Towards a Unified Approach to Identify Business Model Patterns: A Case of E-Mobility Services

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Abstract. The introduction of new technologies creates the pursuit for innovative business models. In order to compare and evaluate such models in new markets, business model patterns can support the provision of new insights. However, so far there is no agreed upon transparent approach that helps to identify these patterns. Based on a combination of established statistical methods we propose a systematical approach that allows to identify business model patterns of any given domain. In order to validate the approach, we apply it on a data set of 58 e-mobility projects and as a result identify five distinct and semantically meaningful business models types. This paper contributes on the one hand by suggesting a new approach to identify different patterns of business models and on the other hand provides a valuable insight of the current state of e-mobility service business models that can further drive the adoption.

Keywords: Business models · Patterns · Clustering · E-Mobility services

1 Introduction

Electric mobility (e-mobility) gains increasing interest in academic research. Great potential is recognized within the automotive industry and the energy sector. From the sustainability perspective it is furthermore believed to contribute to a positive climate change and to overcome global resource shortages [1]. Regardless the obvious advantages of e-mobility, the adoption of electric vehicles in the German market falls short on the expectations [2].

Different authors state a rise of new business opportunities in the field of e-mobility in the near future [1, 3–6]. These opportunities derive – amongst others – from service business models that are widely believed to have the power to overcome the general disadvantages of e-mobility, such as the total cost of ownership, a shorter driving range, a significant thinner charging network and a lack of standardization and, thus, drive a broader adoption [4, 5]. This is not surprising as Chesbrough [7] has already stated the important role of the business model (BM) in capturing the value from a new technology. However, two questions remain: What are the BMs that capture the value of e-mobility services and by what means can we distinguish them?

In order to reduce complexity, enable a simple understanding of a matter and create a level of comparison, patterns can be used [8]. This notion of using patterns to describe

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and compare BMs is not entirely new. Several authors have already contributed work on *business model archetypes* [9] or *business model patterns* [10–12]. However, so far the identified patterns in research are developed based on personal experience and therefore are lacking a transparent method [9–11, 13]. Apart from that, other researchers may apply concrete methods, but do make them transparent during their research process by deriving patterns manually through intuition [14] or choosing manually the relevant dimensions that are used for discriminating the pattern [15].

Following the call for greater methodological sophistication in BM research [16–18] this research aims to tackle the lack of a standardized, observable way of pattern identification in any given domain by suggesting an approach that is replicable and takes advantages of accepted statistical methods. In order to show its general feasibility, we apply the approach to the domain of e-mobility, evaluate its performance and thereby further contribute by identifying patterns in a set of e-mobility service BMs.

The remaining paper is structured as follows: Since clustering BMs in the field of e-mobility services is related to the topics of e-mobility services in general, BM research and analytical pattern identification, Sect. 2 provides context from a literature review of each topic to support the understanding. Section 3 introduces step-by-step the general approach to identify BM patterns. Section 4 applies the approach to the domain of e-mobility services—and reveals five distinct BM patterns. Section 5 evaluates the introduced method, summarizes the contributions, provides implications, illustrates the limitations and addresses future research.

2 Related Work

2.1 E-Mobility Services

As a field of research, the topic of e-mobility has consequently gained increasing interest by a wide range of authors within the last decade [19]. Especially in Germany, the field gained popularity since 2011, when the German government announced the goal to achieve one million electric vehicles on the road in Germany by 2020 [20]. Services play a key role concerning the success of e-mobility, since they serve as potential contact points with users. They help to involve consumers easily which eventually lowers the barrier of entry [21]. In this sense, services act as an e-mobility multiplier. This ultimately accelerates the market penetration of e-mobility related products or services [5]. In order to allow a common understanding, we define e-mobility as "(…) a highly connective industry which focuses on serving mobility needs under the aspect of sustainability with a vehicle using a portable energy source and an electric drive that can vary in the degree of electrification" [19].

