Archetypes of Carsharing Relocation Algorithms: A Perspective on Problem Space, Solution Space and Evaluation

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Abstract: Shared vehicle services like carsharing enable society to achieve a more favorable tradeoff between the societal cost and the individual benefits of physical mobility. To realize this value proposition, numerous carsharing types with unique constraints have emerged. A key challenge of making such offerings available, is the real time coordination of fleet supply tailored to short term customer demands. Researchers developed frameworks, algorithms, and decision support systems to address the corresponding vehicle relocation challenge on strategic, tactical, and operational level. However, subsequent vehicle relocation knowledge must be systematized to ensure that subsequent insights can be reused and further developed. Consequently, we develop a holistic taxonomy for vehicle relocation algorithms in carsharing, which contributes to current research by (1) providing consistent descriptions and analyses of vehicle relocation problems, solutions, and evaluation approaches, (2) identifying archetypes of algorithm instances, and (3) guiding research to work on subsequent research gaps. As a result, we substantiate a resilient and validated relationship between vehicle relocation's problem and solution space.

1 INTRODUCTION

Carsharing businesses have existed for many years and are increasingly emerging in cities across the globe (Shams Esfandabadi et al., 2022). Carsharing services (CS) provide users with the benefits of on-demand access to vehicles without the disadvantages of owning a personal car. Individuals profit from CS with reduced transportation costs and increased mobility offerings (Jochem et al., 2020), while society benefits from reduced traffic congestion, vehicle emissions and fuel consumption, improved road safety, and a decrease in parking space needed (Amatuni et al., 2020; Fan et al., 2008). While station-based services require customers to pick-up and return vehicles at predefined stations, free-floating services operate station-independent within a designated service area (Ferrero et al., 2018). Vehicles can often be rented spontaneously and for one-way trips, which satisfies customer's requirements on flexibility. However, this value preposition also raises up challenges in the design and operation of such service offerings.

Within the past decades, the research community tackled many research questions covering business models, drivers and barriers, customer behavior, and the design and operation of CS (Nansubuga & Kowalkowski, 2021). A key challenge on the way to an entirely smart and sustainable mobility ecosystem is the real-time coordination of fleets tailored to short-term user demands (Ketter et al., 2022). For carsharing to contribute to this, the vehicle relocation problem must be solved. It describes the need to relocate vehicles within one-way systems to encounter vehicle imbalances caused by asynchronous demand and supply (Jorge & Correia, 2013). Consequently, research developed frameworks, algorithms, and decision support systems to solve strategic, tactical, and operational decision problems associated with vehicle relocations (Illgen & Höck, 2019). Related questions also arise from the latest shared mobility systems like scooters

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and e-bike-sharing (Boufidis et al., 2020; Caggiani et al., 2018; Nath & Rambha, 2019; Si et al., 2019).

Existing literature reviews like from Brendel and Kolbe (2022), Ferrero et al. (2017), Golalikhani et al. (2021), Illgen and Höck (2019), Jorge and Correia (2013), and Wu and Xu (2022) structure the research covering the vehicle relocation problem and synthesize findings on a general and universal level. However, the success of novel CS business models (Remane et al., 2016) has created numerous different CS types with individual constraints. This also reflects in more fine-granulated requirements for the solution of the vehicle relocation problem (Brendel & Kolbe, 2022). However, a holistic view of reusable components of vehicle relocation algorithms with special attention on the mapping between observed problems and instantiated solutions is still missing. Consequently, our research is guided by the following research questions:

RQ1. From a decision support perspective, what are the dimensions and characteristics of carsharing relocation algorithms?

RQ2. Which archetypes of carsharing relocation algorithms emerge from previous empirical studies?

RQ3. Which research gaps prevail in vehicle relocation research?

To answer the first research question, we propose a taxonomy of vehicle relocation algorithms following the methodology of Kundisch et al. (2022) based on Nickerson et al. (2013). We perform a cluster analysis on our categorized empirical sample to address the second research question. To answer the third research question, we analyze, interpret, and discuss the results from RQ1 and RQ2 in regard of prevailing gaps.

2 RESEARCH BACKGROUND

As a response to customer requirements, nowadays, most carsharing systems offer flexible access to shared vehicles, where users do not need to specify when and where to pick up and return a car in advance (Liao & Correia, 2022). This leads to asynchronous trips inside the system that could cause local supply shortages. Consequently, providers need to organize vehicle relocations to maintain high service levels. Components of a vehicle relocation algorithm should aim to forecast and predict where possible shortages occur, which vehicle should be relocated to which position, and who can perform the actual relocation (Illgen & Höck, 2019).

