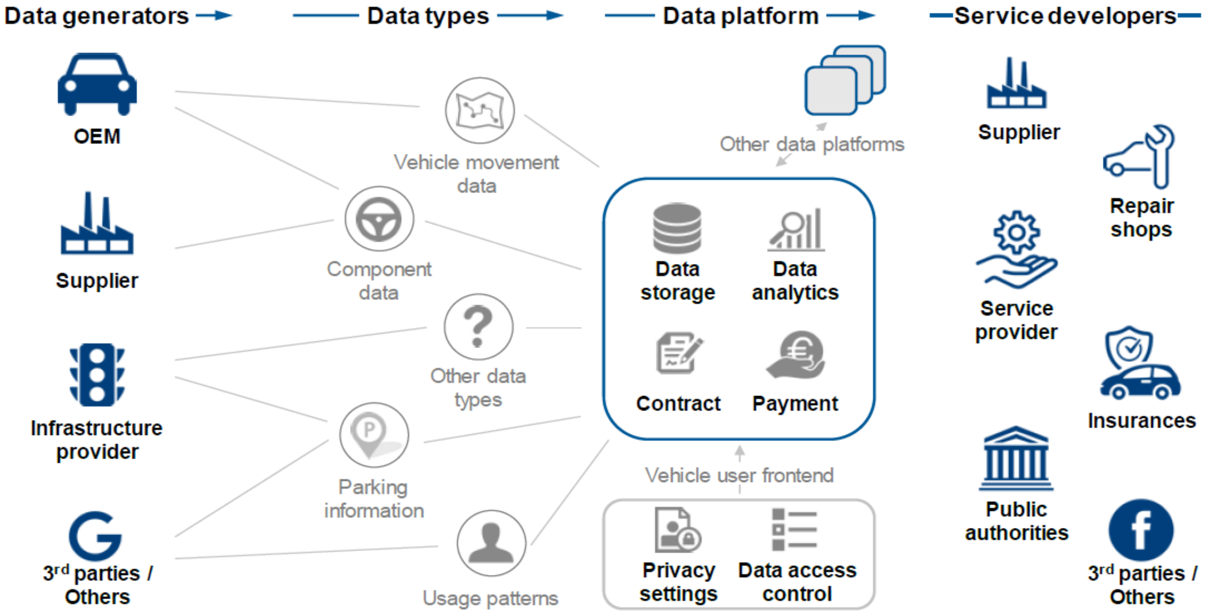


Figure 2.12: Concept of a data access platform (Koehler et al., 2016, p.11)

6) Service development

The data from the data access platform is used to develop a data-driven service for a potential end-customer. The service developers can combine the purchased data with data from other sources, which are not available on the data access platform. (Koehler et al., 2016, p.7ff)

7) Service Access Platform

In the service access platform, the service developed in the previous process step is offered to an end customer. The service access platform is similar to the data access platform, a marketplace, where different products are offered. (Koehler et al., 2016, p.7ff)

8) Service use

The final step of the automotive data value chain is the use of the developed service by an end customer. This process step is the most obvious, but not the only one, regarding data monetization. Automotive data can be monetized in all other steps as well. (Koehler et al., 2016, p.7ff)

Not all market players in the automotive industry are under control of the whole automotive data value chain. The following considerations show the situation of OEMs, suppliers and third parties.

2.3.3.1 Automotive Data Value Chain of OEMs

As OEMs are designing the car, inclusive the data access points and communication gateways, they are in a strong starting position. According to the extended vehicle data architecture proposed by the automotive industry (ACEA, 2016), all car data would be collected exclusively on OEMs data servers. (Martens & Müller, 2018, p.5)

As shown in Figure 2.13, the OEMs are in control of the data generation, and they are monitoring the end of the value chain, the service use, as well. This means that the OEMs have a connection to the end customer. By controlling the starting point and the endpoint of the value chain, they can monitor which data is generated and which services are offered. The strong position of the OEMs is mainly focused on the vehicle itself. Concerning vehicle data, they can act as price setters in a monopolistic market (Martens & Müller, 2018, p.5). Regarding data from devices or other sources used in their cars, such as smartphones or smartwatches, they have no control. (Koehler et al., 2016, p.12f)

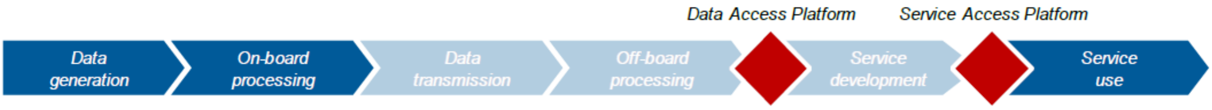


Figure 2.13: OEM automotive data value chain (Koehler et al., 2016, p.12)

In most cases, the data transmission, the off-board development and the service development are not under full control of the OEM (Koehler et al., 2016, p.12f).

2.3.3.2 Automotive Data Value Chain of suppliers

Suppliers have a strong position in the field of data generation, on-board processing, and service development. Nevertheless, they are in a weak position compared to OEMs. One substantial point therefore is that they have no direct point of contact with the end users. Another disadvantage compared to OEMs is that they only have limited access to in-vehicle data. On the other side, suppliers can act across multiple OEMs. They are well positioned to develop services that appeal to multiple OEMs at the same time. To create value from data, suppliers are well advised to establish a strong grip on on-board data aggregation, storage, and transmission. They can develop independent data access platforms for multiple OEMs. The automotive data value chain for suppliers is shown in Figure 2.14. (Koehler et al., 2016, p.12ff)

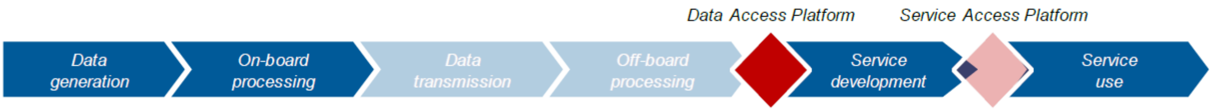


Figure 2.14: Supplier automotive data value chain (Koehler et al., 2016, p.12)

2.3.3.3 Automotive Data Value Chain of 3rd parties

The 3rd parties can be divided into the big tech players, like Google or Apple, and smaller specialized third parties. The automotive data value chain of these parties is shown in Figure 2.15. They have their capabilities in data processing, platform solutions as well as service development and service offering. (Koehler et al., 2016, p.12ff)

As the third parties are not in possession of the generated car data, they have to buy it from the OEMs. An alternative data supply channel would be the OBD Plug, but this would only be a partial solution compared to OEM data channels. (Martens & Müller, 2018, p.5)

Figure 2.15: 3rd party automotive data value chain (Koehler et al., 2016, p.12)

New data-driven businesses arrange many tech giants to push into the automotive and mobility area (McKinsey&Company, 2016a, p.13). In contrast to OEMs and suppliers, they are highly skilled in data handling, data analytics, and service development. They can act across multiple OEMs, as suppliers do. The big tech-giants have limited access to on-board vehicle data, but they already have an end-customer point of contact through smart devices. To improve their position, they should focus on their competencies in data handling, data analytics, and service development to build up data and service access platforms.

Smaller third parties, like for example start-ups, are often more specialised in a single area. Especially service developers for the automotive eco-system belong to this category. They are early movers, which brings them in a strong position. When partnering with single or multiple OEMs, these third parties can take advantage of this situation. For OEMs and suppliers, they are valuable because of their high specialisation in the area they are in. By cooperating, OEMs and other suppliers can compensate potential lack of capabilities in data handling. Like tech giants, they also have only limited access to on-board vehicle data. Therefore, cooperations with OEMs are even more important. (Koehler et al., 2016, p.12ff)

2.3.4 Car Data Monetization

The potential to make money based on car data monetization is growing exponentially. Industrial players have three main opportunities to monetize car data along the value chain. According to McKinsey&Company (2016b, p.12), these categories are: generating revenues, reducing costs and increasing safety and security.

Generating Revenues
The category of generating additional revenues based on car-related data monetization can be further divided into three sub-categories: (McKinsey&Company, 2016b, p.12)

- **Direct monetization**
  It is the most direct form of generating revenues. The provider sells data-based services, features or products to the customer. Two typical use cases of direct monetization are: over the air software add-ons or fleet management solutions. (McKinsey&Company, 2016b, p.12)

- **Tailored advertising**
  This type of revenue generation uses car-related data to offer services, products or features to the individual customer. The offer is tailored to the needs of the car or the individual driver. Predictive maintenance is a typical example for a car-tailored offer. (McKinsey&Company, 2016b, p.12) This service utilises car data to inform the driver before a failure occurs (Riot Research, 2018, p.8). In contrast, location-based promotion is a typical use case for a customer-related offer (Peterson & Groot, 2009, p.4).

- **Selling data**
  In this sub-category of generating revenues, the data generating party is collecting and reselling the data to third parties. A typical example for this category are OEMs that sell collected data to insurance companies. (Riot Research, 2018, p.6)

Reducing costs
The second value creation model is cost reduction based on car-related data. This category can be further divided into three sub-categories: (McKinsey&Company, 2016b, p.12)

- **R&D and material cost reduction**
  To reduce this type of cost, companies gather product field data from connected vehicles and use this data to learn from it. In a broader sense, this car-related data provides an insight into the real behaviour of the observed parts. Based on this data, companies can improve their R&D processes and reduce material costs. (Riot Research, 2018, p.8)

- **Customers' cost reduction**
  This form of cost reduction focuses on analysing actual product/services usage patterns to reduce customers' usage, repair, and downtime costs (McKinsey&Company, 2016b, p.12). A typical example for customers' cost reduction is predictive maintenance. This service informs the driver,

before the problem becomes more serious. The economic benefits for the customer are lower costs due to less repair work and the avoidance of consequential damages. (Riot Research, 2018, p.8)

- **Improved customer satisfaction**
  The third sub-category of reducing costs is improved customer satisfaction. The aim of this sub-category is a better brand image and consequential market share gains (Riot Research, 2018, p.8). Examples for improved customer satisfaction are early recall detection and remote hardware upgrades. (McKinsey&Company, 2016b, p.12)

Increasing safety and security
The third value creation model is about collecting and forwarding warnings in real time. Most systems focus on in-vehicle data recording for evaluation of driving behaviour and safety (Toledo & Lopan, 2006, p.112). Examples are driver's condition monitoring service, emergency call- and breakdown call-service (McKinsey&Company, 2016b, p.12).

2.3.5 Types of Car Data

Today, a conventional car transfers about 1 MB of data per day. As mentioned in chapter 1.1, the amount of data transferred by a connected car is twenty times higher compared to a conventional car. A fully autonomous car will transfer about 16 GB per day, which is 800 times more than a connected car. (Koehler et al., 2016, p.4)

These data come in different types, each of them with specific current and future use cases. The different types of data are ranked by perceived privacy sensitivity, from low to high. The low-sensitivity-data consists of the following categories: "external road and environmental conditions", "the technical status of the vehicle", and "vehicle usage data". Consumers are most willing to share data from these categories. This is perceived to be objective data which is generally less critical. In contrast, "Personal data and preferences" and "direct communications" are data-categories with a high perceived privacy sensitivity. (McKinsey&Company, 2016c, p.16)

External road and environmental conditions
This type of generated data is not about the car itself, but about its surrounding conditions. Swarm data from various cars is used to provide information about their environment. This data category allows customers to take advantage of location-based services such as real-time maps (Future of Privacy Forum, 2014, p.7). An example will be local hazard warnings like heavy rainfall or dangerous curves. (Seibert & Gründinger. 2018, p.20)

As there might be more connected vehicles on the road in the future, it will result in the possibility to create live road condition reports, which allow an early detection of road damages (Chatterjee et al., 2018, 1ff). The perceived privacy sensitivity for that kind of data is quite low (McKinsey&Company, 2016c, p.16).

Technical status of the vehicle
The technical status data is data regarding the components and systems in a vehicle. Typical examples are temperature data (e.g. oil, engine), technical malfunction reports and airbag deployment data. This kind of data is used for technical issues like repair diagnostics but also for safety issues like an automatic emergency call. Further development will make data from that category suitable for predictive services like predictive maintenance. (Seibert & Gründinger. 2018, p.20) That data is only in a small extent depending on the driver. Therefore, the perceived privacy sensitivity is quite low. (McKinsey&Company, 2016c, p.16)

Vehicle usage data
Vehicle usage data is mainly technical data with a direct relation to the driver. Therefore, this type of data should also be subject to privacy regulations. (Seibert & Gründinger. 2018, p.20)

Data from that category is directly related to the driver, which results in a higher perceived privacy sensitivity compared to the technical status data of a vehicle. Vehicle usage data contains for example speed data, location data or even data regarding the average load in the trunk. A current use case of vehicle usage data is the so-called pay-as-you-drive (PAYD) insurance. The insurance fee in a PAYD insurance depends on the driving behaviour of the driver. Vehicle usage data analytics leads to a better understanding of the customers/drivers and a better understanding of their requirements. In engineering, these insights can be used to reduce costs. (McKinsey&Company, 2016c, p.16)

Personal data and preferences
Data from that category is completely driver specific. This form of data is very attractive to third parties as it can be used for product personalization. That is the reason why the perceived privacy sensitivity level is high. (Seibert & Gründinger, 2018, p.20)

Typical examples of this data category are: driver/passenger identity, preferred radio station and use patterns of applications. The usage of internal cameras and sensors will allow cars to identify the driver and to change the car settings to accommodate different driving profiles (Future of Privacy Forum, 2014, p.9). A further use-case will be customized e-commerce in the car. Targeted advertisements will play a major role in this data category in the future. (McKinsey&Company, 2016c, p.16)

Direct communications from the vehicle
This data category contains private information about the driver, which leads to the highest perceived privacy sensitivity. Data included in this category are for example calendar data, telephone data, and e-mail data. A current use case is for example speech control of messaging. (McKinsey&Company, 2016c, p.16)

2.4 Summary

This chapter provides information required in order to gain a better understanding of the thesis and its background. The first sub-chapter describes big data and its characteristics volume, velocity, variety and veracity. Additionally, the development of data, the value chain and the requirements for big data analytics are described. Big data analytics utilizes AI and machine learning solutions.

Since the amount of valuable data is increasing sharply, ways to utilize it are becoming more important. Different ways of utilization are described in the second sub-chapter. Furthermore, the second sub-chapter is focussing on data-driven business models, including its definition and framework. According to Hartmann et al. (2014, p.6), the characteristic of a data-driven business model is data as a key resource. When investigating the framework of a data-driven business model, six key dimensions can be identified. Those are: value proposition, key resource, key activity, market/customer segment, revenue stream, and cost structure.

The third sub-chapter describes trends in the automotive industry and its data-business. Four global macrotrends will change the automotive industry in a substantial way. These macrotrends are the autonomous driving, the powertrain electrification, the connected cars, and the trend towards shared mobility. AI is expected to become a key technology in these macrotrends. Additionally, this chapter contains information regarding different types of car data and ways to monetize those. The most important ways therefore are the data-driven generation of revenues, the reduction of costs as well as the increase of safety and security.

3 Empirical Investigation

In this chapter, the practical work steps are described. These work steps include the identification of market participants, the identification of relevant data-driven services, tools, platforms and other data-based activities, the data collection, the cluster definition & categorization, and the result processing. The aim of this chapter is to provide valuable data in a way, that is suitable for result interpretation and visualization.

3.1 Market Player Identification and Data Collection

This part of the thesis deals with the identification of relevant market players, the identification of their data-driven value propositions and activities, as well as with the categorization of this gathered data by using clusters.

3.1.1 Identification of Market Participants

The identification of relevant market participants is a prerequisite for the analysis. According to AVL, the focus of this thesis should be on Engineering Service Providers (ESPs), IT-companies, and start-ups. The IT-companies and ESPs were identified in accordance with AVL by using rankings. These rankings identify the biggest ESPs worldwide, and the biggest IT-companies in Germany, based on their yearly turnover in the automotive industry. The considered start-ups are based on a query by the company Innospot. For each group, additional companies of relevance were added by AVL. 53 companies were considered in total. These 53 consist of 25 ESPs, seventeen IT-companies and eleven start-ups.

3.1.1.1 Engineering Service Providers

In this thesis, 25 ESPs were analysed. The full list is shown presented in Appendix 1. The identification of relevant companies is based on the ranking “Engineering Enterprises, Top 75 Ranking” (ATZ Extra, 2016). The enterprises are ranked on their yearly revenue in the automotive industry. The leader of this ranking is the AVL. In accordance with AVL, the analysed enterprises have been restricted to the Top 20 enterprises of this ranking, provided that those companies are relevant for AVL. Another reason for this restriction is that smaller enterprises often provide less information which is necessary for an appropriate analysis.

To identify the relevant companies of those twenty, a criterion had to be defined. The criterion is defined as the assignability of a company to at least one of the thematic areas listed below. The thematic areas are the main areas AVL is active in, adjusted by some additional areas of special interest, requested by AVL.

List of thematic areas:
- Powertrain Development
- Complete Vehicle Development
- Simulation Solutions
- Software Development
- Testing/ Validation
- Advanced Driver Assistance Systems
- Activity in the field of Connected Cars
- Activity in the field of Autonomous Driving
- Activity in the field of Electrification/ E-Mobility

To identify if a company is active in at least one of those thematic areas, the “Relevant main focus areas”, which are part of the considered ranking (see Appendix 1), were used. If at least one criterion applied, the enterprise was identified as relevant and got analysed. That was the case for all enterprises ranked from 1 to 19. The enterprise MVI Group GmbH on rank 20, did not fulfil the criteria. In addition to these 19 companies, two more companies from that ranking were analysed:

- AKKA Digital (former Gigatronic Holding)

This enterprise is on rank 22, but also of high interest for AVL, as the former Gigatronic Holding got acquired by the MBtech Group/AKKA Technology which is on rank eight. With this acquisition, AKKA has expanded its expertise in the area of digital services. In accordance with AVL, it was decided to add AKKA Digital to the list of companies that should be analysed. In this thesis, AKKA Technology and AKKA digital are considered as the AKKA Group.

- MAGNA Powertrain Engineering Center Steyr

MAGNA Powertrain Engineering Center Steyr is on rank 28. This company, as well as the Magna Steyr Engineering on rank thirteen, are part of the Magna International Inc. Those companies are situated in Austria, like AVLs Headquarter, and some of their main focuses are equivalent to those of AVL. In accordance with AVL, it was decided to add MAGNA Powertrain Engineering Center Steyr to the list of companies that should be analysed.

Other companies, which have been requested for analysis by AVL, are:

- Bosch Engineering

Bosch Engineering is an ESP and supplier for the automotive industry. The turnover of Bosch Engineering in the automotive industry was about 480 million Euro in 2016 (Automobilwoche, 2018). Bosch Engineering was not listed in the “Engineering Enterprises, Top 75 Ranking”.

Further, following companies were investigated:

- B-plus
- C-More automotive
- Control-Tec
- Vispiron
- Tracetronic

The turnover of these companies is too low for being listed in the ranking, but they are specialized in data-driven businesses in the automotive industry. Therefore, they were added to the list of companies that should be analysed.

3.1.1.2 IT-Companies

The first approach for the identification of the relevant IT-companies was based on their market capitalization. Therefore, three different Top 100 rankings of listed companies were used to determine relevant IT-companies. The different rankings included the Top 100 Worldwide (Boersennews, 2019a), the Top 100 Europe (Boersennews, 2019b) and the Top 100 Germany (Boersennews, 2019c) of listed IT-companies. In addition to the rankings, a list of the 25 biggest IT-service providers in the German automotive industry, based on their turnover in the automotive industry (Nagel, 2018), has been a source for relevant IT-companies. The focus was set on Germany due to its strong position in the worldwide automotive industry (International Organisation of Motor Vehicle Manufacturer, 2019, p. 1).

After consultation with AVL, the analysis of IT-companies was restricted to the 10 companies with the highest turnover from the 25 biggest IT-service providers in the German automotive industry.

Additionally, the companies Alibaba, Amazon, Google, and Microsoft, were taken into account due to their relevant cloud solutions, which many OEMs are already using.

Further, following companies were investigated:

- SAS Software
- NVIDIA Corporation
- Genpact.

The complete list of analysed IT-companies is provided in Appendix 1.

3.1.1.3 Start-ups

Due to the high number of start-ups and the complexity of identifying the important players, AVL ordered an analysis by the start-up scouting company Innospot. The search field for the scouting were start-ups with a focus on data-driven services and data-driven business models in the automotive B2B market. Innospot analysed their start-up database, consisting of more than 440,000 start-ups, to identify the most important ones. This analysis was based on the use of AI. The result of the scouting project is a list of 43 start-ups which fulfill the searching criteria (Weindorf, K., 2019).

In accordance with AVL, this thesis focuses on the 10 most relevant start-ups, which were identified by Innospot. Additionally, the start-up Pitstop Connect was requested by AVL. The complete list of analysed start-ups is provided in Appendix 1.

3.1.2 Identification of relevant data-based Offerings and Activities

To identify data-driven services, tools, and platforms which should be considered in the analysis, AVLs Powertrain Engineering Portfolio was taken into account. The data-based application areas listed in the description below should be considered when analysing other market players. Nevertheless, the analysis is not restricted to these areas. Therefore, other data-based application areas and information regarding the data-business of the market players, are also of relevance for the analysis. These additional areas and information are being identified when analysing the market participants. Activities like cooperations, takeovers, projects, and research, should be considered too. An overview of investigated information is listed in chapter 3.1.3.4

The automotive value chain of AVLs Powertrain Engineering consists of seven main phases which are shown in Figure 3.1

Figure 3.1: Automotive value chain (AVL Data Intelligence Services, 2018)

Since AVL is an ESP with a focus on the phases concept, development and validation, these three phases were considered as highly relevant for the analysis. The phases production, aftersales and workshop, are characterized by producing large quantities of potentially valuable data. Therefore, they were taken into consideration too.

The phase in-use was not taken into account in this thesis. This phase mainly includes so-called “smart services” like smart parking and smart navigation. These services or products are of low interest for the AVL. Therefore, they were not considered in further investigations.

Data-based application areas can be allocated to each of these six relevant phases. AVL has provided information regarding the potential applications for each phase. In the following, each phase, including its applications, will be described. The mentioned data-based applications should be considered when analysing the other market players.

Concept

Figure 3.2: Automotive value chain - Concept (AVL Data Intelligence Services, 2018)

In the concept phase, data is used for requirement engineering. Typical data-based applications are:

- Data-driven target setting
- Artificial intelligence system modelling
- Image processing

A benefit created by using data-based services or products in the concept phase is a market-driven target determination with a high focus on end-customer requirements. (AVL Data Intelligence Services, 2018)

Development

Figure 3.3: Automotive value chain - Development (AVL Data Intelligence Services, 2018)

In the development phase, data is used for product and service development. Typical data-based applications are:

- Calibration data management
- RDE reporting
- Machine learning calibration functions

One fundamental benefit of using data-based services or products is the reduced necessity for on-road testing. This results in time and cost savings. Improved test coverage can be named as another benefit. (AVL Data Intelligence Services, 2018)

Validation

Figure 3.4: Automotive value chain - Validation (AVL Data Intelligence Services, 2018)

In the validation phase, data is used for verification and validation. Typical data-based applications are:

- Calibration, On board diagnostic (OBD)
- Fleet analytics
- Endurance testing
- ADAS sensor validation

A benefit of using data-based services or products in this phase might be a so-called “Zero gap documentation”. This implies a complete documentation, for example from an endurance testing, without missing information. The overall benefit is the saving of time which leads to cost reduction. (AVL Data Intelligence Services, 2018)

Production

Figure 3.5: Automotive value chain - Production (AVL Data Intelligence Services, 2018)

Typical data-based applications in the production phase are:

- Quality improvement
- Predictive maintenance
- End-of-line testing quality influencers

The benefits of using data in an intelligent way, are improved quality and higher efficiency in production. In monetary terms, this results in cost savings. (AVL Data Intelligence Services, 2018)

Aftersales

Figure 3.6: Automotive value chain - Aftersales (AVL Data Intelligence Services, 2018)

In the aftersales phase, data is used for purposes after the product was sold. Typical data-based applications are:

- Diagnostic insights
- Issue identification
- Predictive maintenance
- Warranty issues analytics
- Digital twins

The overall benefits of an intelligent data use in the aftersales phase are an improved end-customer satisfaction and a reduction of costs. (AVL Data Intelligence Services, 2018)

3.1.3 Data Collection

This chapter deals with the used sources for information gathering, as well as with the recorded data regarding global locations, data-driven services, tools, platforms and other data-based activities.

3.1.3.1 Sources for Data Collection

Gathering appropriate data about offered data-driven services, tools, platforms, and other data-based activities, is a major part of this thesis. There are different ways, to receive relevant information. Some possibilities are internet research, interviews with employees or information gathering at fairs and conferences.

Since the number of ESPs, IT-companies, and start-ups, which were considered in this thesis, is high, the data gathering process was based on internet research. When analysing companies’ homepages, the focus was set on their range of services and other offerings such as tools or platforms. As the thesis should not simply concentrate on services, tools, and platforms, other information sources like the company news or company journals were used to identify data-based activities such as projects with customers, research activities, cooperations, and takeovers.

3.1.3.2 Market Participants' global Locations

As AVL is a global ESP, the locations of the other market players are of high interest. This information was tracked especially for the group of ESPs and IT-companies. Therefore, if the company shares the information with publicity, the country where the headquarter is located as well as the locations of branches were considered. This information could then be used to identify the competitive situation in specific geographical areas. A limitation of this consideration is the fact that companies can be active in a country, even without a branch. This may represent the competitive situation in a geographical region as smaller as it actually is.

When analysing the four cloud providers Alibaba, Amazon, Google, and Microsoft, instead of their global locations, the countries where their cloud services are available were considered. More detailed information is provided in chapter 3.2.2.

3.1.3.3 Data-Driven Value Propositions

The analysis of market competitors was based on data-driven services, tools, and platforms as well as additional information, regarding data-related content. This information includes cooperations, takeovers, research activities, and projects. Information with these characteristics can be an indicator for future activities and therefore it needs to be considered. To store this tracked information properly, it was necessary to define characteristics that allow a classification of the gathered data. The defined characteristics are listed in Table 2.

The identified data-driven services, tools, platforms, and other data-based activities are collected in an Excel-list, which is enriched with additional information. Table 1 shows exemplarily how this list looks like and which information it contains. Four example entries are listed.

Table 1: Data storage framework

Nr.	Intern Nr.	Company	Type I	Type II	Designation	Cluster	Customer Value	Description
36	1	EDAG	Service		Predictive Maintenance	Predictive Services Production	Predictive Maintenance for machines in production	Service offered by EDAG PS (Production Solutions), work with big OEMs
41	3	IAV GmbH	Tool		IAV Ameda	Testing- Data acquisition Testing- Data analytics	Analyzed test trip data	The IAV AMeDA is used to gather and record test trip data of vehicles. The tool chain is capable of importing and analyzing all common measurement data formats used in the automotive industry as well as many data formats of data loggers
230	4	Zubie Inc.	Platform		Fleet Connect	Fleet Solutions Aftersales	GPS fleet tracking, vehicle health data and driver performance data	Zubie Fleet Connect is an easy-to-use service that starts with plugging a small device into the diagnostics port of your vehicle. It provides GPS fleet tracking, vehicle health data and driver performance data.
561	8	Bosch		Research	AMELI 4.0	Predictive Services Production		Research Project AMELI 4.0, to develop the sensor system of the future for connected manufacturing, or Industry 4.0. The system is intended to monitor machines and immediately detect deviations from their normal operating status.

Description of the data storage framework

- **Column 1: Nr.**
  The first column is a consecutive number. This number allows the explicit identification of entries in the list.

- **Column 2: Intern Nr.**
  This number is not unique within all the entries, but it is unique within the entries of a single company. Additional information regarding this entry, for example, data sheets of a product or prints of webpages, are stored as a document, named with this number.

- **Column 3: Company**
  This column provides the company´s full name or an abbreviation.

- **Column 4 and 5: Type I and Type II**
  These columns classify the type of the entry. For example, if it is a service, a tool or something else. The different characteristics are listed in Table 2.

  Table 2: Characteristics of entries

Type I	Type II
Platform	Cooperation
Service	Project
Tool	Research
	Takeover
Other	

  A differentiation between these two types of characteristics is necessary as they are not on the same level. Type I entries characterize platforms, services, and tools, all things, a company can offer to its customers. In contrast, Type II entries are company internal activities that cannot be offered to customers.