2.2 Business Models

Research in BMs has gained momentum within the last decade [16, 18, 22]. Despite the apparent interest in the BM as a concept, the research field presents itself as an intangible topic. Researchers offer a wide range of explanations on what a BM represents, since different research motivations lead to divergent roles and functions assigned to the individual BM concept [18]. Therefore, existing definitions only partly overlap in the literature [16]. That leads to a variety of representations that aim to describe a BM. The representation supports explaining the business, running the business, and developing the business [17]. The commonly used component-based approach is a textual representation of a variety of dimensions and characteristics of the BM [23]. These dimensions describe certain elements of the BM such as key resources, key activities, and revenue model. While there is wide range of possible dimensions, at its core the BM describes how value is created (value creation), what value is offered to the customer (value proposition) and how this value is then captured (value capturing) [24].

BM research in the field of e-mobility has a tendency to only conduct analysis of BMs in a particular and isolated context. For example, there are approaches that develop BMs around the electric vehicle using it as the central and solely element of the business [1]. Others suggest BMs which are focused on a certain industry like the energy or automotive sector [25]. Some approaches even aim to develop BMs for an even more narrowed area of e-mobility, for example for the fast commercialization of plug-in cars [26]. Kuehl et al. introduce a unified BM framework for e-mobility services to support comprehension and make services comparable [19]. It describes the essential dimensions of a BM value creation (key resources, key activities, cost structure), value capturing (revenue streams, customer segments) and value proposition.

2.3 Pattern Identification

The term pattern was decisively coined by the architectural theorist Christoph Alexander [27]. It is universally applicable to different topics [8]. An analysis of existing BMs with regard to underlying patterns has been carried out by several researchers. Abdelkafi et al. [4] conduct a research on publications dealing with BM patterns and identified 200 patterns in total, which were partly overlapping. Weill et al. [9] aim to distinguish different BM configurations in order to analyze the business performance of the largest 1000 companies in the US economy on a two dimensional taxonomy. Andrew and Sirkin [13] investigate different forms of businesses which successfully manage to achieve a payback from their investment on innovation and differentiate between three types of BM patterns. Johnson [10, 28] provides a categorization of BMs based on his own definition of the BM and gives an overview of 19 patterns. A similar work is conducted by Osterwalder and Pigneur [11], who introduce five patterns based on the BM canvas proposed by Osterwalder [29]. Gassmann et al. [12] carries out the most extensive research on BM patterns in the reviewed literature as they observe 55 different patterns which are meant to serve as innovative concepts for developing new business ideas upon. These authors do not apply a formal method to develop the patterns but suggest that patterns can be formed by a personal observation of firm's BM configurations [9–11, 13]. However, finding patterns within BM configurations by close observation highly depends on the individual analyzing the data set. This eventually leads to a non-replicable and possibly biased result. Other researchers apply systematic approaches to unveil BM patterns in a specific industry. Echterfeld et al. [14] introduce a pattern-based BM design methodology to exploit disruptive technologies. Hartmann et al. [15] analyze a data set of 100 BMs from start-up firms that rely on data as a resource of major importance for their business. They configure the data according to a pre-defined BM framework and apply the k-Medoids clustering algorithm. Kuehl et al. [19] undertake an investigation of BM patterns in the field of e-mobility services, where data is analyzed by two separate methods (k-Means and a greedy-like algorithm).

Although these authors contribute to seizing the business model pattern identification discipline, certain shortcomings need to be mentioned. Kuehl et al. [19] applies two very transparent algorithms, but does not include any form of validation. Hartmann [15] and Echterfeld [14] introduce a method that could be generally applied in any domain. However, both require unguided decisions during the research process in order to identify patterns. Hartmann [15] decides at one point for the dimensions that are used for the algorithm. Echterfeld [14] requires a personal decision by revealing patterns manually in a graphic.

