

ORIGINAL ARTICLE

Open Access



Driving into the future: a cross-cutting analysis of distributed artificial intelligence, CCAM and the platform economy

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Abstract

The future of driving is autonomous. It requires a comprehensive stack of embedded software components, enabled by open-source and proprietary platforms at different abstraction layers, and then operating within a larger ecosystem. Autonomous driving demands connectivity, cooperation and automation to form the cornerstone of autonomous mobility solutions. Platform economy principles have revolutionized the way we produce, deliver and consume products and services worldwide. More and more businesses in the field of mobility and transport appear to implement transaction, innovation, and integration platforms as core enablers for Mobility-as-a-Service and transport applications. Artificial intelligence approaches, especially those dealing with distributed systems, enable new mobility solutions, such as autonomous driving. This paper contributes to understanding the intertwining role between distributed artificial intelligence, autonomous mobility and the resulting platform ecosystem. A systematic literature review is applied, in order to identify the intersection between those aspects. Furthermore, the research project Belntelli is considered as a hands-on application of our findings. Taking into account our analysis and the aforementioned research project, we pose a blueprint architecture for autonomous mobility. This architecture is the subject of further research. Our conclusions facilitate the development and implementation of future urban transportation systems and resulting mobility ecosystems in practice.

Keywords: Autonomous Mobility, Cooperative Connected and Automated Mobility, Distributed Artificial Intelligence, Intelligent Infrastructure, Platform Development, Platform Economy

1 Introduction

Autonomous mobility solutions for both passenger and cargo transport are being investigated, tested, and partially implemented by authorities, corporates, startups and research institutes across the globe. However, autonomous operation of vehicles, specifically in urban environments, still poses major challenges [1]. The integration of autonomous vehicles into mixed traffic requires not only

technical feasibility, appropriate policies and economic soundness, but also requires all road users to learn how to interact with these vehicles. Manually operated vehicles, such as other cars, scooters, bicycles, and pedestrians must get acquainted with how autonomous vehicles behave and work from an operational perspective. It is not only about technical innovation, the right technical approach, standards, feasibility and implementation; nor policy-making and societal acceptance and economic fit, but more about how these different parts work in an autonomous mobility and transportation system. The conception, design and implementation of such systems therefore require a framework that takes into account the underlying struc-

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tures, respectively. This framework can act as a blueprint for connecting the different parts as a support system for the conception, implementation and validation of future autonomous mobility solutions.

Continuous technological advances in computing units, sensor and actuator systems are impacting research initiatives on autonomous driving and its use cases leading to new solutions. Approaches consider the type of sensor setup for vehicles, software or hardware dominant architectures, or the consideration of the road-side infrastructure which claims to enable safe autonomous driving maneuvers in mixed traffic spaces. While organizations such as Google's Waymo, GM's Cruise, Tesla or Mercedes-Benz have advanced their solutions for assisted and automated driving, research is still exploring how to achieve fully autonomous vehicles and operate these in public space. Testbeds in urban or rural space across the globe [1] are making space for testing new approaches to autonomous driving.

When talking about an intelligent system, it often refers to a distributed intelligent system. While in the past single-agent constellations, with a single agent collecting data in isolation and performing actions that were independent of other agents were considered, it became apparent early on that a multi-agent approach was required in practice [2]. Even more so, in the context of autonomous vehicles where a single autonomous vehicle must always be considered in the context of its environment, with which it ultimately interacts. Since its environment may contain other intelligent components, such as adjacent autonomous vehicles, and Road-Side Units (RSUs), we call such a setup *Distributed Artificial Intelligence (DAI)*. However, it is not only the intelligent components of the respective agents that form the system that make autonomous mobility solutions possible, rather, it is a multitude of technologies that makes this mobility and transportation system applicable in practice. Communication, in particular, plays a central role in this respect. If the introduced relevant technologies are present, we commonly speak of *Connected, Cooperative, and Automated Mobility (CCAM)* [3].

These new technologies do not only demand disruption, they create new ecosystems in which stakeholders interact, conceptualize, develop and test novel approaches and solutions to mobility and transportation. This requires platforms on which data, services, development tools and other resources can be offered and demanded. This is known as *Platform Economy (PE)*, which can respond to the distributed intelligence approach for autonomous mobility [1]. The PE is considered as an umbrella for the operationalization of the supply and demand of data, services, and tools, all against an environment where digitalized vehicles and road-side infrastructure interact. This allows actors to consume acquired data which might already have been pre-processed for in product and service use.

Despite the immense potential that DAI, CCAM, and PE have independently, their intersection has been insufficiently explored in research, leading to a limited understanding of how DAI for CCAM can help develop autonomous mobility solutions in PE. This work reviews the core attributes of DAI for CCAM and within the platform economy in order to shed light on the current theoretical background of these three intertwining areas of interest. The research question then is: what interplay and principles derive from the intersections? Based on this analysis, we propose a blueprint architecture for autonomous mobility systems, subject to further research investigation.

