Computing Incentives for User-Based Relocation in Carsharing

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Abstract. Carsharing offers an environmentally friendly alternative to private car ownership. However, carsharing providers face the challenging task of matching shifting vehicle supply with fluctuating customer demand to prevent related operational inefficiencies and ensure customer satisfaction. To date, researchers have improved existing relocation strategies and developed new concepts with the use of information technology tools. Still, current literature lacks research on optimization and implementation of user-based relocation solutions. The most urgent need currently lies in the development of algorithms to compute and implement effective incentives for user-based relocation.
We address these needs by utilizing a design science research approach to develop an automated machine learning-based incentive computation solution for incentivizing user-based relocation. We use a survey of 274 participants resulting in 1370 individual data points to train an incentive computation model, which is then applied within a small-scale field test. Results suggest that the algorithm computes appropriate incentives.

Keywords: Design Science Research, Carsharing, User-based Relocation, Incentive Computation, Green IS

1 Introduction

The demand for new sustainable mobility options as substitutes to private vehicles has increased in recent years. However, to be considered a valid alternative, new mobility options should not only be sustainable but also be flexible enough to meet dynamic customer and environmental needs. In this context, the use of alternate mobility services can be a possible solution, with carsharing as a prime example [1–3].

Current research in the area of carsharing views balancing vehicle supply and demand as one of the key enablers for this to happen [4–6]. Carsharing providers face the challenge of a shifting vehicle supply and demand, leading to insufficient vehicle supply at some locations. Consequently, some customers may request a vehicle, but may have their rental request rejected [7–9]. This situation reduces revenue and leads customers to view carsharing as inflexible and inferior to a privately owned vehicle [5].

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Hence, there is a need for carsharing providers to take countermeasures to sustain a sufficient vehicle distribution. The common counter-measure is to relocate vehicles in advance by operator-based relocation [6, 10], a process in which employees move vehicles between stations or areas to comply with local demands [3, 5, 6]. However, this procedure has high costs (e.g. personnel and fuel) associated with it, while lowering these operating costs remains a key success factor for carsharing [3, 9, 11].

Therefore, to provide an alternative researchers have developed a new concept called user-based relocation. The idea of user-based relocation is to motivate users to return currently rented vehicles to locations with high vehicle-demand [4, 12]. This relocation approach is deemed to be less expensive [3, 12], but is yet to be implemented within a real-world commercial carsharing system. Inducing user-motivation to perform relocation using the right mechanisms, e.g. offering monetary incentives, is a major obstacle in this process, as methods to compute sufficient incentives are still lacking [3, 4, 13]. Current carsharing research often uses a simplified function to compute incentive costs for their scenarios [4, 12] without real-world application. However, the incentive must be derived from various factors, such as weather, distance or time. To close this research gap, we aim in this paper to answer the following question:

RQ: How can a cost-efficient incentive be computed for user-based relocation?

2 Related Research

Carsharing systems can be distinguished into three forms [6]:
(1) **Station-based two-way carsharing:** Vehicles can be rented by customers from any station and the vehicles have to be returned to the same station.
(2) **Station-based one-way carsharing:** Vehicles can be rented from any station but can also be returned at any available station.
(3) **Free-floating carsharing:** Unlike station-based carsharing, free-floating carsharing allows cars to be rented and returned anywhere within the operation area of the carsharing provider.

The flexibility of station-based, one-way, and free-floating carsharing possesses a drawback in the form of the vehicle relocation problem – vehicle distribution is altered by rentals, leading to an under-supply of vehicles at some stations or in some areas. Hence, carsharing providers have to manage vehicle distribution by vehicle relocation to achieve a more balanced system [14].

Currently, vehicle supply and demand management measures can be distinguished into three forms:
(1) **Operator-based relocation:** Staff members rearrange the vehicles by driving, towing or ride-sharing them to the desired location [15].
(2) **User-based relocation:** Selected users are motivated by the carsharing provider during a rental to return their currently rented vehicle at a station with a high vehicle demand, when their initial destination has sufficient vehicle supply [12].
(3) **Prevention-based:** Through territorial pricing strategies and other price incentives, attempts are being made to proactively encourage users to use certain vehicles and park

them at selected locations in order to maintain a balanced supply-demand ratio with regard to vehicle locations [16, 17].

