Modeling the Business/Operating Areas of free-floating Carsharing Systems

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ABSTRACT: Free-floating carsharing systems with (and without) electric vehicles are emerging and there is limited knowledge where such concepts will succeed. Within this knowledge gap, the definition of the business/operating area is a key aspect. Inside this area a carsharing vehicle can be more or less picked-up and dropped-off everywhere at any time. This research aims to develop a model that helps to determine business areas a-priori by predicting inner-city booking hot-spots. The approach is based on modeling success factors. For this, first "success" and its manifestation are defined and then success factors which impact the definition of the business area are explored. These findings are combined in a regression analysis, resulting in a model that is later evaluated for its applicability.

Keywords: carsharing, free-floating carsharing, business area, operating area, success factors

1 INTRODUCTION

A variety of factors, such as rising oil prices and global warming, challenge the current individual mobility paradigm which is based on gasoline-fuelled cars in private ownership. These challenges are amplified through regulatory measures (e.g. congestion charges) and result in social changes such as collaborative consumption. These social changes together with technological changes (e.g. battery innovations, IT) are likely to lead to a new mobility paradigm - one based on new offerings and new business models. Energy-efficient, low-carbon mobility services will emerge and electromobility and carsharing are very likely future scenarios [1, 2].

Nowadays, "carsharing" means that a car is shared by a community and professionally organized by mobility providers, offering different vehicles at different places to their customers. There can be station-based and free-floating carsharing. Station-based concepts offer vehicles available at fixed stations whereas free-floating concepts allow the return of a car anywhere in a given business or operating area [3]. The research presented in this paper focuses on free-floating systems.

However, there is still little knowledge where such concepts will be successful and which factors drive this success. This knowledge is important as not only markets can be chosen according to this knowledge, but also the business model could be adapted to local circumstances. One aspect of this local adaptation is the determination of the operating area for a free-floating system. This is the place of offer as well as it defines usage patterns and the market and customer segment indirectly. In a previous study 150 adoption determinants or success factors were identified [4], which might influence whether the concept is adopted or not. This work builds up on these results and focuses on the quantification of the most critical success factors for the determination of an optimal business area for free-floating carsharing systems with and without electric vehicles. As a result, a regression model based on real booking and trip data of a carsharing provider will be developed which allows to predict areas within a city, where there is a high likelihood of a high booking density (usage) or in other words, hot-spots. The model is validated with another independent data sample of real bookings. Derived from the prediction of these inner-city hotspots, decision makers are aided in defining business areas successfully.

2 WHAT IS SUCCESS?

Before modelling success factors for the determination of business/operating areas, it must be defined what success is and how it can be measured. Naturally, carsharing providers must be profitable to achieve economic goals as well as it is a prerequisite that the concept – along with its ecological, economical, and social profits – diffuses in our societies. For this work, success is understood as profit which is (simplified) revenue minus costs. Costs can be easily assessed and are often induced by revenue (the more bookings, the more cars for example). The revenue side however is hard to predict as many external forces have an effect on it (see chapter three).

Revenue itself however is also influenced by a variety of company internal decision, e.g. prices, discounts, free minutes etc. For this reason, an unbiased success variable must be found and three indicators are proposed: duration of bookings, number of bookings and number of customers (see Figure 1):

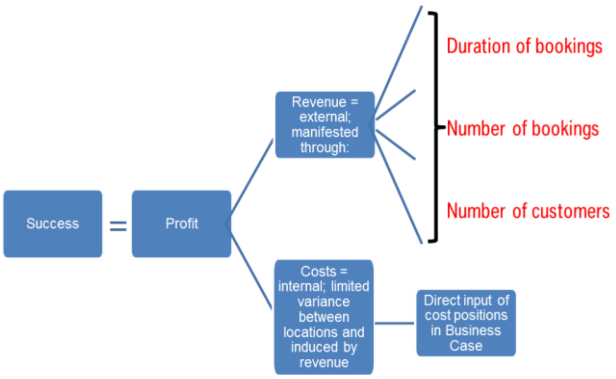

Figure 1: Derivation of success variables

A comparative analysis of these factors through descriptive statistics and mapping revealed, that the number of bookings appears as a good indicator for the success of a free-floating carsharing operation as the duration of bookings and the number of customers are well represented through this indicator. In order to be able to locate and locally differentiate success, specific booking densities per square kilometre were computed for different segments (a city of one million inhabitants consists of approximately 1,000 of such segments). For each of the segments the booking information of an free-floating carsharing provider was available. Furthermore, detailed further statistics, like population density, restaurant density, average rent, household income etc., was available [6].