2 Contributions and outline

This paper draws on both research presented in the literature and the two research projects introduced below on autonomous driving, all advancing the distributed intelligence approach to autonomous mobility and within the platform economy. We found that research has neglected to examine the role of DAI for CCAM and towards PE. Specifically, definitions and classifications in this context have not been made. We therefore highlight the cross-cutting intersections and consider the role, function, use requirements, and use itself for each observed entity, and then classify the evolving intersections between the three entities. We identified that each part enables core mechanisms for enabling autonomous mobility solutions; namely, DAI provides an approach for distributed agents and computing streamlined for Automated Driving (AD), CCAM is the entity structuring and encompassing technologies that enable communication, connection, cooperation and automation, and PE is presenting the overarching model for value creation between market actors. In this context, DAI acts as a complement to CCAM, and against this background, the PE principles form the basis for emerging platform ecosystems in the field of autonomous mobility. These findings feed into a blueprint architecture, which are then utilized towards devising a platform economy model for autonomous mobility.

As this paper is concerned with surveying the intertwining of DAI, CCAM, and PE, we conduct an in-depth survey of attributes and intersections between those in Sect. 3. Section 4 introduces the research projects DIGINET-PS¹ and BeIntelli,² their relation to above analyzed entities and present learnings and challenges towards implementing DAI for CCAM in the context of PE. Both research projects help classifying the proposed blueprint model in Sect. 5. Section 6 concludes our findings, followed by a discussion on the requirements and consequences for emerg-

¹DIGINET research project on connected and automated driving. Available at <https://diginet-ps.de/>; accessed on September 9, 2022.

²BeIntelli research project on AI in Mobility based on Platform Economy. Available at <https://be-intelli.com/>; accessed on September 9, 2022.

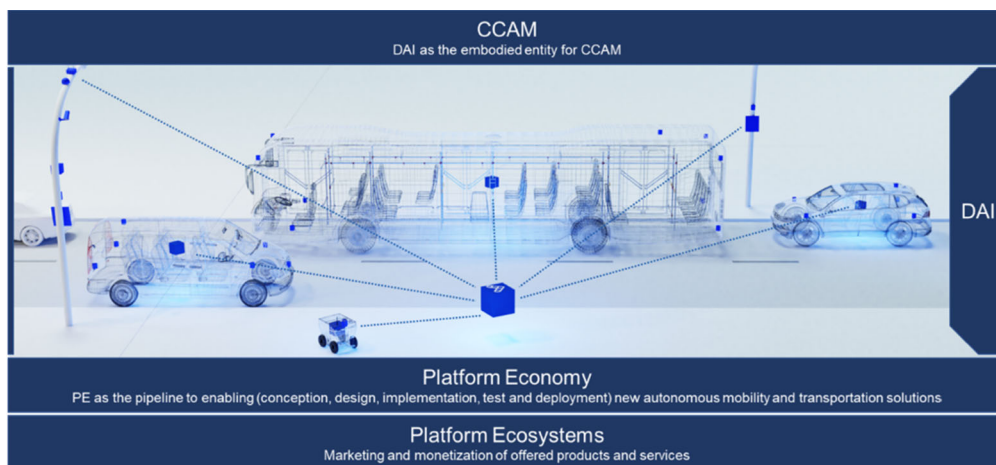


Figure 1 Relation between CCAM, DAI, Platform Ecosystems and PE (adopted from the Belntelli project)

ing autonomous mobility and transportation solutions in Sect. 7.

3 Definition and analysis of DAI, CCAM and PE concepts

We define Distributed Artificial Intelligence (DAI) in the context of autonomous mobility as an approach that spans three entities, Vehicle, Edge, and Cloud, which are interconnected in such a way that their actions can be supported by the flow of information between these entities. Furthermore, we consider the Cooperative, Connected and Automated Mobility (CCAM) terminology as an umbrella for applications encompassing functions that enable mobility and transportation solutions; embodying the attributes mentioned in the term. This includes use cases such as smart parking [4], Green-Light Optimized Speed Advisory (GLOSA) [5], platooning [6], and vehicle on-demand [7], to name just a few examples. Furthermore, we define the platform ecosystem as the resulting system parts (actors, applications, etc.), which operate on a platform. The platform sides are the platform owner, the suppliers and the users, which by exchanging data and building complementary innovations create positive network effects, then addressing the Platform Economy (PE). The subsequent Fig. 1 displays relations between those observed entities Vehicle, Edge and Cloud that are linked through hardware components, respectively:

Figure 1 points to DAI being the threefold approach that are embodied in means of transport and transport mode road. It further presents CCAM as the technology umbrella that encompasses DAI. The platform, its services, and actors are parts of the platform economy, then enabling platform-driven ecosystems. Autonomous mobility solutions require information being displayed and processed at specific locations and time. The processing of

large data sets at different locations, time and pace requires the design of scalable, adaptable environments, energy supply and the provision of sufficient computational power. Furthermore, a secure and reliable transfer of information across the network is needed. Research domains such as distributed computing provide not only the basis for implementing autonomous driving in urban infrastructures but go beyond for developing mobility and transportation solutions for other means of transport such as scooters or cyclists as well as pedestrian's smartphone applications for moving conveniently and affordable throughout traffic space.

3.1 Distributed AI

Research has evoked a variety of different subject areas in the field of distributed computing for autonomous mobility. Core instances are vehicles, road-side edges and cloud systems, which inhabit the acquired and processed data and AI models as well as allow to further train, share and provision data as services.

