Deliverable Meilensteinbericht
CRF4 — Service Driven Mobility

Herausforderungen und Konzepte nachhaltiger Shared Mobility Services

Zentrum für digitale Innovationen Niedersachsen

Eingereicht am: [19.03.2021]
Eingereicht von: Sebastian Kuschmitz Autor: Prof. Dr. Jörg Müller
Zentrum für digitale Innovationen Niedersachsen (ZDIN)

TU Clausthal [Institut für Informatik, TUC-IFI], LU Hannover [Institut für Kartographie und Geoinformatik, LUH-IKG], TU Braunschweig [Institut für Automobilwirtschaft und Industrielle Produktion, TUBS-AIP]

Im vorliegenden Dokument wir der Zeitraum von 01.03.2020 bis 28.02.2021 dargestellt.
Das vorliegende Deliverable gehört zum Teilprojekt Zukunftslabor Mobilität / Service-Driven Mobility.

Table of Content

1 General Information

1.1 Summary

The CRF Service-Driven Mobility takes (hybrid) services as an essential part for future mobility and transportation. Based on the high degree of interconnectedness of vehicle systems and infrastructure (car2x), new services and business models for smart vehicles (e.g. function-on-demand services) and intermodal mobility concepts shall be developed and tested. The focus is set on methods for developing and evaluating services for the individual mobility planning as well as on the conceptualization and implementation of digital business models for digital connected mobility.

The focus in terms of content for deliverable *M2.1 Herausforderungen und Konzepte nachhaltiger Shared Mobility Services* is set on the consideration of multi-provider platforms for shared mobility services and respective mechanisms of cooperation in a resulting coopetitive set-up. Referring to selected scenarios, challenges and requirements for future service-based mobility platforms will be analyzed. Furthermore, new solutions based on architectures and methods of federated learning are elaborated.

1.2 Contributing working packages for this Deliverable

AP 5.1 Spezifische Problem- und Bedarfsanalyse (M6-M38)

Beteiligte Partner*innen	**Institut für Informatik der TU Clausthal, Institut für Kartographie und Geoinformatik, LU Hannover, Institut für Automobilwirtschaft und Industrielle Produktion / Dienstleistungsmanagement**
Bearbeiter*in	**Müller, Sester, Woisetschläger, Fiosina, Gremmel, Koetsier**
Praxispartner	**Nolting/Graen, VW Nutzfahrzeuge Loeck/Heese, U-Turn Better Mobility Willand, MHP GmbH**
Beginn der Arbeiten Einreichungsdatum bzw. Frist	**Bearbeitung seit 03.2020 11.2022**

AP5.2 Initiale Konzipierung von Methoden und Lösungsansätzen (M13-M30)

Beteiligte Partner*innen	**Institut für Informatik der TU Clausthal, Institut für Kartographie und Geoinformatik, LU Hannover, Institut für Automobilwirtschaft und Industrielle Produktion / Dienstleistungsmanagement**
Bearbeiter*in	**Müller, Sester, Woisetschläger, Fiosina, Gremmel, Koetsier**
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Beginn der Arbeiten Einreichungsdatum bzw. Frist	**Bearbeitung seit 10/2020 03/2022**

2 Results on WP 5.1 Specific Problem and Requirements Analysis

2.1 Stakeholder analysis

Data sharing is a crucial but hard to manage topic for data owners (e.g. OEMs), resulting from a goal conflict between proprietary rights to keep critical data confidential on the one hand, and the interest to commercialize the collected data as well as the results of analyzing it, on the other hand. In order deepen our understanding on this, we explored potential use cases of data sharing relationships between a data owner and potential stakeholders (e.g. shared mobility service providers or insurance companies) in an ecosystem built on vehicle or traffic data. This stakeholder analysis addresses the data owners' perspective of the sharing problem: what are possible scenarios data owners are willing to share, respectively to sell portions of their collected data? Thereby, the analysis aims to identify specific problems and requirements for exchanging vehicle data guided by the questions which problems could be solved for the external stakeholder with a data product from the data owner and what kind of data is required to solve the problem and facilitate the stakeholder's own business model?

The stakeholder analysis is based on meetings with our industrial partners, a workshop and desk research to identify stakeholders with an interest of specific portions from OEM collected vehicle data.