  It is possible that an entry has a characteristic of both types. An example therefore is a tool (Type I) which was developed in cooperation (Type II) with another company. It is also possible that a single entry is characterized by two characteristics of a Type. A research-cooperation is a typical example for this.

- **Column 6: Designation**
  The designation is the name or the title of the listed entry. It can either be the name of the offering, or the heading of a news-article.

- **Column 7: Cluster**
  See chapter 3.1.3.4.

- **Column 8: Customer Value**
  This column describes the customer value of the offered platform, service or tool. In case the entry is characterized as a project, the value proposition was defined if it was possible. For entries characterized as cooperation, research or takeover, no customer value is listed in the table.

- **Column 9: Description**
  The description is meant to provide basic information of the entry. Some relevant information for a better understanding may be included. The detailed description of the entry is available as a file, which is stored like explained in point “Column 2: Intern Nr.”.

3.1.3.4 Clusters

Each entry in the data storage framework gets assigned to one or more defined clusters. By using the clustering method, same or at least similar entries of companies get allocated to the same cluster (Omran et al., 2007, p.1). One significant benefit of this clustering is the possibility of identifying whether a company is active in a specific cluster or not. This method makes companies comparable regarding to their activity. Another benefit of using clusters for classification of services, tools, platforms and other activities is being able to filter them in the list. This allows to create a customized overview of desired entries.

The development of clusters is based on the number of identified data-based entries. If at least three market participants provided information regarding a specific data-based topic, a cluster was generated. If less than three companies provided information regarding a thematic area, this information was classified with the superordinate cluster “Others”.

Less than three of the analysed companies provide information regarding data-based activities in the “Concept” and the “Workshop” phase. Therefore, no clusters were defined for these two phases. The defined clusters are shown in Figure 3.7.

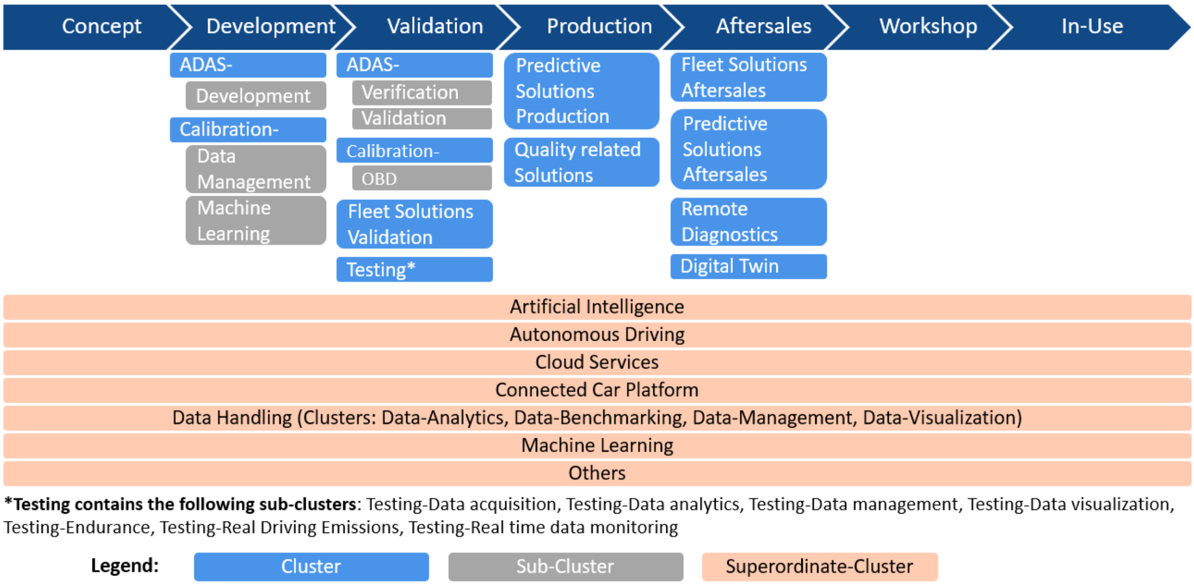


Figure 3.7: Defined clusters

Many of the data-based applications, listed in chapter 3.1.2, are at the same time clusters. The reason why there are data-based applications that are not identified as a cluster is that less than three of the analysed companies provide information regarding these applications.

In this thesis, it is distinguished between three types of clusters. There are clusters that can be allocated to a phase in the automotive value chain. In Figure 3.7 these clusters are highlighted blue. Some of these clusters can be split into more detailed sub-clusters, which describe a specific thematic area within a cluster. Depending on the degree of detailed information of the available data, some clusters are split into sub-clusters. In this thesis, the clusters ADAS, Calibration, and Testing are considered on a sub-cluster level. The sub-clusters are highlighted grey.

The third group of clusters are the superordinate-clusters. Those are more general and cannot be assigned to a specific phase in the automotive value chain. The technologies behind those superordinate-clusters may have their application along the whole automotive value chain. Table 3 describes the phases of the automotive value chain and their assigned clusters.

Table 3: Clusters assigned to the automotive value chain

Phases of the Automotive VC	Description
Concept	No cluster was identified for the concept phase.
Development	The development phase consists of the cluster “ADAS” with the sub-cluster “ADAS development”, as well as the cluster “Calibration” with the sub-clusters “Calibration Data Management” and “Calibration Machine Learning”.
Validation	The validation phase consists of four clusters. Part of this phase is the cluster “ADAS” with its sub-clusters “ADAS Verification” and “ADAS-Validation”, the cluster “Calibration” with its sub-cluster “Calibration-OBD”, the cluster “Fleet Solutions Validation” and the cluster “Testing” with a variety of sub-clusters, listed in Figure 3.7.
Production	In production, the identified clusters are “Predictive Solutions Production” and “Quality related Solutions”.
Aftersales	Four clusters can be assigned to the aftersales phase. Those are: “Fleet Solutions Aftersales”, “Predictive Solutions Aftersales”, “Remote Diagnostics” and “Digital Twin”.
Workshop	No cluster was identified for the workshop phase.
In-Use	The in-use phase is excluded from this thesis.

Definition of the Clusters

The definition specifies the services, tools, platforms and other activities that are part of each considered cluster.

- **ADAS**

Information regarding the activity of companies in the three sub-clusters was tracked for each sub-cluster separately. If there is information available regarding companies’ activity in at least one of the mentioned sub-clusters, the company was identified as active in the cluster ADAS.

ADAS-Development

This sub-cluster contains ADAS-Development services, platforms, and tools, as well as information regarding research activities and projects in the area of ADAS-Development.

ADAS-Verification

This sub-cluster contains testing services and tools for ADAS-Systems.

ADAS-Validation

This sub-cluster contains ADAS-Validation services, platforms, and tools. Research activities are also included in this cluster.

- **Calibration**

Information regarding the activity of companies in the three sub-clusters was tracked for each sub-cluster separately. If there is information available regarding companies' activity in at least one of the mentioned sub-clusters, the company was identified as active in the cluster Calibration.

Calibration Data Management
This sub-cluster contains services and tools for calibration data management and analysis.

Calibration Machine Learning
This sub-cluster contains machine learning services and tools for calibration purposes. For example: machine learning calibration functions.

Calibration OBD
This sub-cluster contains services and tools for OBD calibration.

- **Testing**

Information regarding the activity of companies in the seven sub-clusters was tracked for each sub-cluster separately. If there is information available regarding companies' activity in at least one of the mentioned sub-clusters, the company was identified as active in the cluster Testing.

Testing-Data Acquisition
This sub-cluster contains services, tools, and platforms for the acquisition of testing data.

Testing-Data Management
This sub-cluster contains services, tools, and platforms for the management of testing data. Data storage is also included in this sub-cluster.

Testing-Data Analytics
This sub-cluster contains services, tools, and platforms for testing-data analytics. They should extract valuable information from testing-data

Testing-Data Visualization
This sub-cluster contains services, tools, and platforms for testing-data visualization. In many cases, it comes in combination with testing-data analytics.

Testing-Endurance
This sub-cluster contains automotive endurance testing services.

Testing-Real Driving Emissions (RDE)
This sub-cluster contains RDE services, tools, and platforms.

Testing-Real Time Data Availability
This sub-cluster contains services, tools, and platforms for remote, live data monitoring of test systems. These test systems include test benches and test vehicles.

- **Fleet Solutions Validation**
  This cluster includes services, tools, and platforms for the management of testing fleets and analytics of fleet-testing data.

- **Fleet Solutions Aftersales**
  Fleet Management services, tools, and platforms for the automotive aftermarket. Cooperations and projects are also included. This cluster focuses on monitoring a fleet and increasing its efficiency. In contrast to Fleet Solutions Validation, there are no testing-data analytics.

- **Predictive Solutions Production**
  This cluster includes services, tools, and platforms for predictive maintenance applications in production, as well as projects and research activities.

- **Predictive Solutions Aftersales**
  This cluster contains services, tools, and platforms for predictive maintenance of cars. Projects where companies applied predictive maintenance are considered too.

- **Quality related Solutions**
  The focus of this cluster is on services and tools to improve quality in production.

- **Remote Diagnostics**
  Services, tools, and platforms, which allow remote access to different kind of vehicle diagnostic data such as fault memory data, trouble codes, or device status.

- **Digital Twin**
  In this cluster, services and tools offered for digital twin development, as well as projects and research activities, are included.

- **Artificial Intelligence**
  This cluster contains Artificial Intelligence (AI) solutions offered by companies as a service. Additionally, platforms with AI tools for advanced analytics are considered. Since AI is a superordinate cluster, the applications are not restricted to a specific use case.

- **Autonomous Driving**
  This cluster contains information regarding autonomous driving offered by companies. Since autonomous driving is a superordinate cluster, the information it contains is not restricted to a specific application.

- **Cloud Solutions**
  This cluster contains the development of customer specific cloud services. The developed solution is not restricted to be a connected car service.

- **Connected Car Platform**
  This cluster contains platforms, which are offered by companies, to develop connected car services or to make use of already developed services. These services are based on car-data.

- **Machine Learning**
  This cluster contains machine learning services, tools, and platforms to develop machine learning solutions for the automotive industry, but not restricted to a specific use case. Cooperations and projects with a focus on machine learning, are considered too.

Data Handling
Different services, platforms, and tools in different phases of the automotive value chain include data handling clusters. Those clusters are used for data-based services, tools, platforms, regarding data analytics, benchmarking, management or visualization, where an assignment to one of the other identified clusters is not possible. Testing-data is excluded from the Data Handling-Clusters as there is a separate cluster for testing-data. Data Handling is the superordinate term for the following clusters:

- **Data Management**
  This cluster contains services, tools, and platforms for the management of data. Data management that cannot be assigned to one of the other defined clusters. Example: Product Data Management

- **Data Analytics**
  This cluster contains services, tools, and platforms for data analytics solutions that cannot be assigned to one of the other defined clusters. General data analytics solutions are included too in this cluster.

- **Data Visualization**
  This cluster contains services, tools, and platforms for data visualization as well as data visualization that cannot be assigned to one of the other defined clusters. In many cases, it comes in combination with data analytics.

- **Data Benchmarking**
  This cluster contains services, tools, and platforms for data benchmarking. An example is benchmarked data-as-a-service.

3.2 Data processing for Evaluation

This chapter describes how the collected data got processed to be suitable for further evaluation and visualization.

3.2.1 Companies' Activity in investigated Clusters

That part of the thesis illustrates how the entries from the data storage framework, shown in chapter 3.1.3, got evaluated. The evaluation is done in form of tables, separately for each group of market participants. A matrix-visualization method was chosen, which gives a holistic overview of all companies and clusters (Wu et al., 2008, p.1). In order to gain a better understanding, the structure is shown in Figure 3.8. This visualization is called the activity matrix.

	ADAS- Development	ADAS- Validation	ADAS- Verification	**ADAS**	Calibration Data Management	Calibration Machine Learning	Calibration OBD	**Calibration**	Digital Twin	Fleet Solutions Aftersales	Fleet Solutions Validation	Predictive Solutions Aftersales	Predictive Solutions Production	Quality related Solutions	Remote Diagnostics	Testing- Data acquisition	Testing- Data analytics	Testing- Data management	Testing- Data visualization	Testing- Endurance	Testing- RDE	Testing-Real Time Data Mon.	**Testing**	Artificial Intelligence	Autonomous Driving	Cloud Solutions	Connected Car Platform	Data Analytics	Data Benchmarking	Data Management	Data Visualization	Machine Learning	**Companies' Cluster-Sum**
Company 1	1	1		1								1					1	1	1				1	1								1	5
Company 2						1		1																		1	1	1					4
Company 3												1												1									2
Company 4					1	1		1		1		1															1					1	5
Company 5	1	1	1	1							1				1	1	1	1	1	1	1	1	1	1				1					6
Cluster-Sum	2	2	1	2	1	2	0	2	0	1	1	3	0	0	1	1	2	2	2	1	1	1	2	3	0	1	2	2	0	0	0	2	

Figure 3.8: Structure of the activity matrix

The first column of this activity matrix lists the analysed companies, separately for each group of market players. The figure shows five example companies (Company 1 to Company 5).

In the first line, the defined clusters with its sub-clusters are listed. As explained in chapter 3.1.3.4, the three clusters ADAS, Calibration, and Testing consist of several sub-clusters. If a company is active in one of the sub-clusters, it is defined as active in the associated cluster. If a company is active in one of the defined clusters, the cell is marked with a 1 and highlighted red. This method of visualization provides an overview of companies' activity areas.

The last column is named “Companies Cluster-Sum”. This sum determines the number of clusters the company is active in. The number of sub-clusters, they are active in, is not counted due to the fact that the results may be distorted. An example should illustrate this claim: If a company is active exclusively in six sub-clusters of Testing, and each sub-cluster is counted, Companies Cluster-Sum will result to 6. Compared to companies that are active in six clusters, they are far less diversified, but Companies’ Cluster-Sum would not show this circumstance.

The last row is named the “Cluster-Sum”. This sum identifies the number of companies active in a specific cluster. The Cluster-Sum is calculated four times. Once for each of the three market player groups separately and additionally in total, considering all three groups.

All results shown in chapter 4, are based on data from this activity matrix.

3.2.2 Companies’ global Locations

The global locations were identified for each ESP and IT-company. Start-ups were not included in this investigation as they do not have as many branches as ESPs and IT-companies have. Therefore, the information content of an analysis which considers the global branches is negligible. The structure of the global location data collection is shown in Figure 3.9. Due to the high number of countries in Europe, the data was not recorded for each country separately. If a company is active in any country of Europe, it was identified to be active in Europe.

Regarding the continents North America, South America, Africa, and Asia, the structure does not contain all countries of these continents. Only specific countries, with a competition intensity of at least three competitors, were considered separately. When analysing Asia, additionally to important countries like China or India, two geographical regions were used for classification. The countries Brunei, Burma (Myanmar), Cambodia, Timor-Leste, Indonesia, Laos, Malaysia, Philippines, Singapore, and Thailand were condensed to the geographical region South-East Asia, and the countries Bahrain, Cyprus, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, Turkey, United Arab Emirates, Yemen, and Vietnam were condensed to the geographical region Middle East. If a company was identified to be active in at least one country of a specific geographical region, it was defined to be active in this region. The continent Africa was defined to consist of the geographical region North Africa and the country South Africa. North Africa can be split into the countries Algeria, Egypt, Libya, Morocco, Sudan, Tunisia and Western Sahara. For the other countries no locations were identified.

As additional information, the country where the headquarter of the company is located was recorded. The full list of companies’ global locations is provided in Appendix 2.

		Europe	North America			South America		Asia							Africa		Australia
ESPs	HQ		USA	Canada	Mexico	Brazil	Argentina	China	India	Japan	SEA	Korea	Middle East	Russia	North Africa	South Africa	
Company 1	HQ 1	1	1		1	1	1	1	1	1	1	1	1	1			1
Company 2	HQ 2	1	1			1		1	1			1					
Company 3	HQ 3	1	1					1									
Company 4	HQ 4	1	1					1		1							
Company 5	HQ 5	1	1		1	1		1	1	1	1			1			

Figure 3.9: Companies' global locations – Structure

3.3 Cluster Classification

This chapter contains four methods for further classification of the defined clusters. These classifications should provide more information regarding the cluster itself. The first method is a ranking of the clusters, based on the number of companies active in each individual cluster. The second method is a 3-dimensional classification of clusters, where a cluster is being classified according its assignability to a phase in the automotive value chain, the data value chain and to its field of application. The third method is the cluster-portfolio, which classifies a cluster based on the competition intensity and market potential. The cluster landscape is the fourth method. It characterizes a cluster based on the number ESPs and IT-companies active in it and their shares.

3.3.1 Ranking of Clusters based on Companies Activity

This classification method ranks all clusters defined in chapter 3.1.3.4, based on the number of companies active in them. According to chapter 3.2.1, the number of companies active in a cluster is called the cluster-sum. The aim of this classification is to identify the competition intensity of each cluster and its composition regarding number of ESPs, IT-companies and start-ups active in it. In addition, the clusters should become ranked for each group of market players separately. To allow a comprehensive consideration, four rankings were created. These four rankings consist of one ranking each for ESPs, IT-companies and start-ups and one ranking which considers all market player groups. The results of this classification are illustrated in chapter 4.2.1.

3.3.2 3-dimensional Classification of Clusters

The aim of this method is to classify the clusters, defined in chapter 3.1.3.4, according to their position in the automotive and data value chain and the field of application, this specific cluster is related to. Only clusters that are assigned to a phase in the automotive value chain, as defined in chapter 3.1.3.4, are considered for this classification. The superordinate clusters defined in chapter 3.1.3.4 are not part of this consideration. If a cluster cannot be assigned to a phase in the automotive value chain, the information content of a classification is seen as neglected.

Automotive value chain
The automotive value chain is described in chapter 3.1.2. It consists of the six phases, shown in Figure 3.10

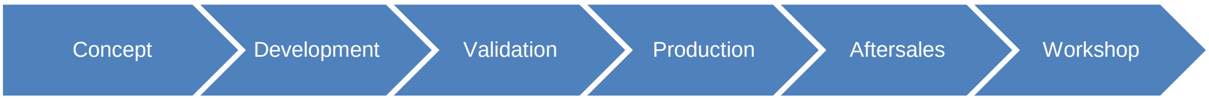


Figure 3.10: Automotive value chain without in-use phase (AVL Data Intelligence Services, 2018)

Data value chain
A detailed description of the data value chain according to Curry et al. (2014, p.1f) is provided in chapter 2.1.2. It consists of the following phases:

- Data acquisition
- Data analytics
- Data curation
- Data storage
- Data usage

The data value chain does not fit exactly to the data structure used in the analysis. Therefore, it needs to be adapted in order to meet the requirements of the analysis. The focus of the two phases data curation and data storage is mainly on management of data. This allows combining these two phases to a single phase called data management. The adapted data value chain, which fits now to the existing data structure, is illustrated in Figure 3.11.

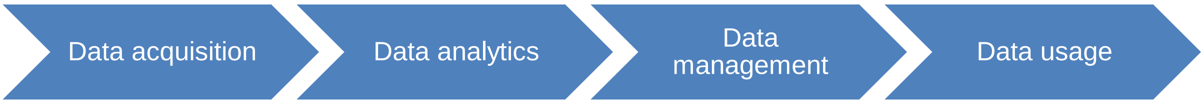


Figure 3.11: Adapted data value chain (adapted Cherry et al., 2014, p.1f)

Field of application

The field of application shows, where the considered cluster can be applied. Three categories were defined:

- Vehicle Component or System, e.g.: ADAS, Engine, Battery, Transmission
- Complete Vehicle
- Machine in Production

An assignment of clusters and sub-clusters to all three dimensions was only possible for the four defined clusters “Predictive Solutions Aftersales”, “Predictive Solutions Production”, “Remote Diagnostics”, and “Testing”, and the two sub-clusters “Calibration Data Management” and “Calibration Machine Learning”. For the other defined clusters, a clear allocation to at least one of the value chains was not possible due to a lack of data. In order to assign all clusters to both value chains, a highly detailed data acquisition would be needed. As this was not the focus of this thesis, it will not be discussed in any further detail. The result of this assignment is shown in chapter 4.2.2.

3.3.3 Cluster Portfolio

The cluster portfolio visualizes the market potential of clusters and its competition intensity in a single diagram. The aim of this visualization is to provide an aggregated diagram which allows an identification of clusters’ competitive situation and economic potential in a single figure. The structure of this portfolio is illustrated in Figure 3.12.

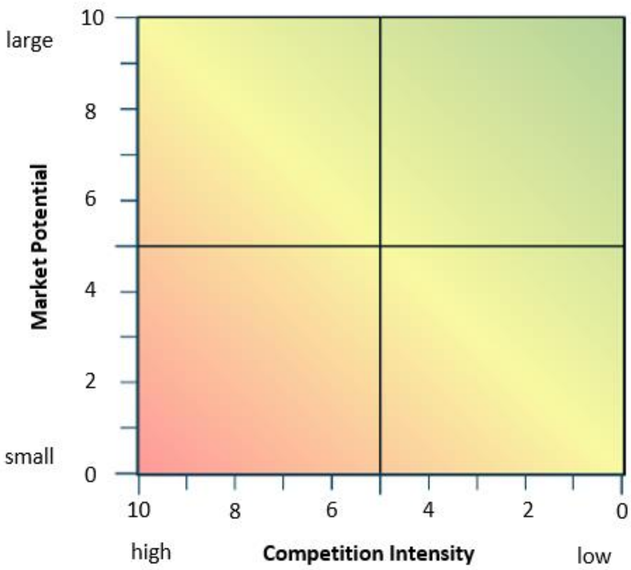


Figure 3.12: Structure cluster portfolio (AVL internal, 2019)

On the horizontal axis, the competition intensity of clusters, with a scale from 10 (high) to 0 (low) is plotted. In this analysis, the competition intensity can be understood as the number of market players active in the investigated cluster.

The vertical axis shows the market potential of a cluster with a scale from 0 (small) to 10 (large). The market potential considers the two characteristics market size and Compound Annual Growth Rate (CAGR), each ranked from 10 (large/high) to 0 (small/low). Both characteristics are weighted with fifty percent.

The portfolio consists of four quadrants and three areas, which are characterized by different colours. The red coloured area is defined by a small market potential and a high competition intensity. On the contrary, the green coloured area is defined by a low competition intensity and a large market potential. The area between these two cases is highlighted yellow.

Determination of the Cluster Portfolio

The portfolio was created for clusters, for which forecasted revenue data was available. This data is needed for calculation of the market potential. The following clusters fulfil this requirement:

- Autonomous Driving
- Cloud Services
- Fleet Solutions Aftersales
- Predictive Solutions Aftersales
- Quality related Solutions

In the following, the cluster portfolio is being determined. Therefore, a calculation of the market potential and a determination of the competition intensity is required.

1) Market potential

The market potential consists of the characteristics market size and CAGR, which are both equally ranked. This consideration of two characteristics requires a standardization of each, to enable the calculation of the market potential.

- **Market size**

The market size of the mentioned clusters is considered in million US-Dollars for the year 2018 (see Table 4). It is ranked by using standardized values from 0, which corresponds to 0 million USD, to 10, which corresponds to 300 million USD. The defined market size range from 0 to 300 million USD is an assumption based on the available data. The relation between these two cases is linear.

Table 4: Market size of clusters (SNS Research, 2018, p.139ff)

Cluster	Market size 2018 [million USD]	Market size 2018 [0-10]
Autonomous Driving	150	5.0
Cloud Services	250	8.3
Fleet Solutions Aftersales	200	6.7
Predictive Solutions Aftersales	150	5.0
Quality related Solutions	220	7.3

- **CAGR**

The CAGR was calculated from the year 2018 to 2030, which is the last year where forecasted revenue data was available. According to Investopedia (2019a), it is calculated with formula (1).

$$CAGR\ [\%] = \left(\left(\frac{Ending\ balance}{Beginning\ balance}\right)^{\frac{1}{n}} - 1\right) * 100 \qquad (1)$$

Ending balance…………………… Forecasted revenue 2030 (million USD)
Beginning balance………………….Revenue 2018 (million USD)
n………………………………………Years between beginning- and ending-balance

The calculated CAGR for each considered cluster is listed in Table 5. The standardized value has a range from 0, which corresponds to a CAGR of 0%, to 10 which corresponds to a CAGR of 30%. The defined CAGR-range from 0% to 30% is an assumption based on the available data. The relation between a CAGR of 0 and a CAGR of 10 is linear.

Table 5: CAGR of investigated clusters

Cluster	CAGR [%]	CAGR [0-10]
Autonomous Driving	22	7.3
Cloud Services	22	7.3
Fleet Solutions Aftersales	11	3.6
Predictive Solutions Aftersales	16	5.3
Quality related Solutions	9	3.0

The market potential is calculated for each cluster in Table 6. It is the arithmetic mean of the market size and the CAGR.

Table 6: Market potential of investigated clusters

Cluster	Market size [0-10]	CAGR [0-10]	Market potential [0-10]
Autonomous Driving	5.0	7.3	6.15
Cloud Services	8.3	7.3	7.80
Fleet Solutions Aftersales	6.7	3.6	5.15
Predictive Solutions Aftersales	5.0	5.3	5.15
Quality related Solutions	7.5	3.0	5.25

2) Competition intensity

The competition intensity can be understood as the number of market players active in the considered cluster. In chapter 3.2.1, this number of market players active in a cluster is defined as the cluster-sum.

The competition intensity is a standardized value from 0 to 10. If no company was identified to be active in the considered cluster, the competition intensity was defined to be 0. If 30 of the 53 analysed companies were identified to be active, it was defined to be 10. The defined competition intensity-range from 0 to 30 is an assumption based on the available data. In total, 53 market participants were included in this thesis. The relation between the competition intensity of 0 and the competition intensity of 10 is linear. Table 7 shows the competition intensity of the investigated clusters.

Table 7: Competition intensity of investigated clusters

Cluster	Cluster-sum	Competition intensity [0-10]
Autonomous Driving	22	7.3
Cloud Services	20	6.7
Fleet Solutions Aftersales	13	4.3
Predictive Solutions Aftersales	18	6.0
Quality related Solutions	5	1.6

3.3.4 Cluster Landscape

In this chapter, the defined clusters are being classified based on two criteria. Those criteria are the share of ESPs active in the cluster, and the number of ESPs and IT-companies active in the cluster. The aim of this cluster landscape is to illustrate the competition intensity of a cluster, and the characteristic of the cluster regarding the distribution of ESPs and IT-companies active in it, in a single figure.

The cluster landscape diagram consists of a horizontal and a vertical axis. On the vertical axis, the number of ESPs and IT-companies active in the cluster is plotted. This is the measure for the competition intensity in the investigated cluster. The horizontal axis shows the share of ESPs active in the cluster. A share of 100% means, that only ESPs and no IT-companies were identified to be active in the cluster. In contrast, a share of 0% means that no ESPs, but only IT-companies were identified to be active in this cluster. Another characteristic value is the 50% share, where the number of ESPs and IT-companies, active in the cluster, is equal.

Due to the different numbers of ESPs (25 companies analysed) and IT-companies (17 companies analysed), the calculation of the share has to be standardized. This is ensured by dividing the number of ESPs in the considered cluster by 25 and the number of IT-companies in the considered cluster by 17. The result is called the "standardized number of ESPs in the cluster" and "standardized number of IT-companies in the cluster". The summation of these two values results in the "standardized sum of ESPs and IT-companies in the cluster". The formula for the calculation of the "Share of ESPs in a cluster" is shown below.

$$Share\ of\ ESPs\ in\ a\ cluster = \frac{standardized\ number\ of\ ESPs\ in\ the\ cluster}{standardized\ sum\ of\ ESPs\ and\ IT\ companies\ \ in\ the\ cluster} \qquad (2)$$

If this standardization is not made, the result would be falsified due to the different numbers of ESPs and IT-companies considered in this thesis. An example, provided in Appendix 7, should illustrate this circumstance.

The cluster landscape with all defined clusters is visualized and described in detail in chapter 4.2.4.

3.4 Comparison of AVL with other Market Players

In this chapter, the clusters, market players have in common with AVL, are identified. According to the activity matrix shown in chapter 4.1, AVL is active in thirteen clusters. In Figure 3.13, these clusters are highlighted red.