Based on the literature review conducted in this work, further classification is provided in Fig. 2. The scheme starts from the introduced three entities Vehicle, Edge and Cloud, also presented in [1]. Each entity involves data acquisition and processing, then addressing distributed and federated computing approaches. Research has approached edge computing from various angles; for instance, [8] examines its opportunities, [9, 10] look into IoV and the role of the mobile edge and [11] provides insights to vehicular applications using the edge. Both [12] and [13] investigate infrastructure-supported autonomous vehicles, then considering the edge. Application areas for distributed computing are image processing [14] and real-time IoT [15] to support autonomous vehicles. Computing

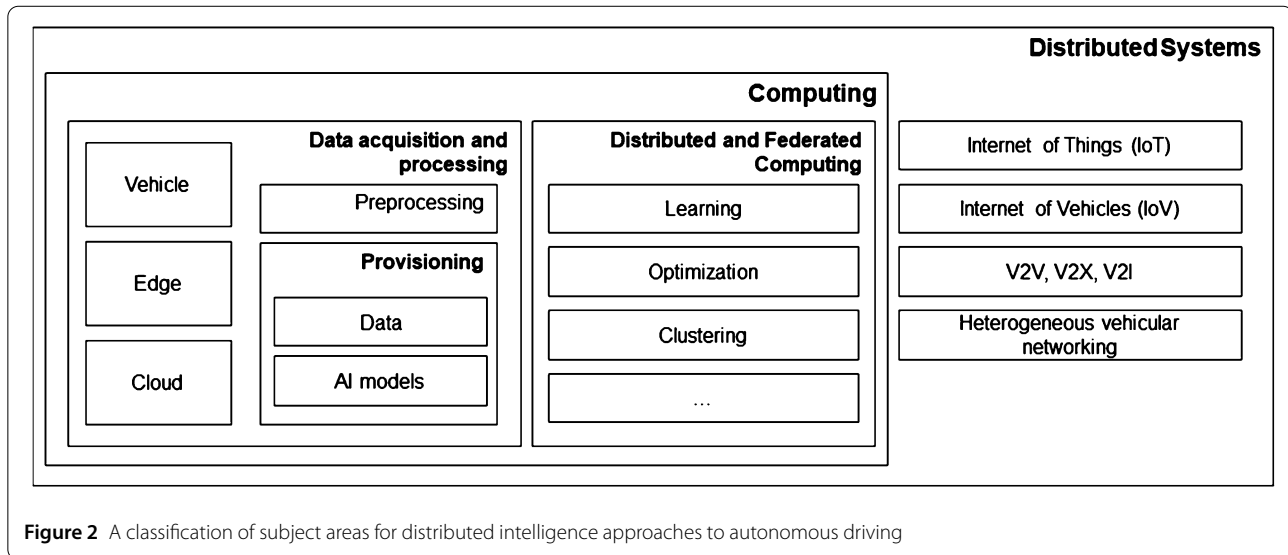


Figure 2 A classification of subject areas for distributed intelligence approaches to autonomous driving

for AD includes data acquisition and processing for the entities: Vehicle, Edge and Cloud as well as distributed and federated computing. The elements of distributed systems can be represented by agents, thus enabling distributed computing. Considering AD, aspects such as IoT, IoV, V2X and vehicular networking become important parts for implementation.

The Internet of Things (IoT) describes networks of smart objects that interact and communicate with each other. Analogously, Internet of Vehicles (IoV) is used for those objects limited to the context of automotive [16]. These systems consider computing, communication and control technologies as integrated parts [15]. The deployment of sensors and actuators which are interconnected and blended with the environment is an integral part of IoT. Real-time communication and data processing are key components for cooperation between autonomous vehicles [15]. Delays can be reduced by processing the data at the location where they appear, meaning close to the next available edge [15], rather than at the cloud or edge. Philip et al. claimed that the traditional centralized cloud approach for data processing may not be suitable for large-scale real-time applications [15].

In comparison, Multi-Access Edge Computing (MAEC) applies computing at the edge of the network. MAEC is already considered helpful to execute computer vision tasks, in order to help increase safety at the road-side [17] and support autonomous driving applications. Furthermore, MAEC may act as an extended component for autonomous vehicles in providing useful information for a car's decision making [17]. It may also help minimizing latency issues [11, 18]. Sasaki et al. explained that while edge computing allows for very low latencies, it still does not replace computing power available at cloud level [18]. To address this issue, they proposed a so-called infrastructure-

based vehicle control system which helps disseminating tasks and allocate computational resources dynamically [18]. Furthermore, more approaches are considered to ship basic functionalities of autonomous vehicles, such as object detection, to the edge [19].

What the terms Edge and IoT/IoV have in common is the idea that computing should be distributed rather than exclusively local. Here, computing is understood to be the pure relocation of computing power as well as the joint interaction between different entities that creates added value for the individual entity. The same applies to distributed intelligence. Various researchers such as Gopalswamy and Rathinam [13] have proposed a distributed intelligence approach for autonomous driving. Also, research- and industry-driven projects across the globe have addressed various approaches to solving these issues [1]. Gopalswamy and Rathinam considered distributed intelligence as an approach which assigns responsibility between vehicles and digitalized infrastructure [13]. Liu and Gaudiot [20] posed that digitizing road infrastructure contributes to an increase in traffic efficiency and safety at the example of traffic light control. They proposed to combine intelligent roads and vehicles for building an integrated, intelligent transportation system [20]. Khan [21] examined at the example of traffic light data alongside the DIGINET-PS research project in Berlin that infrastructure digitalization helps to accurately predict traffic patterns and resource demands. Furthermore, Callegaro et al. discussed the use of unmanned aerial vehicles (UAV) for extending infrastructure perception [12]. Elias provided insights of Bosch's understanding towards the role of distributed systems which reliably act as an enabler for infrastructure-assisted fully automated driving [22]. As the US government and the State of Arizona approved a law allowing for such an approach, Bosch and

partners are developing a fully autonomous public transportation system for people and goods. This system considers on-demand and services and prediction mechanisms for people transportation [22].