From the analysis, several scenarios and use cases are identified in which a data product from the OEM could facilitate external stakeholder's business models. Moreover, stakeholders (e.g. shared mobility service providers or insurance companies) could be identified and arranged in a business ecosystem around the vehicle data. By this, problems and challenges for every stakeholder were explored.

In summary, the stakeholder analysis delivered first insights of specific problems and challenges for a data owner to share vehicle data. Therefore, besides the business potential of the actual data product for facilitating an external business model, the technical requirements for the way of sharing the data is essential for the data owner.

2.2 Characterization, Requirements, Challenges of multi-provider shared mobility (MPSM) platforms

Platforms can be conceptualized as technology enabled networks that serve to mediate transactions between two or more sides of a market, such as buyers and sellers (e.g. eBay) or shared mobility service provider and consumers (e.g. Whim) (McIntyre & Srinivasan, 2017). Although the concept of platforms is not new, with an increasing digitization, digital platforms are receiving large practitioners and researchers interest. Nowadays, digital platforms are controlling key areas such as social networks, retailing or specific mobility options (e.g. Uber) (Bharadwaj et al., 2013). Multi-provider shared mobility platforms have the potential to connect the fragmented market and by this, making traveling with different modes of mobility convenient (Ho et al., 2018).
Based on the analysis in 2.2 and the above definition of MPSM platforms, we identify the following special features and challenges of these platforms:
Figure 1 illustrates the core stakeholders and their relationships. Interactions on the platform are orchestrated by a platform owner (sometimes called platform provider), as the organizing entity. The

platform owner connects the two other roles as players in the market: the (mobility) service providers and the consumers of these services. Shared mobility service providers are e.g. car-, ride-, or bike sharing provider as well as taxi provider or the public transportation. Note that in Shared Mobility, the same agent can act as providers (e.g. offering rides) and consumers (booking rides offered by others) at the same time. The fact that MPSM typically sustain multiple services, and multiple providers per service, raises considerable issues concerning security, tradeoffs between privacy and quality requirements, and efficiency issues.

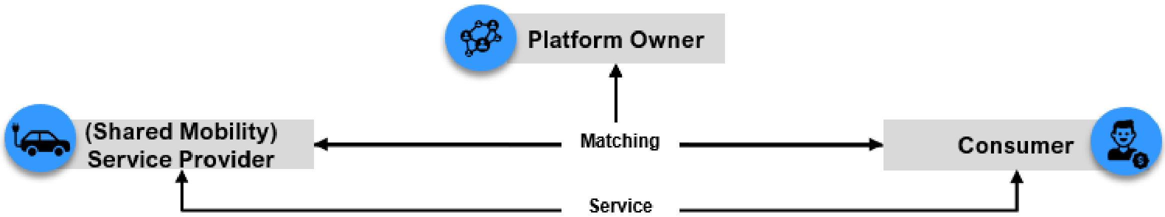

Figure 1: Relationships on multi-provider shared mobility platform

We observe a need and potential to create added-value services by flexibly combining services from different providers (e.g. ride-sharing + parking-sharing) or automatically plan an intermodal trip for the customer. The business model of the platform owner is driven by the strategic options and governance mechanisms applied (e.g. the degree of openness for consumers or shared mobility service provider). Also, we observe that there is often a chance of different service providers to learn from each other; however, fear of data loss and resulting information-hiding considerably limits the extent to which the potential of this learning can be exploited.

Technically, enabling secure and privacy-preserving shared learning at and among service providers requires solving complex combinatorial and data-intensive problems (Cottrill et al., 2016), e.g. involving distributed versions of of AI methods for clustering, classification, prediction, and optimization. Also, user acceptance problems (in particular, “Algorithm aversion”) are reported in the literature (Castelo et al., 2019), confirming in studies that AI methods are often avoided by decision-makers based on subjective negative experience, despite objective evidence that these algorithms outperform humans.

Noticing the yet unsatisfactory degree of acceptance and market uptake of shared mobility services (ING Think, 2018)(McKinsey, 2018), we hypothesize that by providing improved privacy, transparency and explainability both for service providers and service consumers in MPSM, there is a considerable potential for boosting overall service, which should be beneficial for platform owners, service providers, and consumers alike.