We conducted a literature review [18] to evaluate the current status quo of user-based vehicle relocation research and identify relevant research gaps. For this, we conducted a tailored keyword search to ensure that the results fit the carsharing domain and user-based concept within the following databases: ScienceDirect, EbscoHost, JSTOR, and AIS electronic library. Variations of the following search query were used:

((“car sharing” OR “carsharing”) AND (“relocation” OR “rebalancing” OR “allocation”) AND (“user-based” OR “user based” OR “userbased”))

After filtering, the search resulted in 13 separate publications. Next, we did a forward and backward search, identifying 10 additional publications. All together, we gathered 23 publications on the topic of user-based relocation (see Table 1). In the following, we will present the incentive computation methods for user-based relocation that we found through our research.

Brendel et al. [12] presented a function of time for relocation to compute the incentive. They derived the function from a survey of 26 participants. However, the sample is relatively smaller and lacks an evaluation. Furthermore, only using time for relocation simplifies the problem significantly.

Wagner et al. [4] developed an incentive concept based on the idle time reduction a relocation grants. The user is offered free-minutes in relation to the idle time reduction. However, they do not specify a method to determine the amount of time required to motivate users to relocate.

Angelopoulos et al. [17] call their approach user-based but it does not fit the common definition of user-based relocation. Their approach refers to a dynamic allocation of vehicles to users, based on incentive systems that use reservations to manage mismatches between supply and demand, to create price incentives for rewarding users when they agree to fetch their vehicle from an oversupplied station and/or hand it over to an undersupplied station. On that account, it is a preventive vehicle supply and demand management approach. The other articles found are mainly concerned with providing technical (e.g. algorithmic) support for future implementations of user-based relocations.

Table 1. Literature Overview - Carsharing Vehicle Relocation Research

Article	*Incentive Computation Method*	*Free-Floating*	*Station-Based*
Angelopoulos et al. [17]	**(X)**		**X**
Bannerjee et al. [19]			**X**
Barth and Todd [15]			**X**
Barth et al. [20]			**X**
Bianchessi et al. [21]			**X**
Brandstätter et al. [22]			**X**
Brendel et al. 2016 [12]	**X**		**X**
Cepolina and Farina [23]			**X**
Cepolina and Farina [24]		**X**	**X**
Chow and Yu [25]			**X**

Clemente et al. [26]		**X**	
Clemente et al. [3]			**X**
Di Febbraro et al. [27]			**X**
Gavalas et al. [28]		**X**	**X**
Herrmann et al. [29]		**X**	
Jorge et al. [30]			**X**
Jorge and Correia [9]J			**X**
Laarabi et al. [31]			**X**
Schulte and Voß [13]		**X**	
Wagner et al. [4]	**(X)**	**X**	
Wang et al. [32]		**X**	
Waserhole et al. [33]			**X**
Wang et al. [34]		**X**	
∑ ***23***	***3***	***8***	***17***

X ≙ covers topic completely; (X) ≙ addresses topic partially

For instance, Wagner et al. [4] develop a support system for user-based relocation within free-floating carsharing, which detects imbalances in vehicle distribution based on idle time patterns. Discounted alternative stations are simulated. Bianchessi et al [21] present the "Feedback Dynamic Pricing" approach, which is based on modelling a vehicle sharing system as a dynamic system, aiming to control fleet balancing by varying the price of the service in real time. For this purpose, a simulator was developed. Both articles stand exemplary for the current focus of user-based relocation research. Novel and sophisticated algorithms for detecting and counteracting vehicle imbalances are developed, while necessary incentives are often a comparative side note and not investigated as profoundly.

In summary, current research has not engaged with the topic of incentive prediction from a practical standpoint. The approach of Brendel et al. [12] comes closest to a practical application. However, their study focuses on estimating the potential costs of user-based relocation and is not intended for practical application. Thus, it is visible that developing a practice-ready incentive computation method for user-based relocation is still an evident research gap.