3 Methodology

In order to develop an approach for extracting BM patterns the Knowledge Discovery in Databases (KDD) process is used as a framework that composes of the elementary steps for identifying patterns in data [30]. Based on previous work by Halkidi (2001) [32] the introduced approach uses the four steps data preparation, data analysis, validation as well as interpretation (shown in Fig. 1).

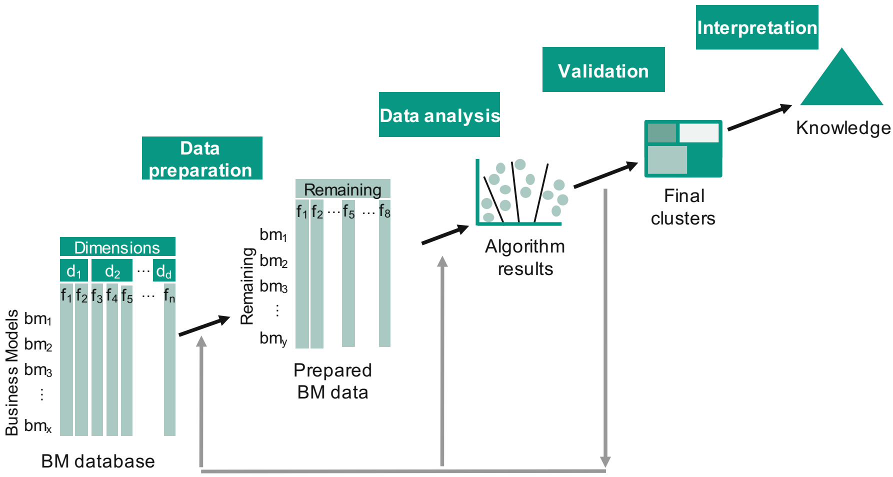

Fig. 1. The Knowledge Discovery Process based on [32].

The identification of BM patterns starts with a database of BMs which are coded according to a BM framework. A BM framework consists of multiple dimensions (e.g. key resources, key activities, etc.) with multiple characteristics (e.g. key activity: providing, aggregating, etc.). For a single BM i therefore follows: $bm_i = \{f_1, f_2, f_3, \ldots, f_n\}; f_m = \{0; 1\}; m = \{1, 2, 3, \ldots, n\}$., where f represents the BM characteristics described in the BM framework. 1 indicates the presence, 0 the absence of a characteristic within a BM. The initial database consequently consists of a binary matrix in which columns represent the potential BM characteristics and rows represent individual BMs.

3.1 Data Preparation

This phase aims to create a target data set for a pattern identification process. Any information within the data which is not of relevance for a data mining task need to be filtered since the may interfere the results [32]. Therefore, the data preparation phase is twofold.

First a selection of BM framework characteristics is include in the pattern identification process. Only those can be further considered which describe a distinct incident. Characteristics being absent in every BM are neglected since they do not add value to the process of finding patterns of similar BMs. Accordingly, characteristics which are only considered by a single BM are neglected since they comprise a BM's unique characteristic.

Second is projecting the remaining data set. This step aims to reduce the effective number of characteristics under consideration by finding useful components to represent the data [30]. The projection is applied using the Principal Components Analysis (PCA). The PCA is favored over similar statistical methods due to the precise order of priority concerning the principal components. This allows to define distinct decision rules for the selection of relevant principal components during the research process which allows to reduce dimensionality by neglecting the irrelevant ones.

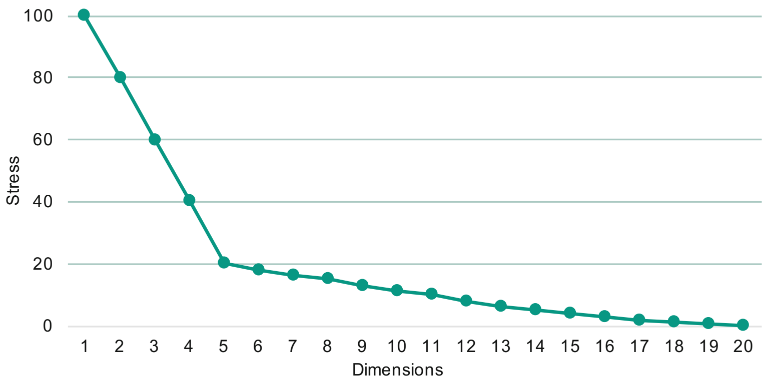

Fig. 2. Ideal scree plot for applying the elbow criterion; adapted from [33].