As an entry point for our literature review, we searched for existing literature reviews and taxonomies that aim to structure the knowledge base of carsharing and carsharing relocation research. Nansubuga and Kowalkowski (2021) clustered carsharing research streams into the four categories of *business models*, *drivers & barriers*, *customer behavior*, and *fleet & system management*. Table 1 shows our analysis on which research streams are covered by each of the 13 articles we identified in our initial search.

The category *fleet & system management* includes research on the vehicle relocation problem and consequently serves as filter criteria for literature reviews and taxonomies that are further reviewed for knowledge on relocation dimensions and archetypes. The articles of Cepolina et al. (2014), Nansubuga and Kowalkowski (2021), Schmöller and Bogenberger (2020), and Shams Esfandabadi et al. (2022) do not explicitly name dimensions or archetypes, and consequently are excluded from further assessment.

According to Gregor and Hevner's (2013) definition, the vehicle relocation problem is a “wicked real-world problem” that could be addressed by designing complex information systems (IS). To ensure that extant and new knowledge can be reused and further developed, specific research contributions must maintain a resilient and validated relationship between problem and solution space (vom Brocke et al., 2020). Consequently, a holistic categorization of vehicle relocation algorithms should address the three components of design knowledge, namely *problem space*, *solution space*, and *evaluation*. Table 2 shows our analysis of those components that are covered by related work and which dimensions they suggest to structure knowledge on vehicle relocations.

To summarize our review of related work, we found three main gaps in current articles that aim to structure knowledge on relocation algorithms: First, a holistic view of problem space, solution space, and evaluation of research articles is missing. Ignoring the problem space refrains readers from evaluating the context and boundaries where design knowledge can be applied. Ignoring to specify the solution space limits the overall practical and theoretical contribution by disregarding the problem-solving character of design. Ignoring evaluation constrains the reader's ability to assess design knowledge's validity and objectivity. Second, suggested categories like methodology are too generic to get a deep understanding of particular algorithm design aspects. Third, none of the analyzed articles presents archetypes of algorithms that can be applied as a solution template for a class of problems.

Table 1: The literature review of conceptual work addressing carsharing.

Article	Research Domain	Business Models	Drivers & Barriers	Customer Behavior	Fleet & System Management
Brendel and Kolbe (2022)	Transportation				X
Cepolina et al. (2014)	Service Science		X		X
Degirmenci and Breitner (2014)	IS		X	X	
Ferrero et al. (2017)	Sustainability	X			X
Golalikhani et al. (2021)	Transportation		X		X
Illgen and Höck (2019)	Transportation				X
Jorge and Correia (2013)	Transportation			X	X
Liao and Correia (2022)	Transportation		X	X	
Nansubuga and Kowalkowski (2021)	Service Science	X	X	X	X
Remane et al. (2016)	IS	X			
Schmöller and Bogenberger (2020)	Transportation			X	X
Shams Esfandabadi et al. (2022)	Sustainability	X	X	X	X
Wu and Xu (2022)	Transportation				X

Table 2: The literature review of conceptual knowledge about the vehicle relocation problem.

Article	Problem Space	Solution Space	Evaluation	Relocation Dimensions
Brendel and Kolbe (2022)	X			Vehicle Types, Additional Services, Vehicle Booking, Vehicle Access, Pre-defined Spatial Information, Rental Time, Parking, Infrastructure, Number of Stations/Areas, Number of Vehicles, Number of Customers, Parking Space, Average Number of Rentals per Day, Organizational, Ownership, Maintenance, Refueling and Recharging, System Access, Vehicle Relocation Method, Price Structure, Cost Structure, Vehicle Engines, Charging Infrastructure, Charging, Network, Charging Duration, Range Limitations
Ferrero et al. (2017)	X			Mode, Engine, Optimization Objectives, Time horizon, Methodologies
Golalikhani et al. (2021)		X		Procedure, Objective, Methodology
Illgen and Höck (2019)		X		Reservation Policy, EV charging policy, Location planning, Pricing policy, Vehicle type, Fleet Size, Relocation Policy, Data, Model, Target, Solution Approach
Jorge and Correia (2013)		X		Topic addressed, Modelling Approach, Type of carsharing
Wu and Xu (2022)		X	X	Service Type, Fleet Type, Objective, Model, Solution Method, Evaluation

3 RESEARCH APPROACH

The taxonomy development method proposed by Nickerson et al. (2013) is a widely applied method in IS to provide structure and organize knowledge in a field. It was applied to generate a variety of taxonomies, such as recently published for peer-to-peer sharing platforms (Chasin et al., 2018), data strategy development (Gür et al., 2021), data monetization (Sterk et al., 2022), AI integrated customer service (Poser et al., 2022), and conversation agent design (Diederich et al., 2019).

