Designing Smart Mobility Systems: Mapping the future to Human-Centered Intelligent MaaS

Collins Senyemi
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TABLE OF CONTENTS

LIST OF TABLES AND FIGURES

TABLES

FIGURES

1.1 Introduction

Recent technological advancements have opened a world of opportunities for key players within the mobility ecosystem, with several versions of multi-modal mobility services being adopted in notable cities in several parts of the world. This mobility evolution and the possibilities artificial intelligence (AI) and the Internet of Things (IoT) present for personalized transport solutions is helping to shape a data-driven, human-centered future for mobility services. As Mobility as a Service (MaaS) grows in popularity around the world, researchers and mobility ecosystem players constantly seek to unlock the complexities of a truly inclusive mobility innovation using big data and machine learning, and other related technologies. This report takes a closer look at current and emerging smart mobility designs powered by big data and artificial intelligence, drawing from relevant industry journals and conferences, academic and white papers to shed more light on ways of implementing a truly smart human-centered mobility system. Further, the report details key applications of big data and artificial intelligence in the design of smart mobility and provides insights on areas for future research and opportunities for a human-centered intelligent mobility solution. The study is aimed at identifying how cities around the world are dealing with mobility challenges using new technology, the role AI and other new technologies play in the design smart mobility systems, and who the key players are in the application of AI to smart mobility design.

The rest of the report is structured as follows: the next section in this chapter overviews the methods used in this study. Chapter two overviews the development of intelligent MaaS and the trends that are driving such a shift. Chapters three and four covers the key terms used in this study and applications of AI in mobility in AI in intelligent and smart mobility design respectively. Chapter five looks at the shoft towards AI-driven, service dominant mobility design, followed by chapters six and seven which discusses challenges with designing smart AI-driven smart mility systems and possible mitigations to these challenges respectively. The report then wraps up in chapters eight and nine with conclusions and areas for further research.

1. 2 Methodology

In this section, the report highlights the method(s) used to narrow down on the selected literature and previous work within artificial intelligence, human-centered design, and mobility as a service. The purpose of this is to give a clear indication of the steps involved in this study to aid in the validation of the findings or replication of the research in the future (Kallet, 2004; Ojala and Lehner, 2018).

Keywords	Search Sources	Inclusion Criteria
Artificial Intelligence in Smart Mobility	Scopus IEEE digital library ACM Digital Library Web of Science Google Scholar	Within the last decade
Smart Mobility and AI		Filtered by relevance to the subject matter
Human-centered smart mobility design		Within the area of Computer Science and Information Systems
Intelligent mobility design		Peer reviewed

Table 1:*Keywords, bibliographic search sources, and inclusion criteria*

As human-centered intelligent systems and MaaS relates to the field of information systems and computer science, a bibliographic search was conducted to source relevant resources from leading journals within information systems. The chosen databases were Scopus, IEEE Xplore digital library, ACM Digital Library, and Web of Science databases. These were preferred as they contain relevant resources within information systems and are leading repositories trusted by researchers worldwide.

For the inclusion criteria, papers and reports from within the last decade were preferred, given the popularity of human-centered intelligent systems and MaaS and its rapid development in cities around the world (United Nations, 2020). The relevance of the resources to human-centered intelligent systems and MaaS was also considered, to limit the search yield and narrow the results to include papers that mostly mention artificial intelligence, mobility as a service, intelligent mobility or smart mobility in their keywords and abstracts. The report also looked at papers that were within the field of computer science and information systems that had been peer-reviewed. The analysis covered several references and document sources, not within the aforementioned scope, but were relevant to the scope of the search. These resources were not directly identified within the main databases highlighted for the search, but are included as they are necessary and relevant to the purpose of this study.

The literature search was then conducted using the aforementioned criteria, using a combination of the keywords, and filtered to be within the last decade. The subject areas were limited to computer sciences and information systems and further filtered to cover author keywords.