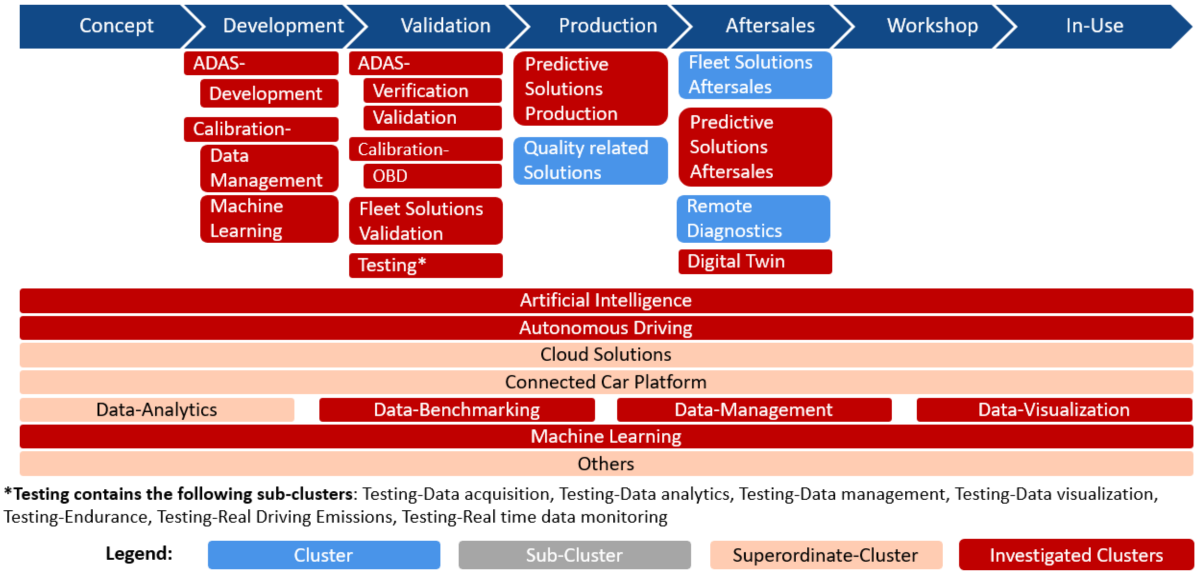


Figure 3.13: AVLs clusters of activity

The aim of this analysis is to identify the similarities of market players with AVL, in terms of clusters the companies are active in. The consideration is done for the ESPs, IT-companies, and start-ups separately. The results are shown in chapter 4.3.

3.5 Investigation of Clusters AVL is not active in

In contrast to chapter 3.4, which analysed companies in the clusters AVL is active in, this chapter focuses on clusters AVL is not active in. According to the activity matrix shown in chapter 4.1, AVL is not active in six of the nineteen defined clusters. In Figure 3.14 these clusters are highlighted red.

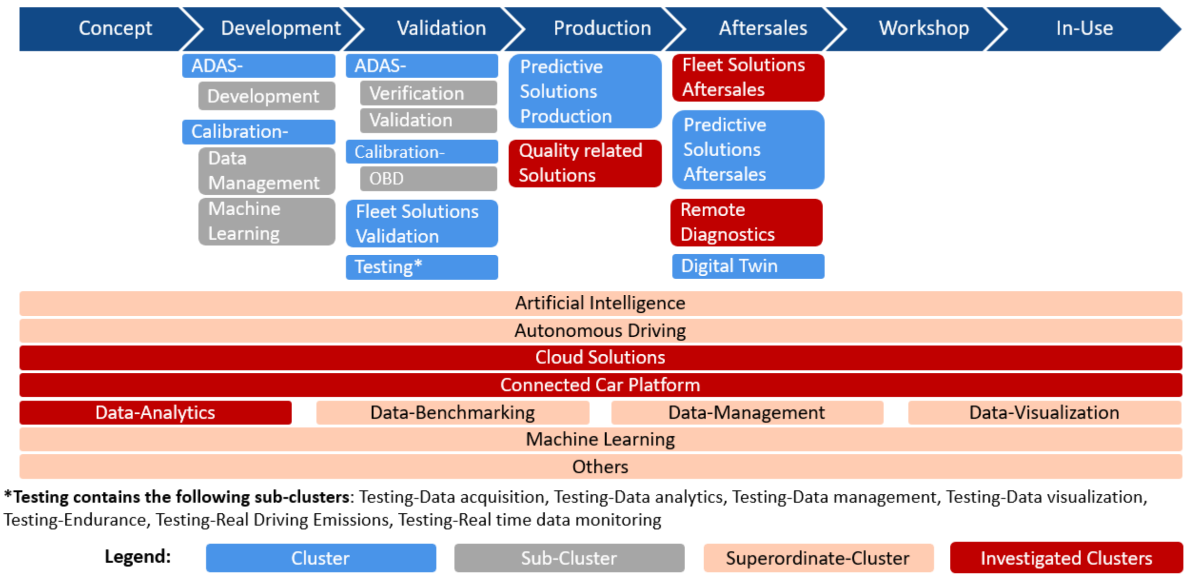


Figure 3.14: Clusters AVL is not active in

The aim of this analysis is to identify the companies that are active in those clusters and to rank them according to their activity. The results are shown in chapter 4.4.

3.6 Market Players Activity along the Automotive Value Chain

This analysis gives an overview of market players activity in the different phases of the automotive value chain. The consideration was made for each of the market player groups separately. To identify market players activity in the phases, the defined clusters which can be assigned to a phase in the automotive value chain, defined in chapter 3.1.3.4, were used. If a company is active in a cluster or sub-cluster, shown in Figure 3.15, it is defined to be active in the phase of the automotive value chain, this cluster is assigned to.

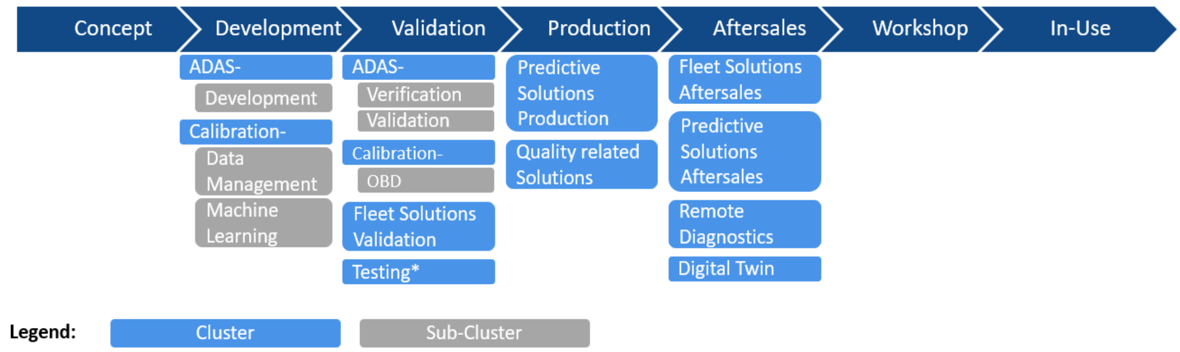


Figure 3.15: Clusters and sub-clusters assigned to the automotive value chain

The clusters ADAS and Calibration need to be considered on a sub-cluster level due to their assignment to two phases of the automotive value chain. The sub-cluster ADAS-Development was assigned to the development phase and the sub-clusters ADAS-Verification and ADAS-Validation were assigned to the validation phase in the automotive value chain. The sub-clusters Calibration Data Management and Calibration Machine Learning were assigned to the development phase and the sub-cluster Calibration OBD was assigned to the validation phase of the automotive value chain. The sub-clusters of the cluster Testing do not need to be considered separately. Those are per definition in the validation phase of the automotive value chain. The results of this investigation are shown in chapter 4.5

3.7 Determination of Market Players Activity Field

This chapter identifies the activity field of the considered ESPs, IT-companies and start-ups. The activity field of each market player group is the surface in the diagram, which covers all companies from this group. The diagram, which illustrates the market players activity field, consists of a vertical and a horizontal axis.

On the vertical axis, the “Number of Clusters a company is active in”, is plotted. This information is available in the activity matrix, shown in chapter 4.1. It is a measure which characterizes companies’ diversity of thematic areas they are active in.

On the horizontal axis the “Degree of Activity of ESPs in investigated clusters” is plotted. This characteristic needs to be calculated, for each company separately, with formula (3).

$$\textit{Degree of activity of ESPs in investigated clusters} = \frac{\textit{Sum of shares of ESPs in clusters the company is active in}}{\textit{Number of clusters the company is active in}} \quad (3)$$

The range of this indicator is from 0 to 100. The two borderline cases are 0, which means that the considered company is active only in clusters where exclusively IT-companies are active in, and 100 which means that the considered company is active only in clusters where solely ESPs are active in.

The “Shares of ESPs in the clusters the company is active in” is information from chapter 3.3.4, which was calculated for each cluster. It is a standardized key figure with a range from 0 to 100. The sum of these shares of all clusters, the considered company is active in, then gets divided by “Number of clusters the company is active in”. This results in an average company cluster, called “Degree of activity of ESPs in investigated clusters”. More details regarding the calculation of the “Degree of activity of ESPs in investigated clusters”, and an example, are provided in Appendix 8.

The market players activity fields with all analysed companies are visualized and described more detailed in chapter 4.6.

3.8 Companies working in ADAS-related Activities

One of the macrotrends in the automotive industry, described in chapter 2.3.1, is autonomous driving. A prerequisite for autonomous driving vehicles are advanced driver assistance systems (ADAS). AVL and many other companies from the three considered market player groups are active in the field of autonomous driving and especially in the area of ADAS. In order to identify the companies with the highest activity in this area, the superior cluster “ADAS-related Activities” was created. This superior cluster consists of the five clusters, described below.

Definition of the superior cluster “ADAS-related Activities”

In Figure 3.16 the investigated clusters are highlighted red. Further details regarding the defined clusters are provided below. The mentioned clusters and sub-clusters are defined in chapter 3.1.3.4.

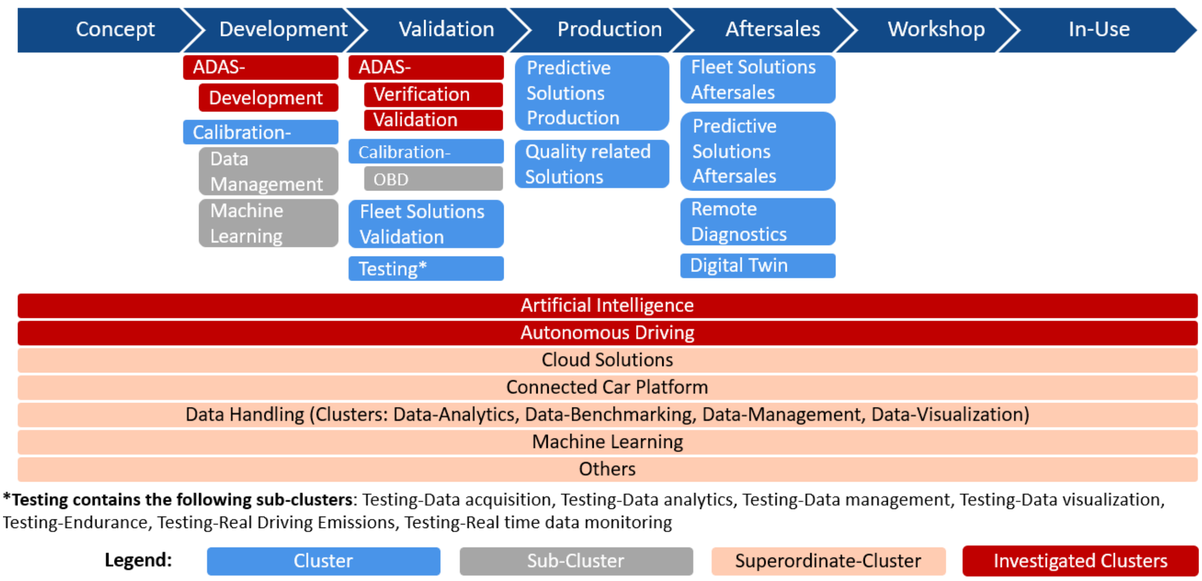


Figure 3.16: Clusters investigated as ADAS-related activities

Cluster ADAS

According to the definition of the cluster in chapter 3.1.3.4, it is separated into its three sub-clusters ADAS-Development, ADAS-Verification and ADAS-Validation. For each of these sub-clusters, the information, if a company is active in it or not, was tracked separately. This allows an independent consideration of each sub-cluster. ADAS-Development, ADAS-Verification and ADAS-Validation were added to the superior cluster "ADAS-related Activities".

Cluster Artificial Intelligence

As Artificial Intelligence plays an essential role in ADAS and autonomous driving cars (Sulaiman, 2018, p.1ff), this cluster was considered as relevant and added to the superior cluster "ADAS-related Activities".

Cluster Autonomous Driving

The cluster Autonomous Driving was added to the superior cluster "ADAS-related Activities".

In chapter 4.7, the investigated market players are being ranked based on their activity in the defined clusters. In order to identify the competition intensity in geographical areas, the global locations of these market players were taken into consideration. The result of these investigations is provided in chapter 4.7.

3.9 Companies active in the Cluster Testing

As testing is a core competence of AVL, a detailed analysis of the considered market players and their data-based offerings, in the cluster Testing, was implemented.

The cluster Testing, defined in chapter 3.1.3.4, is, according to Figure 3.17, allocated in the validation phase of the automotive value chain.

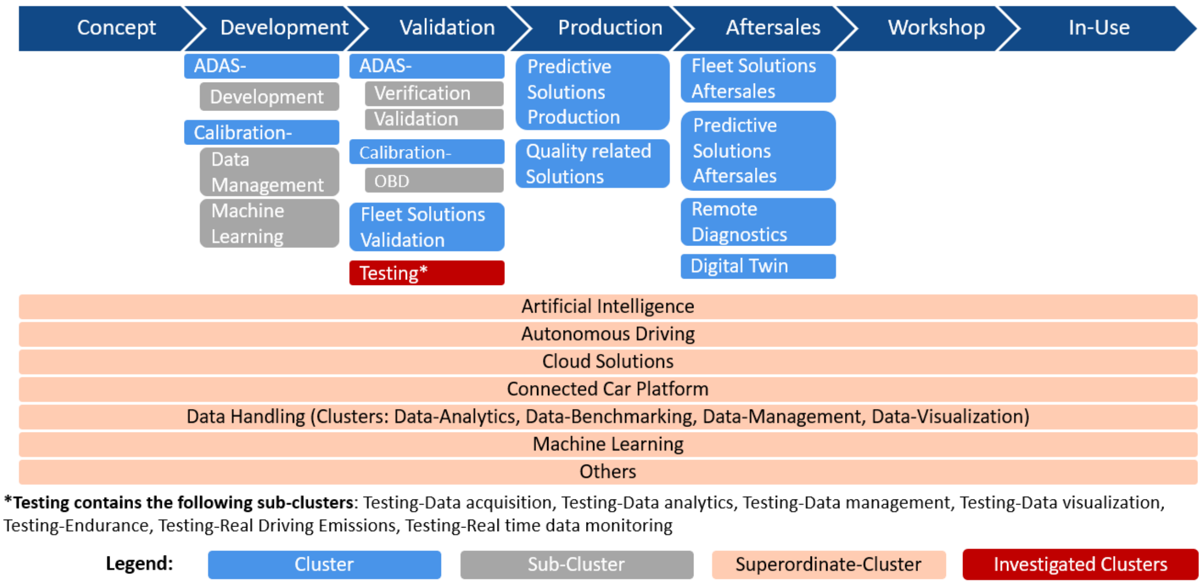


Figure 3.17: Clusters along the automotive value chain – Testing

The cluster Testing consists of seven sub-clusters. For each sub-cluster, the activity of market players was tracked separately. This allows taking a closer look at this cluster. The mentioned sub-clusters are:

- Testing – Data Acquisition
- Testing – Data Management
- Testing – Data Analytics
- Testing – Data Visualization
- Testing – Endurance
- Testing – Real Driving Emissions (RDE)
- Testing – Real-time Data Availability

In order to rank the market players regarding their activity in the cluster Testing, the number of sub-clusters they are active in, was identified. Additionally, the global locations of the market players were considered. The results of these investigations are shown in chapter 4.8.

3.10 Companies' offered Services

As AVL is a highly specialised ESP in the service business, it is of special interest to further analyse the gathered data, with a focus on services.

As described in chapter 3.1.3.4, the entries in the data storage framework can be classified by the Type I and Type II characteristics shown in Table 8. In an additional exploration, only entries of the data storage framework, which are characterized as "Service", were investigated. As described in chapter 3.1.3.3, an entry in the data storage framework can be classified by more than one characteristic, such as a service offered on a platform. Therefore, all entries, which are among others categorized as service, have been taken into account.

Table 8: Defined characteristics

Type I	**Type II**
Platform	Cooperation
Service	Project
Tool	Research
	Takeover
Other	

It has to be mentioned that this analysis has some limitations. The focus on services may lead to a loss of potentially relevant information.

In some cases, the investigated companies provide information regarding general services, like calibration as a service, but no further details are given. With this provided information, an allocation of the service to the defined calibration sub-clusters was not possible as too little is known about which specific services they are offering in calibration. In some cases, more details are getting visible, when the companies describe their offered tools. However, they often do not provide information regarding the use of these tools in their offered services. If the companies use these tools for their offered services, it results in a loss of data, because the tools were not considered in this investigation. The results of this investigation are shown in chapter 4.9.

4 Results

In this chapter, the results of the analysis are listed and evaluated. Result visualizations in the chapters 4.2 to 4.8, were created with the business analytics tool Microsoft PowerBI.

The first sub-chapter describes the activity matrix, which identifies companies' areas of activity in the investigated clusters. All the other results are based on a further analysis of this activity matrix. The four different cluster classifications are included in the results. Those cluster classifications are the ranking of clusters regarding the number of companies active in it, the 3-dimensional cluster classification, the cluster portfolio, and the cluster landscape. In addition, this chapter contains information regarding a comparison of AVL with other companies, information about companies' activity along the automotive value chain, market players activity fields and a detailed elaboration of companies' ADAS-related activities and testing activities.

4.1 Activity Matrix

This matrix identifies the activity areas for each company of the three considered market player groups. The activity areas are defined as the clusters and its sub-clusters. The results from chapter 4.2 to 4.9 are based on this activity matrix. Figure 4.1 shows a selection of companies and their activity areas. The companies' cluster-sum identifies in how many of the defined clusters, the companies are active in. The sub-clusters were not considered when calculating this sum.

ESPs	**ADAS**	ADAS- Development	ADAS- Validation	ADAS- Verification	**Calibration**	Calibration Data Management	Calibration Machine Learning	Calibration OBD	Digital Twin	Fleet Solutions Aftersales	Fleet Solutions Validation	Predictive Solutions Aftersales	Predictive Solutions Production	Quality related Solutions	Remote Diagnostics	**Testing**	Testing- Data acquisition	Testing- Data analytics	Testing- Data management	Testing- Data visualization	Testing- Endurance	Testing- RDE	Testing-Real Time Data Mon.	Artificial Intelligence	Autonomous Driving	Cloud Solutions	Connected Car Platform	Data Analytics	Data Benchmarking	Data Management	Data Visualization	Machine Learning	**Companies' Cluster-Sum**
AVL List	1	1	1	1	1	1	1	1	1		1	1	1			1	1	1	1	1	1	1	1	1	1				1	1	1	1	13
AKKA Group	1		1									1				1	1		1		1	1	1		1			1		1	1		7
Altair Engineering	1	1								1						1		1		1						1		1		1	1	1	8
Alten																1					1					1				1			3
Altran Germany	1	1		1									1											1	1							1	5
Applus IDIADA	1	1	1	1	1			1			1					1		1							1				1				6
Assystem Group	1	1	1	1					1															1		1	1	1	1			1	8
Bertrandt	1	1	1		1			1	1				1	1	1	1		1	1				1	1	1			1	1			1	12
Bosch										1		1	1		1	1					1	1		1	1			1		1	1		10

Figure 4.1: Companies' areas of activity - Selection

A list with all analysed companies and their activity areas is provided in Appendix 3.

4.2 Cluster Classification

This chapter deals with four different evaluations regarding the classification of clusters. The different results should provide additional cluster information and characteristics.

4.2.1 Ranking of Clusters based on Companies' Activity

This investigation shows the defined clusters ranked by the number of companies active in it. In total, four different rankings were created to describe companies' activity in the clusters. In Figure 4.2, the ranking, which considers all market player groups, is illustrated. The rankings, which consider each market player group separately, are shown in the Figures 4.3, 4.4, and 4.5.

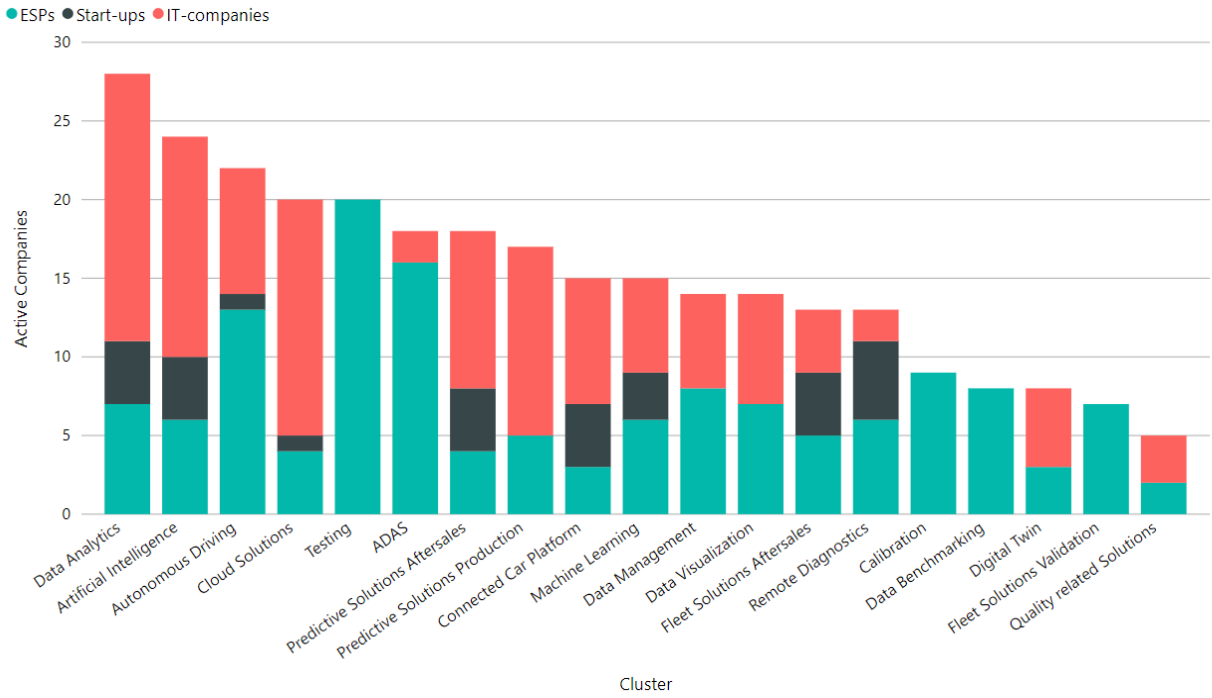


Figure 4.2: Clusters ranked by number of companies active in them

The diagram in Figure 4.2, shows the clusters ranked by activity, considering all three market player groups. The share of each group is illustrated in a different colour. In this ranking, the three superordinate clusters Data Analytics, Artificial Intelligence, and Autonomous Driving are those, where most companies were identified to be active in. In all these clusters, companies from the three market player groups are active in. The two clusters Cloud Solutions and Testing share the fourth rank with twenty active players. Testing is the highest ranked cluster where solely a single group of market players, in this case ESPs, is active in.

In the cluster Quality related Solutions, least companies were identified to be active in. Only five of the 53 analysed companies provide services related to this cluster.

The diagram shown in Figure 4.3 illustrates the ranking of clusters when only considering ESPs.

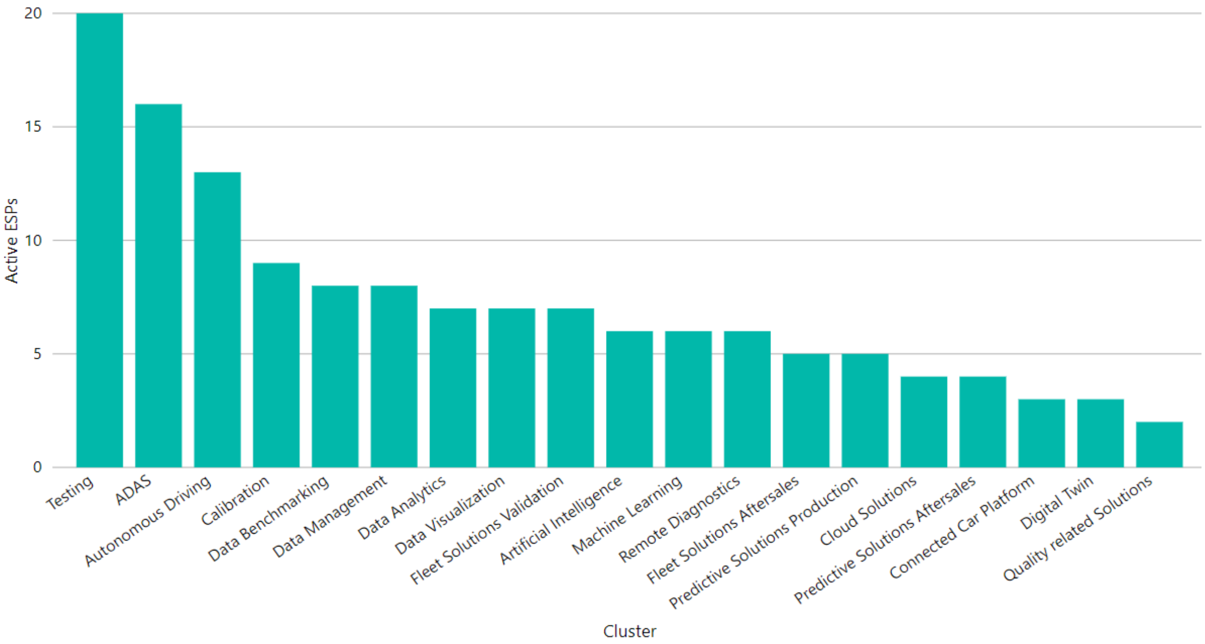


Figure 4.3: Clusters ranked by number of ESPs active in it

In this ranking, the clusters Testing, ADAS, and Autonomous driving are those where most companies are active in. These three clusters can be said to be typical clusters where ESPs are active in. A low activity was identified in clusters such as Quality related Solutions, Digital Twin, and Connected Car Platform.

The diagram in Figure 4.4 illustrates the cluster-ranking of IT-companies.