Kundisch et al. (2022) advance the methodological guidance given by Nickerson et al. (2013) by focusing on taxonomy evaluation that is inspired by the design-science research methodology (Hevner et al., 2004;

Peffers et al., 2007). We follow Kundisch et al. (2022) and Nickerson et al. (2013) to iteratively develop a taxonomy and identify archetypes based on existing conceptual knowledge and empirical observation. Our complete research approach consists of three phases (I) setup database, (II) develop and evaluate taxonomy, (III) conduct cluster analysis, and is described in the following sections.

3.1 Phase 1: Setup Database

The objective of the first phase was to build conceptual and empirical knowledgebases to be considered in the taxonomy development phase. Therefore, we conduct two systematic literature reviews following vom Brocke et al. (2009) and Webster and Watson (2002) (see Figure 1).

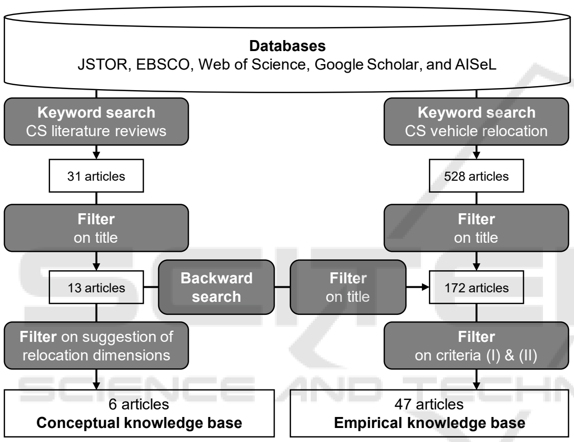

Figure 1: The literature search process.

The conceptual knowledge base was analyzed in section 2 and was also used as a source for empirical knowledge by performing a backward search on covered references.

The review of empirical knowledge started by querying scientific databases with the following keywords, adapted to the specific syntax requirements of the distinct database: "('relocation' OR 'rebalance' OR 'allocation' OR 'reposition' OR 'rebalance') AND ('carsharing' OR 'car sharing')." To ensure scientific quality and up-to-date knowledge, only articles published in peer-reviewed journals and conferences after 2010 are considered. We filtered articles retrieved from the databases and the backward search based on their title addressing a vehicle relocation problem in carsharing. Publications that focus on general relocation problems from other research areas, other carsharing-related topics (e.g., business models, system setup, empirical usage analysis), or do not have an operational focus on the relocation problem, are not considered for our knowledge base. The final screening of retrieved articles was done by applying the following two filter criteria: (I) Articles that do not cover the design and demonstration of a relocation algorithm in carsharing and apply their findings to a transparent reference case are excluded. (II) Articles, where successor work based on the same dataset exists, are also excluded.

Our final empirical knowledge base covers 47 articles and builds the foundation for the empirical-to-conceptual cycles in taxonomy development and cluster analysis.

3.2 Phase 2: Develop and Evaluate Taxonomy

The goal of the second phase was to systematically develop and evaluate a taxonomy for vehicle relocation algorithms that contains holistic dimensions on problem space, solution space, and evaluation based on the method described by Kundisch et al. (2022). For our research, we defined carsharing vehicle relocation algorithms as the meta-characteristic for the taxonomy form which all subsequent dimensions follow. During the development process, we applied seven of the eight objectives and all five subjective ending conditions (concise, robust, comprehensive, extendible, and explanatory) from Nickerson et al. (2013).

We ran through five iterations until all publications from the research database were satisfactorily classified. Our first cycle was a conceptual-to-empirical cycle incorporating a synthesis of the dimensions suggested by Brendel and Kolbe (2022), Ferrero et al. (2017), Golalikhani et al. (2021), Illgen and Höck (2019), Jorge and Correia (2013), and Wu and Xu (2022) (see Table 2). We then performed three empirical-to-conceptual cycles to classify all items from our knowledge base successfully. To address the extended taxonomy design process suggested by Kundisch et al. (2022), we evaluated our taxonomy in iteration five by hosting a workshop with four mobility researchers with at least three years of experience in research or practice. As a result of the workshop, we refactored the names of our dimensions and categories to improve comprehensibility. We also formulated obvious opposites for some dimensions as the final conceptual to empirical cycle. After incorporating the suggestions, all subjective and objective ending conditions were met. The results of the taxonomy development are presented in section 4.1.