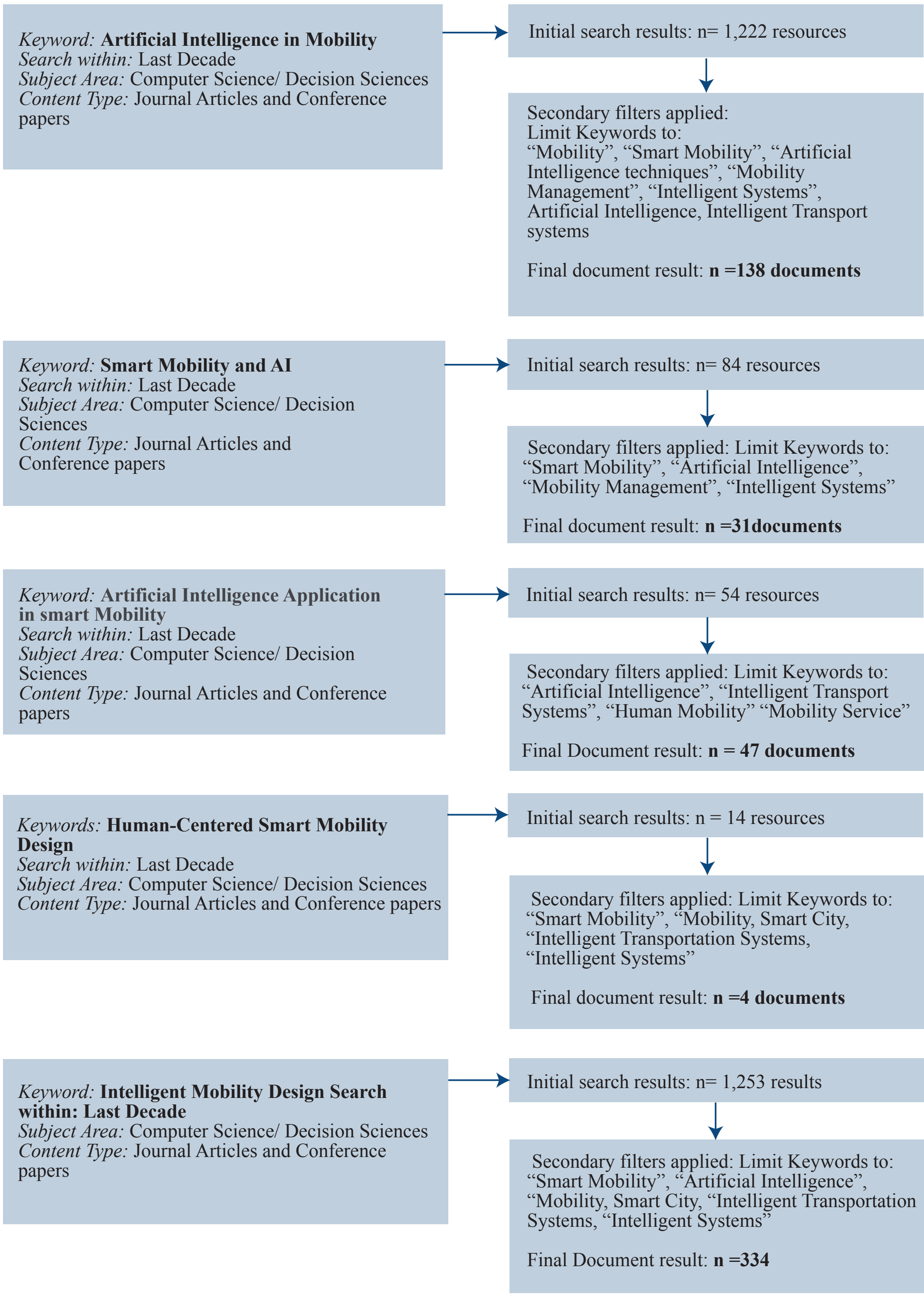

Figure1: Scopus Database keyword search and shortlist process and results

The combination of the keyword searches from the Scopus database yielded a total of 554 documents after the attributes and the chosen filters were applied. The chosen keywords were searched for sequentially, with "Artificial Intelligence in Mobility" yielding 138 final documents after filters and were applied as indicated in Figure 1. The same process was repeated for the keywords "Smart mobility and AI, “Artificial Intelligence application in smart mobility”, “human-centered mobility design”, “intelligent mobility design”, “AI- powered MaaS" yielding 31, 47, 4, 334, and 0 documents results respectively. Total documents shortlisted were 554.