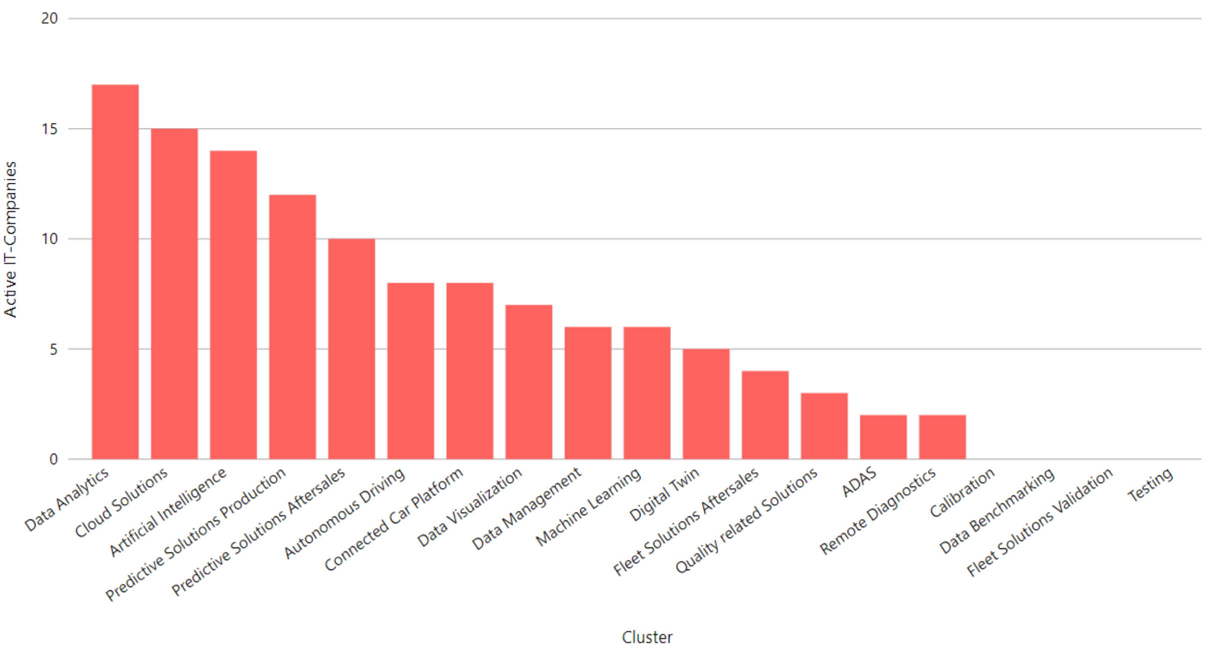


Figure 4.4: Clusters ranked by number of IT-companies active in it

Most of the analysed companies are active in providing Data Analytics services or tools, Cloud Solutions, and Artificial Intelligence Solutions. These Top 3 clusters, most IT-companies were identified to be active in, are solely superordinate clusters, which means that they cannot be assigned to a specific phase in the automotive value chain. ESPs are active in these three clusters, but their activity is significant lower compared to the typical ESP clusters like Testing, Calibration and Fleet Solutions Validation.

The ranking of clusters by the number of start-ups active in, is shown in Figure 4.5.

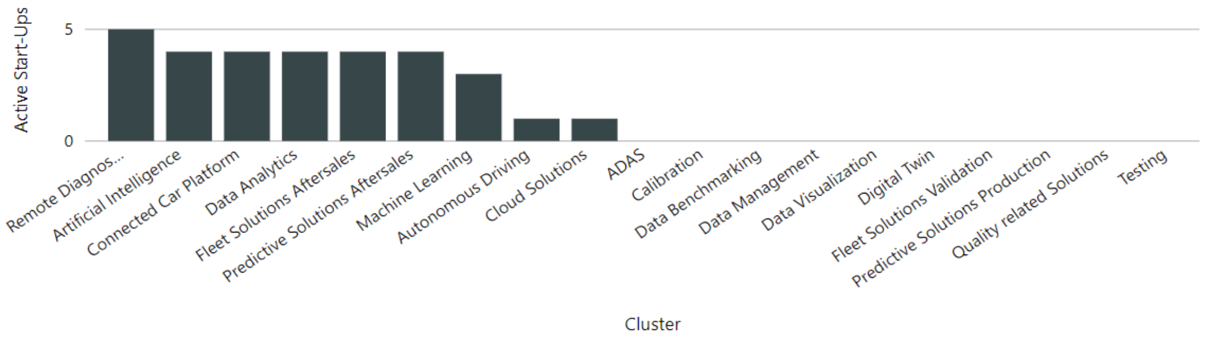


Figure 4.5: Clusters ranked number of start-ups active in it

Only nine clusters, where the considered start-ups are active in, were identified. Typical clusters of activity are Artificial Intelligence, Predictive Solutions Aftersales, Fleet Solutions Aftersales and Machine Learning. The low number of identified clusters, nine clusters in total, may be explained by the low number of start-ups considered in the analysis of this thesis and the fact that most start-ups are focussing on a specific thematic area.

4.2.2 3-dimensional Cluster Classification

This evaluation shows the cluster classification regarding the three dimensions automotive value chain, data value chain, and field of application. A classification was done for two sub-clusters and four clusters. Those classifications are shown in the Figures 4.7 to 4.12. The legend is described in Figure 4.6.

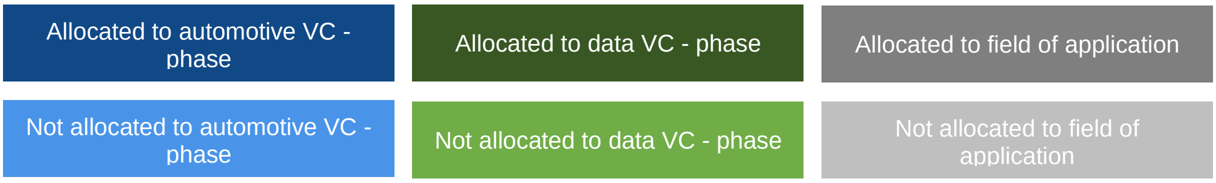


Figure 4.6: 3-dimensional cluster classification - Legend

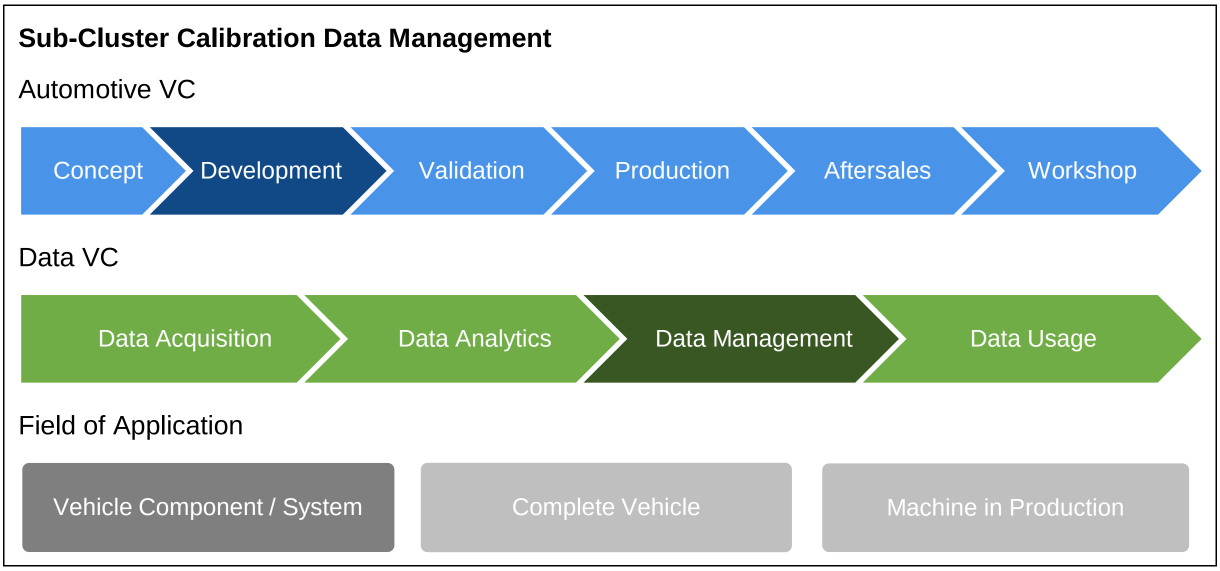


Figure 4.7: Classification of sub-cluster Calibration Data Management (AVL Data Intelligence Services) (adapted from Cherry et al., 2014, p.1f)

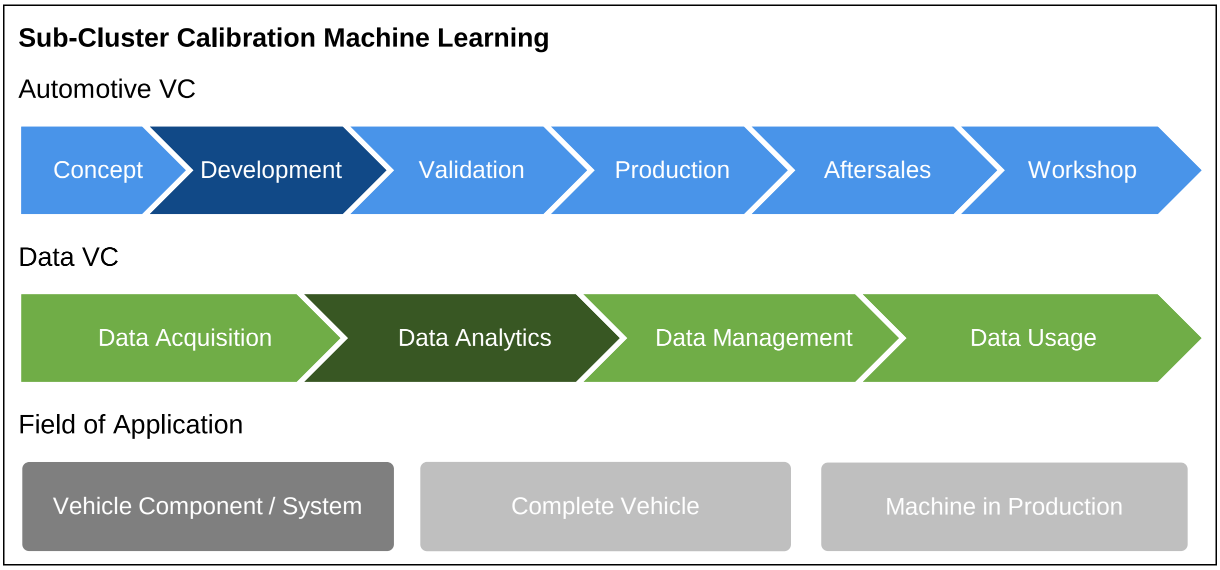


Figure 4.8: Classification of sub-cluster Calibration Machine Learning (AVL Data Intelligence Services) (adapted from Cherry et al., 2014, p.1f)

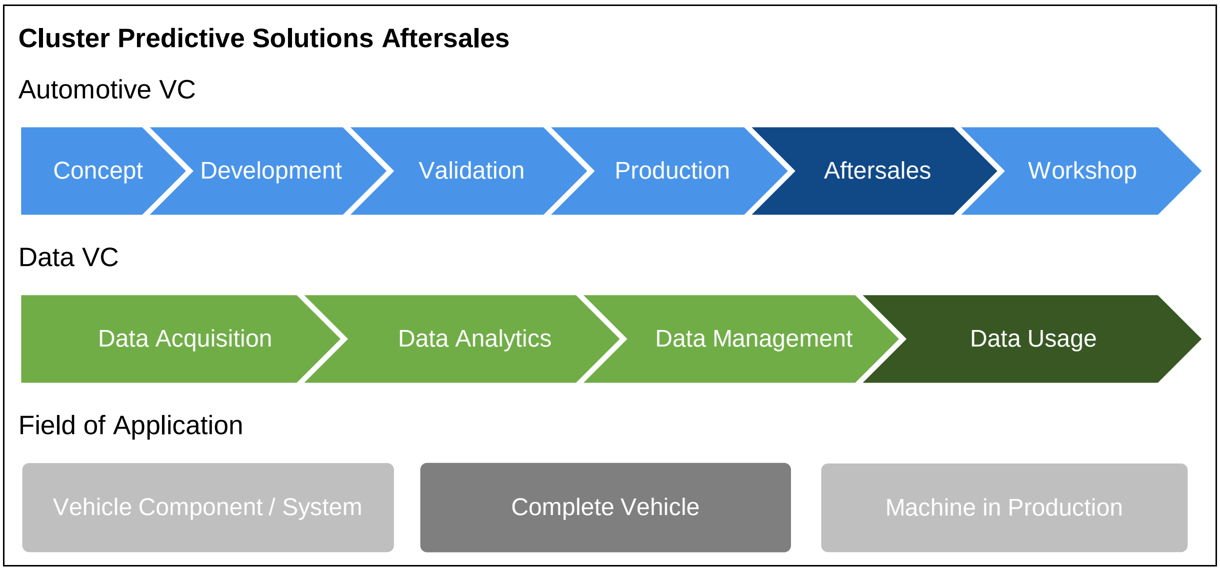


Figure 4.9: Classification of cluster Predictive Solutions Aftersales (AVL Data Intelligence Services) (adapted from Cherry et al., 2014, p.1f)

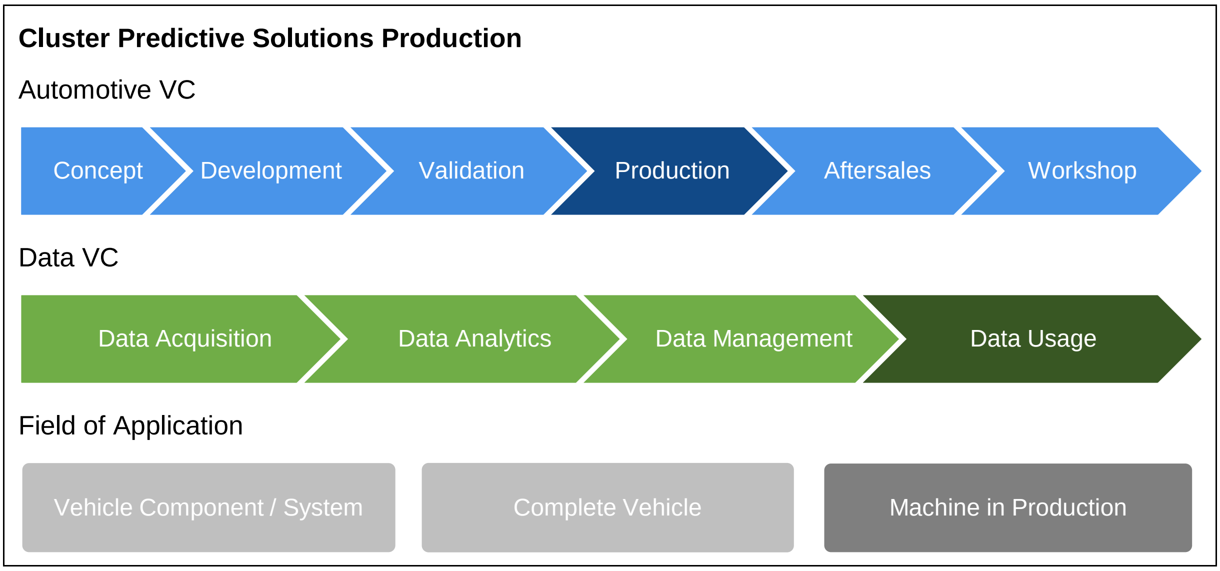


Figure 4.10: Classification of cluster Predictive Solutions Production (AVL Data Intelligence Services) (adapted from Cherry et al., 2014, p.1f)

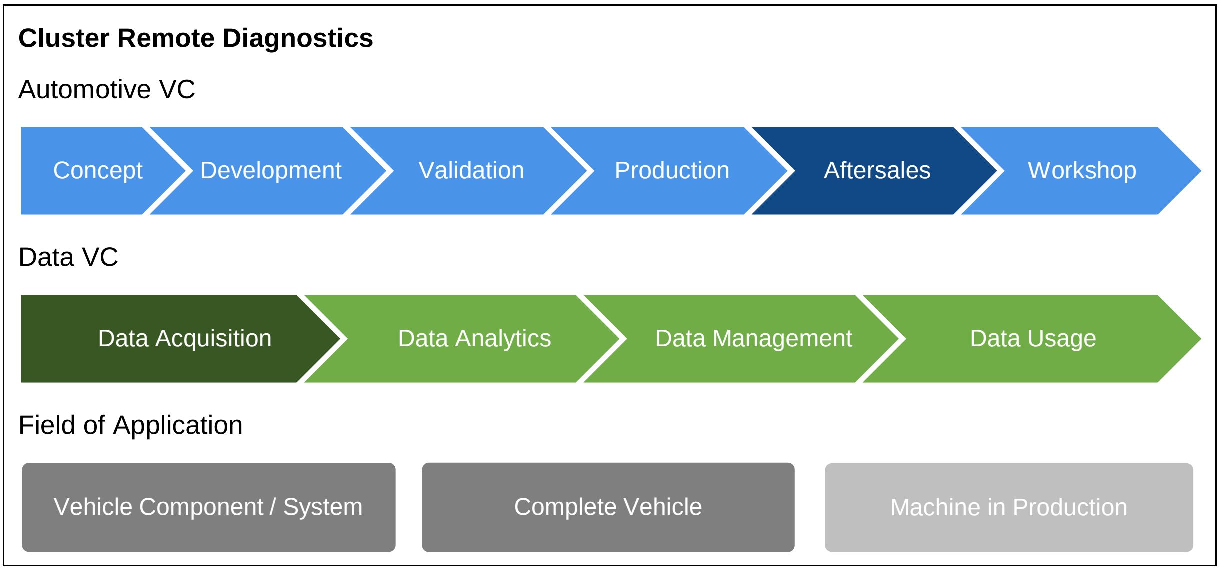


Figure 4.11: Classification of cluster Remote Diagnostics (AVL Data Intelligence Services) (adapted from Cherry et al., 2014, p.1f)

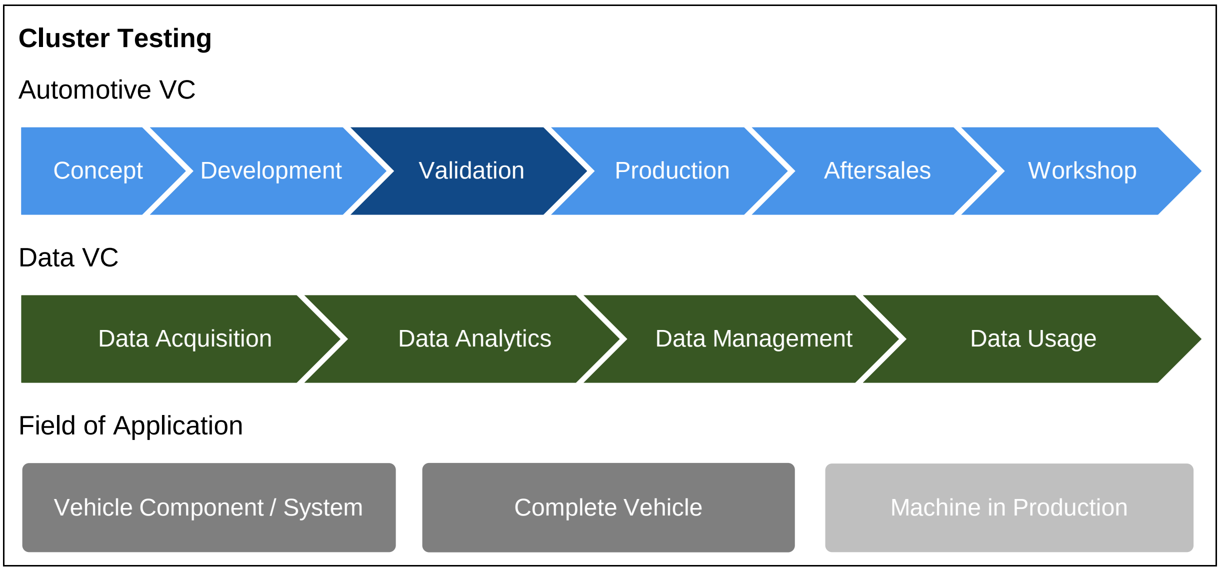


Figure 4.12: Classification of cluster Testing (AVL Data Intelligence Services) (adapted from Cherry et al., 2014, p.1f)

Remark: If a cluster was assigned to more phases in a value chain or to more fields of application, this does not imply that each service, tool, platform or other identified activity in this cluster, can be assigned to all those phases or fields. An example of this limitation is the cluster Testing. The whole cluster can be assigned to all phases of the data value chain, but within the cluster there are single services, tools, platforms that cannot be assigned to all phases of the data value chain.

4.2.3 Cluster Portfolio

The cluster portfolio is a method for the classification of clusters. It visualizes the market potential of clusters and its competition intensity in a single diagram. The following clusters got classified:

- Autonomous Driving
- Cloud Services
- Fleet Solutions Aftersales
- Predictive Solutions Aftersales
- Quality related Solutions

For each cluster that should be classified by the cluster portfolio, current and forecasted revenue data is required. The restriction to these five clusters is based on the availability of this data. The visual classification of the mentioned clusters is shown in Figure 4.13. It is based on their market potential and competition intensity. More details regarding the calculation of those characteristic values are provided in chapter 3.3.3.

If the competition intensity is 0, no company was identified to be active in the cluster. If it is 10, 30 of the 53 analysed companies were identified to be active in the cluster. The relationship between 0 and 10 is linear. The market potential depends on the market size and the Compound Annual Growth Rate (CAGR). The calculation is provided in chapter 3.3.3.

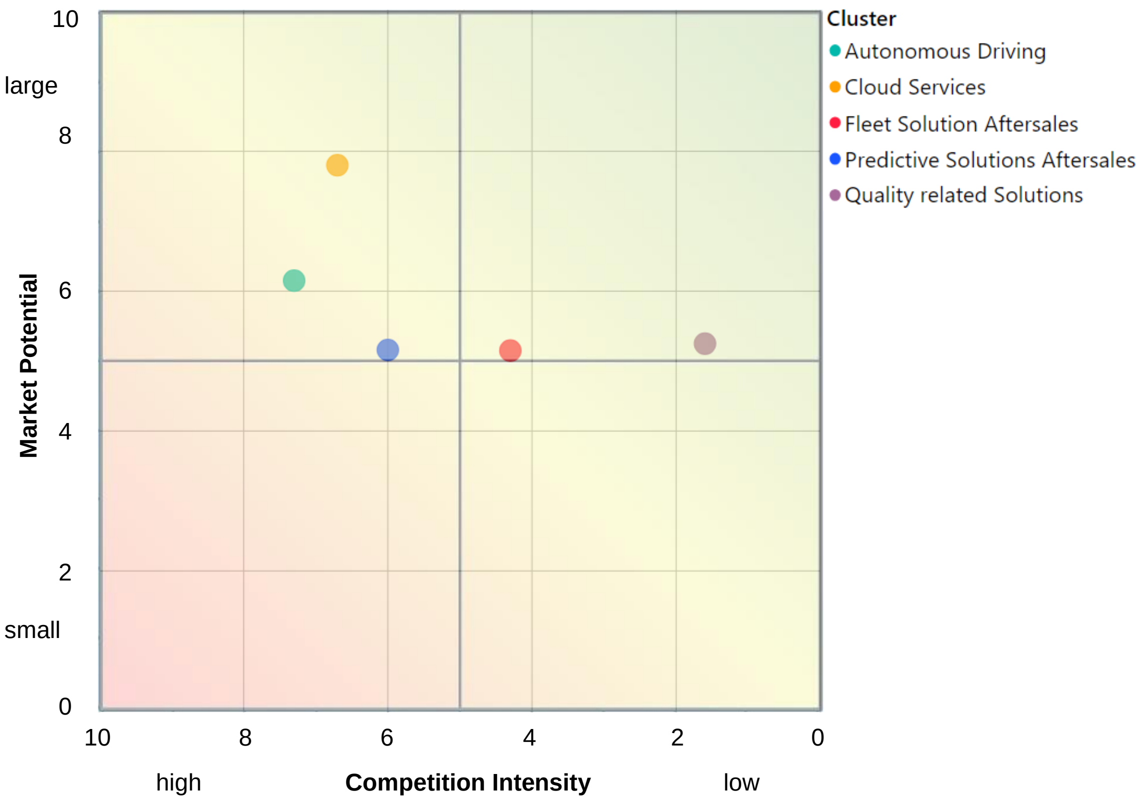


Figure 4.13: Cluster portfolio

Cloud Services have a high market potential but also a high competition intensity. The field of Cloud Services was identified as an emerging market, with a high number of competitors. The market potential of the other analysed clusters is moderate, with a varying competition intensity. The cluster Quality related Services has a low competition intensity compared to the other investigated clusters.

When considering the diagram in general, clusters in the upper right corner, which are characterized by a high market potential and a low competition intensity, are promising clusters regarding potential success. In contrast, clusters in the lower left corner are characterized by a high competition intensity and a low market potential. Therefore, clusters in this area are not advisable to start a business in.

4.2.4 Cluster Landscape

This chapter shows the defined clusters classified based on their share of ESPs active in them, plotted on the horizontal axis, and the number of ESPs and IT-companies active in them, on the vertical axis. The formula for the calculation of the ESP-share is provided in chapter 3.3.4.

In Figure 4.14, the landscape of the defined clusters is visualized. Clusters which are pictured as squares are the superordinate clusters, described in chapter 3.1.3.4. The clusters that are pictured as circles are those, which are, according to chapter 3.1.3.4, directly assigned to a phase in the automotive value chain.

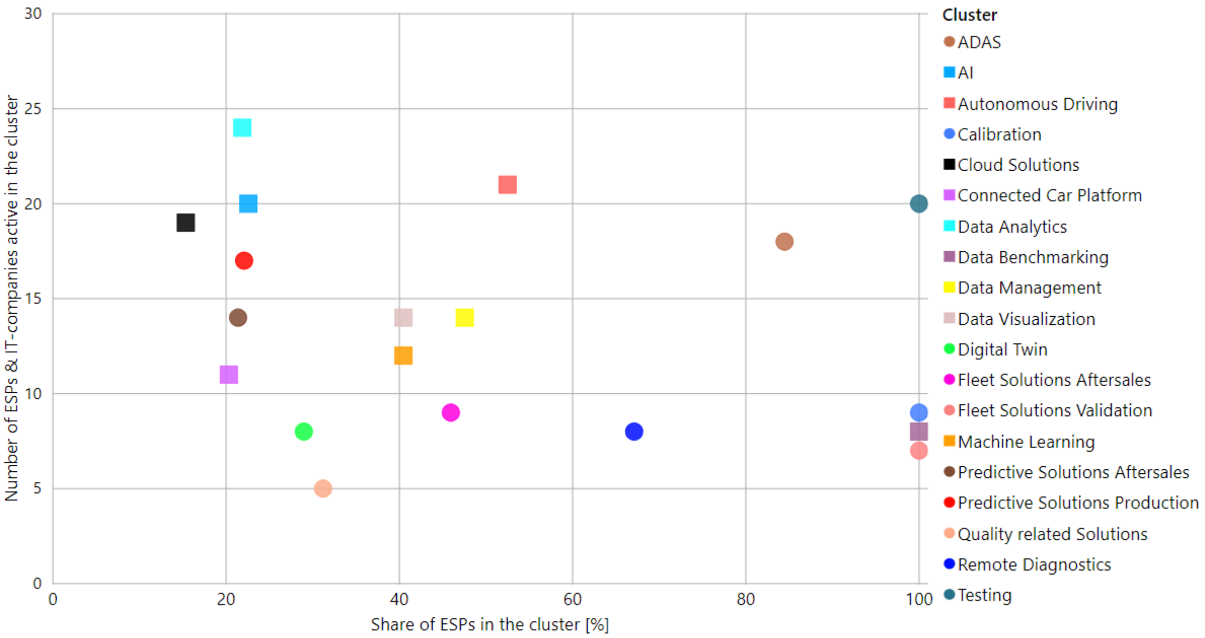


Figure 4.14: Cluster landscape

The aim of Figure 4.14 is, to classify a cluster regarding its competition intensity and the share of ESPs active in it. A low share of ESPs implies that the share of IT-companies is high. The four clusters Calibration, Data Benchmarking, Fleet Solutions Validation, and Testing are clusters where only ESPs were identified to be active in. The clusters ADAS and Remote Diagnostics are dominated by ESPs. The majority of the defined clusters have an ESP-share lower than fifty percent. A list with the “Share of ESPs in the cluster” and the “Number of ESPs & IT-companies active in the cluster” is provided for all clusters in Appendix 7.

The following two diagrams shown in Figure 4.15 illustrate the clusters where start-ups are active in and where they are not.