3.3 Phase 3: Conduct Cluster Analysis

The aim of the third research phase was the empirical identification of carsharing relocation algorithm archetypes. For this purpose, we performed a two-stage clustering approach to group objects as similar as possible in one group and as dissimilar as possible to the other groups (Kaufman & Rousseeuw, 1990; Punj & Stewart, 1983). The clustering analysis was performed using Python 3.8 with pandas 1.5.3, numpy 1.24.1, and Kmodes 0.12.2.

The first stage is to find the optimal number of clusters with the Ward method. The dimensions encoded as categorical variables serve as input for the distance calculation between articles in our taxonomy. The Hamming distance was used as a distance metric since it is suitable to measure distances between categorical variables. We determined the corresponding number of clusters by using a dendrogram and conducting the elbow rule.

The second stage is to cluster our empirical database using the K-modes method, an iterative partitioning procedure, extending the common k-means clustering algorithm for categorical domains (Huang, 1997). We also analyzed which dimensions have a high significance on cluster affiliation. Consequently, we repeated stages one and two with those dimensions that have the highest explanatory power on relocation design. After interpreting possible archetype centroids for four and seven clusters, we chose four archetypes as a local optimum between complexity and explanatory pow-er. The results are presented in section 4.2.

4 RESULTS

In the following, we present our taxonomy for carsharing relocation algorithms (RQ1) and provide examples for platforms to demonstrate their respective characteristics. We then describe the archetypes of algorithms we identified in the two-step cluster analysis (RQ2). Finally, we analyze our findings and suggest research gaps be closed by the design of forthcoming relocation algorithms (RQ3).

4.1 Taxonomy

The final taxonomy consists of 26 dimensions and 82 characteristics, with the number of characteristics per dimension varying between 2 to 5 (see Table 3, Appendix). Each of the 47 relocation algorithms from our empirical knowledge base can be described by exactly one characteristic in each dimension. For numerical characteristics such as the number of cars in the system, we derived characteristic ranges from visually analyzing the histogram for local maxima. The characteristics are ordered descending according to their coverage in the literature base.

4.1.1 Problem Space

The problem space describes characteristics targeting the context for which the relocation algorithm was designed.

System Characteristics

The *Distribution Model* describes whether the algorithm applies to station-based systems, where vehicles are picked up and returned at designated stations, or free-floating systems, where vehicles are picked up and returned at public spaces inside a defined operating area.

The *Reference System* indicates whether the algorithm was designed for a real-world system with practice-relevant problem specifications or an artificial system with theoretically oriented problem specifications. The latter is also often used when exploring the algorithm's sensitivity to variables like the number of stations, personal, vehicle, or special pricing models.

The *Region Size* refers to the number of citizens living in the area to which the algorithm was adapted. Our categorization follows OECD (2023), where areas are classified as large metropolitan if they have a population of 1.5 million or more, metropolitan if their population is between 500000 and 1.5 million, medium-sized urban if their population is between 200000 and 500000, and small urban if their population is between 50000 and 200000.

The *System Size* indicates the number of cars within the system that serves as proof-of-work for the algorithm. Whenever multiple vehicle setups were simulated, the optimal or mean configuration was considered characteristic.

Demand Profile

The *Input Data* describes the character of the dataset that the algorithm is designed for and, consequently, the dataset that is required to apply the algorithm. Datasets covering past trips at least contain start and end positions and timestamps of satisfied historical demand. Stochastic demand models anticipate that a baseline demand model varies depending on circumstances like time within the day or population density around a spot. They often are represented as a likelihood of when and where a rental will take place and when and where it will end. Agent-based behavior covers a model of potential travel decisions over a mobility mode. It simulates, for example, that a certain number of agents living in a residential area must commute to work in an industrial zone by likely using a concrete mode of transport. From such a model, concrete demand for modes like vehicles can be derived. Search requests extend the trip dataset by including unsatisfied user requests from vehicle booking IS. They often contain a timestamp and when and where a concrete vehicle was requested. Reservations extend the trip's dataset with future bookings from the vehicle booking IS.

The *Dataset Source* describes the origin of the dataset used to design and evaluate the relocation algorithm. Artificial implies that the dataset was generated by anticipating a certain stochastic profile. This is sometimes done to overcome relocation bias (Brendel et al., 2017) and to observe how system behavior performs when different demand profiles are applied (Boyacı et al., 2015, 2017). Historic observation means that data were provided from a carsharing operator and mirror real system behavior. Real-time system data describe when an interface to an operational system was integrated to retrieve system status and to book information in real-time.

The *Time Span* characterizes the number of days the algorithm's effectiveness was observed. It also represents the size of the problem class, where the handling of computational complexity was successfully demonstrated.