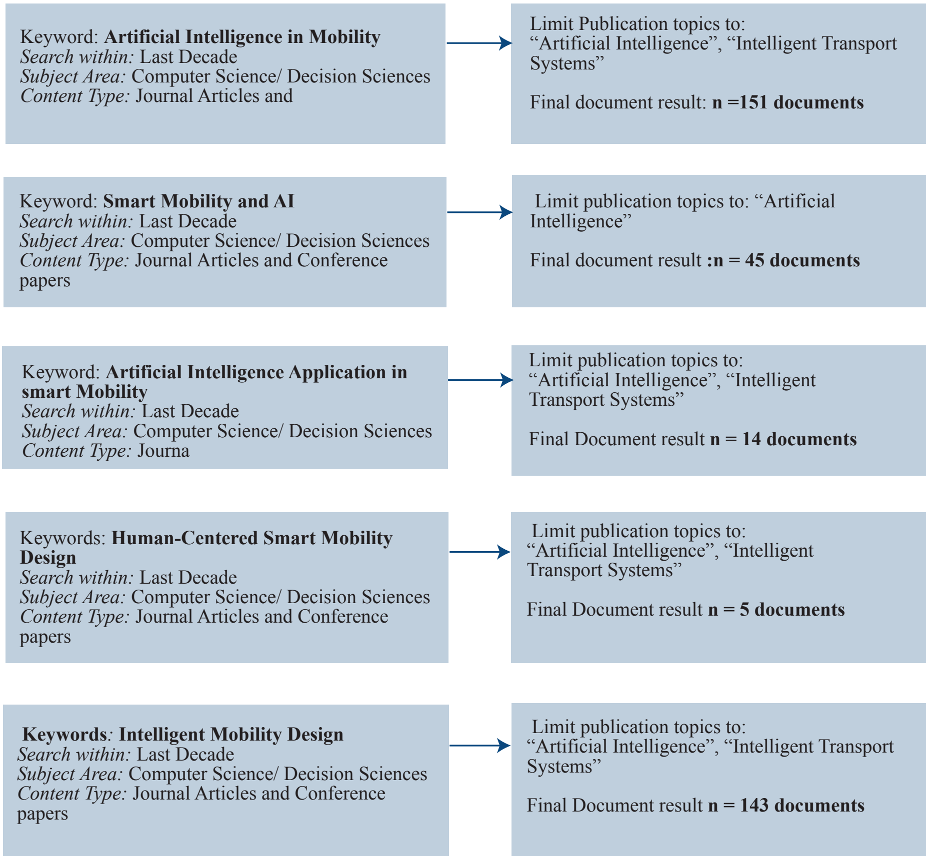

Figure 2: Database search process for IEEE Xplore digital library

The next database searched was the IEEE Xplore digital library, using the same keywords and filters as used in the Scopus database search.

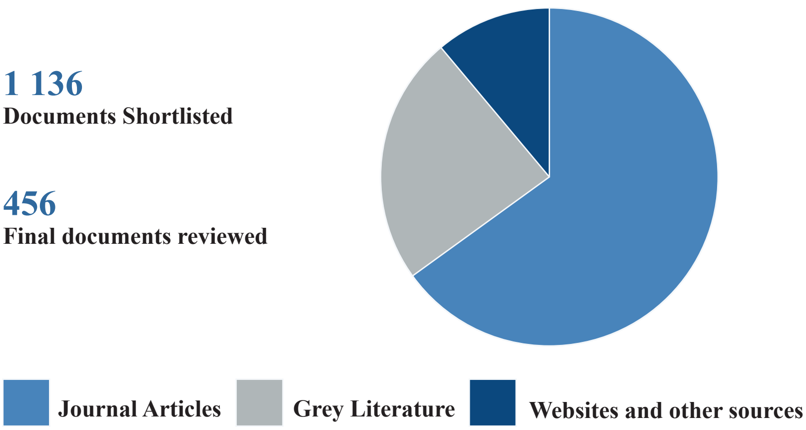

Figure 3: Types of documents used for the literature search

The keyword searches yielded a total of 344 results, a combination of results from "artificial Intelligence in mobility (151), smart mobility and AI (45), artificial intelligence application in smart mobility (14), human-centered smart mobility design (5), and intelligent mobility design (143) as shown in Figure 2.

The next databases searched were the ACM digital library and Web of Science, which yielded 202 and 36 documents respectively, as shown in Figures 3 and 4. In all, a total of 1,136 documents were shortlisted, after which a final resource list of 156 was chosen based on relevance to the human-centered intelligent systems and MaaS and deduced from document titles and abstracts, and after eliminating duplications. Zotero was used as a tool for referencing as well as managing duplications. Other sources from Google Scholar and Google Search were used.

Keyword combination: **“Artificial Intelligence in Mobility” or “Smart Mobility and AI” or “Artificial Intelligence Application in smart Mobility”, or “Human-Centered Smart Mobility Design”, or “Intelligent Mobility Design”**
Search within: Last Decade
Subject Area: Computer Science/ Decision Sciences
Content Type: Journal Articles and Conference papers

→

Limit results to highest cited and author keywords

Final document result: **n = 202 documents**

Figure 4 :ACM Digital library search process

Keyword combination: **“Artificial Intelligence in Mobility” or “Smart Mobility and AI” or “Artificial Intelligence Application in smart Mobility”, or “Human-Centered Smart Mobility Design”, or “Intelligent Mobility Design”**

Search within: Last Decade
Subject Area: Computer Science/ Decision Sciences
Content Type: Journal Articles and Conference papers

→

Limit publication topics to:
“Artificial Intelligence”, “Intelligent Transport Systems”

Final Document result: **n = 36 documents**

Figure 5: Web of Science database document search process

2. The development of intelligent mobility as a service

One of the common problems faced by many countries around the world today is urban congestion resulting from transportation, whose effects such as the direct impact on travel time and fuel consumption and its attendant emission challenges affecting human health (Masoud and Jayakrishnan, 2017). With the world’s population estimated to reach approximately 8.5 billion by 2030 (United Nations, 2019), majority of which is projected to be virtually absorbed by urban areas (United Nations, 2018), city authorities will need to effectively design sustainable and green mobility solutions to meet the needs of city dwellers and commuters as a way to reduce the congestion (Basile et al., 2020; Horn and Schönefeld, 2020).