Nevertheless, open challenges remain. One of the myriad challenges towards the implementation of autonomous driving is the limited perception range and the occurrence of processing latencies caused by the limitations of the on-board computing units, see [18], then leading to slight delays in the vehicle's decision-making process. Vehicular networks are tremendously challenged by allowing low-latency and processing of numerous tasks [9]. Processing pace and efficiency becomes core in, for instance, recognizing obstacles for which sufficient computing resources must be provided [9]. As a consequence, an autonomous driving approach that also includes digitalized infrastructure (edge computing and communication units as well as embedded sensors) is indispensable to overcome these issues. In terms of network, recent research shows that communication between vehicles (V2V), vehicles and roadside infrastructure (V2I) are increasingly reliable [9, 10].

3.2 Cooperative, connected and automated mobility

Today's vehicles are more and more embedded in a large network with stakeholders to perform cooperative actions, for instance realizing maintenance functions. Considering DAI principles and technologies, also the connection in terms of vehicle-to-vehicle, vehicle-to-cloud, vehicle-to-edge, cloud-to-edge, will further provide opportunities for effective and efficient services. Research discussions in the field of technology-supported mobility and transportation solutions revolve around three major attributes: 1) connected, 2) cooperative, and 3) automated. The technologies underlying CCAM are far-reaching, starting with communication such as 5G, cooperative perception, low-latency communication approaches, to distributed control algorithms, and more [23].

To realize CCAM in practice, the European Commission has initiated a strategy called Cooperative Intelligent Transport Systems (C-ITS), to facilitate deployment of C-ITS services in the foreseeable future. The general acceptance of CCAM in society is given by the potential improvements in transport safety. In addition, efficiency gains can be expected, as transport under the CCAM paradigm would directly lead to an increased avoidance of congestion due to traffic optimization. Consequently, sustainability goals can be better achieved. The economic factors also play a major role in the realization of CCAM [3] towards enabling efficient and cost-effective transportation of people and goods. For more information about the social impact of CCAM, see [24].

3.3 Platform economy

Due to increasing complexity of technologies used and participants involved, today's mobility and transportation

products and services are widely embedded in data and service platforms, to facilitate the interconnection and interaction between those. Scholars in information systems define a platform as a set of stable components that provides core functionalities in a system by constraining the interfaces through which they operate [25, 26, 41]. Application Programming Interfaces (APIs) enable components and users' communication and interaction, as well as third parties to provide additional services [27] which create value for the platform. The interplay between platform owners, service providers, solution providers and users creates cross-side network effects [28], which translate into previously untapped value.

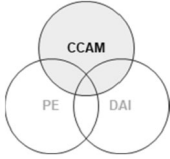
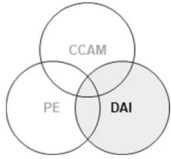
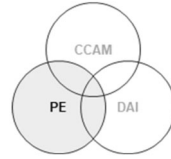
Nonetheless, unlocking platform network effects and overcoming the chicken-and-egg problem where no side will join without the other depends on the configuration of the platform mechanisms [29]. Decisions on firm scope, platform sides, and digital interfaces [28] dictate the business model of the platform as well as the resources available for platform owners, users and developers to exchange data (in a transaction platform), create complementary innovations (in an innovation platform) or both (in a hybrid platform) [30]. This paradigm shift in mobility where the intelligent use of data translates into value-adding solutions for users, encourages current players to make siloed data available and monetizable, as well as future players to innovate. For instance, mobility data platforms aggregate data from different players such as original equipment manufacturers (OEMs), public transportation companies and digital infrastructure providers to create use cases which are implemented by other mobility players [29]. So is the case for mobility data platforms such as Otonomo,³ CARUSO Dataplace⁴ or Wejo⁵ who collect in-vehicle data from OEMs which is then normalized, anonymized and aggregated into several use cases. Some of the present use cases include hardware/software on demand (e.g., car sharing and hailing, fueling on demand, Vehicle-on-Demand VoD), infrastructure planning and optimization (e.g., GLOSA, emissions management, multimodal preferences), mobility insurance (e.g., pay-as-you-drive, pay-how-you-drive) and seamless mobility experience (e.g., smart parking, navigation, charging alert). These are just a few examples of evolving mobility and transportation offerings currently investigated and developed - all embedded in a larger mobility and transportation ecosystem.

³Otonomo, global platform and marketplace for in-vehicle data available at <https://otonomo.io>. Accessed on October 10, 2022.

⁴CARUSO dataplace, German platform for in-vehicle data available at <https://www.caruso-dataplace.com/>, Accessed on October 10, 2022.

⁵Wejo, global platform for in-vehicle data available at <https://www.wejo.com/about>, Accessed on October 10, 2022.