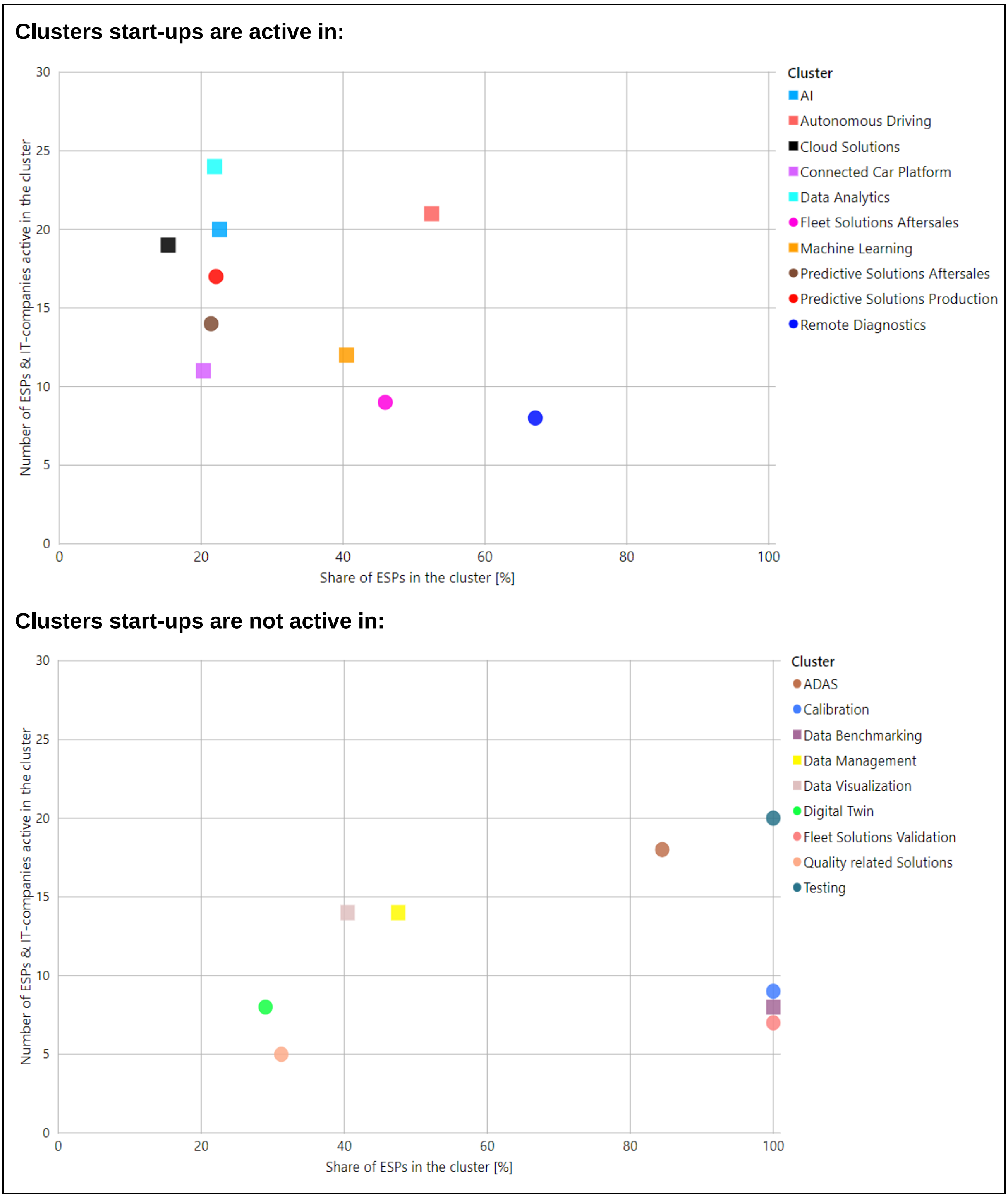


Figure 4.15: Clusters start-ups are active/ not active in

These two diagrams show that start-ups are active mainly in clusters with a lower share of ESPs. In the typical ESP clusters Calibration, Data Benchmarking, Fleet Solutions Validation, and Testing, no start-up was identified to be active in. In clusters which have an ESP-share higher than 70%, they were not identified to be active in at all.

In the visualization of clusters shown in Figure 4.14, three groups that are condensed in the evaluation, were identified. Each of those identified groups of clusters is framed in Figure 4.16.

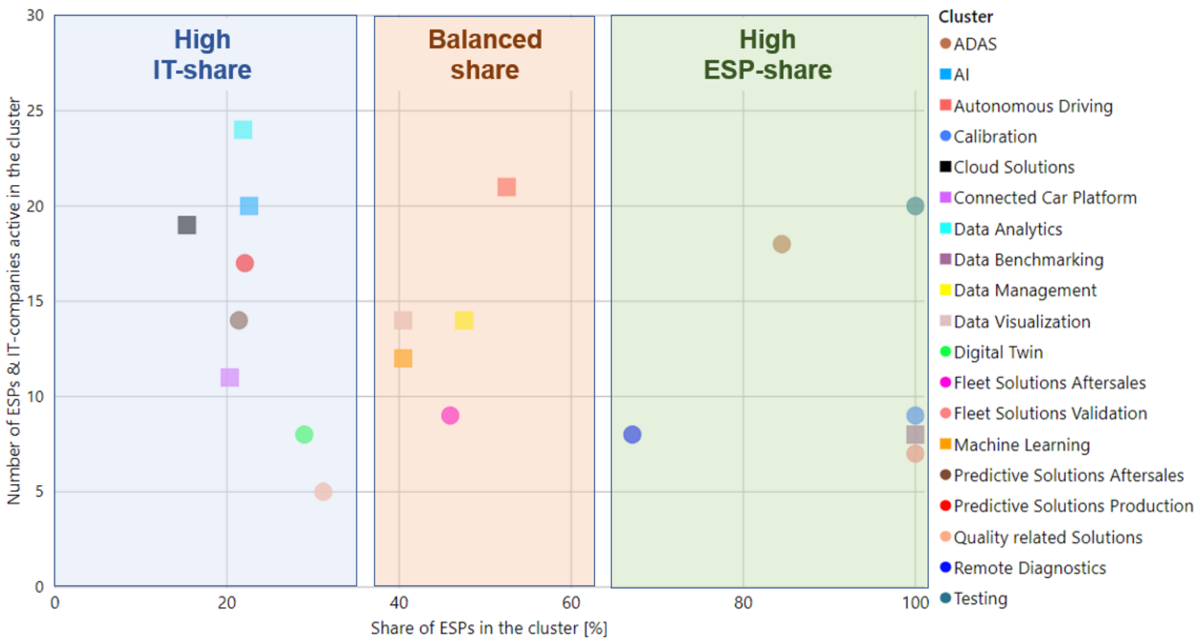


Figure 4.16: Three defined cluster groups

The clusters of the three groups shown in Figure 4.16 are listed in Table 9.

Table 9: Clusters of the three defined groups

High IT-share	Balanced share	High ESP-share
Artificial Intelligence	Autonomous Driving	ADAS
Cloud Solutions	Data Management	Calibration
Connected Car Platform	Data Visualization	Data Benchmarking
Data Analytics	Fleet Solutions Aftersales	Fleet Solutions Validation
Digital Twin	Machine Learning	Remote Diagnostics
Predictive Solutions Aftersales		Testing
Predictive Solutions Production		
Quality Related Solutions		

Following, each group is analysed in detail. This analysis ranks market players according to their activity in the clusters, for each group separately.

1) Investigation of clusters with a high IT-share

In Figure 4.17, the companies that are active in the defined clusters with a high IT-share are ranked by the number of clusters they are active in. This visualization aims to identify the most active companies and their clusters of activity in this group. All companies that are active in at least one of those eight defined clusters are listed.

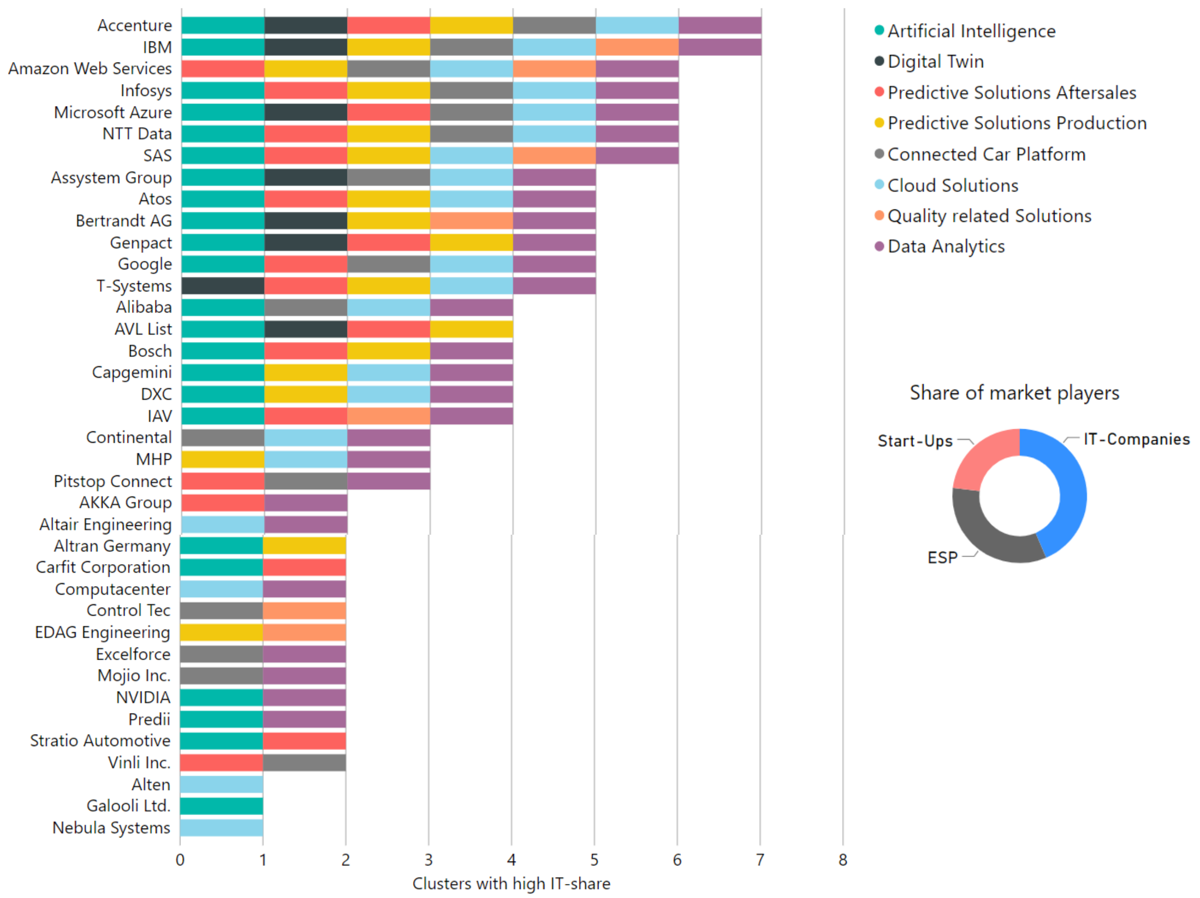


Figure 4.17: Companies activity in clusters with a high IT-share

In total, this group consists of eight clusters. As described in Table 9, these are:

- Artificial Intelligence
- Cloud Solutions
- Connected Car Platform
- Data Analytics
- Digital Twin
- Predictive Solutions Aftersales
- Predictive Solutions Production
- Quality Related Solutions

The companies with the highest activity in this group of clusters are Accenture and IBM. Both were identified to be active in seven of eight of those clusters. The seven companies with the highest activity in this group, are IT-companies.

The listed companies of Figure 4.17 consist of seventeen IT-companies, twelve ESPs, and nine start-ups. The ring-shaped diagram shows the share of each market player group. By selecting one of these groups in the ring-shaped diagram, the companies of this group become highlighted in ranking.

2) Investigation of clusters with a balanced share

Figure 4.18, the companies that are active in the clusters with a balanced share are ranked by the number of clusters they are active in. The aim of this visualization is to identify the most active companies and their clusters of activity. Therefore, companies that are active in at least one of the five defined clusters are listed.

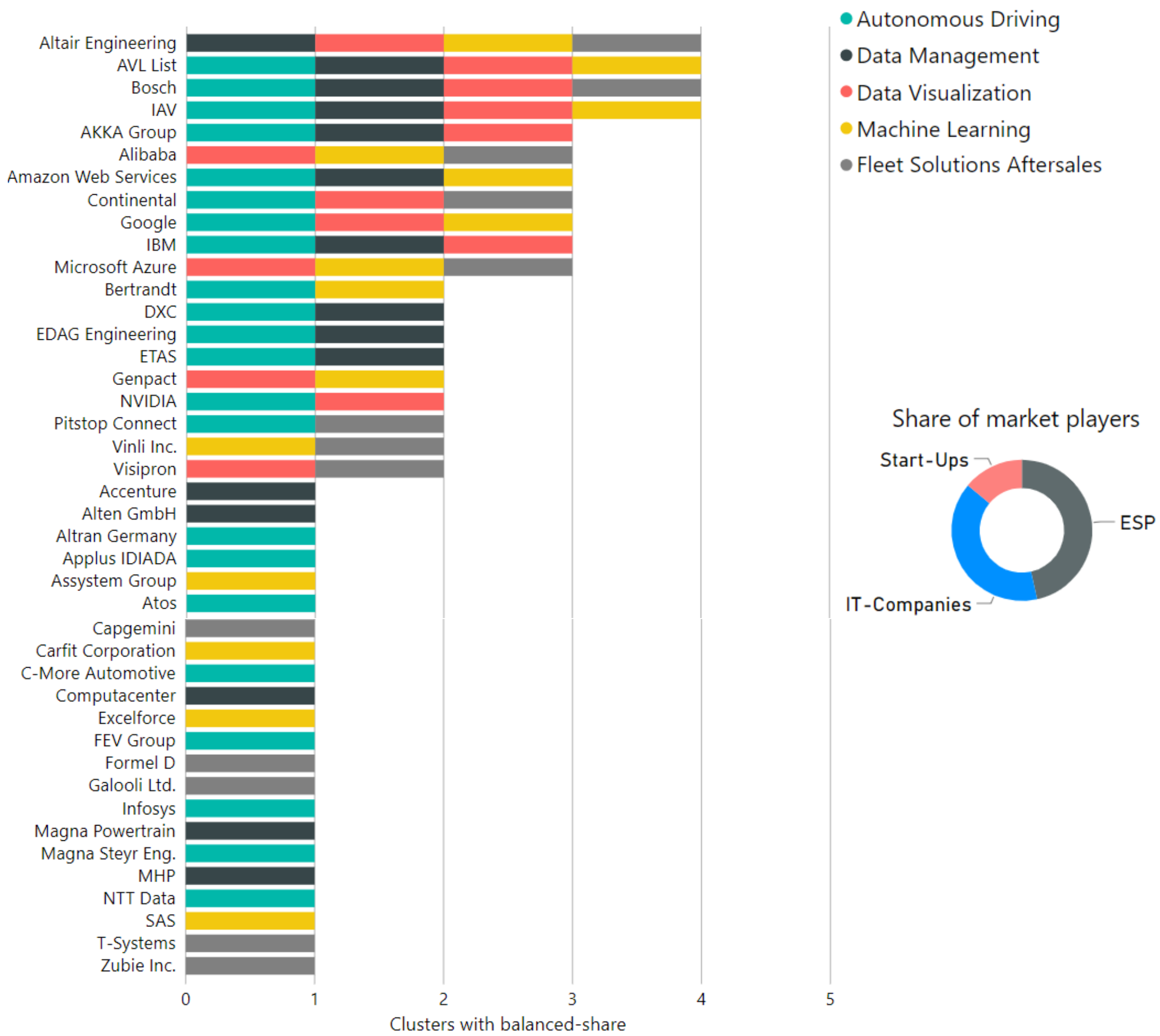


Figure 4.18: Companies activity in clusters with a balanced share

This group consists of five clusters. As described in Table 9, these clusters are:

- Autonomous Driving
- Data Management
- Data Visualization
- Fleet Solutions Aftersales
- Machine Learning

Companies with the highest activity in this group of clusters are active in four of those five clusters. These companies are solely ESPs. Seven companies are active in three of the defined clusters. These companies consist of two ESPs and five IT-companies.

The listed companies of Figure 4.18 consist of nineteen ESPs, seventeen IT-companies, and six start-ups. The ring-shaped diagram shows the share of each market player group. By selecting one of these groups in the ring-shaped diagram, the companies of this group become highlighted in ranking.

3) Investigation of clusters with a high ESP-share

In Figure 4.19, the companies that are active in clusters with a high ESP-share are ranked by the number of clusters they are active in. The aim of this visualization is the identification of the most active companies and their clusters of activity. Therefore, companies that are active in at least one of the six defined clusters are listed.

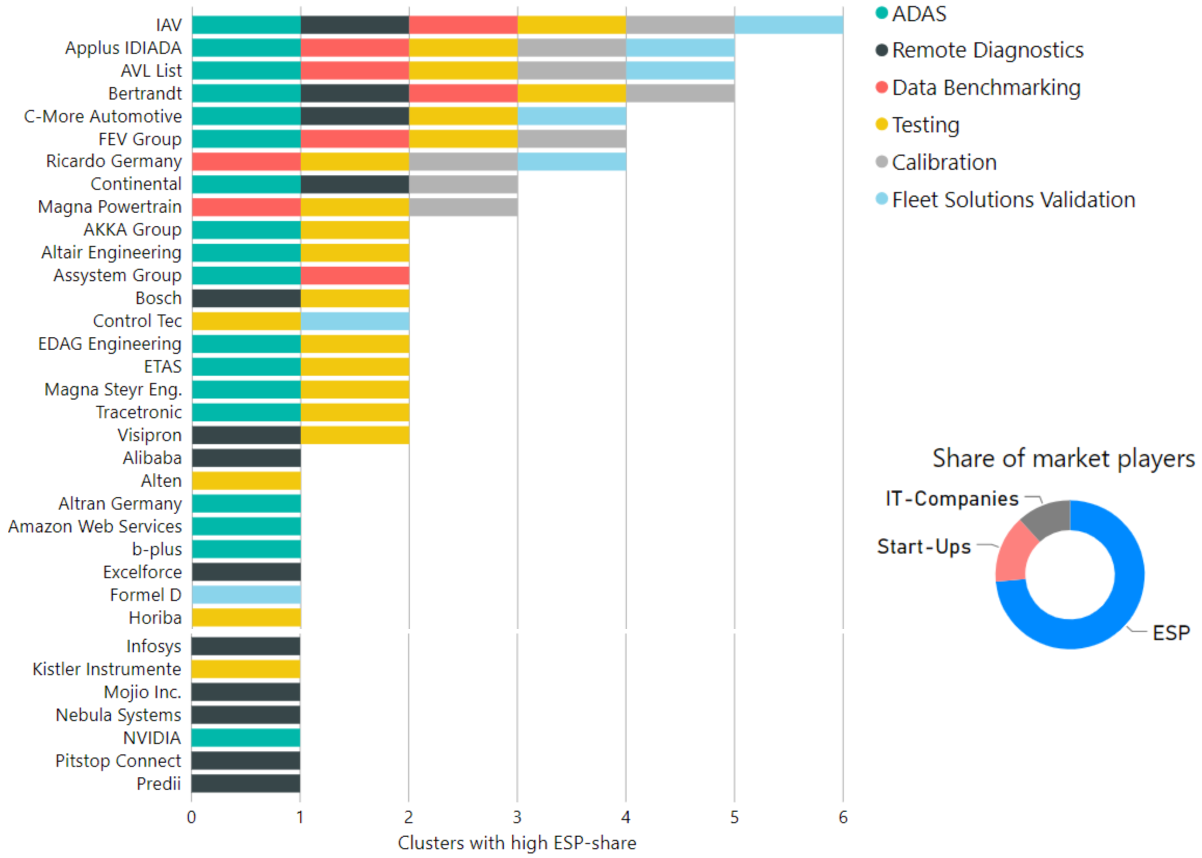


Figure 4.19: Companies activity in clusters with a high ESP-share

In total, this group consists of six clusters. According to Table 9, these clusters are:

- ADAS
- Calibration
- Data Benchmarking
- Fleet Solutions Validation
- Remote Diagnostics
- Testing

The company with the highest activity in this group is the ESP IAV, with an activity in all defined clusters. AVL was identified to be active in five of the six defined clusters. These clusters are ADAS, Data Benchmarking, Testing, Calibration, and Fleet Solution Validation. The only cluster, AVL is not active in, is Remote Diagnostics.

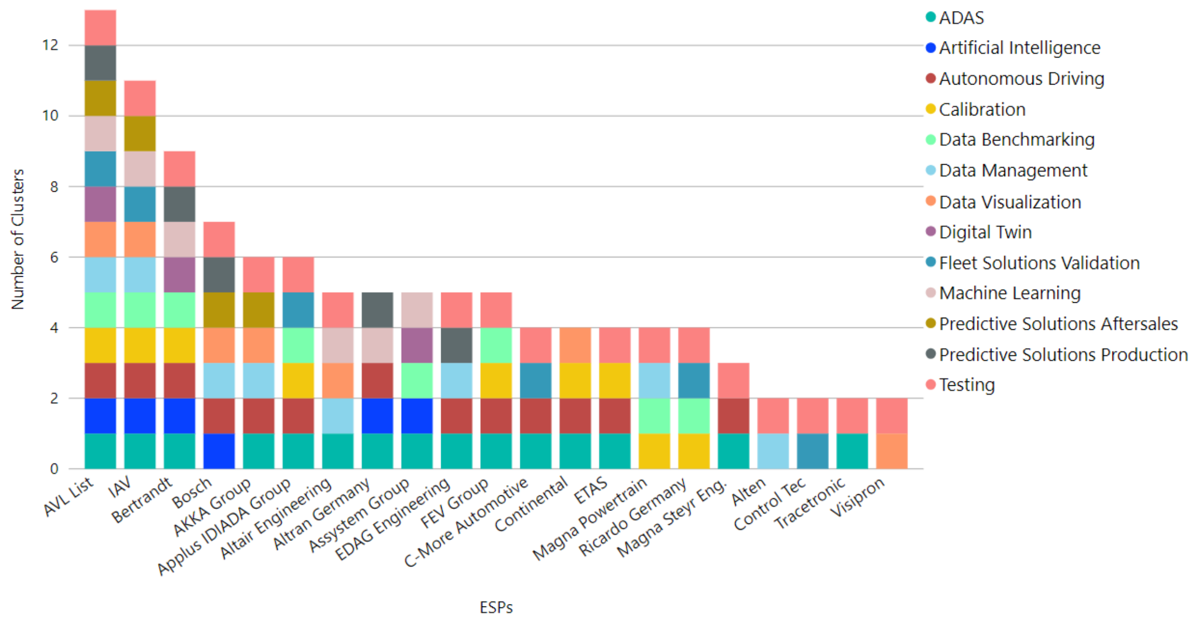
The listed companies in the ranking of Figure 4.19, that are active in at least two clusters, are exclusively ESPs. The analysed IT-companies or start-ups are active in one of these clusters at maximum. The ring-shaped diagram shows the share of each market player group. By selecting one of these groups in the ring-shaped diagram, the companies of this group become highlighted in ranking.

4.3 Comparison of AVL with other Market Players

This chapter shows the clusters AVL has in common with other companies. AVL was identified to be active in thirteen of the nineteen defined clusters. These thirteen clusters were considered when analysing the companies. Therefore, the clusters another company has in common with AVL are regarding to those thirteen clusters, AVL is active in. The consideration is done for the ESPs, IT-companies, and start-ups separately.

4.3.1 Comparison of Clusters: AVL – ESPs

This chapter ranks the ESPs by the number of clusters they have in common with AVL. Each ESP is represented by a bar, which is split into the corresponding clusters. The ESPs which have at least two clusters in common with AVL are shown in Figure 4.20.



*only ESPs listed which are active in at least two of the clusters, AVL is active in

Figure 4.20: Overlapping clusters AVL - ESPs

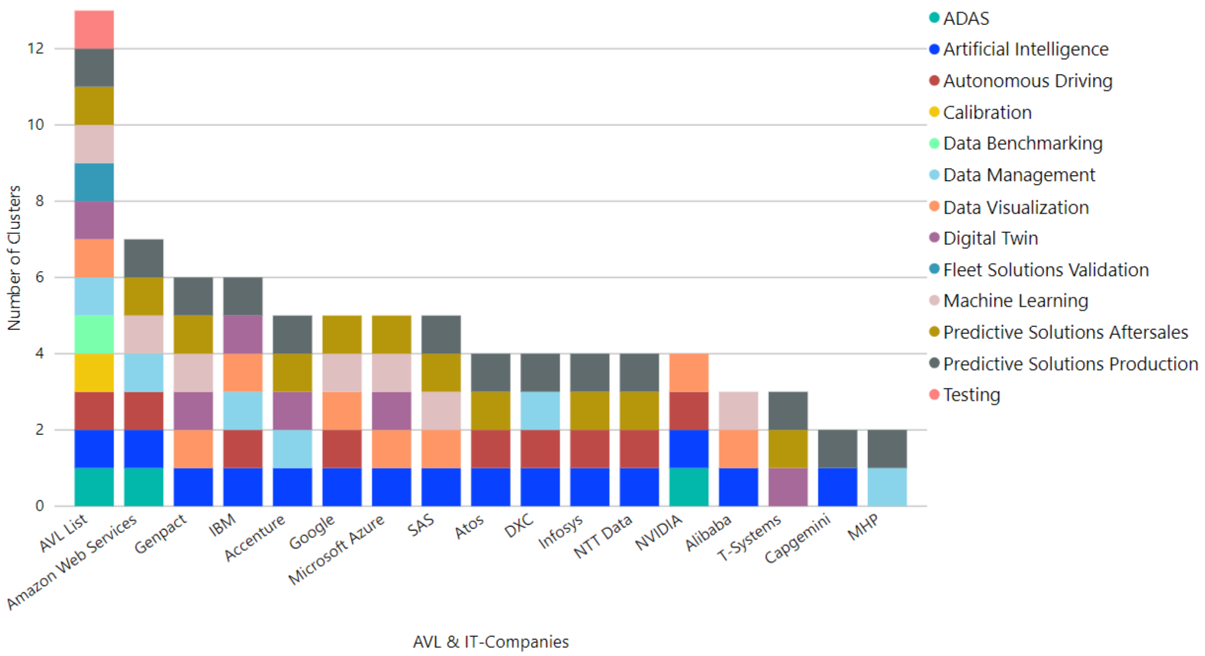
The company IAV has eleven of thirteen clusters in common with AVL, which corresponds to an overlapping rate of 85%. These eleven clusters are:

- ADAS
- AI
- Autonomous Driving
- Calibration
- Data Benchmarking
- Data Management
- Data Visualization
- Fleet Solutions Validation
- Machine Learning
- Predictive Solutions Aftersales
- Testing

With IAV, Bertrandt, and Bosch, three ESPs have an overlapping rate higher than fifty percent. The other analysed ESPs have an overlapping rate lower than fifty percent. A list with all ESPs and their overlapping clusters with AVL is provided in Appendix 4.

4.3.2 Comparison of Clusters: AVL – IT-companies

This chapter ranks the IT-companies by the number of clusters they have in common with AVL. Each IT-company is represented by a bar, which is split into the corresponding clusters. The IT-companies which have at least two clusters in common with AVL, are shown in Figure 4.21.



*only IT-companies listed which are active in at least two of the clusters, AVL is active in

Figure 4.21: Overlapping clusters AVL - IT-companies

Compared to the ESPs in chapter 4.3.1, only a single company, namely Amazon Web Services, has an overlapping rate higher than fifty percent. In general, it can be said that the similarity of IT-companies and AVL, regarding clusters, is lower, compared to ESPs and AVL. A list with all IT-companies and their overlapping clusters with AVL is provided in Appendix 4.

4.3.3 Comparison of Clusters: AVL – Start-ups

This chapter ranks the start-ups by the number of clusters they have in common with AVL. Each start-up is represented by a bar, which is split into the corresponding clusters. The start-ups which have at least one cluster in common with AVL are shown in Figure 4.22.