3 Research Approach

We followed a combination of the frameworks by Hevner et al. [35] and Hevner [36]. The DSR setting and its interrelated cycles are depicted in Figure 1. The relevance cycle connects the design activities of the design cycle with the artifact's intended environment. By this, it enables researchers to assemble real-world requirements to describe and later solve the subsequent real-world problems. Furthermore, artifacts are introduced to the environment as part of a relevance cycle. The rigor cycle relates the design activities to the existing body of knowledge. Thus, existing knowledge can be integrated into design activities and research results can later extend the knowledge base. The central part of a DSR process is the design cycle. It represents the design and evaluation activities of the researcher.

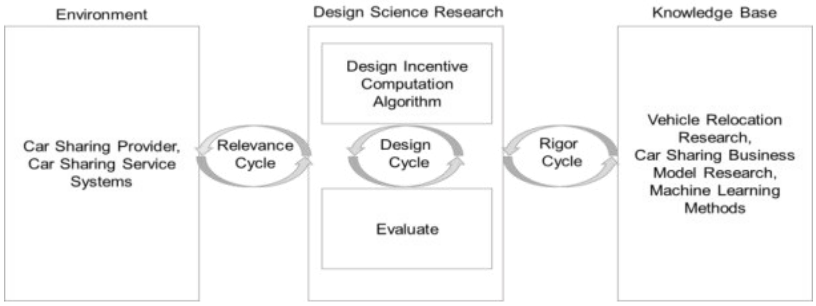

Figure 1. Design Science Research Setting (following [32])

Additionally, during the research process, we also applied a theorizing process similar to heuristic theorizing [37] as described by Brendel, Brennecke, et al. [16] for the development of a design theory. The development of a six component design theory [38] is achieved by implementing the following steps after each research activity:
(1) Review the current design theory and evaluate the need for refinement of each of the six components.
(2) If refinement is needed, iteratively add new components and/or adjust existing components until all new knowledge is incorporated.

For this, we abstracted and de-abstracted the requirements, the development process and the artifact to obtain context specific or meta-components [37].

The DSR process started with a relevance cycle (see Table 2), revealing a lack of implemented user-based relocation system and methods to compute incentives for user-based relocation (see the Literature Review section). To validate our findings, we discussed these results with two carsharing providers. During both the interviews with the managing directors, we presented and discussed the concept of user-based relocation and the related research gap. For this, we prepared the following open questions:
(1) What general limitations and restrictions come to your mind when you think about incentives and user-based relocation in general?
(2) What are the requirements to be considered for the development of an algorithm that can compute appropriate incentives for user-based relocation?

Our findings were confirmed, resulting in the identification of a practice relevant problem manifested as a lack thereof incentive prediction methods for user-based relocation. Furthermore, we gathered requirements for the algorithm design process.

As a second step, we performed a rigor cycle to draw from existing vehicle relocation publications. While seeking a starting point for the design process, we identified machine learning as the basis for our development. This decision was made based on the potential of machine learning [39] and its already successful application in the contexts of carsharing and vehicle relocation [6, 13]. Machine learning can identify patterns within given datasets and predict values based on them. Therefore, it can be considered a potential approach for developing an incentive computation algorithm.

Table 2. Overview of Performed Relevance, Design and Rigor Cycles

	Relevance Cycle	*Rigor Cycle*	*Design Cycle*
Inputs	• Publication databases	• Research database	• Machine learning literature
Methods	• Literature review • Expert Interviews	• Literature review	• Survey • Field study
Steps	• Gather publications from literature reviews • Analyze publications • Discuss findings with experts • Gather requirements	• Analyze publications • Identify input knowledge for design process	• Identify requirements • Design machine learning algorithm • Gather dataset • Train algorithm • Test algorithm in field study
Results	• Research database • Identification of a lack of incentive prediction methods for user-based relocation	• Identification of machine learning methods as a possible solution	• Machine learning algorithm for incentive computation

In the following design cycle, we developed an algorithm based on machine learning and evaluated it by training and testing it with a dataset. As datasets for incentives in the context of user-based relocation are currently not available and cannot be referenced, we had to gather a dataset via survey.