The method computes a set of k orthogonal vectors (principal components) which are linear combinations of all original variables (BM characteristics) and function as a new set of axes for the data explaining the same information as the original ones. The relevant principal components are selected using a scree plot and the 'elbow' criterion [33]. The scree plot graphs the variance explained by each principal component in a decreasing order over the number of the corresponding principal components (exemplarily illustrated in Fig. 2). The elbow marks the graph's dramatic change in the stress of variance and leads to the selection of the principal components to the left of this elbow which can equally represented the data objects with little distortion [33]. In this way, components which only provide a low contribution to the explained variance of the original data set can be eliminated. In the case of Fig. 2 the criterion would select the first five components and therefore reduce the dimensionality from 20 to 5 dimensions for further analysis.

The data preparation phase ends with the selection of the relevant principal components and a non-binary target data set is passed to the next process phase.

3.2 Data Analysis

This phase aims to apply a data mining task on the non-binary target data set. Since labels for classes of patterns with similar BM configurations are not previously known in the data set, the research objective turns into an unsupervised learning data mining task [34]. It requires to group the data into classes of similar objects which is called clustering. It hereby singles out characteristics, which coin different groups distinctively.

Different types of clustering algorithms exist in the literature [34]. In the context of this clustering task a partitioning method is appropriate for the analysis since the research intends to unveil mutual exclusive clusters. More precisely, the k-medoids algorithm is chosen to cluster the data set at hand. This algorithm groups n objects into c clusters by minimizing the sum of dissimilarity between each object p within cluster i and the cluster's representative object o_i [36]:

$$\min \sum_{i=1}^{c} \sum_{j \in C_i} \mathrm{dist}(p, o_j) \tag{1}$$

The k-medoids algorithm is chosen over the contemplable k-means algorithm due to the cluster's corresponding point o_i (medoid), an actual data object which is most centrally located in the cluster. It brings a twofold advantage over the k-means which uses the mean value of the cluster's objects to represent the center of the cluster. On the one hand, medoids form a more meaningful cluster's center in this context. They can serve as archetypes for clusters later in the investigation process. On the other hand, k-medoids is less sensitive to outliers in the data set in general [34].

After the data projection is performed only assumptions can be made on how the data looks likes, since it retrieves a non-binary data set in k-dimensional Euclidean space. Hence, the Euclidean distance as the conventional distance measure in this space is used to measure dissimilarity between data objects [36]:

$$\mathrm{dist}(x, y) = \sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \tag{2}$$

Afterwards, the number of clusters *k* is determined. The parameter influences the granularity of the results since it manages a trade-off between the accuracy of each object to fit its assigned cluster and the compression of the data set to a small number of groups. A rule of thumb is provided in the literature by setting the number of clusters to $\sqrt{n/2}$ for a data set of n objects [37]. In case the resulting number does not provide a clear suggestion on which number to choose both the lower and upper discrete bound are further examined. Additionally, the silhouette coefficient is plotted over the number of clusters. The number of clusters with the highest value then represents the best solution for k. There is, however, no right procedure to determine the correct number of clusters. Instead, the clustering result needs to be validated and eventually conducted again if the cluster analysis reveals poor results. This iterative procedure unveils the optimal number of clusters as the one with the best overall clustering result.