As part of efforts to reduce urban congestion, players within the transportation ecosystem have over the years deployed solutions to aid the smooth movement of people and goods (Stiglic et al., 2018). In varying forms, these innovative mobility solutions are helping city authorities to reduce the systemic congestion in city spaces, contributing to livability and sustainable environments (Impedovo and Pirlo, 2020). As mobility is seen as the backbone of any society and a key contributor to economic development (Hannon et al., 2016), solving mobility challenges through innovation is key on the agenda of smart cities (Olszewski et al., 2018). Rapid population growth makes the need for better and more efficient innovation in mobility services more urgent than ever (Skouby et al., n.d.) which is a key reason why smart mobility has become a common theme of the sustainability agenda, as part of responses to pursue more sustainable transportation systems in the big cities, with considerations on identifying the key drivers of intelligent mobility (Munhoz et al., 2020).

In response to the growing mobility demand (Franco et al., 2020), coupled with the failure of passenger transport services to ensure uniformity in mobility services for all, partly due to the complexity of different transport modes and payment challenges (Murati, 2020) - MaaS, a general term for multi-modal on-demand mobility services has emerged in recent times as one of the answers to the ever-growing demand for mobility services (Hensher et al., 2020). The MaaS phenomenon has so far delivered platforms that provide consumers and users with alternatives to private transportation, helping city authorities to reduce traffic congestion and promote better and efficient transport means for citizens (Paiva et al., 2021). Several shareable transportation systems embedded with smart technologies are also being used in many smart cities towards attaining a user-friendly and environmentally sustainable mobility solution at lower implementation costs (Munhoz et al., 2020).

Smart mobility service providers and integrators like Whim, Ubigo, Moovel, Uber, Lyft, Arro, BlaBla Car, Bridj, Cabify, DidChixing, FlyWheel, Brab, Hitch, Curb, and many more are facilitating easy access and on-demand mobility in various parts of the world. These applications and they are quite many, are helping to make door-to-door mobility better (Schulz and Überle, 2018), and ushering in a new era of smart mobility. With the growing need for better and more personalized mobility solutions, however, the need for city authorities and mobility service providers to pursue smart mobility solutions including algorithm optimization for people and vehicles, reduction of congestion through smart traffic management, and intelligent solutions for the movement of logistics among others is more urgent than ever (Viechnicki et al., n.d.).

In recent times, new technologies like AI and IoT are opening more possibilities for using big data for transportation research and mobility solutions, featuring in studies around the world, some aimed at investigating mobility patterns by relying on mobile phone trace data of millions of users as well as odometer readings from safety readings to gain deeper insights into mobility patterns (Calabrese et al., 2013). Other studies have focused on using commuter's transport history data for personalized route descriptions to produce more effective and cognitive turn-by-turn directions (Su et al., 2019) and the use of blockchain to facilitate MaaS (Andersson and Torstensson, 2017). In the area of goods transport, several robot prototypes that deliver necessities to homes are being used in cities around the world (Paiva et al., 2021), opening even more possibilities for AI in mobility.

3. Key Terms

Challenges related to Urban Mobility(Closer, 2021) is gradually referred to as different types of challenges that require new types of solutions. Therefore, it is common to find terms like smart mobility, intelligent mobility, human-centered mobility, and similar terminologies emerge in various urban use-cases and applications. While these terms share a similar mobility theme and, in some cases, could be referring to the same concept, an understanding of what these terms mean concerning the human-centered intelligent systems and MaaS will help to provide a clearer perspective on the focus of this study. An overview of definitions of the key terms is provided in the ensuing section.

3.1 Mobility as a Service (MaaS)

MaaS has gained popularity deservedly in recent times (Jittrapirom et al., 2017) due to its efficiency in delivering mobility innovation (Cruz and Sarmento, 2020) and its promise of delivering sustainable transport solutions (Esztergár-Kiss et al., 2020).

As a constantly evolving concept (Minchin, 2021), a one-size-fits-all definition for MaaS will not be enough to thoroughly describe what MaaS encompasses (Jittrapirom et al., 2017). A considerably large number of definitions for MaaS was uncovered in the compilation of this report, with each definition approaching the delivery of multimodal mobility services from various angles, but sharing an underlying theme of a user and service-oriented bundled mobility service. Sampo Hietanen, described as the “godfather” of MaaS (Murati, 2020) defined it as a cooperative, interconnected mobility ecosystem, delivering bundled mobility services to users, through one interface, similar to phone price- plan packages (Hietanen, 2014).