Table 1 Cross-sectional overview of CCAM, DAI and PE

Element			
Attributes			
Role	Frames aspects and standards for mobility and transportation solutions	Addresses data processing efforts for vehicle, road-side (edge) and cloud	Displays use for data-driven business models
Function	Implements use cases that concern connectedness, cooperative and automation	Supports use cases that concern the use of distributed data sources, computational power and intelligence	Provides a framework for data-driven ecosystems which consider network effects
Requirements for use	Autonomous enabled technology, policy and societal acceptance for use	Digitized and digitalized entities such as vehicles, road-side and applications which address connectivity	Platform serves as data broker and provisioner, and provider for development tools and services.
Use	Public transport space in urban and rural environments as well as on transport modes such as rail, air and waterway	Resource-oriented and aware processing of data in distributed places for various CCAM applications	Processing, storage and handling of data in different instances and its provision for the use in data-driven CCAM business ecosystems

3.4 Cross-sectional overview of DAI, CCAM, and PE

As CCAM becomes widespread, the aforementioned use cases will evolve to fit the future user’s needs who would tend to switch from private transportation to more environmentally and space sustainable mobility modes [31]. For instance, hardware/software on demand will be a crucial component of a future with costly autonomous vehicles, where their usage will be concentrated on transportation networking companies (TNCs) [32] offering autonomous ride services and subscriptions instead of vehicle ownership.

Research and industry initiatives across the globe have approached connected, cooperative, and automated driving or mobility from different perspectives [1]. The implementation of CCAM solutions in the market - not limited to the road transport mode, but arbitrary - requires comprehensive interfaces between DAI, CCAM and PE. These interfaces include, on the one hand, the platform infrastructure for data pre-processing, processing, storage and provisioning, and service delivery, and, on the other hand, the foundations for the development of data-driven mobility and transport business models. This also includes the network effects of the platform economy and the resulting ecosystem. In Table 1, we provide an overview about key attributes for the respective observed elements DAI, CCAM and PE.

The intersection between DAI and CCAM is a technical one. DAI provides CCAM with services such as cooperative perception [33], swarm optimization [34], federated [35] and distributed learning [4] of ML models, just to name a few examples. Furthermore, DAI provides a reference point for implementing such a system in practice, for instance how an intelligent agent should be modeled [36], how to secure it, etc. [37].

In comparison, the intersection between CCAM and PE is of a ‘how-to do’ nature, where PE is the umbrella of how to embody and place data-driven mobility and transport solutions. This is underpinned by the fact that PE goes one step further in the thought process than CCAM, through the concrete question of how a possible system like CCAM can be concretely transformed into an ecosystem. However, from this question, there are immediate effects that can be mapped onto CCAM itself.

The intersection between DAI and PE is given by the modeling of a large multi-agent system, which on the one hand includes the agents aligned with the distributed infrastructure (vehicles, edge agents, and cloud agents), and on the other hand, physical agents, namely, end users and platform providers. These actors interact and communicate by using the platform ecosystem and in turn make use of other agents as well as deployed development tools and data provisioning interfaces.

4 The case of the research project Belintelli on CCAM, DAI and PE

Alongside the completed DIGINET-PS research project, we aimed at investigating principles for digital and intelligent infrastructures for connected and automated driving. We designed, planned and implemented a digital test track that has been integrated into real urban and complex traffic environments at the heart of Berlin [1, 21, 38]. Furthermore, we tested the distributed intelligence approach for connected and automated driving (CAD), especially the communication between vehicle and infrastructure, which consists of three data instances: vehicle, road-side areas - so called edges, and the cloud. The project presents that the perception of vehicles can be greatly enhanced by digitalizing the road-side and the cloud, which is also shown

in [21]. Enhanced road-side visibility allows drivers to see traffic in areas such as intersections before entering the traffic area. The cloud system provides additional predictions, such as traffic volume, parking lot occupancy, to name just a few. By considering multiple entities and data sources such as vehicles, road-side infrastructure sensors and the cloud, platforms become a central instrument for solutions to unfold. Linking, connecting and fusion data and intelligence from these different entities is the subject of the distributed artificial intelligence (DAI) approach tested in the DIGINET-PS research project.

With the ongoing BeIntelli research project, not only an approach for CAD is tested but a holistic approach to AI in mobility based on the platform economy framework is conceptualized and tested in the created and enhanced real-laboratory environment. The project consists of four main pillars: 1) development of a scalable, adaptable software-stack for autonomous driving (ADAS++), 2) development of autonomous test vehicles and extension of the DIGINET-PS test bed, 3) development of a mobility data platform and advanced ADAS functions, i.e., smart parking or GLOSA as well as 4) showcasing project results to society [1, 39]. Additionally, BeIntelli aims at 1) extending the developed test track to in total 20 kilometers, comprising critical and challenging traffic areas in the heart of Berlin, 2) conceptualizing, designing and digitizing several autonomous test vehicles, 3) developing an adaptable, scalable software-stack for CCAM, 4) designing and implementing a platform for data provisioning and supply of development tools and 5) showcasing knowledge gained and making autonomous mobility tangible to society at large.

Both the Diginet-PS project, and the ongoing follow-up research project BeIntelli are examining the extensive distributed intelligence approach to autonomous mobility while considering various types of vehicles, and the potential of application of digital platforms within the platform ecosystem. We explore the interplay between the mostly independently conducted research in the fields of distributed systems, CCAM and platform dynamics, and shed light on the intertwinements between those in order to 1) explore autonomous driving in complex traffic environments of urban areas, and 2) show how data and service platforms can respond to distributed intelligence approaches.