3.3 Validation

The clustering results are presented as a list of clusters with their assigned objects. The silhouette coefficient is then used to validate the clustering results. It offers the advantage of only depending on the partition of the data set, but not on the clustering algorithm itself. This makes the validation process independent from the previous research steps and allows a comparison to other clustering results from different studies on the data set [38]. The silhouette coefficient $s(i)$ measures how well an object i has been clustered compared to closest neighbor cluster on a ratio $-1 \leq s(i) \leq 1$ [38]. Accordingly, the average silhouette width denotes the average s(i) for all objects i within a cluster and overall silhouette width the average $s(i)$ for all clusters.

The validation phase is two-stepped. First, the overall silhouette width will be examined. Clustering results featuring an overall width of less than 0.25 will be neglected. According to Kaufmann and Rousseeuw [35], a silhouette coefficient under 0.25 suggests that no substantial structure in the data exists. In this case, the research process returns to the data analysis phase. Second, if the overall width indicates an underlying clustering structure ($s \geq 0.25$), the average silhouette width for each cluster will be consulted. Only clusters with at least an underlying structure will be further interpreted. In order to validate the retrieved results, the clustering process is carried out several times. In case the clustering solution show consistency, the clustering result can be considered reliable [39].

4 Application to E-Mobility Services

In the following section, we present the results from applying the approach to e-mobility services. As already pointed out, services play a key role concerning the success of e-mobility and, thus, provides an ideal opportunity to apply the introduced method in order to search for patterns of BMs exploiting e-mobility as a bundle of new technologies. According to the proposed methodology, we give insights about the data source, the data preparation, data analysis as well as the validation. Finally, we interpret the clustering results.

4.1 Data Source

The initial data set is provided from a government-funded web platform. It collects BM information of 58 e-mobility services, which are directly entered by the e-mobility projects themselves [19]. The unified e-mobility services BM framework serves as its basis (see Fig. 3). Applying this framework to real projects results in the required format to process it for the proposed BM clustering (c.f. Sect. 3).

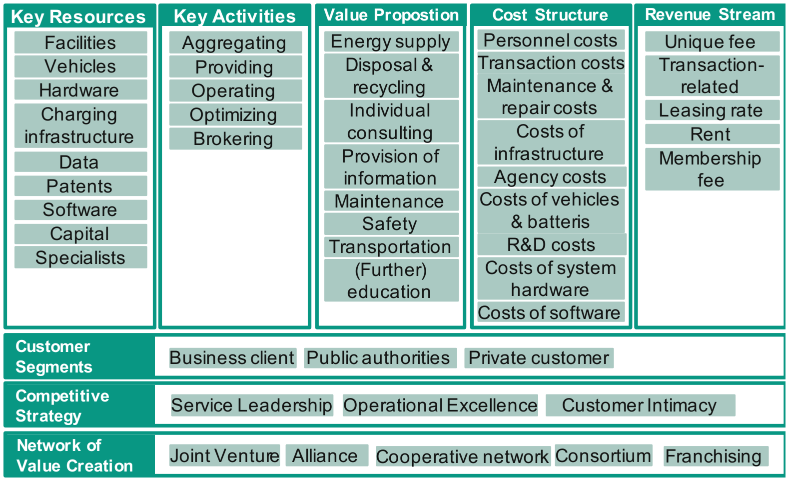

Fig. 3. BM framework for e-mobility services based on [19]

4.2 Data Preparation

As part of the data preparation, we remove 39 characteristics in total for the analysis. Note that this does not mean these are irrelevant in terms of business model research. Instead, they could not add value to the data mining process. The web platform offered the option for the projects to select 'unclear' for the dimensions *cost structure*, *revenue stream*, *customer segments*, *competitive strategy* as well as *network of value creation*. In order to only regard completely filled BM, we neglect these dimensions. Because the