3 WHAT INFLUENCES SUCCESS?

A previous study [4] identified 150 success factors for (E-) carsharing, based on a comprehensive literature review and a case study that involved 34 interviews with companies, experts, and customers. These 150 factors can be grouped in factors regarding the environmental context, adopter characteristics, and innovation attributes [5], see Figure 2:

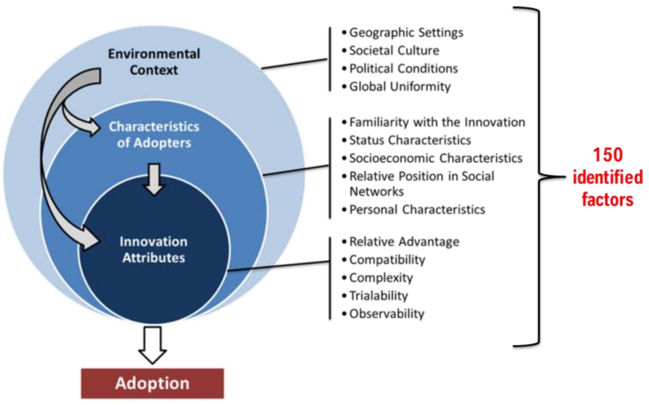

Figure 2: Previous approach for the determination of success factors [4]

Since this research is interested in local (inner city) success for the determination of a business/operating area, the factors were argumentatively explored whether a factor varies inbetween cities and also within a single city. This approach is depicted in figure 3:

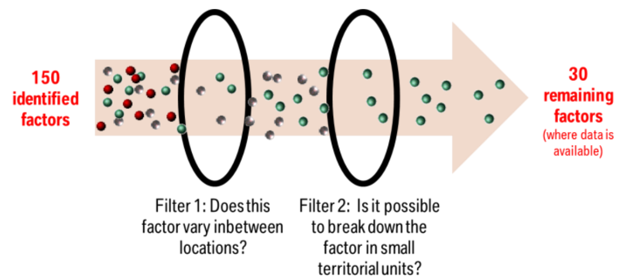

Figure 3: Argumentative Exploration

The remaining 30 factors stem from the environmental context (city dimension) or adopter characteristics (customer dimension) and include population density, city typologies, intermodal-infrastructure, tourism, openness, ecological awareness, status of cars, social status, age, etc. These factors can often not be measured exactly or are not available – e.g. it is not possible to measure ecological awareness directly. For this reason, each factor that cannot be measured directly is represented through one or more indicators. For example, ecological awareness is measured through an affinity index for natural gas vehicles.

4 ANALYSIS & MODELING

After having identified indicators for success and explanatory variables which influence success, this step aims to identify which possible explanatory variables do have a measurable impact on the success indicator (booking density) and how these factors can be quantified in order to build a model which can be used to predict local booking hot-spots.

To identify these hot-spots it is important to examine the explanatory factor in a relative way. For example, when looking at the factor "rent" of a segment then typically the average rent differs between two cities. To be able to compare different cities with this factor, an index was introduced which states the rent of a segment compared to the average rent of the analyzed city. Since this research is interested in the local (inner-city) influence of an explanatory factor, indices for every factor were determined. Let x_{it} be the value of an explanatory factor i in segment t of an observed city. Then the index p_{it} is derived the following way:

$$p_{it} := \frac{x_{it}}{\overline{x_i}} \quad \forall\, i\,,$$

where $\overline{x_i} = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ is the average of explanatory variable i in the observed city (T is the number of segments in the city).

Methodologically, the analysis concept is based on a regression analysis and data from two German cities and consists of two steps:

First step is the examination of all explanatory variables through scatter plots and simple regression analysis to determine whether there is a relationship and which form it has. Figure 4 shows this step exemplary with the factor population density:

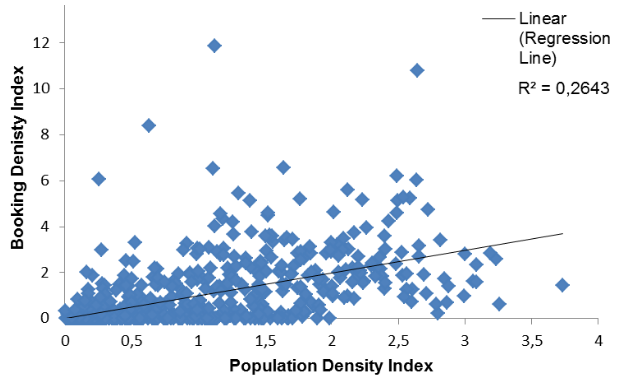

Figure 4: Scatter Plot of Population Density over Booking Density

As a result, thirteen potentially influential success factor indices have been identified in this step:

- population density
- company density
- rent
- distance to an ICE train station
- distance to the city center (town hall)
- restaurant and hotel density
- natural gas vehicle affinity
- lifestyle (type down-to-earth)
- lifestyle (type materialistic oriented)
- car density
- one person households
- UMTS affinity
- high-tech affinity

Step two consists of an exploratory regression to determine which combination of the thirteen potential influential factors results in the best ordinary least square model based on different statistical criteria. Within this method, all possible ordinary least square models were evaluated and those models, that best explain the dependent variable within the context of the pre-specified criteria, were sorted out.