We created the following component graph (Fig. 3) as a model for addressing autonomous driving and the distributed intelligence approach, which then is embedded in a larger platform economy ecosystem. This model was first presented in Guerreiro Augusto et al. [1] and undergoes continuous development alongside the BeIntelli research efforts. Being subject to further investigation, this model can be developed into a blueprint architecture for the conception, implementation and validation of autonomous mobility solutions. In the subsequent section, we provide

application examples and pose a blueprint architecture, respectively.

Our model assumes three core elements: 1) attributes derived from CCAM namely ‘connectedness’, ‘cooperation’, ‘automation’ as well as the required ‘distributed computing’ capabilities. These attributes are realized through several components and on the three layers: Vehicle, Edge and Cloud: ‘Hardware’ comprises all devices that make up a digitalized vehicle, road-side infrastructure and cloud system. These comprise sensors, such as cameras, lidar, radar, ultrasonic sensors, as well as the computation and communication units. The ‘AI-Middleware’ encompasses aspects such as data preprocessing, V2X communication, HD-Maps for localization and cybersecurity which should ensure safe communication across all agents. The Advanced Driving Assistant System (‘ADAS++’) is responsible for the modules perception, planning and control as well as implement the threefold approach Vehicle, Edge and Cloud presented and tested in the BeIntelli project. The ‘AI-platform’ component consists of the data platform (processing and provisioning of data at different granularity levels) and service platform as runtime environment for smart services (GLOSA, Smart Parking, Platooning, etc.). The displayed Attributes, Components and Layers are core components of the software stack, then addressing the DAI approach for CCAM, as presented in Fig. 3. We now propose to integrate this approach in the Platform Economy, incorporating platform elements such as data provisioning and transaction, development and testing tools as well as PE principles that are actors, services, platform owner, complementors, and users. This model then suggests that these parts are essential for emerging Platform Economy Ecosystems which leverage network effects for scalability.

5 Towards an architecture blueprint for autonomous mobility solutions

Digital platforms are taking a central role in the development of holistic and intelligent mobility systems. The provision of multi- and intermodal mobility and transportation solutions relies on data from various entities. In the context of the BeIntelli research project, these are threefold: vehicles, road-side infrastructure (Edges) and the cloud (see layers introduced in Fig. 3). These layers transpose to the presented components hardware, middleware, ADAS and platform, all considering attributes such as connectivity, cooperation, automation and distributed behavior. On the platform ecosystem layer, data provision, development and tools, as well as test and validation become key components for developing new solutions. Such an ecosystem is a direct output of a PE.

Research initiatives such as the BeIntelli project, equipped with the resources and assets of autonomous vehicles, a digitized test track, an autonomous driving software stack, and a runtime environment for use cases such