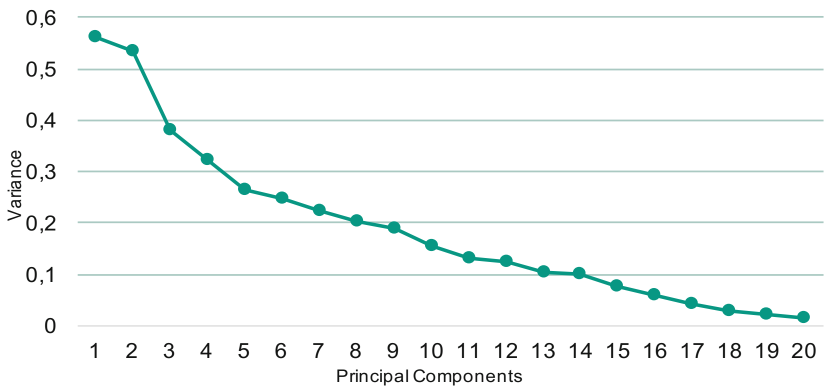

Fig. 4. Scree plot resulting from PCA.

characteristics *patents* and *hardware* (both key resources) are continuously absent, they are also neglected. The data reduction leaves 20 characteristics to describe the collected BMs. They consist of the dimensions *value proposition*, *key resources*, and *key activities* with the characteristics depicted in Fig. 3 (without *patents* and *hardware*).

The resulting scree plot from the PCA unveils that the additional variance provided by each component beginning from component five lies on a similar, low level (see Fig. 4). Because there is no clear elbow component, both potential candidates (three and five) are included for the following steps until the validation.

4.3 Data Analysis

The k-Medoids algorithm is initialized with a random seed for both PCA component cases. The clustering is run several times with different random seeds. The rule of thumb for determining the number of clusters suggests to search for $k = \sqrt{58/2} \approx 5,39$ clusters. Therefore, five and six clusters are examined closer in the overall silhouette width plot for validation.

4.4 Validation

Table 1 shows the average silhouette coefficients for the relevant cases. It indicates that six clusters with three PCA components are the superior choice with $s(c = 3, k = 5) = 0.32$.

Table 1. Average silhouette coefficient for combinations of PCA components and clusters.

Average silhouette coefficient s(c, k)		
# Clusters ►	k = 5	k = 6
# PCA components ▼		
c = 3	0.31	**0.32**
c = 5	0.30	0.27

This indicates a weak, but existing clustering structure. Based on the average silhouette width of 0.16 one cluster with 10 BMs is not further considered. The rest of the clusters show an average silhouette width of 0.25 or higher and are therefore further considered in the research process. The clustering result therefore consists of five vectors entailing the assigned objects' names. Subsequently, the entries of each cluster's vector are matched with the original row names of the binary matrix. By doing this, a binary data subset for each cluster is obtained. Each subset now reflects the binary BM configuration again which describes the presence or absence of the respective characteristic in the BM. This fragmentation of the initial data set consequently represents the final clusters of the data analysis.

4.5 Interpretation

In the following the clusters are described with regard to the BMs characteristics' frequency. This is carried using a bar plot for each BM cluster. It is exemplarily shown in Fig. 5. Afterwards, the cluster's prevalent characteristics are identified and used to interpreted the clusters as BM types. Again, the approach is not supposed to unveil components being irrelevant to a business model. Instead, insights of different business model types and their core components are supposed to be derived.