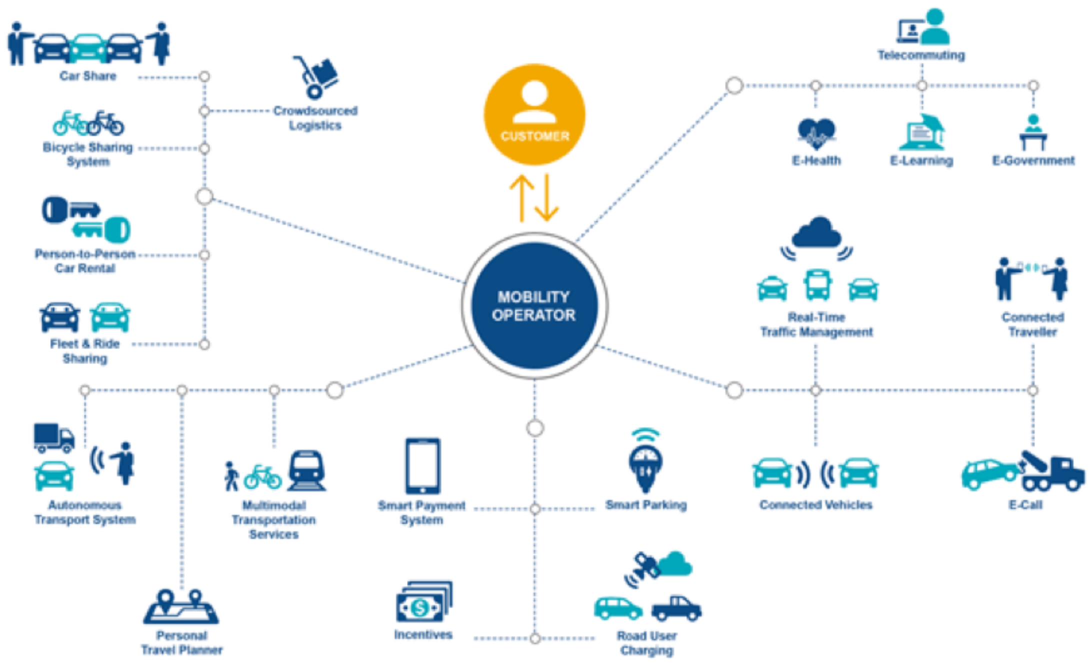

Figure 6: MaaS ecosystem, adapted from (BusinessMaaS, 2017)

This definition all but summarizes what Maas embodies - a user-centric mobility solution involving one or more modes of transport (Polydoropoulou et al., 2020; Santos and Nikolaev, 2021). Other authors like Hensher et al. (2020) describe MaaS as a one-stop shop of private and public transport services bundled together. The key concepts that define MaaS cover the merging of different mobility modes (Jittrapirom et al., 2017), needs-based and customizable (Karlsson et al., 2016) door-to-door mobility solutions (Hietanen, 2014), powered by integrated payment systems (Pangbourne et al., 2020; Polydoropoulou et al., 2020) and brokered via digital platforms connecting users and service operators (Pangbourne et al., 2020). Table 2 highlights some definitions of MaaS collated from the literature. This summary is however not exhaustive as one report cannot adequately cover the wealth of information on MaaS.

KEYWORD	DEFINITION	AUTHOR(S)
MOBILITY AS A SERVICE	MaaS is a distribution model that delivers users' transport needs through one single interface of a service provider, combining different transport modes to offer tailored mobility packages.	Hietanen, (2014)
	A personalized, one-stop travel management platform digitally unifies trip creation, purchase, and delivery across all modes. For customers, it offers total integration across public, intermediate (ride-sourcing, micro- transit, and taxi), and private (through car-sharing or cycle hire) modes of transport.	Ho et al., (2018)
	MaaS is a service that integrates different modes and services in subscription, packages to cover an individual's travel needs through a single interface; the MaaS operator.	Georgakis et al., (2020)