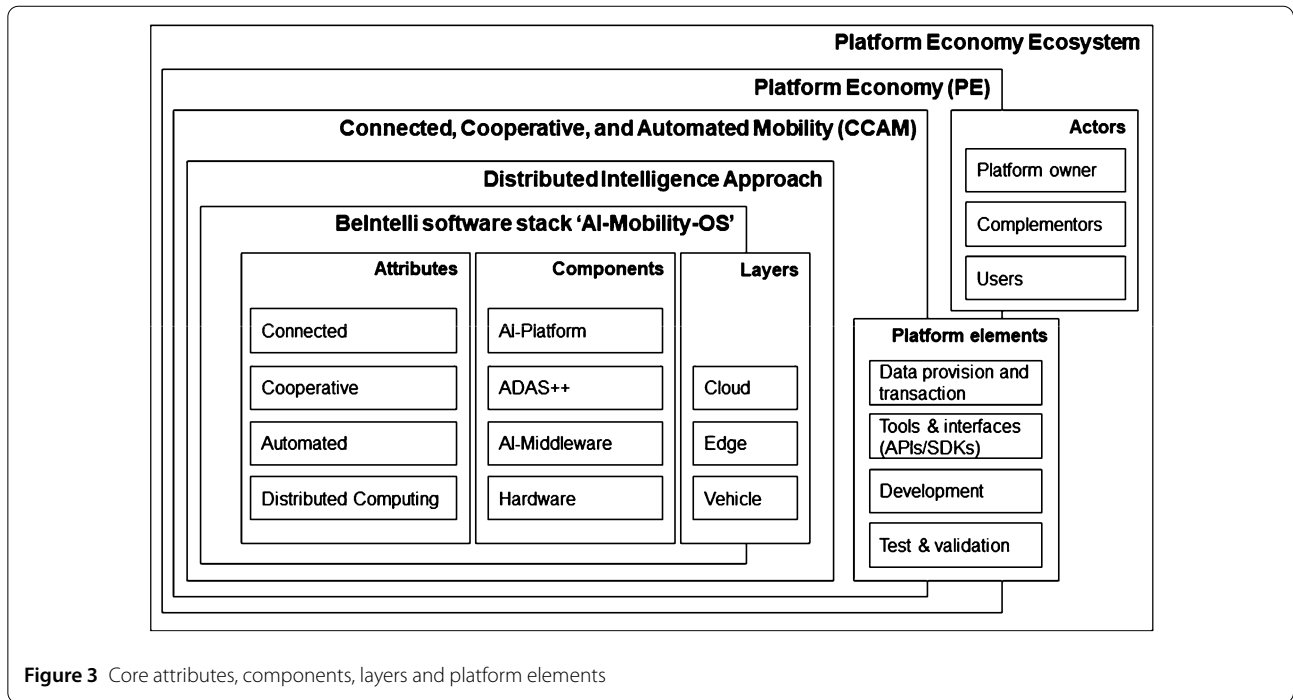


Figure 3 Core attributes, components, layers and platform elements

as Smart Automated Parking or GLOSA, together embody a real laboratory environment for in-depth design, implementation, deployment, testing, and validation of existing and new mobility solutions. The project’s architecture allows startups and industry to develop test, pilot and validate solutions, and academia to further bridge theory and practice towards proposing an architectural blueprint for future mobility solutions.

Results of this setup include, among others, the BeIntelli AI Mobility Contest,⁶ which allowed students and startups to apply and pitch business ideas in the field of mobility and transportation. The resources of the real lab were then provided to the three winning teams. In addition, large industrial companies are entering the real laboratory environment for various purposes. For example, a German automotive supplier collaborates on the adaptation and integration of their Electronic Control Unit (ECU) system in a test vehicle (van) with the goal of testing their autonomous driving solutions in BeIntelli’s real lab environment. Another large vehicle manufacturer collaborates towards equipping one of their high-end vehicle models with the BeIntelli software stack and testing it on the digitalized test track. Both projects use the developed BeIntelli hardware reference architecture (sensor, communication and computing setup) and the BeIntelli software stack - depicted in Fig. 4.

These examples demonstrate the benefit of the BeIntelli real lab environment and approach. Based on the in-

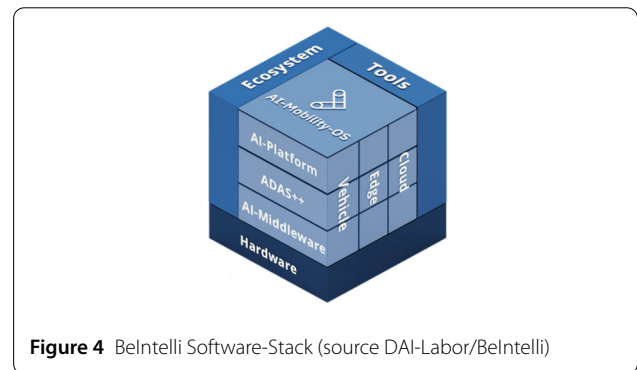


Figure 4 BeIntelli Software-Stack (source DAI-Labor/BeIntelli)

roduced core attributes presented in Fig. 3, we pose a blueprint architecture for autonomous mobility.

The BeIntelli platform ecosystem uses both a data and an AI platform. The data platform is designed to store, process and deliver data at different levels of granularity. It provides functions such as stream processing, data aggregation and prediction on the one hand, and databases, test environments and APIs and SDKs on the other. While the AI platform is designed to enable the development, deployment and testing of applications (runtime environment), it specifically provides AI models, service management, its provisioning, monitoring and diagnostics, data analytics and applications deployed in an app store. Both the data platform and the AI platform share common components, such as user and role management, runtime and test environments, on which they are based. Both the data and the AI platform contribute to the larger mobility and

⁶<https://be-intelli.com/contest/>, accessed on November 9, 2023.