Constraints

The *Vehicle Fleet* describes whether the algorithm considers fleets with homogenous or heterogeneous vehicles. While vehicles in homogenous fleets are expected to have similar characteristics, vehicles in heterogeneous fleets differ from each other and thus are more tailored to different customer requirements.

The *Vehicle Engines* means whether the algorithm addresses specific engine types like combustion or electric engines and their special requirements. Whenever no engine type was specified, we considered the fleet to be powered by combustion engines. Vehicles with electric engines have special requirements because of range limits and time-consuming recharging.

The *Catchment Area* expresses the algorithm's expectation of customers to walk to the next available vehicle. Customer demand at a certain position will be considered satisfied when a free vehicle is available closer to the catchment area shaped by the willingness to walk. Whenever the algorithm is designed to work with walking times, we converted them to walking distance following Montufar et al. (2007).

The *Acceptance Degeneration* describes the algorithm's expectation of how the strength of the catchment area fluctuates with rising distance. Binary means that all potential customers inside the catchment area will accept to take the vehicle at the centrum of the area. Distances between vehicles and customers are often measured by air distance or walking distance. Gravitational means that the strength of the catchment area fluctuates with increasing distance or is influenced by determinants like whether the walk is in line with the destination.

4.1.2 Solution Space

The solutions space describes characteristics targeting the representation and design knowledge of the relocation algorithm.

Relocation Considerations

Parking Spaces imply whether the algorithm design considers available parking space for vehicles at service stations or on public roads.

Staff Availability means whether the algorithm design considers a limited availability of agents to perform relocations or whether it is always expected that relocations can be performed.

Staff Relocation describes how the algorithm design integrates the relocation requirement of the agents performing the vehicle relocations. By car means that a second agent follows the relocating agent by car and picks them up after the relocation. Foldable bicycles and e-scooter can be transported in the vehicle's trunk to relocate and thus be used to return after the relocation. Public transport and walking mean that agents must use public transport or walk to return.

Maintenance implies that the algorithm design considers the requirement of vehicles to be maintained. It combines operational tasks like cleaning, tire changes, or routine maintenance with relocation jobs.

Refueling/Recharging means that the algorithm design integrates the fulfillment of charging or fueling requirements. This is especially relevant for electric vehicles because the vehicle will be unavailable for a certain period. The dimension also specifies whether the process is completed by the operator or the customer, e.g., at the end of a rental.

Competition shows whether the relocation algorithm makes a decision isolated from the status of other transportation modes or whether it considers the availability of rivalry (e.g., other carsharing systems) or substitutional modes (e.g., public transport or micro-mobility sharing).

Relocation Algorithm

Data Enrichment implies to which extent the algorithm enriches the dataset provided from the problem context. No enrichment means that the dataset is not extended by any feature having a causal relationship with the occurrence of demand. Temporal features mean timestamps enriched with context information within a weekend or a holiday. Spatiotemporal features cover the mapping of positions and timestamps with context information like the weather or the opening time of grocery shops nearby.

Demand Forecast describes how the algorithm determines user demand at a certain time and position. The deterministic approach means that the demand is known in advance and does not need to be forecasted. Basic stochastics implies that demand is modeled with baseline techniques like deriving historical requests. Advances stochastics describe the determination of demand with more sophisticated approaches like machine learning.

The Determination Approach shows how the algorithm determines which car needs to be relocated to which position. Mathematical solvers (e.g., CPLEX, MMILP) propose a relocation due to an optimization procedure. They are also often used to check the sensitivity of input parameters (e.g., fleet size, pricing, and several generated demand models). Rule-based algorithms apply a concrete procedure that implements rules on how to select a vehicle (e.g., by oversupply score) and how to select a position to relocate to (e.g., by undersupply score).

Relocation Method implies how the algorithm considers relocations to be realized. Operator-based means that agents of the carsharing provider execute relocations. User-based describes mostly the employment of crowd workers (e.g., Brendel et al. (2022)) or actual customers who receive incentives to change the drop-off location of their trip (e.g., Wagner et al. (2015)).

Relocation Time displays when the algorithm considers relocations to be performed. Continuously means that there is no constraint. Business hours mean that relocations are only performed within a typical working day (e.g., 9 a.m.–5 p.m.), while overnight means that they are only performed within the night (e.g., 9 p.m.–5 a.m.).

4.1.3 Evaluation

The evaluation describes characteristics that provide evidence of how the vehicle relocation algorithm solves the related problem space.

Target Function

Sustainability Metrics describes that the authors measured the validity of their design in terms of sustainability effects. Considered measures are relocation emissions, where the additional emissions caused by the performance of relocations and agent travel emissions caused by the requirement of agents to get to and back from the vehicle to relocate.