The survey included 1370 data points gathered from 274 survey participants (their characteristics are depicted in Table 3). They were questioned on the street, following a structured questionnaire. The questions were designed to mimic the setting of user-based relocation. In user-based relocation, users walk the extra distance from their new vehicle destination to their previously intended one. Hence, they had to evaluate their possible incentive by factoring distance, weather, weekday and time of the day. These factors were derived as an initial explorative step with the partner company and based on accessibility. Other potentially helpful data sources (such as user data from customers) were inaccessible to us.

Table 3. Characteristics of Survey Participants

Characteristics	*Property*				
Age	< 25 46.31%	26-35 33.22%	36-45 4.36%	46-55 9.73%	> 56 6.38%
Education	No Education 3.42%	(High) school 36.99%	Some college or profession 10.62%	College with degree 45.21%	Higher education or PhD 3.77%
Gender	Male: 58.19%			Female: 41.81%	

The partner carsharing company has mainly younger customer base and is located within a University student majority city. For this reason, it is conclusive that the sample is also relatively young, reflecting the actual average age of customer base. Furthermore, we would like to note that we had not specifically targeted nor filtered our questionnaire for younger participants.

Each participant was asked if they would accept a certain incentive to walk a given distance (between 800m and 1,500m) on a specific weekday. The incentive was presented to the participants in a sale by bidding format, starting from 0.50€ and going up to 6€ [12] in 0.50€ steps. Additionally, the participants were distributed with the weather conditions for the walk. The weather was characterized by: (1) temperature, and (2) weather condition (rainy, windy, snowing, cloudy etc.). In total, each participant was surveyed for five different combinations. The first one was the current time and place's weather conditions. In order to ensure a variety of different real-world weather conditions within our dataset, we conducted the survey in two time-windows: one week in April and one week in October 2016. For the other four, each parameter combination was generated randomly, while any sort of illogical combination (e.g. snowy and 30°C) was discarded. Further, each question was asked by corresponding researcher while the participants did not actively fill out the question themselves (preventing wrong inputs within the questionnaire).

We chose to apply a threshold for the maximum incentive and also to utilize the bidding mechanism based on a preceding pre-test. In a small pre-test (of 40 participants), we discovered that participants answered with either very high or low values, when not given a context in the form of a limit. For example, some participants stated that they would like to get an incentive of 50€ or more to walk 800m in good weather conditions. Hence, we limited the participants by putting a cap of 6€ on the incentive (assuming that users demanding an incentive of over 6€ would not participate in user-based relocation) and also by using a bidding style questionnaire. Furthermore, each participant had the option of answering with the statement that they were unwilling to walk the distance under the given circumstances for under 6€. This framework greatly improved the consistency of the gathered data.

The trained algorithm was then evaluated. Normally, machine learning algorithms are evaluated using error metrics. However, as the aim of the developed algorithm is not to predict a value, but rather to iteratively learn to compute incentives, we had to use a different approach. Firstly, the algorithm was trained using the survey data. Secondly, it was evaluated in a small field study. In the field study, 20 carsharing customers were asked to relocate their vehicle during an ongoing rental.

4 Results

4.1 Incentive Computation Algorithm

Building on current user-based vehicle relocation publications [4, 12] and the discussion with carsharing providers, it is evident that despite being an interesting option, implementation of user-based relocation is difficult in the fact that it has to be set within existing infrastructure. Nonetheless, focusing on incentives as key enablers of the concept, we identified the following requirements:

R1 Self-learning: The algorithm must be self-learning to avoid manual adjustments of the computation algorithm.

R2 Context sensitive: The algorithm must consider external factors (like weather), which influence the decision making of customers.

R3 Real time: The incentives must be computed in real-time to achieve a dynamically working user-based relocation system.

R4 Cost-efficient: The algorithm must avoid overpaying customers and paying more than the cost of operator-based relocation.