Hence, our goals in CRF 4 are: 1) to study and create suitable business models and mechanisms to influence user behavior towards uptake of shared mobility services; 2) to study methods to realize added-value composed MPSM services and study their quality and acceptance.

We focus on the acceptability of AI-enabled MPSM services by increasing trust in two aspects: 1) privacy-preserving exchange of sensitive information among providers (Federated Learning); 2) increase user satisfaction by transparent and explainable algorithms. The focus of the first phase of CRF4 is on 1).

2.3 Distributed detection of anomalies in MPSM Services

One important generic data-driven research problem with manifold applications in MPSM platform services relates to detecting and dealing with anomalies, i.e. observations that are unusual. Today's Deep Learning methods have the potential to derive knowledge in a data driven manner. This is particularly relevant in the mobility and traffic context. Thus, reliable information about the (dynamic) environment can be derived from a sensor data, which is collected by the vehicles themselves. The deep neural networks usually need large training data sets to derive reliable information. The training data should represent the reality in the best possible way. This is especially true for the detection and inference e.g. of near-accidents from vehicle data. Such events occur rarely, which means that only few training data is available. In order to be able to learn reliably, it therefore makes sense to integrate all available data sources from as many manufacturers as possible. Sharing data without revealing the data itself is therefore very attractive for manufacturers. This can be achieved by means of federated learning.

2.4 Scenarios

Based on conversation with our industrial contacts and desk research, we identified two scenarios, which are fruitful for future research on the topics defined above. One scenario addresses distributed learning in a cooperative sensing environment, which we imagine as a possible services of an MPSM platform. The second scenario addresses the Connected Learning Buses scenario, in which we can study cooperation between different bus operating companies aiming at effective and adaptive interior surveillance in buses based on models of unusual observations, which are learned in a federated way within and across operators (see Section 3). The two scenarios differ in properties and requirements for learning, together covering a large spectrum of possible service settings for distributed learning.

2.4.1 Smart intersection

Most traffic accidents are caused by human errors reflected in anomalous behavior, which is not expected by other traffic participants. Anomalies are usually defined as irregular patterns that are different from the mainstream. State-of-the-art mobile positioning devices, sensor technologies, machine learning methods and cloud computing technologies allow efficient collecting, processing and analysis of mobile position information (trajectories), which can be used for detection of anomalous behavior of traffic participants. Anomaly detection in vehicle trajectories is an essential component of advanced driver assistance system and traffic monitoring systems by adapting and enhancing vehicle systems to prevent traffic accidents or warn others and thus increasing road safety. Anomalies can be automatically derived by machine learning from large collections of data. Various vehicle producers are interested to incorporate such assistance systems in their vehicles, however to result in better accuracy, a higher installed base of cars with these technological features is necessary. Since market adoption (and replacement of older models) is inherently slow in the car market, cooperation of different car manufacturers and other stakeholder (e.g. cities or fleet operator) could increase the amount of trajectory data collected. Besides evolving the assistance systems, the resulting insights could be beneficial for various stakeholders. For instance, Zhang et al. (2019) mention three potential services for providers, which could benefit from the collaborative driving anomaly detection solution. First, insurance companies could leverage the driving behavior analysis for credit rating and premium adjustment. Second, car manufacturers could use this data to provide value-added services, such as a driving assistant provides driving reference. Third, ride-sharing companies could detect abnormal driving behaviors to increase ride safety and send alarms.

Various data in broader sense are used for anomaly detection. The information about time, vehicle position, speed, acceleration, braking, given signals, like turning and warning signals of the individual vehicle and external environmental information from the vehicle sensors, like point clouds and image data can be coupled with the information from other sources such as surveillance cameras, land-use, weather data, accident and traffic flow statistics, etc. Currently, data owners (e.g. vehicle producer or service operator) refuse to share data due to data privacy rules, limited data volume capacity or because of the risk of sharing information with competitors, which could jeopardize the data owner's competitive advantage.