Profitability Metrics imply that the authors measured the validity of their design in terms of profitability aspects. Revenue is generated by the number of completed rentals derived from rental time and/or distance traveled. Relocation cost describes the cost of performing relocations derived from customer incentives (user-based relocations) or staff costs (operator-based relocations). For its calculation, authors often use an average estimate of costs caused by a single relocation. Earnings are often also represented as a simplified version by reducing revenues with relocation costs. Vehicle idle time indicates the accumulated parking time of vehicles that are not in use.

Availability Metrics show whether the authors exploited the validity of their design in terms of customer acceptance. The acceptance ratio describes the amount of user requests that could be satisfied with vehicle supply divided by the sum of satisfied and unsatisfied user requests.

Performance Measurement displays how the authors determined the measures when applying their algorithm design in terms of sustainability, profitability, and/or availability. The simulation covers agent-based, event-based, or time-based simulations of system behavior when the relocation algorithm is applied to a digital twin of a reference system. The performance is often benchmarked against a simulation, where no or basic relocation algorithms have been applied. Calculated optimum describes when the performance measures are determined by solving a mathematical representation of the system. Field study states that the algorithm was applied and evaluated in a real-world setting. The performance is often benchmarked against former system data, where no or basic relocation algorithms were applied.

4.2 Archetypes

The four clusters contain 15 (archetype 1), 14 (archetype 2), 10 (archetype 3), and 8 (archetype 4) relocation algorithms from empirical work. Algorithms from archetypes 1 and 2 focus on solving scheduling challenges where demand is known in advance, while algorithms from archetypes 3 and 4 also incorporate the challenge of demand forecasts. In the following, we describe the clusters, highlight their distinctive characteristics, and provide examples.

4.2.1 Archetype 1: Station-Based Relocation Algorithm Adapted to Electric Vehicles

The goal of relocation algorithms categorized as archetype 1 is to research how station-based relocation scheduling algorithms can be adapted to systems with specific operational requirements, like maintenance and charging of electronically powered vehicles (e.g., Ait-Ouahmed et al. (2018), Bruglieri et al. (2018), Gambella et al. (2018), Huang et al. (2020), Vasconcelos et al. (2017), and Wang et al. (2019)). Also, special requirements for staff rebalancing are considered in this context (e.g., Boyacı et al. (2017) and Santos and de Almeida Correia (2019)). Most of the researchers in this cluster developed and evaluated their algorithm design based on an artificial system with generated data for one single day of operation. The algorithms are mostly modeled as mathematical equations that resolve deterministic demand profiles. Solution optimality is often evaluated with simulations investigating the target functions of earnings and acceptance ratio.

4.2.2 Archetype 2: Station-Based Relocation Algorithm to Schedule Relocations and Investigate System Sensitivity

Relocation algorithms categorized as archetype 2 aim to determine how relocations in station-based systems should be scheduled in general (e.g., Di Febbraro et al. (2012), Jorge et al. (2014)) and how sensitive the relocation performance is to parameters like system size (e.g., Nourinejad and Roorda (2014)), number of rebalancing staff (e.g., Zakaria et al. (2014, 2018)), demand profiles (e.g., Lu et al. (2017)), or pricing (e.g., Pantuso (2022)). Algorithms considering the impact of rivalry are also part of this archetype (e.g., Martin et al. (2021), Yang et al. (2022)). Most researchers developed their algorithms on flexible and artificial systems with generated demand datasets covering one day of system operation. Demand is furthermore expected as stochastic probability dependent on related factors (e.g., demand is considered as a function of price). As for archetype 1, the algorithms are mostly modeled as mathematical equations that resolve deterministic demand profiles.

In contrast to archetype 1, solution optimality is often evaluated through mathematical optimizations determining profitability parameters.

4.2.3 Archetype 3: Station-Based Relocation Algorithm with Demand Forecast

The objective of relocation algorithms categorized as archetype 3 is to extend relocation scheduling algorithms with strategies to forecast customer demand at pickup stations (e.g., Alfian et al. (2017), Wang et al. (2020, 2021), Zhao et al. (2022)). The algorithms are mostly designed along real-world reference systems in large metropolitan areas, where trip data from historical observations are available. In contrast to archetypes 1 and 2, constraints like parking spaces, staff availability and relocations, refueling requirements, or maintenance are disregarded. Besides operator-based relocations, some algorithms also consider user-based relocations (e.g., Lei Wang et al. (2019)) or relocations with autonomous vehicles (e.g., Brendel et al. (2017)). The demand forecasts are built on top of enriched input data and are mostly per-formed with machine learning. Solution optimality is often evaluated with simulations investigating the target functions of earnings and acceptance ratio.