R5 Simple to implement: The algorithm must be easy to implement to ensure adaptation by other carsharing providers.

R6 Adaptive: The algorithm must be adaptable to different carsharing systems.

R1 addresses the need for an incentive computation algorithm to be self-learning. The customer base of a carsharing system changes over time and incentives must be context sensitive to address price elasticity. Additionally, short-term influences (such as weather) can change the needed incentive and therefore, should be considered during computation (R2). Similarly, an incentive computation algorithm must provide incentives in real-time (R3). User-based relocations must be communicated quickly to potential relocating users to ensure the immediate execution of the relocation. Otherwise, potential users could arrive at their destination to find no cars available or the vehicle distribution could change, leading to relocations that cannot be performed or are unnecessary or even counterproductive. R4 captures the main objective of relocation, as well as the perspective of the carsharing provider. Vehicle relocations must be cost efficient, meaning that the incentives for user-based relocation should be as low as possible, avoiding any overpayment. This allows full leverage of the cost-saving potential of user-based relocation [3, 12]. Due to the fact that carsharing providers are mainly concerned with the "physical" part of carsharing, the implementation of complex algorithms is outside the range of their core-competencies. To ensure a wide adoption of an incentive computation algorithm, it must be designed with an easy implementation in mind (R5), which can maintain an easy and efficient cohesion with the existing infrastructure. Lastly, R6 captures the primary intentions of DSR, which is to develop artificial solutions and to understand solution design on an abstract level, e.g. as design principles [37, 38, 40]. Therefore, the incentive computation algorithm must be applicable in different carsharing systems.

Building on the requirements and a search for relevant knowledge, we decided to use machine learning and apply a regression tree. Machine learning algorithms can find patterns within a given dataset (R1, R6). A regression tree is a well understood and commonly applied algorithm, which has been implemented in one of the most common machine learning programming libraries, e.g. scikit-learn [39], making it simple to implement (R5). It can incorporate different context inputs provided in the dataset (R2, R6) to quickly (R3) compute a numeric output. The cost-efficiency of the computed incentive depends on the provided input data set. If the algorithm can locate robust patterns within the given dataset, the computed incentive will be as cost-efficient as possible (R4). As we used Scikit-learn [39] for our implementation (R5), the Classification and Regression Tree (CART) was used.

In the following design cycle, the gathered requirements and the identified regression tree algorithm were combined to develop an incentive computation algorithm (see Figure 2).

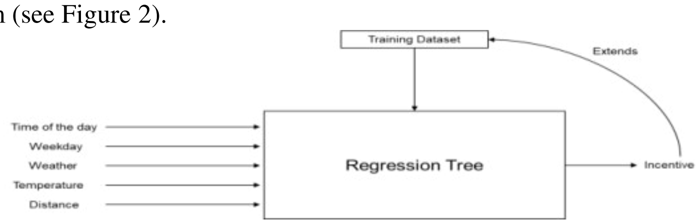

Figure 2. Incentive Computation Algorithm

In the center of the incentive computation algorithm, the regression tree machine learning model is displayed. It is trained via a training dataset (for further information see [41]) and computes incentives based on the time of the day, day of the week, weather, temperature and relocation distance. As a result of the algorithm requiring to adapt to the potentially shifting price sensitivity of the customer base, it likewise requires itself to be self-learning (R1). Hence, we designed the following process: (1) The computed incentive is presented to the users. (2a) If the user accepts – The incentive is decreased by a fixed factor and added to the training dataset along with its parameters. (2b) If the user declines – The incentive is increased by a fixed factor and added to the training dataset along with its parameters. (3) The regression tree is re-trained with the extended training dataset.

The incentives are altered before they are added to the dataset to induce a learning process. Accepted incentives can potentially be too high and the algorithm must learn to compute lower incentives. The same goes for declined incentives. In the circumstance when they are too low, the algorithm must learn to compute higher incentives. This will lead to a training dataset that can increasingly adapt to the application case (R6) and also to the machine learning algorithm.