Yet, the federated approach provides a method to overcome this obstacle through its distributed data processing. We propose to use a federated learning approach after Konecny et al. (2016) and Yang et al. (2019) to organize the inter-organizational collaboration without sharing the data but only model parameters. By applying this approach, the collaborating partners will benefit from participation, especially in the field of safety and security as this paper addresses an innovative problem to overcome that is more likely to be solved in cooperation (Davis (2016)). However, the application of the federated approach leads to a number of challenges connected with data homogeneity, partner trust and misbehavior or systems reliability (Bonawitz et al. (2019)). We address a general concept of federated learning towards detection of anomalous vehicle trajectories. We will propose the federated learning architecture and parameter synchronization algorithm for the considered problem. Furthermore, we will demonstrate the concept benefits at a sample intersection. Our research questions are: 1) Will federated learning improve the detection accuracy of anomalous vehicle trajectories of each individual partner? 2) How and when do stakeholders collaborate to share data in a federated learning approach?

2.4.2 Connected Learning in Public Transport

Recent technical advances in the areas of sensor technology, automotive engineering and information and communication technology are driving the feasibility and usage of self-driving vehicles. This development will also affect public transportation. (Semi-)autonomous buses or other mass transport means will disburden human drivers, increase safety and probably will replace human driver in the long term. Moreover, buses are capable to be equipped with processing power in a matter that allows computation-intensive AI-methods to be run and learned during waiting times.

Nowadays, human drivers fulfill important roles besides driving the public transportation vehicle, like interacting with passengers or monitor the interior of the vehicle attached to. Moreover, the human driver is responsible to help passengers in need of care to access and leave the vehicle or also to dispose luggage.

Hence, it is the human driver who is holding the knowledge of local incidences and by this, collects local data from buses. By that, data will be made available for the focal firm only late or in the case of non-noteworthy incidences from the perspective of the human driver, the focal firm will not receive such data. This is problematic as the focal firm can only react time-delayed to new patterns or circumstances.

Therefore, it is the proposal of the described research idea to (semi-) automatically collect data from interior surveillance (e.g. through video-based image analysis or speech recognition) without sharing the raw data on a central server, but with a decentralized data processing (on the buses) and shared federated learning.

Based on this technical innovation, it would be possible for new forms of cooperative relationships. Hence, it would be beneficial to research potentially arising business models, and the circumstances and incentives for sharing the data from interior surveillance between competitors.

3 Results on WP 5.2 Initial Concepts of Methods and Approaches

3.1 Conceptual architecture for a Service and Data Integration MPSM Platform

The overall architecture of the proposed service and data integration platform for shared mobility services is presented in Figure 1. The participants contribute to the tasks assumed in this architecture in the following: business models, nudging, service network design are researched by (TUBS-AIP), (LUH-IKG) focuses on composing MPSM service design and validation focusing on geo-spatial aspects, and (TUC-IFI) investigates Federated Learning methods in MPSM platform scenarios. The overall objective of the joint work is to contribute to increasing trust in MPSM platforms and services.

3.2 Methods and architectures for federated learning in MPSM environments

In this section, we outline the overall conceptual approach towards methods and architectures that will enable us to address federated learning in multi-provider shared mobility service scenarios. Figure 2 illustrates our high-level view on MPSP platforms, including the core stakeholders, services, platform components, and data flows.