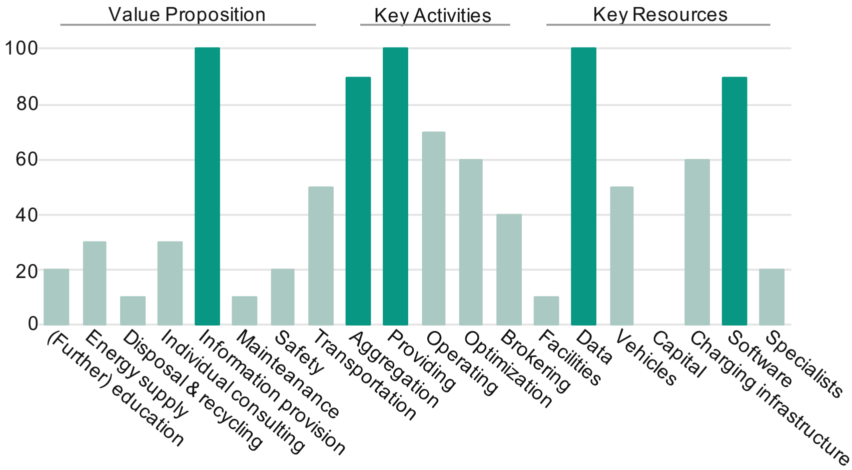

Fig. 5. Characteristics' frequency within BM Type 1: analytics as a service.

BM Type 1: Analytics As A Service. This cluster comprises of 10 BMs which all offer a provision of information to the customer as the value proposition. Additional value proposition is only used in rare frequency. The key resource is represented by data. Additionally, 90% of the BMs also use software as a key resource. The key activity is described by providing information. Moreover, 90% within this cluster perform aggregation as a key activity. Thirdly, 70% of the cluster's BMs consider operating a key activity. Value proposition providing information seems consistent in the context of key resource data from which the relevant information offered seems to be derived. The collection of data is performed through an aggregation by the majority of BMs. Resource software indicates that the businesses derive the necessary information from the data by themselves. Furthermore, operating indicates that the aggregation is conducted by an own infrastructure or platform.

Concluding, data and the distribution of gathered knowledge seems to be the core business of this cluster. In order to collect necessary data, an own infrastructure or platform is mostly operated. The gathered data is then aggregated and analyzed by an own software to gain the information. Therefore, this group is referred to as the analytics as a service cluster.

BM Type 2: Charging As A Service. The 7 BMs in this cluster all use a charging infrastructure as a key resource (100%). Additionally, vehicles and software are also used as key resources by respectively 57% of the BMs. The key activity is expressed by operating (100%). It is enriched through three additional activities: providing (71%), brokering (86%), optimization (71%). The value proposition is represented by the characteristics energy supply (71%) and individual consulting (57%). Summarizing, this BM type addresses the importance of charging infrastructure. They build the core business around the operation of a charging infrastructure. Energy supply as the dominant characteristic for the value proposition seems plausible in combination with the operation of the charging infrastructure. The seven entailed BMs are referred to as the charging as a service type.

BM Type 3: Data As A Service. 15 BMs this cluster mainly offer a provision of information to the customer (80%). The major key resources are presented by data (87%) and enriched through specialists (53%). The aggregation expresses the main key activity (87%). Providing is also noteworthy, but it is less considered since only 67% use this sort of activity. Taking into consideration the main value proposition and key activity of this cluster, it seems very similar to the Analytics as a service BM type. Both seem to use occurring data as the core element of their business and the central linkage between the BM elements. However, the strong differences are revealed when looking at the business characteristics which are consciously not considered in this cluster. The resource software only plays a minor role in this cluster, whereas it is regarded a key resource in the analytics as a service business type. Instead, specialists play a considerable role in the cluster at hand, whereas specialists are not considered crucial at all in the first type. Also, the activity of operating any sort of infrastructure or platform does not reflect an important issue of this BM type. Taking into consideration the previously made observations, this cluster needs to be considered as an own BM type. Since any sort of software is not considered crucial in this cluster, it can be presumed that a transformation process of data does not take place. It is rather the pure aggregation of data which constitutes the core element of the business. Therefore, the 15 BMs in this cluster are referred to as data aggregation services. The characteristics (further) education and safety slightly stand out as characteristics of the value proposition. This gives an indication that the data aggregation and provision service takes place in a wide range of different themes throughout the field of e-mobility.