Table 2: Definitions of MaaS and AI

Table 2 continued

KEYWORD	DEFINITION	AUTHOR(S)
	A user-centric, multimodal, sustainable, and intelligent mobility management and distribution system, in which a MaaS Provider brings together offerings of multiple mobility service providers (public and private) and provides end-users access to them through a digital interface, allowing them to seamlessly plan and pay for mobility.	Kamargianni and Matyas, (2017)
	The integration of various forms of transport services into one single mobility service accessible on demand.	MaaS Alliance, (2017)
	MaaS may contain both public and private sectors, including the operators under crowd-sourced logistics such as car-sharing and rental, transport fleet and infrastructure; trip planner, booking and payment; real-time traffic management, and inter-connectivity information among service platforms; as well as relevant value-added services.	Li et al., (2019)
	A service that integrates different mobility services (e.g. public transport, car sharing, bike sharing, taxi, etc.) and provides one-stop access to these services through a common interface – is being explored as part of the solution.	Karlsson et al., (2016)
	MaaS provides a system whereby traditional services such as public transport can be integrated with other on-demand and shared services—such as ride-, bike- and car-sharing—and a single online interface utilized for payment, journey planning, and other traveler information.	Butler et al., (2021)
	A new transport solution which merges the different available transport modes and mobility services, to provide seamless door-to-door mobility for users, made feasible by the technological advances, the cooperation of different operators, and the bundling of several transport modes.	Jittrapirom et al., (2017)
	A socio-technical paradigm that aims at transporting persons (and sometimes goods) over a predefined distance, often by combining different means, by making intelligent use of ICT (and, less often, ITS) in a way that is distinctly more sustainable than the use of a private car.	Giesecke et al., (2016)
ARTIFICIAL INTELLIGENCE	The incorporation of human intelligence into machines. In AI, machines complete the task based on the stipulated rules and algorithms.	Jakhar and Kaur, (2020)
	A machine-based system is capable of influencing an interlocutor in a particular task by making recommendations, predictions, or decisions for a given set of objectives. It uses machine and/or human-based inputs/data to i) perceive a context; ii) generalize, learn, and abstract perceptions into replicable models with or without human guidance; and iii) interpret the models to posit a humanly interpretable outcome.	(Ballester, 2021)
	An Interactive Human-Centered Artificial Intelligence is an Artificial Intelligence that enables interactive exploration and manipulation in real-time and is designed with a clear purpose for human benefit while being transparent about who has control over data and algorithms.	Schmidt, (2020)
	The capability of a computer system to show human-like intelligent behavior, characterized by certain core competencies including perception, understanding, action, and learning. (. . .) an AI application refers to the integration of AI technology into a computer application field with human-computer interaction and data interaction".	Wirtz et al., (2019)
	Machines that can learn, reason, and act for themselves. They can make their own decisions when faced with new situations, in the same way, that humans and animals can.	Hao, (2018)

Table 2 continued

KEYWORD	DEFINITION	AUTHOR(S)
	AI is defined as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation.	Kaplan and Haenlein, (2019)

3.2 Artificial Intelligence

AI is a concept that has been around for several years, in many forms, powering technological innovations in everyday life and industry (Griffiths, 2019; Morgan, 2019). A buzzword in recent times, AI is often used interchangeably with machine learning and often confused with robotic process automation (Manning, 2020), which is the automation of tasks that reproduce the work that humans do (van der Aalst et al., 2018) with the help of software robots that can perform accurately, repetitive tasks (Ribeiro et al., 2021). The former ia an umbrella tern that includes a broad range of algorithms which performintellegent predictions based on a data set (Nochols et al., 2020). While AI covers systems that combine large amounts of data and processes same at fast speeds with iterative processing through intelligent algorithms (Khayyam et al., 2020).

As AI is being leveraged in mobility innovations worldwide (Maayan, 2020), a clearer understanding of what AI represents, and the improvement opportunities it offers for mobility service design is key. Several authors have attempted to simplify the definition of AI, some of which have been documented in this study. For instance, Russell et al. (2017) described AI as a "proxy for humans", while Nilsson, (1998) describes AI as concerned with "intelligent behavior of artifacts", further explaining intelligent behavior to include perceptional reasoning, learning, communicating, and acting in complex situations (Nilsson, 1998; UITP, 2021). An earlier definition by John McCarthy, often referred to as one of the fathers of AI (European Commission, 2020) describes common sense ability as key to AI (McCarthy, 1959). Nikitas et al. (2020) take the definition a notch further, describing AI as a machine's ability to simulate the human mind by interpreting and learning from data it receives from the environment and using that learning to complete tasks successfully. With more conceptualizations (a compilation of some definitions from the literature search is detailed in Table 2) and use cases for AI especially in designing smart mobility (Majster et al., 2021), the future of mobility is promising (Horn and Schönefeld, 2020).

3.3 Smart Mobility

In an era of "smart" artifacts, it is no surprise that mobility has had its fair share of the 'smart' prefix. Smart mobility describes mobility that uses digital technologies to integrate systems and means of transport that interacts with users, to meet the mobility needs of users in a safe, accessible and sustainable manner (Munhoz et al., 2020). Francini et al. (2021) define smart mobility as the result of a planning process that makes use of technological supports in the use and monitoring of individual and shared transport systems for ensuring safety standards, functionality, and sustainability. Al-Rahamneh et al. (2021) conceived smart mobility as a customized and on-demand service provided to users to solve their mobility needs effectively and efficiently while promoting sustainable mobility and minimizing carbon footprint impact. Smart mobility will undoubtedly transform the future, and with various mobility systems and applications already putting a myriad of mobility options in the palm of users, the prospects are just as promising. Smart mobility brings demand responsive transport, intelligent transport systems, electric mobility and shared mobility and autonomous vehicles under one umbrella (Butler et al., 2020)

Smart mobility and Intelligent transportation systems share similar concepts and are both related to mobility that uses one form of a technology system or another. In the next section, the report details what Intelligent Transportation Systems are and how they differ from smart mobility.