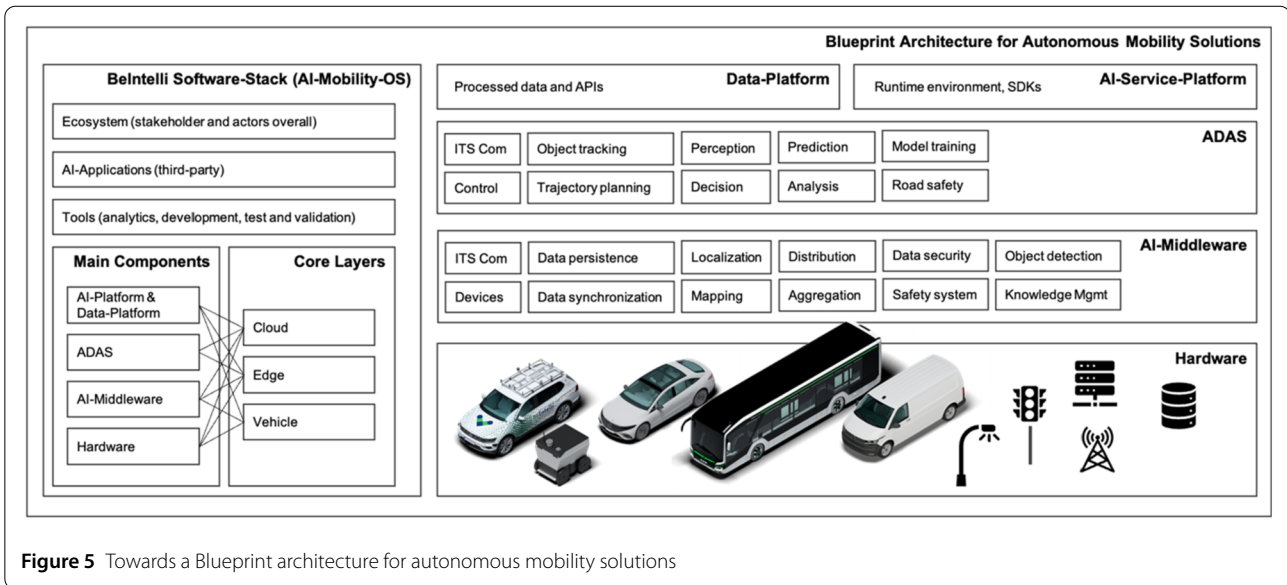


Figure 5 Towards a Blueprint architecture for autonomous mobility solutions

transport ecosystem, consisting of mobility applications, testbeds for piloting, actors involved, and the mechanics of the platform economy, such as the general roles of suppliers and consumers, and evolving network effects. As part of the BeIntelli project, a software stack named ‘AI-Mobility-OS’ is conceptualized (see Fig. 5) and implemented in order to allow vehicles to demonstrate autonomous driving functions deployed on an AI service platform, while also providing data at different levels of granularity for the development of autonomous mobility solutions.

6 Conclusion

This paper provides a cross-cutting analysis of the distributed AI (DAI), connected, cooperative and automated mobility (CCAM) and the platform economy (PE) to shed light on the current theoretical background of these three intertwining areas of interest, as well as to identify how these parts could work together in an autonomous mobility ecosystem. We look at the underlying DAI approach for CCAM to address the conception, design, and implementation of mobility and transportation solutions in the platform economy. We identified that overall limited research at the junction of DAI, CCAM and PE has been conducted, even when we consider the partial intersections of the three.

This paper therefore provides an understanding of the intertwining role distributed artificial intelligence approaches, CCAM and the platform economy reveal for developing autonomous mobility solutions. A literature review is applied by looking at the intersections of the terms, respectively. Further, both the DIGINET-PS and BeIntelli research project on ‘AI in Mobility based on Platform Economy’ are taken as a reference point for classifying

the interplay of the three observed aspects. We found that DAI is acting as an embodied entity for CCAM; and PE can be seen as acting entity for allowing suppliers to make use of the underlying DAI and CCAM structure to develop and supply novel mobility and transportation solutions. We propose an architectural blueprint that incorporates these elements and could serve as an initial reference for building autonomous mobility solutions. We acknowledge that this initial postulation needs to be further refined and tested. This work concludes that well-defined choreographies between DAI, CCAM and platform architectures in the PE may contribute to building effective and efficient MaaS solutions for citizens and cargo transport and may lead to future autonomous mobility landscapes.

7 Discussion and future research

Vehicle and transport infrastructure digitalization has not only opened up a new landscape for mobility and transportation offerings but disrupts paradigms such as travel as a derived demand [40]. The acceptance of mobility products and services, however, still depends on convenience, affordability and attractiveness. Against the backdrop of the digital transformation towards DAI-driven CCAM solutions, the platform economy is taking up a central role for the emergence of new mobility and transportation ecosystems.

A large amount of autonomous mobility use cases and platforms in both research and industry are emerging. Navigation, ticketing, ridesharing and hailing of different means of transport such as bicycles, cars, scooters have become an integral part of peoples’ mobility ecosystem. Further on, use cases such as VoD, GLOSA, Traffic Light Control, Smart Parking and last mile delivery are just a few examples of evolving mobility and transportation offerings

currently investigated and developed - all embedded in a larger mobility and transportation ecosystem. Mobility data platforms are a core enabler for Mobility as a Service and become a crucial component for CCAM solutions.

We identified that literature in the field of mobility data platforms, specifically concerned with enabling DAI-driven autonomous mobility solutions is scarce. Nevertheless, research initiatives and projects across the globe are addressing CCAM. Platforms are unifying data from several entities and offering such data to mobility and transportation products and service providers. Furthermore, research in the fields of artificial intelligence (AI) and specifically machine learning (ML) is supporting the development of more efficient and purpose-fulfilling algorithms for realizing such presented use cases. Nonetheless, research still neglects the intertwining of mobility and transportation actors, their needs towards products and services as well as the derived required underlying structures to be built.

While existing research fails to describe the interplay of DAI, CCAM and PE and consequently to map the requirements, design, architecture, and ultimately potential implementations for a platform and resulting ecosystem that is compliant with the DAI approach for CCAM, future research should focus on examining and illustrating the key interfaces between these three domains. It involves 1) elaborating how a digital platform responds to the DAI approach and 2) how such a platform could look like. It questions the design, types of components, architecture, and information flow, development and user requirements, to name just a few aspects. Moreover, future research should further test and validate the proposed model, enhance it and provide a reference basis for its application, e.g., by the development of an association guide, a so-called “use-case mapper”, which allows applying the blueprint for the conception, implementation and validation of future mobility solutions.

Acknowledgements

We acknowledge the support of the Belntelli research project and the TU Berlin.

Funding

This paper is based on the research conducted in the Belntelli project, funded by the German Federal Ministry for Digital and Transport (BMDV) under the funding reference number 01MM20004.

Data availability

Not applicable.

Declarations

Competing interests

The authors declare no competing interests.

Author contributions

Conceived by the author Marc Guerreiro Augusto; all authors contributed to the design and development of the paper. All authors read and approved the final manuscript.

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Received: 31 October 2022 Revised: 24 November 2023

Accepted: 28 November 2023 Published online: 03 January 2024

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