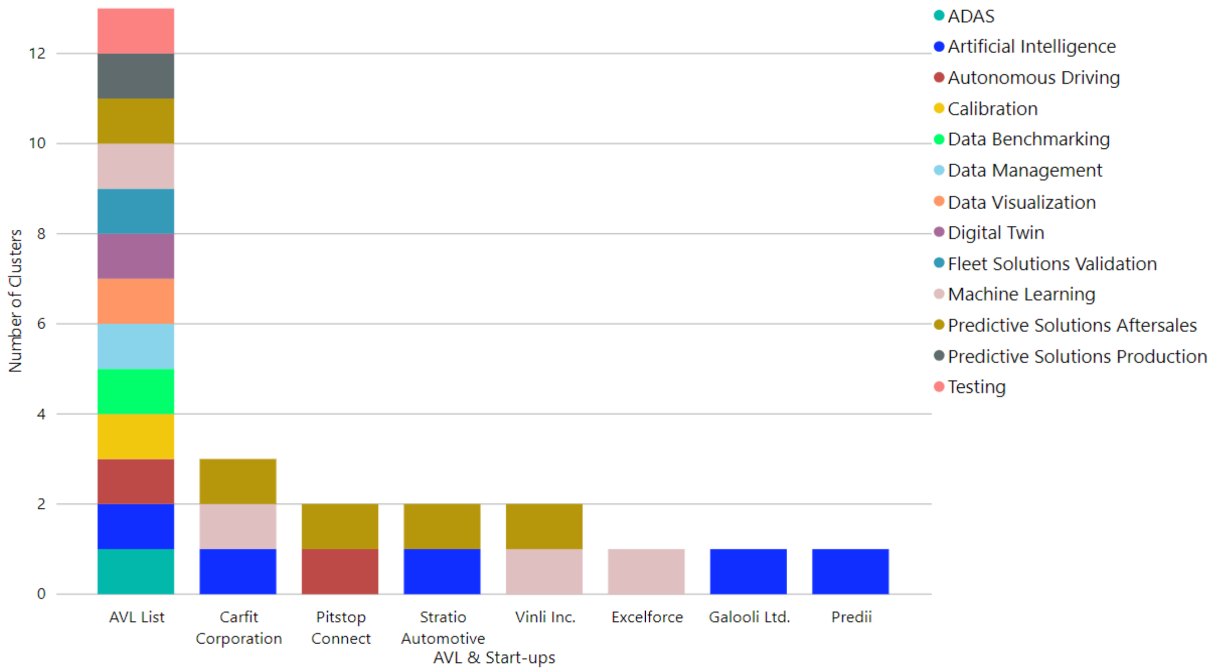


Figure 4.22: Overlapping clusters AVL - Start-ups

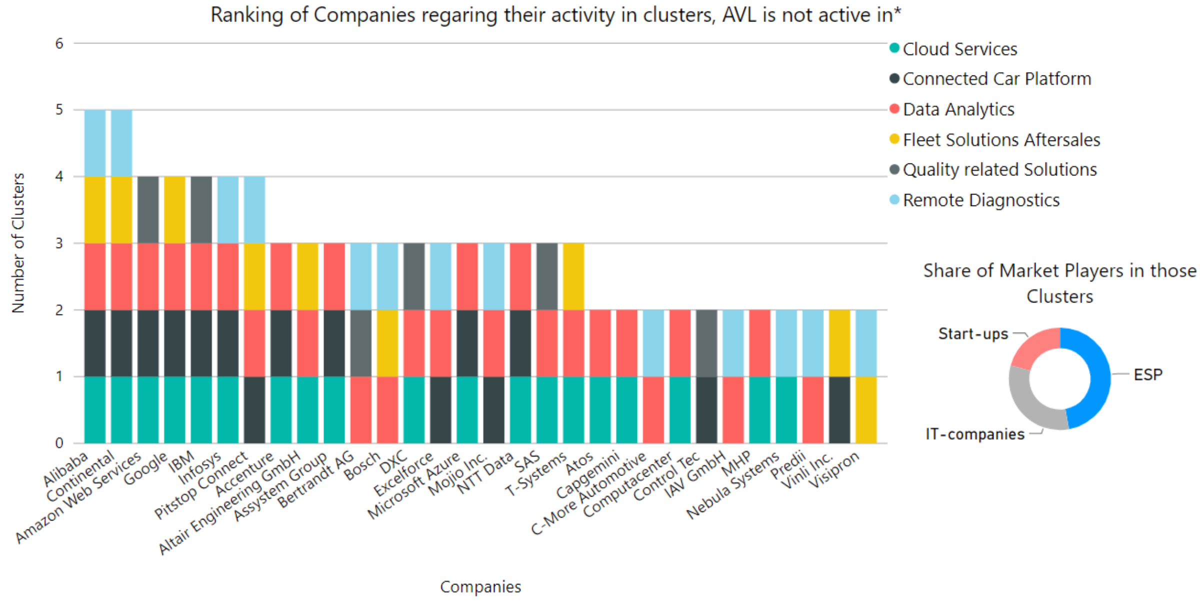
The number of clusters AVL has in common with start-ups is low compared to ESPs and IT-companies. This is mainly due to the fact, that start-ups focus on a specific thematic area, like for example predictive services in the aftersales phase. They are not as diversified as most ESPs and IT-companies are. Out of the 11 analysed start-ups, only seven start-ups have clusters in common with AVL. The others are active in clusters, where AVL is not active in. A detailed list of start-ups and their overlapping clusters with AVL is provided in Appendix 4.

4.4 Investigation of Clusters AVL is not active in

In this thesis, nineteen clusters and thirteen sub-clusters were defined. AVL was identified to be active in thirteen of those nineteen clusters. There was no activity of AVL detected in the six remaining clusters. Those clusters are:

- Cloud Services
- Connected Car Platform
- Data Analytics (as defined in chapter 3.1.3.4, this Data Analytics cluster contains general data analytics services and tools, which cannot be assigned to a specific phase in the automotive value chain)
- Fleet Solutions Aftersales
- Quality related Solutions
- Remote Diagnostics

The companies which are active in those clusters are ranked in Figure 4.23. In order to ensure a clear visualization, only the companies which are active in at least two of the six clusters were listed.



*only companies listed which are active in at least two of the clusters, AVL is not active in

Figure 4.23: Companies activity in clusters AVL is not active in

Fifteen of the thirty market players, that are active in at least two clusters AVL is not active in, are IT-companies, nine are ESPs, and six are start-ups. When looking at market players, that are active in at least four of the defined six clusters, seven companies can be identified. Five of these seven companies are IT-companies. Additionally, this group consists of one ESP and one start-up. This analysis shows that companies with a high activity in those clusters, are mainly IT-companies. The ring-shaped diagram shows the share of each market player group, without the restriction that the company has to be active in at least two of the defined clusters. If the company is active in at least one cluster, it is considered in this diagram. By selecting one of these groups in the ring-shaped diagram, the companies of this group become highlighted in ranking.

A detailed list with all market players and their activity in clusters AVL is not active in, is provided in Appendix 5.

4.5 Market Players Activity along the Automotive Value Chain

This section shows the results of the investigations discussed in chapter 3.6. Figure 4.24 visualizes the activity of all market player groups in each phase of the automotive value chain. In case a company is active in more phases of the automotive value chain, it was considered to be operating in each of those phases. The IT-company Computacenter and the start-up Teraki are not active in a cluster which is assigned to the automotive value chain. Therefore, an assignment was not possible.

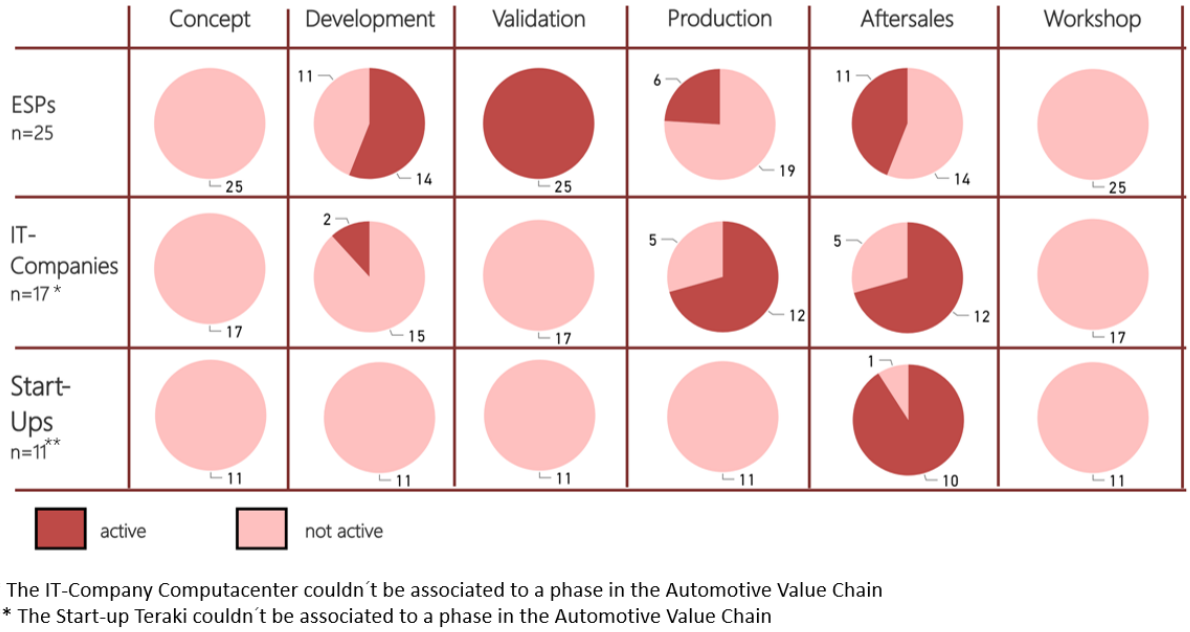


Figure 4.24: Activity along the automotive value chain

More detailed information regarding market players activity in each phase of the automotive value chain is provided in Appendix 6.

ESPs

In total, 25 ESPs were analysed. With fourteen out of 25, more than half of the considered ESPs are active in the development phase. Even all 25 ESPs are active in the validation phase. With six out of 25, about one-fourth of them are active in the production phase. Eleven ESPs operate in the aftersales phase which is less than 50% of the considered ones.

IT-companies

In total, seventeen IT-companies were analysed. The companies Amazon Web Services and NVIDIA are active in the development phase. With twelve active IT-companies in the phases production and aftersales, almost three-quarters of them are working in those.

Start-ups

In total, eleven start-ups were analysed. The only phase in the automotive value chain where an activity was identified, is in the aftersales phase. With ten out of eleven, almost all of the analysed start-ups are active in this phase. The one missing start-up could not be allocated to a phase in the automotive value chain.

A finding of this activity assessment is that the analysed ESPs focus on the development, aftersales and especially the validation phase. The analysed IT-companies are mainly active in the production and the aftersales phase. The analysed start-ups are working solely in the aftersales phase.

4.6 Market Players Activity Field

This chapter shows a classification of each analysed market player and the resulting activity fields of the three analysed market player groups. In Figure 4.25, this classification and the identified activity fields are shown. As mentioned in chapter 3.4, on the horizontal axis, the “Degree of activity of ESPs in investigated clusters”, with a range from 0 (low) to 100 (high), is illustrated. The vertical axis shows the number of clusters the company is active in. The ESPs are pictured as circles, and their area of activity is highlighted blue. The IT-companies are pictured as squares, and the area of IT-companies’ activity is highlighted orange. The last group are the start-ups. Those are visualized as triangles, and their area of activity is highlighted green.

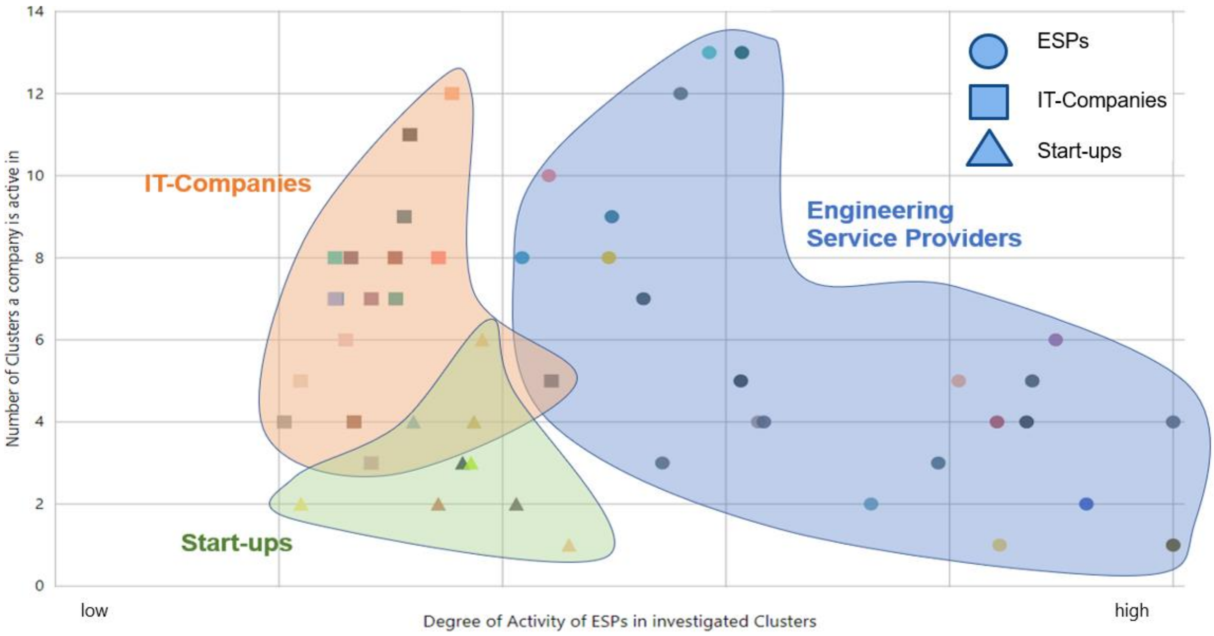


Figure 4.25: Market players fields of activity

Figure 4.26 shows the market players field of activity with some selected companies of particular interest. In order to ensure a clear visualization, not all companies are named. A detailed list which allows identifying each company for this diagram is provided in Appendix 8.

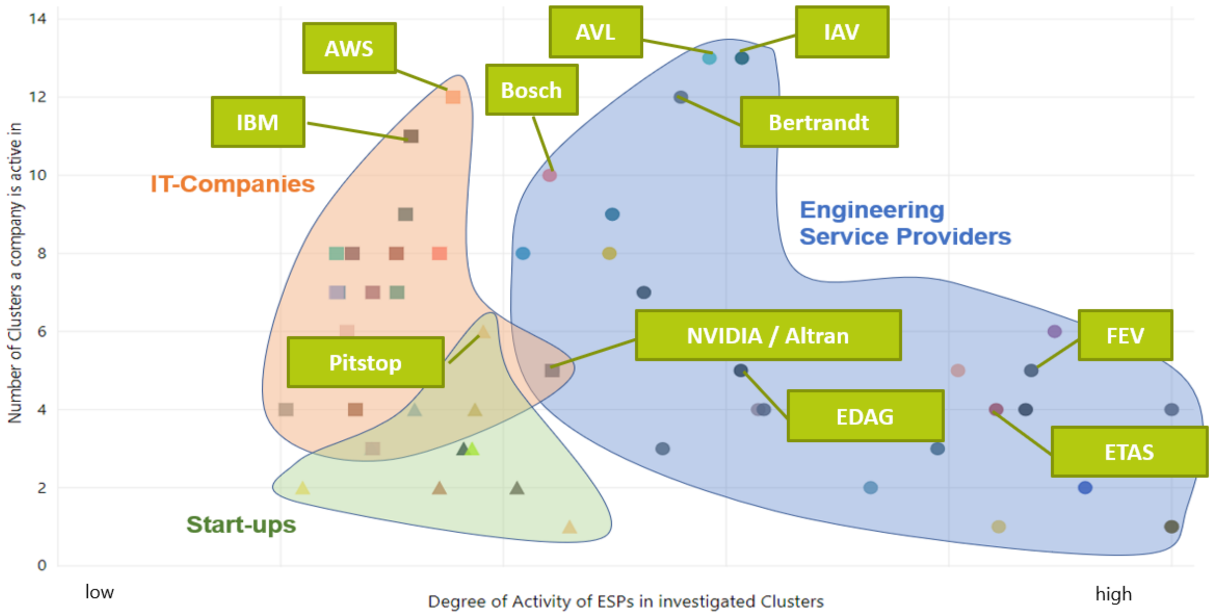


Figure 4.26: Market players fields of activity- Company selection

Smaller ESPs, in terms of clusters they are active in, are more focusing on typical ESP tasks. They are mainly active in clusters where the share of ESPs is high. Bigger ESPs, in terms of clusters they are active in, are more likely to have a higher focus on IT-clusters. The "Degree of Activity of ESPs in investigated Clusters" is lower compared to most small ESPs. AVL, IAV, and Bertrandt were identified to be quite similar in terms of their size and activity. The similarity in activity was also identified in chapter 4.3.1.

IT-companies field of activity (orange surface) is, compared to the ESPs field of activity (blue surface), small. There are smaller and bigger companies, in terms of clusters they are active in, but their "Degree of Activity of ESPs in investigated Clusters" differs only slightly, except of NVIDIA. NVIDIA is the IT-company that has the highest "Degree of Activity of ESPs in investigated Clusters". Amazon Web Services and IBM are the IT-companies identified to be active in most clusters.

Start-ups' "Degree of Activity of ESPs in investigated Clusters" is similar to IT-companies'. This becomes visible when comparing start-ups field of activity (green surface) with the IT-companies field of activity (orange surface). The main difference between start-ups and IT-companies is the number of clusters the companies are active in. Most IT-companies were identified to be active in more clusters than most start-ups. This is mainly due to the high degree of specialisation on one thematic area start-ups have. They are not as diverse as bigger IT-companies are.

The overlap of the ESPs area of activity with the IT-companies area of activity is small. Only the two companies Altran and NVIDIA were identified in this overlapping area. Between ESPs and start-ups, no overlapping area was identified. The overlap between IT-companies area of activity and start-ups area of activity consists of five companies.

No companies were identified in the left fifth of the diagram. This can be explained by the fact that the focus of this thesis was on IT-companies that are also active in the automotive industry. There is no cluster in which all considered companies are IT-companies.

4.7 Companies working in ADAS-related Activities

This chapter shows a ranking of companies, active in the defined superior cluster “ADAS-related activities”. The definition of this superior cluster is provided in chapter 3.8. To rank the market players regarding their activity in the superior cluster “ADAS-related activities”, it was identified in how many of the five considered clusters, they are active in. These five clusters are:

- ADAS-Development
- ADAS-Validation
- ADAS-Verification
- Artificial Intelligence
- Autonomous Driving

The result consists of all companies that are active in at least one of these five clusters. It is shown in Figure 4.27.

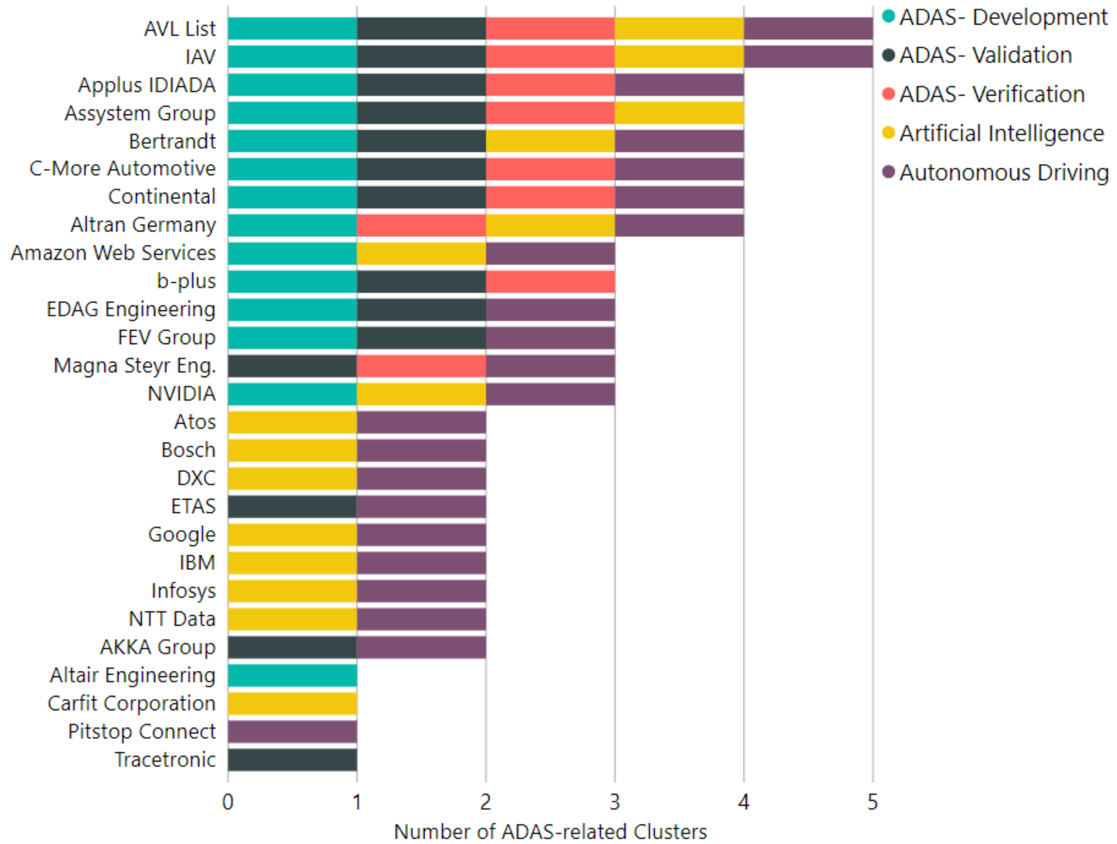


Figure 4.27: ADAS related activities on a company level

In total, 27 companies were identified to be active in at least one of the defined clusters. On top of the ranking, the companies AVL and IAV, which are both active in all five defined clusters, are positioned. ESPs occupy the first eight ranks, which are characterized by an activity in four of the five defined clusters.

23 companies were identified to be active in at least two clusters, fifteen of these 23 are ESPs and eight are IT-companies. IT-companies with the highest activity in those clusters are Amazon Web Services and NVIDIA. Both provide information regarding an activity in ADAS, the other six only share information about an activity in AI and autonomous driving. None of the analysed start-ups was identified to be active in at least two of the defined clusters.

Building on the results shown in Figure 4.27, additional information regarding companies' global presence was added to the analysis. Companies global locations were tracked on a country-level, as described in chapter 3.2.2. This information was used to identify companies' presence in the following defined continents:

- Africa
- Australia
- Asia
- Europe
- North America
- South America

The preparation of the results allows selecting a company of interest from the ranking. When selecting a specific company, the map on the right side highlights the continents, this company has locations in. An example is shown in Figure 4.28. In this example Bertrandt was randomly selected and the map provides the continents in which Bertrandt is located.

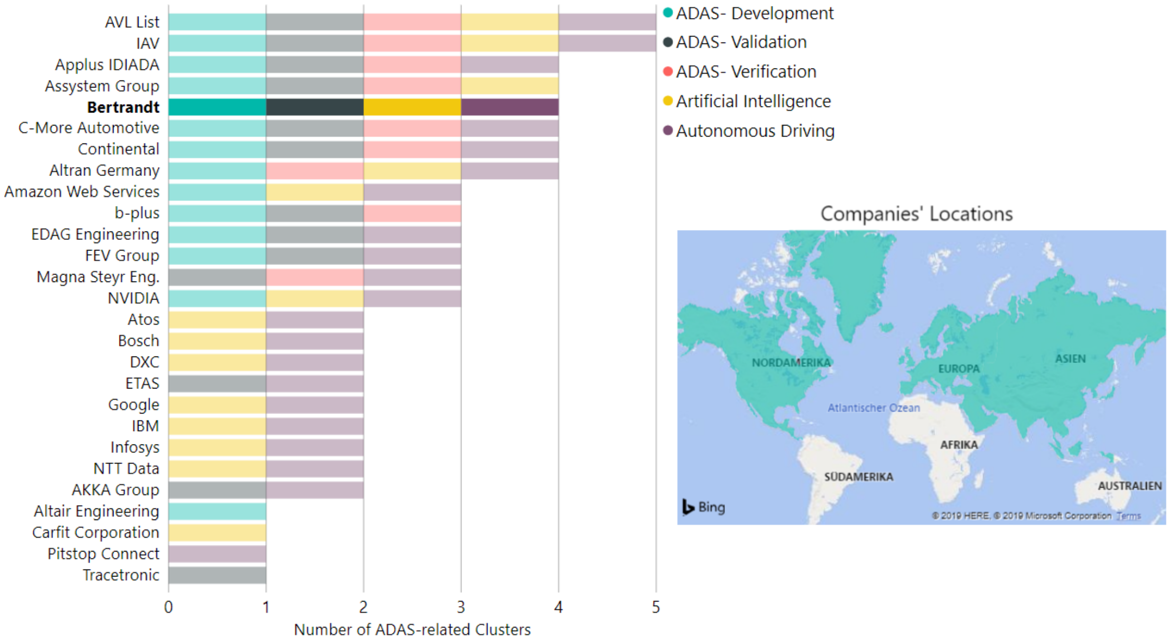


Figure 4.28: Geographical information of companies in ADAS related activities - Example

Except b-plus and C-More Automotive, all companies that are active in at least three of the defined clusters are located globally in the big markets of Asia, Europe, and North America. The branches of b-plus and C-More Automotive are all in Europe.

The result preparation also allows identifying market players, based on their locations in the defined continents. This can be used for a rough assessment of the competitive situation in a specific geographical region. For example, by selecting the defined continent South America, the market players active in this geographical region remain their intense colour in the list. Those which are not active, fade. This example is shown in Figure 4.29.

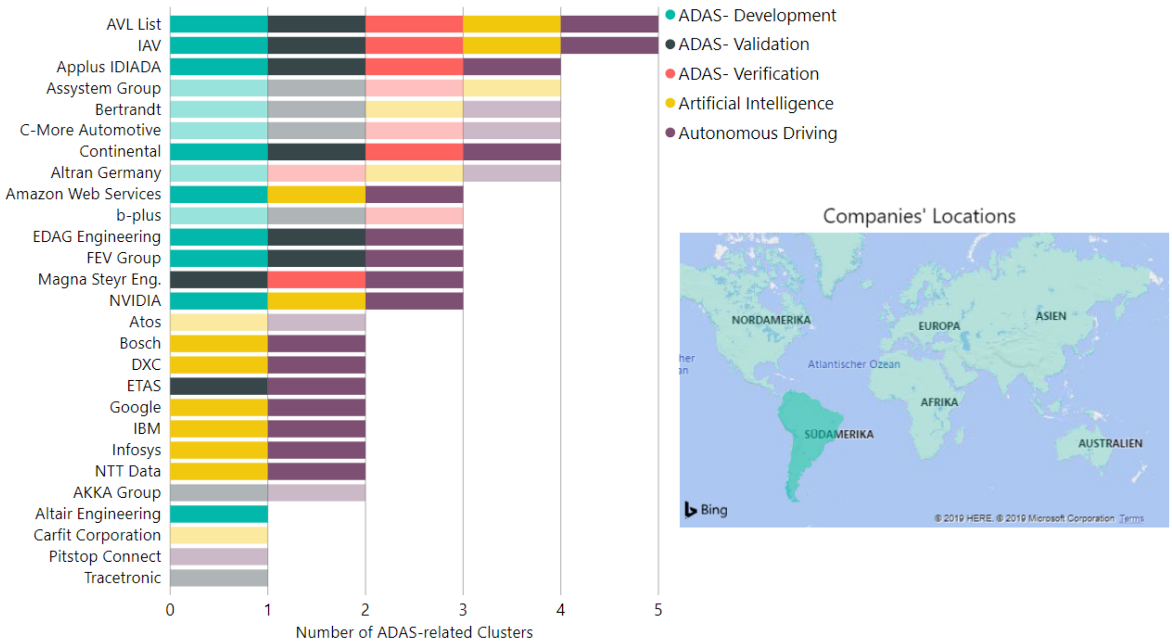


Figure 4.29: Geographical information of companies in ADAS related activities - Example

Europe, Asia and North America are the markets where almost all listed companies are located. In South America, about three quarters of the analysed companies were identified to have locations. With less than half of the companies, the continents Africa and Australia have the lowest rate of company locations.

4.8 Companies active in the Cluster Testing

In this chapter the results of the Testing-cluster investigations are shown. The details of these analyses are described in chapter 3.9. In order to rank the market players regarding their activity in the cluster Testing, it was identified in how many of the seven sub-clusters they are active in. The result, which is illustrated in Figure 4.30, consists of all companies that are active in at least one sub-cluster.