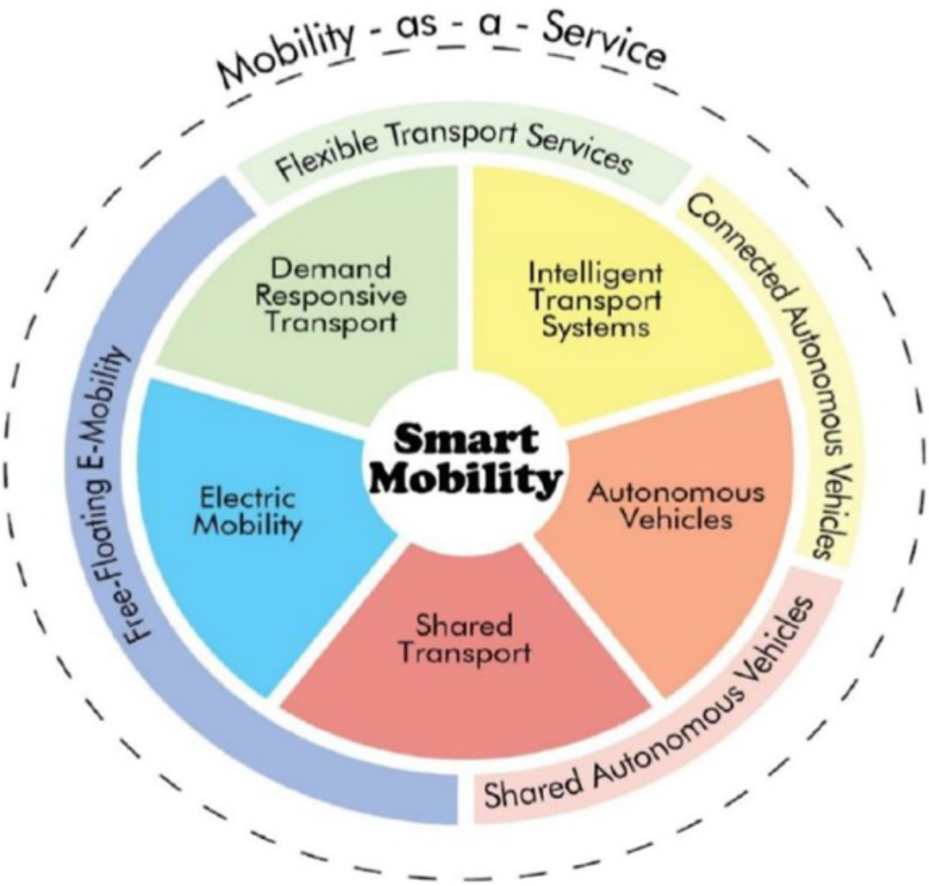

Figure 7: Conceptual framework of smart mobility ecosystem and MaaS adapted from (Butler et al., 2020)

3.4 Intelligent Transportation Systems

Like MaaS and smart mobility, Intelligent Transportation Systems (ITS) are helping to make cities smarter, leveraging information and communication technologies to facilitate mobility of people and goods while ensuring safety (Kanafani et al., 1994). Although often used interchangeably, smart mobility and ITS do not mean the same concept, although the two share close similarities in how they are used within discussions on intelligent mobility. ITS generally involves a computerized system having diverse applications connected with vehicle transportation (Singh et al., 2014) and electronics technologies to monitor and manage traffic flow, reduce congestion and provide time and cost-saving route optimization information to travelers (Singh and Gupta, 2015). ITS uses sensors, communication, and computational technologies to collect, store and process traffic information for the benefit of road users (Sochor, 2013; Wang et al., 2019). ITS has been deployed in major cities around the world, at various levels of implementation, in traffic management to reduce congestion based on online data on traffic patterns, density, speed, travel time, and geographic positioning of vehicles in real-time (Mandhare et al., 2018). Agarwal et al (2015) conceptualized ITS within the smart city context (Figure 7) to cover smart public transport systems, intelligent traffic management and control systems, smart traffic information systems, smart parking management systems, safety management, and emergency systems, and smart pavement management system. An overview of the applications of AI, IoT, and big data within the various application areas of ITS are looked at in the ensuing sections.