The selection criteria were that the model must have one to five explanatory variables and an adjusted coefficient of determination ($\overline{R}^2$) > 0.5. It was further specified, that

- the coefficient's p-value (p-value < 0.05 -> coefficient is supposed to be statistically significant),
- the p-value of the F-statistic (p-value < 0.05 -> indicates overall model significance) and
- the VIF (Variance Inflation Factor) value (VIF < 7.5 -> explanatory variables are not redundant)

meet the defined criteria. From the models which met these criteria, the model with the highest $\overline{R}^2$-value was picked.

As a result of this step, the following model ($\overline{R}^2$-value = 0.53) appeared:

$$bd_i = x + pd_i + rd_i + thd_i + r_i \ \forall\, i$$

where bd_i is the index of the booking density of segment *i*, pd_i is the index of the population density of segment *i*, rd_i is the index of the restaurant density of segment *i*, thd_i is the index of the distance from segment *i* to the town hall of the considered city and r_i is the index of the rent of segment *i*.

This model can be used for carsharing with conventional vehicles as well as with electric vehicles. It must be noted however, that this model does not contain one key aspect of carsharing with electric vehicles – charging infrastructure. Currently, there is no available data which could have been included in the formulation of the model. Hence, the topic must be explored theoretically. A possible success factor for determining the business area for a carsharing concept with electric vehicles is the existing charging infrastructure. When a city has a well-developed charging infrastructure then users have many possibilities to recharge, reducing range-anxiety and keeping operation costs for providers low.

If there is no charging infrastructure available, the model might help to determine where charging hubs might be established and what type of charging technology is needed. In hot-spots for example, the turnover of cars is quick and hence potential charging time is limited. Therefore, quick-charging technology might be employed as users of electric carsharing might find it convenient to find a charging station near a hot-spot. In the area of these points there is usually only limited parking available and a charging station would be a non-monetary incentive to use electric car-sharing because of the attractiveness of a parking spot. On the other hand, cold-spots could be equipped with slower and cheaper charging stations as vehicles probably park a longer time in this area as demand is lower.

5 EVALUATION

In order to test the applicability of the formulated model, it was applied to a third city which was not used to calibrate the model and where real world booking data was available. The results show that the model returns a slightly scattered output since each segment is forecasted individually (around 600 segments for this city). However, a clear clustering of hot-spots can be found and a business model can be intuitively derived.

The comparison of this result with actual booking data reveals its high applicability as deviations (over- and underestimations of the model) occur mainly within hot-spot areas. This does not influence the determination of a business area because the absolute forecast (or the level of relativity) of the booking density is indifferent for this decision. To illustrate this, figure 5 shows a map of the model residuals as well as the modelled and the actual real-world business area:

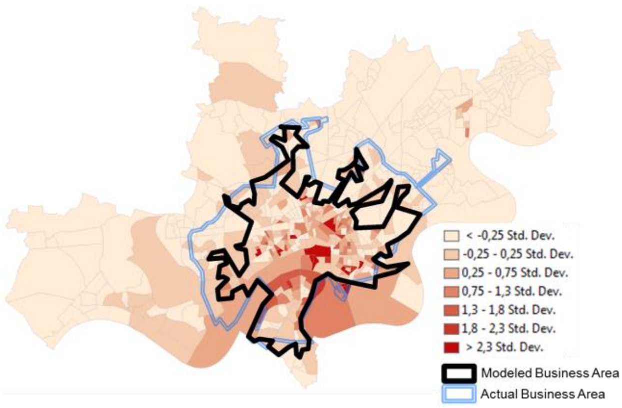

Figure 5: Model Residuals

6 CONCLUSION

The aim of this research was to develop a model that helps to determine business areas by predicting inner-city hot-spots through modeling success factors. First "success" was defined as a representation of profit and "booking density" appeared as adequate manifestation of it. Consequently, a wide variety of possible success factors were argumentatively explored, followed by a regression analysis consisting of two steps. Step one examined all potential factors for their relationship to the success indicator "booking density" with the result of 13 potential factors. In step two, these 13 factors were part of an exploratory regression analysis with a regression model as outcome. This model includes indices for rent, population density, restaurant density and city center (town hall) distance and features a $\overline{R}^2$-value of 0.53.

The evaluation of this model proved its high applicability and practical relevance, as hot-spot and cold-spot areas were correctly identified. However, the model does not give perfect results on absolute numbers but rather gives relative information on the suitability of an area compared to other areas within the same city – an information crucial for determining the business area of free-floating carsharing systems.

Since there is no data available to investigate the impact of charging infrastructure for concepts with electric vehicles, further analysis must be carried out in future. In the meantime, the developed model can be used for all drivetrains and car-sharing providers will have to adopt on local circumstances. If there is a considerable public charging infrastructure providers should make use of it. If there is none, other charging concepts (such as centralized over-night charging) must be applied to fulfil consumers' needs and make the offer successful. Alternatively, the models prediction of hot- and cold-spots can be used to determine which charging strategy and technology can be used at a certain area within a city.

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