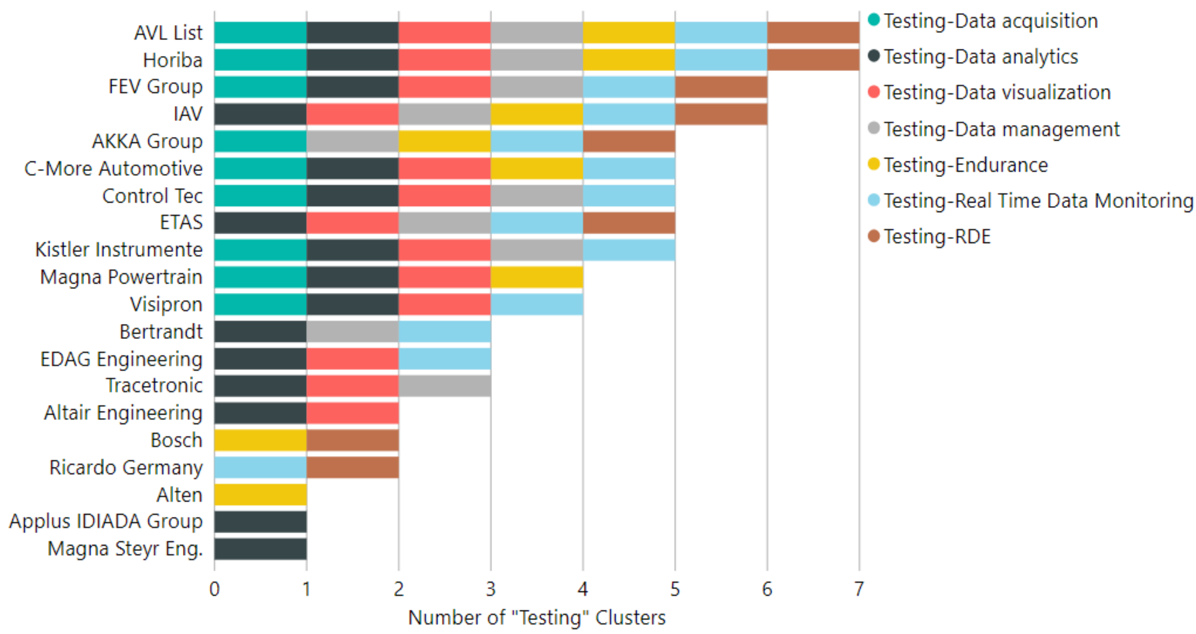


Figure 4.30: Cluster Testing - Company level

AVL List and Horiba head the ranking, followed by the companies IAV and FEV. None of the analysed IT-companies or start-ups were identified to be active in at least one of the sub-clusters. A list of all companies and their sub-clusters of activity is provided in Appendix 10.

Similar to chapter 4.7, the preparation of the results allows selecting a company of interest. The map on the right side then shows the continents where the company is located. An example is provided in Figure 4.31. The result preparation also allows identifying market players, that have locations in the defined continents. By selecting a defined continent, the market players active in this geographical region remain their intense colour in the list, and those which are not active, fade.

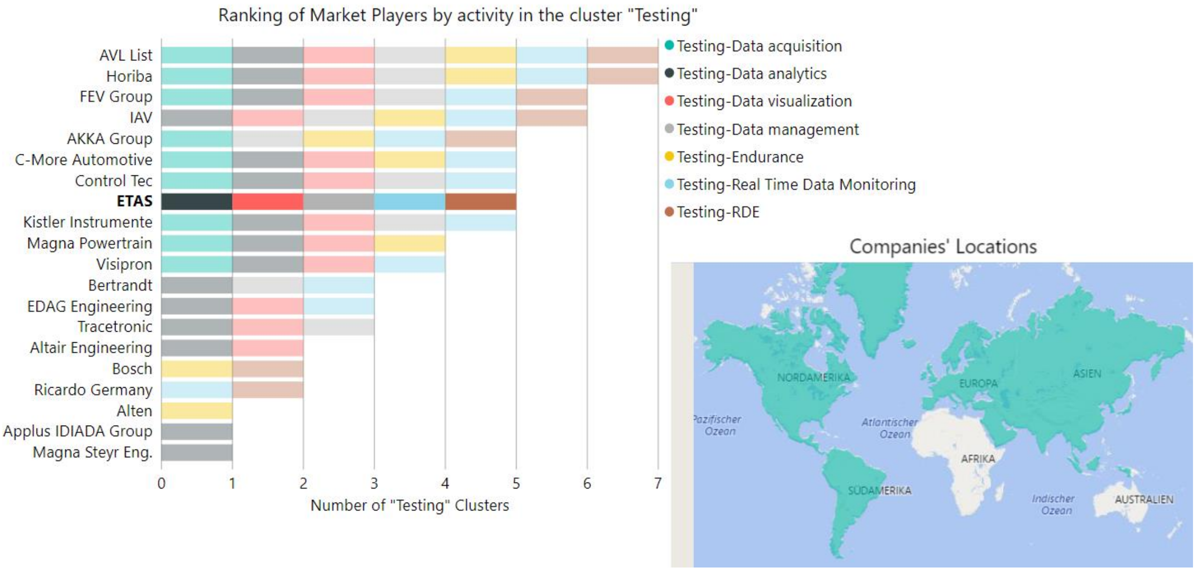


Figure 4.31: Geographical information of companies in Testing-cluster - Example

Except C-More Automotive, Control-Tec and Vispiron, all companies have locations in the big markets of Asia, Europe and North America. Most of them are also situated in South America. Only few companies are located in the markets of Africa and Australia.

4.9 Companies’ offered Services

This evaluation shows the results of the investigations described in chapter 3.10. Figure 4.32 shows a section of a detailed analysis where all companies and the clusters where they offer services are listed. The clusters where the companies offer services are highlighted red and characterized with a “1”. Additionally, the clusters where the company provides information, but no particular service can be identified, are highlighted green. As defined in chapter 3.1.3.4, the clusters highlighted grey are sub-clusters, the blue ones are clusters, and the orange ones are superordinate clusters.

ESPs	ADAS- Development	ADAS- Validation	ADAS- Verification	**ADAS**	Calibration Data Management	Calibration Machine Learning	Calibration OBD	**Calibration**	Digital Twin	Fleet Solutions Aftersales	Fleet Solutions Validation	Predictive Solutions Aftersales	Predictive Solutions Production	Quality related Solutions	Remote Diagnostics	Testing- Data acquisition	Testing- Data analytics	Testing- Data management	Testing- Data visualization	Testing- Endurance	Testing- RDE	Testing-Real Time Data Mon.	**Testing**	Artificial Intelligence	Autonomous Driving	Cloud Solutions	Connected Car Platform	Data Analytics	Data Benchmarking	Data Management	Data Visualization	Machine Learning	**Companies Cluster-Sum**
AVL List	1	1	1	1	1	1	1	1	1		1	1	1								1		1	1	1				1	1	1	1	13
AKKA		1		1								1								1	1		1					1		1	1		6
Altair Engineering										1																1		1		1			4
Alten																				1			1			1				1			3
Altran Germany													1											1								1	3
Applus IDIADA	1	1		1			1	1			1						1						1						1				5
Assystem	1	1	1	1					1															1		1	1	1	1				7
Bertrandt	1	1		1			1	1	1				1					1				1	1					1	1			1	8
Bosch										1		1	1		1					1	1		1	1									6
b-plus																																	0
C-More Automotive	1	1	1	1							1									1			1										3
Continental	1	1	1	1	1		1	1		1					1											1	1	1			1		8
Control Tec											1			1		1	1	1	1			1	1				1						4

Figure 4.32: Services offered by companies - Selection

This analysis should be understood as additional information. Due to the limitations described in chapter 3.10, no further investigations are based on it.

The list with all companies is provided in the Appendix 11.

5 Discussion of Results and Conclusions

In this Master Thesis, data-driven services, tools, platforms, and other data-based activities like projects, research activities, cooperations, and takeovers, of the three defined market player groups were analysed. Those three market player groups are ESPs, IT-companies and start-ups. The analysis of those groups brought a variety of results, which are being discussed in this chapter.

The gathered information was categorized by using clusters. In total, 19 clusters were defined. This thesis contains three different types of clusters. There are clusters that can be assigned to a phase in the automotive value chain. A second type of clusters are the sub-clusters. These divide a cluster into more detailed thematic areas. The third group of clusters are the superordinate clusters. They cannot be assigned to a specific phase in the automotive value chain. As they are more general, they can have their application in various phases of the automotive value chain. Further analysis of those in chapter 3.1.3.4 defined clusters, identified the market potential and the competition intensity of these areas. Cloud solutions and autonomous driving are expected to become big markets with a high monetary potential. These two thematic areas are already characterized by a high competition intensity.

The defined clusters show major differences regarding the number of companies active in them and the structure of the market player groups. The cluster landscape identifies both characteristics for each defined cluster. The clusters Testing, Fleet Solutions Validation, Calibration and Data Benchmarking are characterized by a 100% ESP-share. Only ESPs were identified to be active in these clusters. The cluster Cloud Solutions described above, which has a high potential, is characterized by a high share of IT-companies active in it. While fifteen of the seventeen IT-companies were identified to be active in this cluster, only four of the 25 ESPs are. The cluster ADAS, which is assigned to the automotive value chain, is characterized by a high ESP-share. The general cluster Autonomous Driving is characterized by an ESP-share of about fifty percent and an IT-share of about fifty percent. In comparison to IT-companies, ESPs were identified to have a higher activity in clusters assigned to the automotive value chain.

When looking at the 25 analysed ESPs, most smaller ESPs were noticed to have a high focus on typical ESP-clusters, such as testing or calibration. In addition to the typical ESPs tasks, bigger ESPs are more likely to have a higher focus on IT-clusters. Compared to IT-companies and start-ups, ESPs are more likely to offer concrete data-driven services and tools, for example for ADAS-Development or Testing. In comparison to IT-companies and start-ups, they are more active in clusters that are assigned to the automotive value chain.

The phases of the automotive value chain, where ESPs were identified to be active in, are development, validation, production, and aftersales. All analysed ESPs are active in the validation phase. About one fourth provides solutions for the production, which can be distinguished between predictive solutions and quality related solutions. Fourteen ESPs were identified to be active in the development phase, eleven provide solutions for the aftersales.

As this thesis should give an overview of the competitive landscape to AVL, companies that are similar to AVL, in terms of clusters both are active in, were identified. The company with the highest similarity in activity is the company IAV, followed by Bertrandt and Bosch. IAV is active in eleven of the thirteen clusters AVL is active in. This similarity identifies IAV as a major competitor in the data business. Bertrandt and Bosch were identified to be active in more than fifty percent of the clusters, AVL is active in. The overlapping rate of the other analysed ESPs is lower than fifty percent. There are existing smaller ESPs with a focus on a specific thematic area in the data business. These companies are active in less clusters compared to the big players such as AVL or IAV, but they have high capabilities in specific areas. As an example, the company C-more automotive, which is highly active in the ADAS cluster, can be named. These companies are not represented in the revenue-based rankings as their revenue is too low, but due to their capabilities in specific areas, they are highly relevant market players.

Since AVL was identified to be active in thirteen of the nineteen defined clusters, there are remaining six clusters AVL is not active in. These six clusters are: Remote Diagnostics, Data Analytics (general analytics that cannot be assigned to a phase in the automotive value chain), Quality related Solutions, Cloud Services, Connected Car Platform, and Fleet Solutions Aftersales. These clusters are characterized by a high IT-share. ESPs with a high activity in those clusters are Continental, Altair, Assystem, Bertrandt, and Bosch.

As ADAS is a highly relevant topic for AVL, offerings in this technology were considered in a detailed analysis, which resulted in this area being dominated by ESPs. Among the companies where a high activity was identified are the big ESPs AVL, IAV, Bertrandt, and Continental. The competition in this area is characterized by the big ESPs, by smaller, highly specialised ESPs and by IT-companies. The IT-companies with a high activity in this area are Amazon Web Services and NVIDIA. Both are offering ADAS-Development services. The analysed start-ups do have a low activity in the area of ADAS and autonomous driving.

An activity field of many ESPs is testing. Twenty of the 25 analysed ESPs were identified to be active in this area. The companies with the highest activity are AVL and Horiba, followed by FEV and IAV. Neither IT-companies, nor start-ups were identified to be active in the area of testing.

IT-companies were identified to be more active in typical IT-tasks like data analytics or the development of cloud solutions for automotive purposes. Some of them provide information regarding an activity in the area of autonomous driving, but most of them do not offer concrete services or tools. They are highly active in more general areas that are not restricted to the automotive industry, such as AI. In those areas, many of them provide services for clients of different industries, including the automotive industry. Regarding the automotive value chain, IT-companies are mainly active in the phases production and aftersales, in which their focus is on predictive solutions. The IT-company which has the highest overlapping rate with AVL is the internet giant Amazon, followed by Genpact and IBM. Amazon has seven clusters in common with AVL. They are active in the field of autonomous driving, predictive solutions, AI services, and Machine Learning.

Start-ups happen to be characterized by focussing on a specific topic, like for example predictive maintenance. This results in a low number of clusters, a start-up is active in. When looking at the area of activity, start-ups are similar to IT-companies, except that IT-companies are active in a higher number of clusters. No activity of start-ups was identified in the typical ESP-clusters such as Testing or Calibration. The clusters they are active in, have a high share of IT-companies. In the automotive value chain, the only phase where the analysed start-ups were identified to be active in, is the aftersales phase. The analysed start-ups focus on the utilization of data which is produced by cars that are already in use. Typical use-cases are remote diagnostics and predictive maintenance solutions via a connected car platform.

Cooperations between ESPs and IT-companies are quite common, especially in autonomous driving and AI. Many companies are trying to find a partner for the transformation that is expected to take place in the automotive industry.

6 Limitations

The search and selection of market players and offered services as well as the data analysis expose the research to certain limitations. Due to the number of analysed market players, the statements of this thesis are qualitative, not quantitative.

As described in chapter 3.1.3.1, the gathered data is obtained from the companies' websites. Due to the fact that the number of investigated companies is quite high, another data research method was not considered. This limitation may have a significant impact on the completeness of this thesis. If there might be need for more detailed data, the sources for data collection can be expanded.

At a late stage of this thesis, additional information had become of interest. The clusters assigned to the particular phases of the automotive value chain might as well have a position in the phases of the data value chain. The assignment to the data value chain required additional information, which only was available for a limited number of clusters. In order to fully complete this assignment for the remaining clusters, additional analysis will be required.

A further cluster categorization method is the cluster portfolio described in chapter 3.3.3 and 4.2.3. This categorization classifies a cluster regarding its market potential and competition intensity. The categorization by using this portfolio could only be done for six of the defined nineteen clusters. Forecasted revenues are required for this categorization. Due to the lack of this data, the categorization was not possible for thirteen clusters. To complete this classification for the remaining clusters, further analysis will be required.

The start-ups that got analysed resulted from a query by the start-up scouting company Innospot. This query identified the ten most relevant start-ups for AVL, according to Innospot. Therefore, those ten start-ups were analysed. To gain a better insight into the activity fields of start-ups, it would be necessary to extend the number of analysed companies. Additionally, a more diverse sample of start-ups regarding their position in the automotive value chain would be necessary. The analysed start-ups of this thesis are only active in the aftersales phase.

As described in the theoretical part of the thesis, OEMs are an essential player in data-business. Considering them will result in a more comprehensive view of the automotive market. It is important to mention that OEMs offer their services internally and not for external customers. This makes information difficult to access, as they do not have to advertise their services and tools to external parties. As another additional group of market players, suppliers, such as ZF Friedrichshafen AG, can be considered.

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Appendix

Appendix 1: Analysed Market Players

ESPs:

Source: ETZ Extra (2016)

Table A1: List of analysed ESPs

Rank	Company	Yearly turnover Automotive worldwide in mil. Euro (2015)	Employees Automotive worldwide	Relevant main focus areas
1	AVL List	1270,0	8050	Development, Powertrain, Engines measurement technology, Test Systems, Simulation Software
2	Bertrandt	840,0	12000	Powertrain, Simulation, Testing, Development support services
3	EDAG Engineering	722,0	8139	Complete Vehicle Development
4	IAV	697,0	6500	Electronics development, Powertrain development, Vehicle development
5	HORIBA	478,4	2173	Testing technology
6	Altran Germany	450,0	5500	Driver assistance systems, Connected Car, Powertrain
7	FEV Group	428,0	4000	Engine development, Powertrain development, Vehicle application & integration, Hybrid Vehicles, Electric Vehicles, Testing Technology
8	AKKA Technology	420,0	3200	Complete Vehicle Development, Engine, Powertrain, Electronics
9	Alten	342,1	3900	Product development, Software- & Hardware- development, Testing, Validation, Quality management
10	Kistler Instruments	308,0	1450	Testing technology
11	Ricardo Germany	295,0	2100	Complete vehicle technology development, Engine. Transmission, Hybrid systems, Electronics, Development- software
12	Formel D	212,0	>6000	Testing technology, Quality engineering
13	Magna Steyr Engineering	210,0	2600	Complete vehicle development, Module- development, Safety engineering, Hybrid Vehicles, Electric Vehicles
14	ETAS	189,5	950	Embedded system development, Engineering

15	Assystem Group	185,0	2950	Development, Electronics, Software, Mechanics
16	Altair Engineering	180,0	1500	Simulation, Software
17	Continental Engineering Services	170,0	1280	Powertrain, Testing, Validation, Safety
18	Applus IDIADA Group	161,0	1987	Complete vehicle development, Module development, Testing
….				
22	AKKA Digital	122,0	1034	Electronics, Mobile solutions
….				
28	Magna Powertrain Engineering Center Steyr	90,0	770	Vehicle development, Engine development, Powertrain development, Electronics, Electrification, Simulation services, Testing services
Companies requested by AVL. Not listed in the Ranking:				
	Bosch Engineering	480 (2016)	2100	Software, Connectivity, E/E-Systems, IoT
	B-plus			Electronics, Advanced Driver assistance systmes, Simulation
	C-More automotive	~.9,5 (2016)		Advanced Driver Assistance Systems, Autonomous driving, E-Mobility
	Control- Tec			Edge computing, Over-the-air analytics, Security and data marketplace solutions
	Vispiron	ca. 50		Electronics development, Validation, E-Mobility, Integration, Fleet Management
	Tracetronic			Development embedded systems, ECU development, Testing & Validation Tools

IT-companies:
Source: Nagel, P. (2018)

Table A2: List of analysed IT-companies

Rank	Company	Yearly turnover German automotive industry 2017 in mill. €
1	T-Systems International	760,0
2	IBM Deutschland	540,0
3	Computacenter	389,6
4	Accenture	307,0
5	DXC Technology	300,0
6	MHP Management- und IT- Beratung	290,0
7	NTT Data Deutschland	280,0
8	Infosys.	230,0
9	Atos Information Technology	200,0
10	Capgemini Deutschland Holding	185,0
Companies requested by AVL, not listed in the Ranking:		
	Alibaba	no information regarding turnover in the German automotive Industry available
	Amazon	
	Google	
	Microsoft	
	NVIDIA	
	SAS	
	Genpact	

Start-Ups:
Source: Weindorf, K. (2019)

Table A3: List of analysed start-ups

	Company
1	Carfit.
2	Teraki
3	Stratio Automotive
4	Vinli.
5	Predii.
6	Nebula Systems.
7	Moj.io
8	Zubie.
9	Galooli.
10	Excelfore.
11	Pitstop Connect

Appendix 2: Global locations

ESPs:

Table A4: ESPs' global locations

		Europe	North America			South America		Asia							Africa		Australia
ESPs	HQ		USA	Canada	Mexico	Brazil	Argentina	China	India	Japan	SEA	Korea	Middle East	Russia	North Africa	South Africa	
AVL List GmbH	Austria	1	1		1	1	1	1	1	1	1	1	1	1			1
IAV GmbH	Germany	1	1			1		1	1			1					
Bertrandt AG	Germany	1	1					1									
Bosch Engineering	Germany	1	1					1		1							
EDAG	Germany	1	1		1	1		1	1	1	1			1			
Horiba	Japan	1	1	1		1		1	1	1	1	1					
Altran	France	1	1	1	1			1	1	1			1		1		
FEV Group	Germany	1	1		1	1		1	1	1	1	1	1	1			
AKKA Group	France	1	1	1				1					1	1			
Alten Group	France	1	1	1				1	1				1				
Kistler Instrumente	Switzerland	1	1	1	1	1	1	1	1	1	1		1			1	1
Ricardo Ger.	UK	1	1					1	1	1	1	1	1			1	
Magna	Canada	1	1	1	1	1	1	1	1	1	1	1					
ETAS GmbH	Germany	1	1	1		1		1	1	1		1					
Assystem Techn.	France	1	1	1	1			1	1		1					1	1
Altair Engineering	USA	1	1	1	1	1		1	1	1	1	1	1			1	1
Continental	Germany	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Applus IDIADA	Spain	1	1		1	1		1	1	1	1	1	1	1		1	
C More Automotive	Gemany	1							1								
Control Tec	USA		1														
Tracetronic	Germany	1															
Vispiron	Germany	1															
Formel D	Germany	1	1		1	1		1	1			1		1		1	
b plus	Germany	1															

IT-Companies:

Table A5: IT-companies' global locations

		Europe	North America			South America		Asia							Africa		Australia
ESPs	HQ		USA	Canada	Mexico	Brazil	Argentina	China	India	Japan	SEA	Korea	Middle East	Russia	North Africa	South Africa	
T-Systems	Germany	1	1	1	1	1	1	1	1		1					1	
IBM	USA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Computacenter	Europe	1	1		1						1					1	
Accenture	Europe	1	1	1		1	1	1	1	1	1		1	1		1	1
DXC	USA	1	1	1	1	1	1	1	1	1	1		1			1	1
MHP	Germany	1	1					1									
NTT Data	Japan	1	1	1	1	1	1	1	1	1	1		1	1			
Infosys	India	1	1	1	1	1		1	1	1	1					1	1
Atos	France	1	1					1	1		1		1				
Capgemini	France	1	1	1	1	1	1	1	1	1	1		1			1	1
Infosys	India	1	1	1	1	1		1	1	1	1	1	1			1	1
NVIDIDA	USA	1	1	1		1		1	1	1	1	1	1				
Alibaba*	China	1	1					1	1	1	1		1				1
AWS*	USA	1	1	1		1		1	1	1	1	1	1			1	1
Google Cloud *	USA	1	1	1		1		1	1	1	1					1	1
Microsoft Azure*	USA	1	1	1		1		1	1	1	1	1	1			1	1

* Availability Zones of Cloud Servcies (12.01.2019)

Appendix 3: Companies Activity in Clusters

ESPs:

Table A6: Activity Matrix of ESPs

ESPs	ADAS- Development	ADAS- Validation	ADAS- Verification	**ADAS**	Calibration Data Management	Calibration Machine Learning	Calibration OBD	**Calibration**	Digital Twin	Fleet Solutions Aftersales	Fleet Solutions Validation	Predictive Solutions Aftersales	Predictive Solutions Production	Quality related Solutions	Remote Diagnostics	Testing- Data acquisition	Testing- Data analytics	Testing- Data management	Testing- Data visualization	Testing- Endurance	Testing- RDE	Testing-Real Time Data Mon.	**Testing**	Artificial Intelligence	Autonomous Driving	Cloud Solutions	Connected Car Platform	Data Analytics	Data Benchmarking	Data Management	Data Visualization	Machine Learning	**Companies' Cluster-Sum**
AVL List	1	1	1	1	1	1	1	1	1		1	1	1			1	1	1	1	1	1	1	1	1	1				1	1	1	1	13
AKKA Group		1		1								1				1		1		1	1	1	1		1			1		1	1		7
Altair Engineering	1			1						1							1		1				1			1		1		1	1	1	8
Alten																				1			1			1				1			3
Altran Germany	1		1	1									1											1	1							1	5
Applus IDIADA	1	1	1	1			1	1			1						1						1		1				1				6
Assystem Group	1	1	1	1					1															1		1	1	1	1			1	8
Bertrandt	1	1		1			1	1	1				1	1	1		1	1				1	1	1	1			1	1			1	12
Bosch										1		1	1		1					1	1		1	1	1			1		1	1		10
b-plus	1	1	1	1																													1
C-More Automotive	1	1	1	1							1				1	1	1		1	1		1	1		1								5
Continental	1	1	1	1	1		1	1		1					1										1	1	1	1			1		9
Control Tec											1			1		1	1	1	1			1	1				1						4
EDAG Engineering	1	1		1									1				1		1			1	1		1					1			5
ETAS		1		1	1	1	1	1									1	1	1		1	1	1		1								4
FEV Group	1	1		1	1		1	1								1	1	1	1		1	1	1		1				1				5
Formel D										1	1																						2
Horiba																1	1	1	1	1	1	1	1										1
IAV	1	1	1	1	1	1	1	1			1	1			1		1	1	1	1	1	1	1	1	1			1	1	1	1	1	13
Kistler Instrumente																1	1	1	1			1	1										1
Magna Powertrain					1			1								1	1		1	1			1						1	1			4
Magna Steyr Eng.		1	1	1													1						1		1								3
Ricardo Germany							1	1			1										1	1	1						1				4
Tracetronic		1		1													1	1	1				1										2
Visipron										1					1	1	1		1			1	1								1		4
Cluster-Sum	12	14	9	16	6	3	8	9	3	5	7	4	5	2	6	9	16	10	13	8	8	13	20	6	13	4	3	7	8	8	7	6	

IT-companies:

Table A7: Activity Matrix of IT-companies

IT-Companies	T-Systems	IBM	Computacenter	Accenture	DXC	MHP	NTT Data	Infosys	Atos	Capgemini	Alibaba	Amazon Web Services	Microsoft Azure	Google	NVIDIA	Genpact	SAS	Cluster-Sum
Companies' Cluster-Sum	6	10	3	8	6	4	7	8	6	5	8	11	8	9	5	7	8	
Machine Learning											1	1	1	1		1	1	6
Data Visualization		1									1		1	1	1	1	1	7
Data Management		1	1	1	1	1						1						6
Data Benchmarking																		0
Data Analytics	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
Connected Car Platform		1		1			1	1			1	1	1	1				8
Cloud Solutions	1	1	1	1	1	1	1	1	1	1	1	1	1	1			1	15
Autonomous Driving		1			1		1	1	1			1		1	1			8
Artificial Intelligence		1		1	1		1	1	1	1	1	1	1	1	1	1	1	14
Testing																		
Testing-Real Time Data Mon.																		0
Testing- RDE																		0
Testing- Endurance																		0
Testing- Data visualization																		0
Testing- Data management																		0
Testing- Data analytics																		0
Testing- Data acquisition																		0
Remote Diagnostics								1			1							2
Quality related Solutions		1										1					1	3
Predictive Solutions Production	1	1		1	1	1	1	1	1	1		1				1	1	12
Predictive Solutions Aftersales	1			1			1	1	1			1	1	1		1	1	10
Fleet Solutions Validation																		0
Fleet Solutions Aftersales	1									1	1			1				4
Digital Twin	1	1		1									1			1		5
Calibration																		0
Calibration OBD																		0
Calibration Machine Learning																		0
Calibration Data Management																		0
ADAS												1			1			2
ADAS- Verification																		0
ADAS- Validation																		0
ADAS- Development												1			1			2

Start-ups:

Table A8: Activity Matrix of start-ups

Start-Ups	Carfit Corporation	Teraki GmbH	Stratio Automotive	Vinli Inc.	Predii	Nebula Systems	Mojio Inc.	Zubie Inc.	Galooli Ltd.	Excelforce	Pitstop Connect	Cluster-Sum
Companies' Cluster-Sum	3	0	2	4	3	2	3	1	2	4	6	
Machine Learning	1			1						1		3
Data Visualization												0
Data Management												0
Data Benchmarking												0
Data Analytics					1		1			1	1	4
Connected Car Platform				1			1			1	1	4
Cloud Solutions						1						1
Autonomous Driving											1	1
Artificial Intelligence	1		1		1				1			4
Testing												0
Testing-Real Time Data Mon.												0
Testing- RDE												0
Testing- Endurance												0
Testing- Data visualization												0
Testing- Data management												0
Testing- Data analytics												0
Testing- Data acquisition												0
Remote Diagnostics					1	1	1			1	1	5
Quality related Solutions												0
Predictive Solutions Production												0
Predictive Solutions Aftersales	1		1	1							1	4
Fleet Solutions Validation												0
Fleet Solutions Aftersales				1				1	1		1	4
Digital Twin												0
Calibration												0
Calibration OBD												0
Calibration Machine Learning												0
Calibration Data Management												0
ADAS												0
ADAS- Verification												0
ADAS- Validation												0
ADAS- Development												0