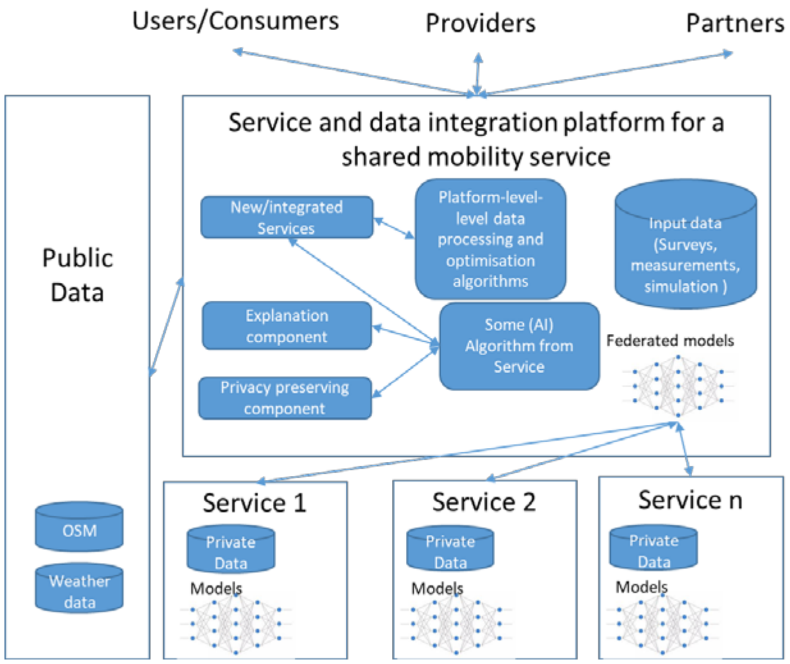

Figure 2: Conceptual view on multi-provider shared mobility platform

Smart intersection scenario: To demonstrate our concept we chose exemplary trajectories of the intersection DR_USA_Intersection_EP0 from the INTERACTION Dataset (Zhang et al. (2019)). Additionally, we manually labeled anomalies by considering trajectory shape, speed, acceleration, heading and interaction. Our learning approach (Figure 3 (left)) is based on the generative adversarial network from Smolyak et al. (2020). The bidirectional generative adversarial network is trained on normal trajectories. After training the normal trajectories are encoded and the latent space representation is clustered with an infinite Gaussian mixture model. In the anomaly detection step any test trajectory is encoded with the trained network and an anomaly score is calculated based on the

Mahalanobis distance to the defined clusters. Low distance scores represent normal trajectories, while high scores indicate anomalous trajectories.

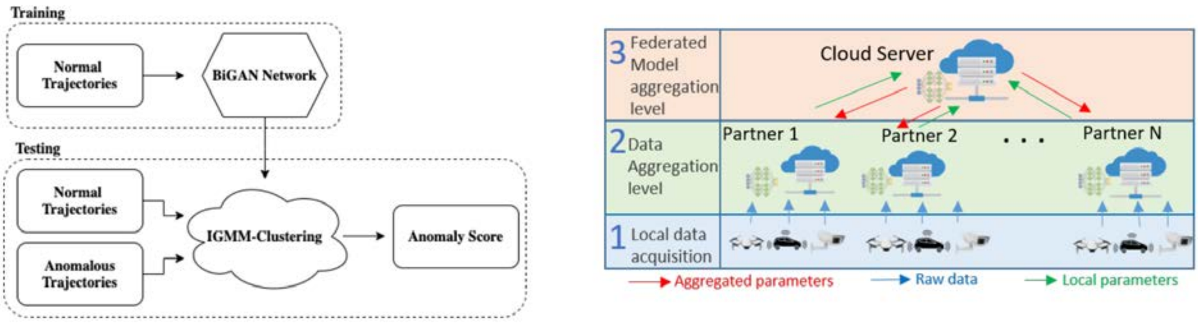

Figure 3: Local learning system architecture (left); and federated anomaly detection (right).

We propose a federated architecture for anomalous trajectory detection presented in Figure 3 (right). At first data is gathered at local data acquisition level from various data sources (e.g. vehicles with sensors and surveillance cameras) by each federated system partner. Then the raw data is aggregated at the second level, where the local anomaly detection models are built and learned with locally available data. Periodically synchronization among local models is performed at a cloud server. Note, that our basis bidirectional generative adversarial network (biGAN) contains different logical modules as a generator, discriminator and encoder, which parameters need to be synchronized at the third federated model aggregation level. We will create synchronization and learning algorithms, which are based on adoption and advancing of approaches proposed in Ito et al. (2020) and Rasouli et al. (2020). Finally, the synchronized models are used at data aggregation level for anomaly detection. The encoded trajectories, provided by the aggregated models, serve as an input of a infinite Gaussian mixture model (IGMM), which identifies regular trajectory clusters and considers the deviation as anomalies. The first experiments show that our collaborative approach simplifies local data labeling procedure and allows to construct more accurate anomaly detection model, than local models keeping data privacy.

3.2.1 Connected Learning in Public Transport

In the following we will describe the general concept of federated learning applied to the future bus shuttle scenario. First of all, the interior surveillance records video data, which is processed towards certain known patterns or anomalies on a local basis in the bus. By this, AI-methods can be trained locally. The locally aggregated models are used as data input for the shared federated learning models. E.g. parameter of the models are sent to the server of the focal firm. Thereby, the data can be processed in accordance to data privacy rules and contain especially no personal data. The parameter of the models are synchronized and further aggregated on the server, so that the now arising aggregated models contain more information, e.g. of new relevant patterns. Those patterns or anomalies that should be detected among the fleet of public transport vehicles are sent back to the local models, which now allows an enhanced interior surveillance. Thereby, the synchronization between the local and the server model should be conducted on a regular basis in order to keep the data up to date.