4.2.4 Archetype 4: Free-Floating Relocation Algorithm with Demand Forecast

The objective of relocation algorithms categorizes as archetype 4 is to solve the rebalancing problem in free-floating systems. Special attention lays on demand forecasts (e.g., Brendel et al. (2018), Herrmann et al. (2014), and Weikl and Bogenberger (2015)) and the implementation of user-based rebalancing methods (e.g., Brendel et al. (2020, 2022), Lippoldt et al. (2019), Schulte and Voß (2015), Wagner et al. (2015)). The algorithms are mostly designed along real-world reference systems, where trip data from historical observations are available. In contrast to the other archetypes, the concept of binary catchment areas and customer willingness to walk are partly considered. As for archetype 3, constraints like parking spaces, staff availability and relocations, refueling requirements, or maintenance are often disregarded. Demand forecasts are implemented without data enrichment and based on basic stochastics like average historical demand at a certain position and timespan. In simulations or real-world field studies, the algorithms are mostly evaluated in long-term cases (> 90 days). Target functions have an emphasis on relocation cost and acceptance ratio.

4.3 Analysis of Research Gaps

First, we interpreted the empirical coverage of characteristics in our taxonomy (see Table 3) to derive general research gaps. Second, we analyzed the individual empirical coverage of each archetype to derive archetype-specific research gaps.

In general, we can confirm two key findings by Brendel and Kolbe (2022). Their first finding was that some characteristics are especially underrepresented in research and often not considered or specified, such as parking space limitations, staff availability and relocations, maintenance, and recharging. Their second finding was that fleets are often seen as homogenous, although multiple vehicle types and customer requirements for fleet diversity exist.

Our analysis furthermore reveals that research lacks contributions on free-floating systems, which are becoming increasingly popular and also share characteristics with other free-floating modes like bike and scooter sharing. Design knowledge from archetypes 1, 2, and 3 should be applied and, if necessary, adapted or extended to also work in the context of free-floating systems. To this end, the potential of enriching demand datasets with other features should be leveraged. This also includes finding features that allow modeling real unconstrained user demand instead of only relying on historical observations or statistic assumptions. Additionally, the relevance of the shape and nature of catchment areas and their influence on demand forecasts and relocation strategies should be further investigated and incorporated into algorithm designs. Another general gap is that carsharing systems are often isolated from rivalry and substitutional mobility modes. Consequently, research should investigate the impact of interdependency on operations considering the existence of overlapping service offerings. Finally, our analysis shows that the research community needs guidance in evaluating algorithms based on their impact on sustainability.

More data from real-world scenarios should be incorporated for research that shares the goal with archetype 1. For example, the charging behavior and range of electric vehicles highly depend on temperature, which has consequences on system operation. Furthermore, the effect of adaption strategies should be observed over longer time ranges than one day since long-term sustainability of operation actions is one requirement for solution relevance. Analog to these gaps, research extending archetype 2 should incorporate more real-world data, especially to prove the long-term empirical validity of assumptions for the sensitivity of several parameters on customer demand. Furthermore, research should also pay special attention to avoid unintended consequences caused by the adaption of technologies like autonomous driving like an increase of empty trips. Our analysis also shows that research that considers the coexistence of user and operator-based relocations was rarely done. The main research gap for articles to complete archetype 3 is to investigate how operations under uncertain demand can be kept robust under consideration of internal requirements (e.g., staff scheduling) and constraints (e.g., recharging). Following our general finding that research should emphasize free-floating systems, our analysis also reveals some specific research gaps for archetype 4. Especially how to adopt relocation algorithms to operational constraints is not fully investigated for the availability of parking spaces, relocation of staff, and maintenance. Lastly, research on data enrichment in high spatiotemporal resolution should be an entry point for tailored relocation algorithms.

5 DISCUSSION

In the following, we discuss the theoretical and practical implications of our developed taxonomy and identified archetypes, followed by a description of the limitations of this study and an overview of opportunities for future research.

Our taxonomy contributes twofold to theory. First, it structures properties of vehicle relocation algorithms along fine granular dimensions and thus gives guidance on how to describe such an algorithm. This especially contributes to the conservation and reusability of design knowledge for future research since it increases transparency, accessibility, and comparability of academic work. Putting a high emphasis on describing all aspects of problem space, solution space, and evaluation ensures the relevance and validity of novel phenomena. This could accelerate the research progress in the domains of sustainability, transportation, operations research, and (green) IS. Second, our derived research gaps direct the research community to relevant and unsolved research problems. Especially focusing on sustainability is a serious matter which should always be considered for evaluation aspects.