To evaluate the performance of the algorithm and to study the real behavior of users and not just the intended one, we carried out a trial field study for one month (February 2017) in a carsharing system environment. 20 carsharing customers were asked to install a simple user-based relocation smartphone application.

During the field study, 11 users interacted with the various relocation requests. The relocation request within the application contained information regarding the desired relocation, e.g. the distance differences intended and relocation destination as well as the offered incentive, computed by the algorithm itself. During the field study, 20 relocations were requested, of which 11 were accepted and 9 rejected. The average accepted incentive was 2.75 Euro, while various weather conditions were represented.

The temperatures were around 9 degrees Celsius and the average relocation distance was 940m. Given that more than half of the participating users accepted the incentive calculated by the algorithm, it is positively affirmed that the developed algorithm potentially fulfills its original purpose.

4.2 Design Theory

Following Gregor and Hevner [40], each DSR process adds to practice and theory by developing new design theories and by explaining "how to do something". Correspondingly, we developed a design theory for an incentive computation approach for user-based relocation. The developed theory corresponds to the model proposed by Gregor and Jones [38].The design theory is summarized in Table 4.

Table 4. Design Theory of an Incentive Computation Approach for User-Based Relocation (following [38])

Component	*Description*
Purpose and Scope	The approach computes adequate incentives to motivate carsharing users to change their rental destination. Requirements: Self-learning, Context sensitive, Real-time, Cost-efficient, Simple to implement, Adaptive
Constructs	Demand, Supply, Vehicle, User, Relocation, Incentive, Accept, Decline, Destination, Location
Principle of Form and Function	Machine learning (e.g. Regression Tree) can be applied to compute incentives for user-based relocation (R1,R2,R4, R5). The value of declined incentives should be increased and added to the training process (R1, R2, R4). The value of accepted incentives should be decreased and added to the training process (R1, R2, R4). The initial training dataset can be gathered via survey, using weather and bidding as frames/anchors (R1, R2, R5, R6). The trainings parameter should include weather, weekday, temperature, distance, time of the day (R2, R6).
Artifact Mutability	The incentive computation algorithm can be adapted using a context-specific dataset. The input factors as well as the regression tree parameters can be changed.
Testable Propositions	The computed incentives motivate users to comply with user-based relocation. A good incentive remains below employee costs (6€) and motivates certain users (50%)
Justificatory Knowledge	Carsharing Literature, Machine Learning Literature

5 Discussion

The presented study contributes to carsharing literature by developing an incentive computation algorithm to be applied to user-based relocation within carsharing service systems. The computation of incentives to motivate users to relocate a rented vehicle is a fairly new research question [4, 12]. Thereupon, the presented algorithm marks a first step into this new problem domain, proving a valuable base for future research.

Ultimately, the findings of this study have implications for the field of sharing economy research. Carsharing is recognized as a prime example of the sharing economy [2]. However, more research is required to establish the ways in which IS can support carsharing service systems [2]. In this regard, the presented development process and artifacts unravel the contribution of IT and IS to providing sustainable sharing services and creating value with and for customers. To be specific, the focus is currently centralized on how IT and IS help increase the comfort and flexibility of carsharing by implementing user-based relocation. The developed algorithm becomes a key enabler for this concept. It is important to note that the algorithm could also be used for other fields of application e.g. enriching dynamic ride sharing. Passengers could be incentivized to walk to a pickup location by cheaper prices and at the same time drivers need to be incentivized by addition revenue to perform detours. Hence, having a good understanding of how to compute incentives would not only help to improve carsharing but also other mobility services [42–44]. The same reasoning would apply to crowdsource delivery. The algorithm could calculate incentives to motive drivers to perform a detour for a delivery or to walk a certain distance to drop off or pick up a parcel [45].

Additionally, as the presented research demonstrates the different ways in which machine learning methods can be used, it contributes to the research body of machine learning, by introducing it to the domain of carsharing. To the best of our knowledge, no previous study has applied and implemented machine learning models to compute the incentive of user-based relocation. Hence, the successful application and evaluation of the algorithm suggests that machine learning should be further researched in this context.