BM Type 4: Transportation Service. The 6 BMs in this cluster mainly offer transportation as the value proposition (83%). In fact, only one BM does not provide this kind of offering. The key resource is mostly represented by vehicles (67%). Additionally, software is used by 50% of the BMs. The key activity is mainly described by operating (67%). Additionally, providing and brokering, are carried out by respectively 50% of the BMs. Summarizing, the value proposition and the key resources suggest a traditional transportation service. Accordingly, key activity operating seems reasonable in the context of a transportation service offering an own electrical powered vehicle fleet. However, the key activities providing and brokering transportation also suggest a car sharing business type as a transport services which uses a software-based business realizing a brokering of vehicles. Therefore, this BM type is referred to as the transportation service.

BM Type 5: Knowledge As A Service. The 10 BMs mainly builds their core business upon specialists as a key resource (70%). Other key resources are represented by a significantly lower percentage. The value proposition is provided by an individual consulting (50%) and (further) education (40%). Both seem weak regarding the percentage of BMs entailing this characteristic. However, they seem to be the superior choice as opposed to the remaining characteristics. Key activities are represented by providing (60%), brokering (60%) and optimizing (50%). This BM type creates value by addressing the need for e-mobility related knowledge. On the one hand, the business configurations suggest the existence of a consulting service provision, carried out by specialists. On the other hand, value seems to be alternatively offered through an e-mobility related education, carried out by specialists. Therefore, this BM type is referred to as knowledge as a service (Fig. 6).

	Value Proposition							Key Activities						Key Resources						
	(Further) education	Energy supply	Disposal & recycling	Individual consulting	Information provision	Mainteanance	Safety	Transportation	Aggregation	Providing	Operating	Optimization	Brokering	Facilities	Data	Vehicles	Capital	Charging infrastructure	Software	Specialists
Type 1	20%	30%	10%	30%	100%	10%	20%	50%	90%	100%	70%	60%	40%	10%	100%	50%	0%	60%	90%	20%
Type 2	14%	71%	0%	57%	29%	14%	14%	14%	29%	71%	100%	71%	86%	14%	43%	57%	29%	100%	57%	29%
Type 3	47%	20%	13%	13%	80%	13%	40%	7%	87%	67%	13%	33%	7%	13%	87%	0%	0%	7%	27%	53%
Type 4	0%	17%	0%	0%	17%	0%	0%	83%	0%	50%	67%	0%	50%	0%	0%	67%	0%	0%	50%	0%
Type 5	40%	20%	0%	50%	20%	0%	20%	20%	0%	60%	0%	50%	60%	0%	10%	20%	0%	10%	10%	70%

Fig. 6. Summary of the identified business model types' core components.

5 Conclusion

The paper at hand proposes a general approach for finding BM patterns by applying established, mathematical methods. The approach combines the Principal Components Analysis, a k-Medoids clustering and the silhouette coefficient as a quantitative evaluation measure. This ensures that the results are replicable and the approach is deterministic—and therefore easily automatable and scalable.

The approach is applied to a dataset from the domain of e-mobility services. We are able to show its general feasibility as we are able to identify five semantically meaningful clusters, namely *analytics as a service*, *charging as a service*, *data as a service*, *transportation service* as well as *knowledge as a service*. Interestingly, an emphasized role of ICT is discovered within e-mobility services as two BM clusters explicitly offer a provision of information to their customers in different ways. One noteworthy aspect is that *analytics as a service, data as a service* and *transportation service* are partially confirmed by the work of Kuehl et al. [19] who already derive a *data-driven* and a *fleet-related* service. It can be seen that the proposed approach creates a more detailed clustering result since the BM clusters are more specified.

The approach has several limitations. First, the analysis was only applied to one domain with a small data set of 58 business models—and while the silhouette coefficient showed structure of the clusters, it could be higher for a strong underlying clustering structure. Second, a bias in the research remains regarding the initial data set since the entered framework information could not be reflected critically. Hence, subsequent single case studies should be conducted for every identified cluster in order to evaluate and illustrate the different business model types.

Nonetheless, the application of the approach was able to deliver interesting results for the field of e-mobility services and future work will apply it to different domains with a higher volume of available data to enable new, quantitative-based insights for the field of business model research.

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