Figure 4 illustrate the different layers of the federated system: (1) local learning at the level of individual buses; (2) federated learning at the focal public transport operator (PTO); (3) federated learning across PTOs. Adopting a two layered federated architecture could allow a federated learning exchange among PTOs, thus enabling AI-supported recognition of new relevant phenomena, e.g., shifts in customer preferences or new forms of vandalism, and to share local and regional observation in order to enable earlier and better reaction to these situations, leading to win-win situations.

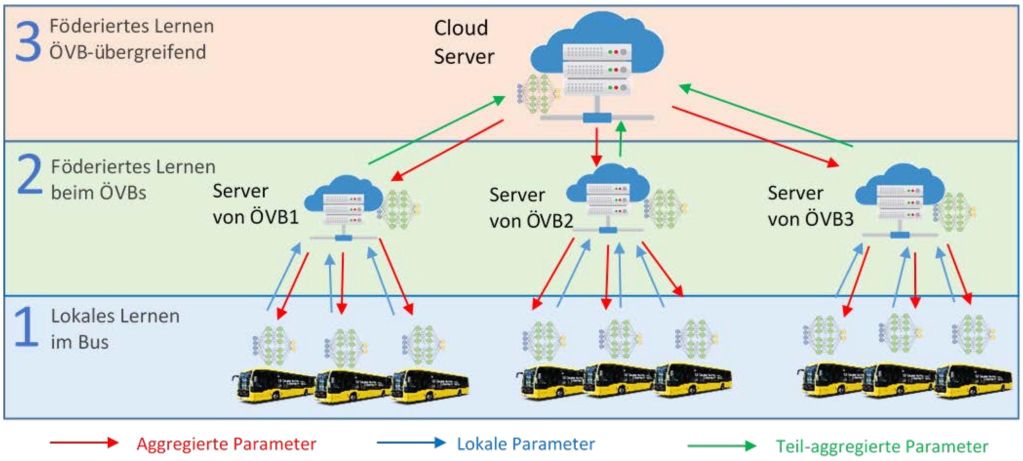

Figure 4 Layered federated learning architecture

4 Publications

Form und Inhalt: tabellarische Auflistung der Veröffentlichungen, die in Zusammenhang mit den hier erzielten Ergebnissen stehen. Bitte fügen Sie nach Bedarf weitere Zeilen hinzu.

Titel / Konferenz/ Journal	Datum der Veröffentlichung	Autorenschaft	Ggf. Link zum Dokument
Federated cooperative detection of anomalous vehicle trajectories at intersections. EWGT 2021.	Abstract accepted. EURO Working Group on Transportation	C. Koetsier, J. Fiosina, J.N. Gremmel, M. Sester, J.P. Müller, D. Woisetschläger.	
Explainable Federated Learning for Taxi Travel Time Prediction, In Proc. of the 7th Int. Conf. on Vehicle Technology and Intelligent Transport Systems, VEHITS 2021, April 28-30, 2021,	Accepted for publication. Scitepress, 2021. To appear.	J. Fiosina	
Trajectory modelling in shared spaces: Expert-based vs. deep learning approach? In Multi-Agent-Based Simulation XXI. pp. 13-27.	2021, Springer International Publishing, Cham	H. Cheng, F.T. Johora, M. Sester, J.P. Müller	Link
An Agent-Based Model for Trajectory Modelling in Shared Spaces: A Combination of Expert-Based and Deep Learning Approaches,19th Internat. Conference on Autonomous Agents and Multiagent Systems, AAMAS '20,	2020, IFAAMAS	F.T. Johora, H. Cheng, J.P. Müller M. Sester,	**Link**
Influence of Spatial Binning and Additional Features on Static Route-Free Estimation of Time of Arrival in Urban Environments. for EWGT2021	Abstract accepted EURO Working Group on Transportation	S. Schleibaum, J.P. Müller, M. Sester	

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