In context of DSR, this study contributes on several levels. Firstly, it serves as an example for the application of DSR in solving the specific problem of incentive computation in carsharing. Secondly, when positioning the developed artifact within the DSR knowledge contribution framework [40], we argue that the problem of incentive computation for user-based relocation participants is a rather new problem domain, constituted by the current state-of-the-art attention focused on user-based relocation algorithms, without engaging in its real-world applications. Hence, it constitutes a novel problem class. Similarly, the application of machine learning to compute incentives can be seen as a transfer of existing knowledge, classifying the solution maturity as high. Hence, the developed artifact constitutes an exaptation, characterized by a low problem domain maturity and a high solution maturity [40]. Furthermore, the contribution of this study is situated on two different levels of theoretical abstraction [40]. The developed framework and principles of form and function can be characterized as a nascent design theory (level 2), while the implemented and tested algorithm provides a tangible instantiation (level 1).

Besides the theoretical contributions, this study holds valuable implications for practitioners. Firstly, this study demonstrates how to develop and implement an incentive computation algorithm for user-based relocation. Combined with previous studies about the identification of necessary relocations [4, 12], it enables user-based relocation implementation and further practical research within the field. Consequently, carsharing providers are now enabled to substitute operator-based with user-based relocation. With this in mind, the overall cost of relocations can potentially be reduced, increasing the yield of carsharing provider, subsequently making carsharing not only a more sustainable transportation service, but also a more profitable one [12]. Secondly, it underlines how to introduce user-based relocation to a carsharing system. Before implementing any related carsharing projects, carsharing providers must survey their users to train the machine learning algorithm. As the artifact evaluations reveal, it shows potential to compute incentives to motivate users within the system to relocate vehicles.

Regarding any limitations, the two evaluations constitute a limitation of its own. The survey data is only partly representative for the special case of inhabitants of the city in which the carsharing provider is located. Hence, other cities and carsharing systems might find survey data to be insufficient as an initial training dataset. Additionally, the limited scope (20 participants) of the field-test constitutes a limitation. Secondly, in order to get initial results, we applied a research process composed of easy and affordable research and evaluation methods, e.g. expert interviews and small-scale single case application. This process ensures efficiency and iterative adaptation according to any forthcoming interim results. Thus, the next step is to carry out a larger-scaled field-test to ensure generalizability of results. In addition, we research opportunities in identifying and including further parameters in the computation process, such as customer information (e.g. age, rental frequency or attitude to sustainability), to potentially increase the accuracy for individual users. Lastly, during the research process, the participants were questioned directly on the street, following a structured questionnaire to derive a proper incentive. However, willingness-to-pay is difficult to convey in surveys, therefore an alternative approach such as the conjoint analysis has been developed (e.g. [46]). Thus, we see potential for future research in addressing this limitation by applying other methods to validate and expand our knowledge on finding the best incentive/pricing option, providing further input for the incentive computation process.

6 Conclusion

This article presents a self-learning algorithm to compute the necessary incentives for user-based relocation. It bases on a machine learning model and was developed following the DSR framework of Hevner et al. [35]. The algorithm was evaluated within a field study, in which it was revealed that the algorithm had the possibility be used in practice and compute sufficient incentives.

The algorithm enables user-based relocation to be implemented within real-world applications. This will help carsharing providers to improve the flexibility and cost-efficiency of their systems. Furthermore, IS researchers can now study user-based relocation within its intended field of application. In addition to that, with a simple and cost-efficient method, we provide the basis for further extensive and complex methods, so that our solution can be further optimized [35]. Accordingly, the results of this study enable benchmarking, which is an important area of DSR [47].

Overall, our study is in line with the demand to focus on applied Green IS research and the guidelines of vom Brocke [48] to develop tangible research results in the form of IS artifacts that contribute to minimizing the gap between sustainability research and practice, a field currently underrepresented in IS research [49]. Against this background, the facilitation of user-based vehicle relocation in carsharing, through the presented artifact, can be an important building block to further increase the sustainable impact of carsharing.

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