Our taxonomy contributes to practice by guiding design knowledge generated by research to address concrete problem instances. This knowledge can be leveraged by practitioners leading to the solution of vehicle relocation challenges, gaining competitive advantages, and increasing the service value proposition, especially in contrast to private car ownership. We also want to encourage operators to exchange more real-world data with research to unleash the full practice potential of the academic discourse.

Regarding the limitations of this study, Nickerson et al. (2013) note that taxonomies can never be truly perfect and complete, but this does not preclude their utility. However, the practicality will become clearer as researchers and practitioners begin to use the taxonomy. One major limitation of our taxonomy is that it was built on an empirical knowledge base and does not incorporate design knowledge from practice. This, for example, leaves a blind spot for regulatory aspects influencing system operation and for the opportunities generated from profiling individual customer behavior.

6 CONCLUSIONS

In this study, we set out to develop a taxonomy of vehicle relocation algorithms (RQ1) and identify their archetypes (RQ2) and prevailing research gaps (RQ3). Based on a conceptual and empirical knowledge base, we derived a taxonomy with 26 dimensions mapped to problem space, solution space, and evaluation. Afterward, we identified four archetypes of relocation algorithms with different aims. Our analysis shows the interdependence between specific problem, solution, and evaluation instances in this context. Lastly, we identified and presented research gaps to guide subsequent research in IS, sustainability, transportation, and operations research.

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APPENDIX

Table 3: The Taxonomy for Carsharing Relocation Algorithms and Empirical Coverage of Characteristics.

		Dimension	*Characteristics*				
Problem Space	*System Characteristics*	*Distribution Model*	Station-Based 79%	Free-Floating 21%			
		Reference System	Real World System 57%	Artificial or Flexible System 43%			
		Region Size	Large Metropolitan 45%	Metropolitan 30%	Small Urban 17%	Medium Size Urban 9%	
		System Size [Cars]	Midsize System (< 1000) 43%	Small System (< 100) 26%	Not specified 19%	Large System (> 1000) 13%	
	Demand Profile	*Input Data*	Trips 57%	Stochastic Demand 21%	Agent-Based Behavior 9%	Search Requests 9%	Reservations 4%
		Dataset Source	Generated / Artificial 47%	Historic Observation 40%	Real-time System Data 13%		
		Time Span	1 Day 45%	2 - 90 Days 26%	> 90 Days 21%	Not specified 9%	
	Constraints	*Vehicle Fleet*	Homogenous 96%	Heterogenous 4%			
		Vehicle Engines	Combustion 55%	Electric 40%	Both 4%		
		Catchment Area	Not considered 77%	500 meters 19%	750 meters 2%	1000 meters 2%	
		Acceptance Degeneration	Not considered 77%	Binary 23%	Gravitational 0%		
Solution Space	*Relocation Considerations*	*Parking Spaces*	Not considered 62%	Considered 38%			
		Staff Availability	Not considered 62%	Considered 38%			
		Staff Relocations	Not considered 60%	Car 19%	Bicycle/E-Scooter 11%	Public Transport 9%	Walking 2%
		Maintenance	Not considered 77%	Considered 23%			
		Refueling / Recharging	Not considered 64%	Operator 34%	Customer 2%		
		Competition	Not considered 89%	Rivalry 6%	Substitutional Modes 4%		
	Relocation Algorithm	*Data Enrichment*	No Enrichment 83%	Spatiotemporal Features 11%	Temporal Features 6%		
		Demand Forecast	Deterministic Approach 57%	Basic Stochastics 26%	Machine Learning / Advanced Stochastics 17%		
		Determination Approach	Mathematical Solver 57%	Rule-Based Algorithm 43%			
		Relocation Method	Operator-Based 60%	User-Based 26%	Operator- & User-Based 11%	Autonomous 4%	
		Relocation Time	Continuously 57%	Business Hours 36%	Overnight 6%		
Evaluation	*Target Function*	*Sustainability Metrics*	Not considered 83%	Relocation Emissions 15%	Agent Travel Emissions 2%		
		Profitability Metrics	Earnings 68%	Relocation Cost 11%	Revenue 9%	Vehicle Idle Time 4%	Not considered 9%
		Availability Metrics	Acceptance Ratio 60%	Not considered 40%			
	Validation	*Performance Measurement*	Simulation 55%	Calculated Optimum 26%	Field Study 15%	Not considered 4%	
Legend for Empirical Coverage			100 % - 76%	75% - 51%	50% - 26%	25% - 0%	