Appendix 4: Comparison of AVLs activity in defined clusters with other market players

ESPs:

Table A9: Common Clusters AVL - ESPs

ESPs	ADAS	Artificial Intelligence	Autonomous Driving	Calibration	Data Benchmarking	Data Management	Data Visualization	Fleet Solutions Validation	Predictive Solutions Production	Predictive Solutions Aftersales	Testing	Digital Twin	Machine Learning	**Overlapping total**	**Overlapping %**
AVL List	1	1	1	1	1	1	1	1	1	1	1	1	1	13	100%
AKKA Group	1		1			1	1			1	1			6	46%
Altair Engineering	1					1	1				1		1	5	38%
Alten						1					1			2	15%
Altran Germany	1	1	1						1				1	5	38%
Applus IDIADA Group	1		1	1	1			1			1			6	46%
Assystem Group	1	1			1							1	1	5	38%
Bertrandt	1	1	1	1	1				1		1	1	1	9	69%
Bosch		1	1			1	1		1	1	1			7	54%
b-plus	1													1	8%
C-More Automotive	1		1					1			1			4	31%
Continental	1		1	1			1							4	31%
Control Tec								1			1			2	15%
EDAG Engineering	1		1			1			1		1			5	38%
ETAS	1		1	1							1			4	31%
FEV Group	1		1	1	1						1			5	38%
Formel D								1						1	8%
Horiba											1			1	8%
IAV	1	1	1	1	1	1	1	1		1	1		1	11	85%
Kistler Instrumente											1			1	8%
Magna Powertrain				1	1	1					1			4	31%
Magna Steyr Eng.	1		1								1			3	23%
Ricardo Germany				1	1			1			1			4	31%
Tracetronic	1										1			2	15%
Visipron							1				1			2	15%

IT-companies:

Table A10: Common clusters AVL - IT-companies

IT-Companies	ADAS	Artificial Intelligence	Autonomous Driving	Calibration	Data Benchmarking	Data Management	Data Visualization	Fleet Solutions Validation	Predictive Solutions Production	Predictive Solutions Aftersales	Testing	Digital Twin	Machine Learning	**Overlapping total**	**Overlapping %**
AVL List	1	1	1	1	1	1	1	1	1	1	1	1	1	13	100%
T-Systems									1	1		1		3	23%
IBM		1	1			1	1		1			1		6	46%
Computacenter						1								1	8%
Accenture		1				1			1	1		1		5	38%
DXC		1	1			1			1					4	31%
MHP						1			1					2	15%
NTT Data		1	1						1	1				4	31%
Infosys		1	1						1	1				4	31%
Atos		1	1						1	1				4	31%
Capgemini		1							1					2	15%
Alibaba		1					1						1	3	23%
Amazon Web Services	1	1	1			1			1	1			1	7	54%
Microsoft Azure		1					1			1		1	1	5	38%
Google		1	1				1			1			1	5	38%
NVIDIA	1	1	1				1							4	31%
Genpact		1					1		1	1		1	1	6	46%
SAS		1					1		1	1			1	5	38%

Start-ups:

Table A11: Common clusters AVL - start-ups

Start-Ups	ADAS	Artificial Intelligence	Autonomous Driving	Calibration	Data Benchmarking	Data Management	Data Visualization	Fleet Solutions Validation	Predictive Solutions Production	Predictive Solutions Aftersales	Testing	Digital Twin	Machine Learning	**Overlapping total**	**Overlapping %**
AVL List	1	1	1	1	1	1	1	1	1	1	1	1	1	13	100%
Carfit Corporation		1								1			1	3	23%
Teraki														0	0%
Stratio Automotive		1								1				2	15%
Vinli Inc.										1			1	2	15%
Predii		1												1	8%
Nebula Systems														0	0%
Mojio Inc.														0	0%
Zubie Inc.														0	0%
Galooli Ltd.		1												1	8%
Excelforce													1	1	8%
Pitstop Connect			1							1				2	15%

Appendix 5: Clusters AVL is not active in

ESPs:

Table A12: ESPs' activity in clusters AVL is not active in

Companies	Data Analytics	Fleet Solutions Aftersales	Remote Diagnostics	Quality related Solutions	Connected Car Platform	Cloud Solutions	Sum of overlapping Clusters
AVL List	0	0	0	0	0	0	0
AKKA Group	1	0	0	0	0	0	1
Altair Engineering	1	1	0	0	0	1	3
Alten	0	0	0	0	0	1	1
Altran Germany	0	0	0	0	0	0	0
Applus IDIADA	0	0	0	0	0	0	0
Assystem Group	1	0	0	0	1	1	3
Bertrandt	1	0	1	1	0	0	3
Bosch	1	1	1	0	0	0	3
b-plus	0	0	0	0	0	0	0
C-More Automotive	0	0	1	0	0	0	1
Continental	1	1	1	0	1	1	5
Control Tec	0	0	0	1	1	0	2
EDAG Engineering	0	0	0	0	0	0	0
ETAS	0	0	0	0	0	0	0
FEV Group	0	0	0	0	0	0	0
Formel D	0	1	0	0	0	0	1
Horiba	0	0	0	0	0	0	0
IAV	1	0	1	0	0	0	2
Kistler Instrumente	0	0	0	0	0	0	0
Magna Powertrain	0	0	0	0	0	0	0
Magna Steyr Eng.	0	0	0	0	0	0	0
Ricardo Germany	0	0	0	0	0	0	0
Tracetronic	0	0	0	0	0	0	0
Visipron	0	1	1	0	0	0	2

IT-companies:

Table A13: IT-companies' activity in clusters AVL is not active in

Companies	Data Analytics	Fleet Solutions Aftersales	Remote Diagnostics	Quality related Solutions	Connected Car Platform	Cloud Solutions	Sum of overlapping Clusters
T-Systems	1	1	0	0	0	1	3
IBM	1	0	0	1	1	1	4
Computacenter	1	0	0	0	0	1	2
Accenture	1	0	0	0	1	1	3
DXC	1	0	0	0	0	1	2
MHP	1	0	0	0	0	1	2
NTT Data	1	0	0	0	1	1	3
Infosys	1	0	1	0	1	1	4
Atos	1	0	0	0	0	1	2
Capgemini	1	1	0	0	0	1	3
Alibaba	1	1	1	0	1	1	5
Amazon Web Services	1	0	0	1	1	1	4
Microsoft Azure	1	0	0	0	1	1	3
Google	1	1	0	0	1	1	4
NVIDIA	1	0	0	0	0	0	1
Genpact	1	0	0	0	0	0	1
SAS	1	0	0	1	0	1	3

Start-ups:

Table A14: Start-ups' activity in clusters AVL is not active in

Companies	Data Analytics	Fleet Solutions Aftersales	Remote Diagnostics	Quality related Solutions	Connected Car Platform	Cloud Solutions	Sum of overlapping Clusters
Carfit Corporation	0	0	0	0	0	0	0
Teraki	0	0	0	0	0	0	0
Stratio Automotive	0	0	0	0	0	0	0
Vinli Inc.	0	1	0	0	1	0	2
Predii	1	0	1	0	0	0	2
Nebula Systems	0	0	1	0	0	1	2
Mojio Inc.	1	0	1	0	1	0	3
Zubie Inc.	0	1	0	0	0	0	1
Galooli Ltd.	0	1	0	0	0	0	1
Excelforce	1	0	1	0	1	0	3
Pitstop Connect	1	1	1	0	1	0	4

Appendix 6: Market Players Activity along the Value Chain

Table A15: ESPs' activity along the Automotive VC

ESP	Concept	Development	Validation	Production	Aftersales	Workshop
AVL List						
AKKA Group						
Altair Engineering						
Alten						
Altran Germany						
Applus IDIADA						
Assystem Group						
Bertrandt						
Bosch						
b-plus						
C-More Automotive						
Continental						
Control Tec						
EDAG Engineering						
ETAS GmbH						
FEV Group						
Formel D						
Horiba						
IAV						
Kistler Instrumente						
Magna Powertrain						
Magna Steyr Eng.						
Ricardo Germany						
Tracetronic						
Visipron						

Table A16: IT-companies' activity along the Automotive VC

IT-Companies	Concept	Development	Validation	Production	Aftersales	Workshop
T-Systems						
IBM						
Computacenter						
Accenture						
DXC						
MHP						
NTT Data						
Infosys						
Atos						
Capgemini						
Alibaba						
Amazon Web Services						
Microsoft Azure						
Google						
NVIDIA						
Genpact						
SAS						

Table A17: Start-ups' activity along the Automotive VC

Start-ups	Concept	Development	Validation	Production	Aftersales	Workshop
Carfit Corporation						
Teraki						
Stratio Automotive						
Vinli Inc.						
Predii						
Nebula Systems						
Mojio Inc.						
Zubie Inc.						
Galooli Ltd.						
Excelforce						
Pitstop Connect						

Appendix 7: Cluster Landscape

Example Cluster Landscape:

Assumption: Ten ESPs and four IT-companies were identified to be active in “Cluster A”. In total, 25 ESPs and 17 IT-companies were investigated in this thesis. The task is, to calculate the share of ESPs in “Cluster A”. Details are listed in Table A18.

Table A18: Share of ESPs in a cluster - Example

Market Players	Investigated Companies	Companies active in Cluster A	Normalised Number of companies active in Cluster A
ESPs	25	10	10/25= 0.40
IT-companies	17	4	4/17= 0.24

$$Share\ of\ ESPs\ in\ a\ cluster = \frac{standardized\ number\ of\ ESPs\ in\ the\ cluster}{standardized\ sum\ of\ ESPs\ and\ IT\ companies\ \ in\ the\ cluster}$$

$$Share\ of\ ESPs\ in\ a\ cluster = \frac{0.4}{0.4 + 0.24} = 0.63\ \triangleq 63\%$$

According to this calculation, the Share of ESPs in Cluster A, amounts to 63%.

Determination of the Cluster Landscape:

Table A19: Cluster Landscape - calculation details

Cluster	ESP	IT	ESP+IT	ESP_normalised	IT_normalised	Share ESP [%]
ADAS	16	2	18	0,64	0,12	84
AI	6	14	20	0,24	0,82	23
Autonomous Driving	13	8	21	0,52	0,47	52
Calibration	9	0	9	0,36	0,00	100
Data Analytics	7	17	24	0,28	1,00	22
Data Benchmarking	8	0	8	0,32	0,00	100
Data Management	8	6	14	0,32	0,35	48
Data Visualization	7	7	14	0,28	0,41	40
Fleet Solutions Validation	7	0	7	0,28	0,00	100
Fleet Solutions Aftersales	5	4	9	0,2	0,24	46
Predictive Solutions Production	5	12	17	0,2	0,71	22
Predictive Solutions Aftersales	4	10	14	0,16	0,59	21
Quality related Solutions	2	3	5	0,08	0,18	31
Remote Diagnostics	6	2	8	0,24	0,12	67
Testing	20	0	20	0,8	0,00	100
Connected Car Platform	3	8	11	0,12	0,47	20
Digital Twin	3	5	8	0,12	0,29	29
Cloud Solutions	4	15	19	0,16	0,88	15
Machine Learning	6	6	12	0,24	0,35	40

Appendix 8: Market Players Activity Fields

Example Market Players Activity Fields:

Assumption: A company is active in four clusters called “Cluster B”, “Cluster C”, “Cluster D” and “Cluster E”. The share of ESPs in each of those Clusters is listed in Table A20.

Table A20: Share of ESPs in the Cluster - Example

Cluster	Share of ESPs in the Clusters [%]
Cluster B	95
Cluster C	70
Cluster D	80
Cluster E	75

$$Degree\ of\ activity\ of\ ESPs\ in\ investigated\ clusters = \frac{Sum\ of\ shares\ of\ ESPs\ in\ clusters\ the\ company\ is\ active\ in}{Number\ of\ clusters\ the\ company\ is\ active\ in}$$

$$Degree\ of\ activity\ of\ ESPs\ in\ investigated\ clusters = \frac{95 + 70 + 80 + 75}{4} = 80$$

According to this calculation, the Degree of activity of ESPs in investigated clusters amounts to 80%.

ESPs:

Table A21: Determination of ESPs' Activity Field

	Share ESPs in the Cluster [%]	ESP	AVL List GmbH	AKKA Group	Altair Engineering GmbH	Alten GmbH	Altran Germany	Applus IDIADA Group	Assystem Group	Bertrandt AG	Bosch	b-plus	C-More Automotive	Continental	Control Tec	EDAG Engineering GmbH	ETAS GmbH	FEV Group	Formel D GmbH	Horiba	IAV GmbH	Kistler Instrumente	Magna Powertrain	Magna Steyr Eng.	Ricardo Germany	Tracetronic	Visipron
Degree of activity of ESPs in investigated clusters [%]			58	53	50	54	44	89	42	56	44	84	81	50	63	61	84	87	73	100	61	100	87	79	100	92	63
Companies' Cluster Sum			13	7	8	3	5	6	8	12	10	1	5	9	4	5	4	5	2	1	13	1	4	3	4	2	4
Machine Learning	**40**		1	0	1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Data Visualization	**40**		1	1	1	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1
Data Management	**48**		1	1	1	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	0
Data Benchmarking	**100**		1	0	0	0	0	1	1	1	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0	0
Data Analytics	**22**		0	1	1	0	0	0	1	1	1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
Connected Car Platform	**20**		0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Cloud Solutions	**15**		0	0	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
Autonomous Driving	**52**		1	1	0	0	1	1	0	1	1	0	1	1	0	1	1	1	0	0	1	0	0	1	0	0	0
Artificial Intelligence	**23**		1	0	0	0	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Testing	**100**		1	1	1	1	0	1	0	1	1	0	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1
Testing-Real Time Data Mon.			1	1	0	0	0	0	0	1	0	0	1	0	1	1	1	1	0	1	1	1	0	0	1	0	1
Testing- RDE			1	1	0	0	0	0	0	0	1	0	0	0	0	0	1	1	0	1	1	0	0	0	1	0	0
Testing- Endurance			1	1	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0
Testing- Data visualization			1	0	1	0	0	0	0	0	0	0	1	0	1	1	1	1	0	1	1	1	1	0	0	1	1
Testing- Data management			1	1	0	0	0	0	0	1	0	0	0	0	1	0	1	1	0	1	1	1	0	0	0	1	0
Testing- Data analytics			1	0	1	0	0	1	0	1	0	0	1	0	1	1	1	1	0	1	1	1	1	1	0	1	1
Testing- Data acquisition			1	1	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	1	0	1	1	0	0	0	1
Remote Diagnostics	**67**		0	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	1
Quality related Services	**31**		0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Predictive Servcies Production	**22**		1	0	0	0	1	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Predictive Servcies Aftersales	**21**		1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Fleet Solutions Validation	**100**		1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	0	1	0	1	0	0	0	1	0	0
Fleet Solutions Aftersales	**46**		0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	1
Digital Twin	**29**		1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Calibration	**100**		1	0	0	0	0	1	0	1	0	0	0	1	0	0	1	1	0	0	1	0	1	0	1	0	0
Calibration OBD			1	0	0	0	0	1	0	1	0	0	0	1	0	0	1	1	0	0	1	0	0	0	1	0	0
Calibration Machine Learning			1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0
Calibration Data Management			1	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	1	0	1	0	0	0	0
ADAS	**84**		1	1	1	0	1	1	1	1	0	1	1	1	0	1	1	1	0	0	1	0	0	1	0	1	0
ADAS- Verification			1	0	0	0	1	1	1	0	0	1	1	1	0	0	0	0	0	0	1	0	0	1	0	0	0
ADAS- Validation			1	1	0	0	0	1	1	1	0	1	1	1	0	1	1	1	0	0	1	0	0	1	0	1	0
ADAS- Development			1	0	1	0	1	1	1	1	0	1	1	1	0	1	0	1	0	0	1	0	0	0	0	0	0

IT-companies:

Table A22: Determination of IT-companies' Activity Field

	Share ESPs in the Cluster [%]	IT-Companies	T-Systems	IBM	Computacenter	Accenture	DXC	MHP	NTT Data	Infosys	Atos	Capgemini	Alibaba	Amazon Web Services	Microsoft Azure	Google	NVIDIA	Genpact	SAS
Degree of activity of ESPs in investigated clusters [%]			22	32	30	26	30	28	25	31	26	21	35	35	27	31	45	29	24
Companies' Cluster Sum			5	11	3	8	7	4	7	8	6	4	8	12	8	9	5	7	7
Machine Learning	**40**												1	1	1	1		1	1
Data Visualization	**40**			1									1		1	1	1	1	
Data Management	**50**			1	1	1	1	1						1					
Data Benchmarking	**100**																		
Data Analytics	**24**		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Connected Car Platform	**20**			1		1			1	1			1	1	1	1			
Cloud Solutions	**15**		1	1	1	1	1	1	1	1	1	1	1	1	1	1			1
Autonomous Driving	**52**			1			1		1	1	1			1		1	1		
Artificial Intelligence	**23**			1		1	1		1	1	1	1	1	1	1	1	1	1	1
Testing	**100**																		
Testing-Real Time Data Mon.																			
Testing- RDE																			
Testing- Endurance																			
Testing- Data visualization																			
Testing- Data management																			
Testing- Data analytics																			
Testing- Data acquisition																			
Remote Diagnostics	**67**									1			1						
Quality related Services	**25**			1			1							1					1
Predictive Services Production	**22**		1	1		1	1	1	1	1	1	1		1				1	1
Predictive Services Aftersales	**21**		1			1			1	1	1			1	1	1		1	1
Fleet Solutions Validation	**100**																		
Fleet Solutions Aftersales	**46**			1									1	1		1			
Digital Twin	**29**		1	1		1									1			1	
Calibration	**100**																		
Calibration OBD																			
Calibration Machine Learning																			
Calibration Data Management																			
ADAS	**84**													1			1		
ADAS- Verification																			
ADAS- Validation																			
ADAS- Development														1			1		

Start-ups:

Table A23: Determination of start-ups' Activity Field

	ADAS- Development	ADAS- Validation	ADAS- Verification	**ADAS**	Calibration Data Management	Calibration Machine Learning	Calibration OBD	**Calibration**	Digital Twin	Fleet Solutions Aftersales	Fleet Solutions Validation	Predictive Servcies Aftersales	Predictive Servcies Production	Quality related Services	Remote Diagnostics	Testing- Data acquisition	Testing- Data analytics	Testing- Data management	Testing- Data visualization	Testing- Endurance	Testing- RDE	Testing-Real Time Data Mon.	**Testing**	Artificial Intelligence	Autonomous Driving	Cloud Solutions	Connected Car Platform	Data Analytics	Data Benchmarking	Data Management	Data Visualization	Machine Learning	**Companies' Cluster Sum**	**Degree of activity of ESPs in investigated clusters [%]**
Share ESPs in the Cluster [%]				**84**				**100**	**29**	**46**	**100**	**21**	**22**	**25**	**67**								**100**	**23**	**52**	**15**	**20**	**24**	**100**	**50**	**40**	**40**		
Start-ups																																		
Carfit Corporation												1												1								1	3	28
Teraki GmbH																																	0	0
Stratio Automotive												1												1									2	22
Vinli Inc.										1		1															1					1	4	32
Predii															1									1				1					3	38
Nebula Systems															1											1							2	41
Mojio Inc.															1												1	1					3	37
Zubie Inc.										1																							1	46
Galooli Ltd.										1														1									2	34
Excelforce															1												1	1				1	4	38
Pitstop Connect										1		1			1										1		1	1					6	39

Appendix 9: ADAS-related Activities

ESPs:

Table A24: ESPs working in ADAS-related Activities

Company	ADAS- Development	ADAS- Validation	ADAS- Verification	Artificial Intelligence	Autonomous Driving	Sum
AVL List	1	1	1	1	1	5
AKKA Group		1			1	2
Altair Engineering	1					1
Alten						0
Altran Germany	1		1	1	1	4
Applus IDIADA	1	1	1		1	4
Assystem Group	1	1	1	1		4
Bertrandt	1	1		1	1	4
Bosch				1	1	2
b-plus	1	1	1			3
C-More Automotive	1	1	1		1	4
Continental	1	1	1		1	4
EDAG Engineering	1	1			1	3
ETAS		1			1	2
FEV Group	1	1			1	3
Formel D						0
Horiba						0
IAV	1	1	1	1	1	5
Kistler Instrumente						0
Magna Powertrain						0
Magna Steyr Eng.		1	1		1	3
Ricardo Germany						0
Tracetronic		1				1
Visipron						0

IT-companies:

Table A25: IT-companies working in ADAS-related Activities

Company	ADAS- Development	ADAS- Validation	ADAS- Verification	Artificial Intelligence	Autonomous Driving	Sum
IBM				1	1	2
DXC				1	1	2
Accenture				1		1
NTT Data				1	1	2
Infosys				1	1	2
Atos				1	1	2
Capgemini				1		1
Alibaba				1		1
Amazon Web Services	1			1	1	3
Google				1	1	2
NVIDIA	1			1	1	3
Genpact				1		1
SAS				1		1

Start-ups:

Table A26: Start-ups working in ADAS-related Activities

Company	ADAS- Development	ADAS- Validation	ADAS- Verification	Artificial Intelligence	Autonomous Driving	Sum
Carfit Corporation				1		1
Teraki						0
Stratio Automotive				1		1
Vinli Inc.						0
Predii				1		1
Nebula Systems						0
Mojio Inc.						0
Zubie Inc.						0
Galooli Ltd.				1		1
Excelforce						0
Pitstop Connect					1	1

Appendix 10: Testing-Activities

Table A27: ESPs' activity in the cluster Testing

Companies	Testing- Data acquisition	Testing- Data analytics	Testing- Data management	Testing- Data visualization	Testing- Endurance	Testing- RDE	Testing-Real Time Data Mon.	**Sum**
AVL List	1	1	1	1	1	1	1	7
AKKA Group	1		1		1	1	1	5
Altair Engineering		1		1				2
Alten					1			1
Altran Germany								0
Applus IDIADA Group		1						1
Assystem Group								0
Bertrandt		1	1				1	3
Bosch					1	1		2
b-plus								0
C-More Automotive	1	1		1	1		1	5
Continental								0
Control Tec	1	1	1	1			1	5
EDAG Engineering		1		1			1	3
ETAS		1	1	1		1	1	5
FEV Group	1	1	1	1		1	1	6
Formel D								0
Horiba	1	1	1	1	1	1	1	7
IAV		1	1	1	1	1	1	6
Kistler Instrumente	1	1	1	1			1	5
Magna Powertrain	1	1		1	1			4
Magna Steyr Eng.		1						1
Ricardo Germany						1	1	2
Tracetronic		1	1	1				3
Visipron	1	1		1			1	4

Appendix 11: Data-Driven Services only

The following tables show the companies and the clusters where they provide services in. Those are highlighted red. Additionally, the clusters where the company provides information about, but no concrete service can be identified, are highlighted green.

ESPs:

Table A28: ESPs' Activity Matrix - Services only

ESPs	AVL List	AKKA	Altair Engineering	Alten	Altran Germany	Applus IDIADA	Assystem	Bertrandt	Bosch	b-plus	C-More Automotive	Continental	Control Tec	EDAG Engineering	ETAS	FEV	Formel D	Horiba	IAV	Kistler Instrumente	Magna Powertrain	Magna Steyr Eng.	Ricardo Germany	Tracetronic	Visipron	Cluster Sum
Companies Cluster-Sum	13	6	4	3	3	5	7	8	6	0	3	8	4	3	0	3	2	1	7	0	2	3	4	1	2	
Machine Learning	1				1			1											1							4
Data Visualization	1	1										1														3
Data Management	1	1	1	1										1					1							6
Data Benchmarking	1					1	1	1													1		1			6
Data Analytics		1	1				1	1				1														5
Connected Car Platform							1					1	1													3
Cloud Solutions			1	1			1					1														4
Autonomous Driving	1																		1			1				3
Artificial Intelligence	1				1		1		1																	4
Testing	1	1		1		1		1	1		1		1			1		1	1		1	1	1	1	1	16
Testing-Real Time Data Mon.								1					1			1			1				1			5
Testing- RDE	1	1							1														1			4
Testing- Endurance		1		1					1		1							1	1		1					7
Testing- Data visualization													1						1					1	1	4
Testing- Data management								1					1			1			1					1		5
Testing- Data analytics						1							1					1	1		1	1		1	1	8
Testing- Data acquisition													1								1					2
Remote Diagnostics									1			1														2
Quality related Solutions													1													1
Predictive Solutions Production	1				1			1	1					1												5
Predictive Solutions Aftersales	1	1							1																	3
Fleet Solutions Validation	1					1					1		1				1		1				1			7
Fleet Solutions Aftersales			1						1			1					1								1	5
Digital Twin	1						1	1																		3
Calibration	1					1		1				1				1			1				1			7
Calibration OBD	1					1		1				1				1			1				1			7
Calibration Machine Learning	1																		1							2
Calibration Data Management	1											1				1										3
ADAS	1	1				1	1	1			1	1		1		1			1			1				11
ADAS- Verification	1						1				1	1							1			1				6
ADAS- Validation	1	1				1	1	1			1	1		1		1			1			1				11
ADAS- Development	1					1	1	1			1	1				1			1							8

IT-Companies:

Table A29: IT-companies' Activity Matrix - Services only

IT-Companies	T-Systems	IBM	Computacenter	Accenture	DXC	MHP	NTT Data	Infosys	Atos	Capgemini	Alibaba	Amazon Web Services	Microsoft Azure	Google	NVIDIA	Genpact	SAS	Cluster Sum
Companies Cluster-Sum	6	6	2	8	6	4	7	8	6	4	7	11	8	7	3	7	4	
Machine Learning											1	1	1	1		1		5
Data Visualization		1											1	1	1	1	1	6
Data Management		1	1	1	1	1						1						6
Data Benchmarking																		0
Data Analytics	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
Connected Car Platform				1			1	1			1	1	1	1				7
Cloud Solutions	1	1		1	1	1	1	1	1	1	1	1	1	1			1	14
Autonomous Driving		1			1		1	1	1			1						6
Artificial Intelligence		1		1	1		1	1	1	1	1	1	1	1	1	1	1	14
Testing																		
Testing-Real Time Data Mon.																		0
Testing- RDE																		0
Testing- Endurance																		0
Testing- Data visualization																		0
Testing- Data management																		0
Testing- Data analytics																		0
Testing- Data acquisition																		0
Remote Diagnostics								1			1							2
Quality related Solutions												1						1
Predictive Solutions Production	1			1	1	1	1	1	1	1		1				1		10
Predictive Solutions Aftersales	1			1			1	1	1			1	1	1		1		9
Fleet Solutions Validation																		0
Fleet Solutions Aftersales	1										1							2
Digital Twin	1			1									1			1		4
Calibration																		0
Calibration OBD																		0
Calibration Machine Learning																		0
Calibration Data Management																		0
ADAS												1						1
ADAS- Verification																		0
ADAS- Validation																		0
ADAS- Development												1						1

Start-ups:

Table A30: Start-ups' Activity Matrix - Services only

Start-Ups	Carfit Corporation	Teraki GmbH	Stratio Automotive	Vinli Inc.	Predii	Nebula Systems	Mojio Inc.	Zubie Inc.	Galooli Ltd.	Excelforce	Pitstop Connect	Cluster Sum
Companies Cluster-Sum	3	0	2	4	3	2	3	1	2	4	6	
Machine Learning	1			1						1		3
Data Visualization												0
Data Management												0
Data Benchmarking												0
Data Analytics					1		1			1	1	4
Connected Car Platform				1			1			1	1	4
Cloud Solutions						1						1
Autonomous Driving											1	1
Artificial Intelligence	1		1		1				1			4
Testing												0
Testing-Real Time Data Mon.												0
Testing- RDE												0
Testing- Endurance												0
Testing- Data visualization												0
Testing- Data management												0
Testing- Data analytics												0
Testing- Data acquisition												0
Remote Diagnostics					1	1	1			1	1	5
Quality related Solutions												0
Predictive Solutions Production												0
Predictive Solutions Aftersales	1		1	1							1	4
Fleet Solutions Validation												0
Fleet Solutions Aftersales				1				1	1		1	4
Digital Twin												0
Calibration												0
Calibration OBD												0
Calibration Machine Learning												0
Calibration Data Management												0
ADAS												0
ADAS- Verification												0
ADAS- Validation												0
ADAS- Development												0