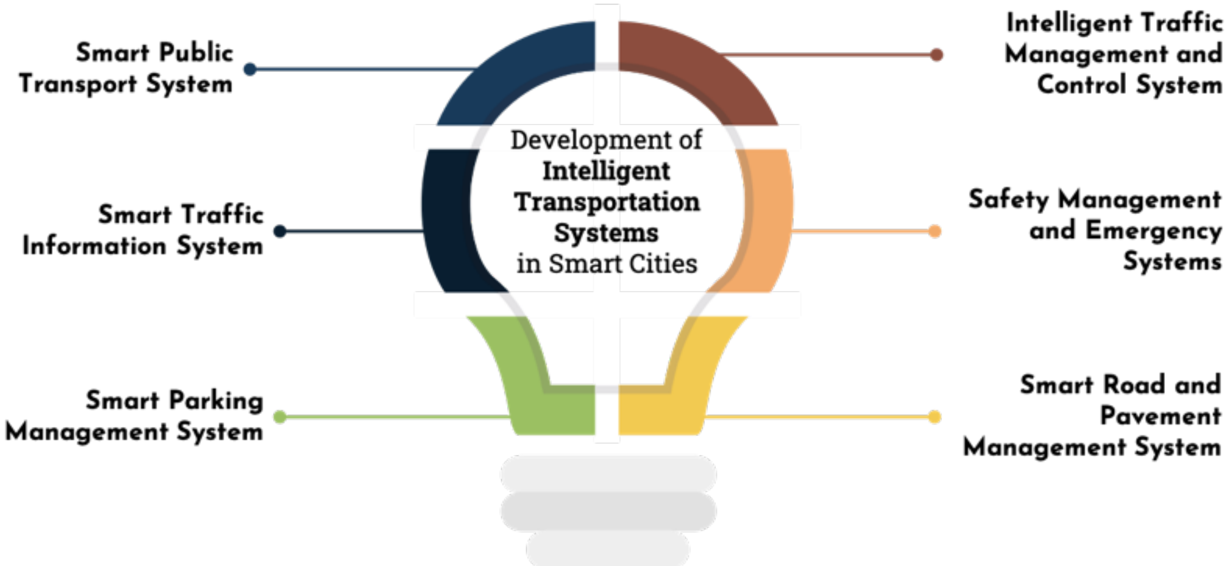

Figure 8: Intelligent transportation systems in smart cities, adapted from (Agarwal et al, 2015)

3.4.1 Smart Public Transport System

Public transport systems are used in many cities across the world. Within ITS in smart city contexts, smart transport covers all types of vehicles that use state-of-the-art information and communication technologies to efficiently transport people and goods, monitor locations, facilitate vehicle-vehicle communication, and assist in traffic management (Boreiko et al., 2019). These connected solutions for various shared passenger transport services usually feature integrated passenger information systems, ticketing and payments systems, traffic control and analytics (Öberg, et al., 2017). Smart public transport systems use real-time data and algorithms to provide passengers with route choosing flexibility, departure times, transport modes, etc, thanks to the integration of varying transport modes from various service providers (Porru et al., 2020). As digital technologies open new possibilities, city authorities are constantly looking for new ways to leverage AI and IT to improve travel experiences. Within the Nordic region for instance, ambitious visions for efficient and inclusive user-centered smart public transport are in motion. In Copenhagen, a target of 75% of all trips by public transport, bike or foot has been set, to be achieved by 2025 (Öberg, et al., 2017). Leading public transport operators like Nordina and MTR are keen on exploring new opportunities created by digital technologies to improve passenger experience, by exploring a number of AI-driven solutions in-cabin personalization experience to make public transport more appealing (Öberg, et al., 2017)

3.4.2 Smart Traffic Information System and Intelligent Traffic Management and Control System

Another use case for ITS is smart traffic management and control systems, for monitoring traffic and event information, often using algorithms and real-time data to coordinate the proper flow of traffic and incident management (Quessada et al., 2020). Traffic lights have been in existence for long, often serving traditional roles of being manned to direct traffic in an orderly manner. The advent of recent technologies has however seen several heterogeneous components within modern traffic monitoring systems using IoT and processing real-time traffic information intelligently (Omar, 2015). Within the same context of smart cities, intelligent traffic management and control systems are being applied for Advanced Traveller Information Systems, to improve overall traffic system performance, reduce emissions, noise, and travel times. (Allström et al., 2017).

As technology advances, more use cases for AI and IoT are being discovered and studied by researchers, for the improvement of smart traffic management and control, for the smart cities of the future. For instance, an Intelligent Traffic Management System and Smart Traffic Signal controller based on the internet of vehicles was proposed in a study by Mohamed and AlShalfan (2021), for local traffic management using an adaptive algorithm to reduce commuting time, provide reasonable traffic flow, and give priority to emergency vehicles. A similar low-cost, highly scalable intelligent traffic administration system based on IoT, wireless sensing, and vision detection technologies was proffered in a study by Omar (2015). The future of smart traffic management and control looks promising, as new design visions leveraging IoT and big data are studied and experimented with, be it in the area of smart wireless digital traffic lights (Toh et al., 2020), or intelligent traffic control systems based on wireless sensor networks (Hilmani et al., 2020).

3.4.3 Safety Management and Emergency Systems

One of the challenges with transportation is the possibility of road traffic accidents, with its attendant injuries, fatalities, and property damages. A 2018 World Health Organisation report estimates the number of global annual road traffic deaths worldwide at 1.35 million in 2016, painting a grim picture of the severity of road crashes, particularly as the leading killer of people aged between 5 and 29 years (WHO, 2019). Various interventions are being adopted to reduce the fatality of road crashes and ensure safety for road users worldwide. In 2018, the European Commission proposed a new policy approach to road safety in the EU, - “Vision Zero”, aimed at pursuing a short term vision of reducing deaths and injuries from road fatalities, an interim target of 50% fewer deaths and serious injuries from road crashes between 2020 and 2030, and a long-term target of zero deaths and serious injuries by 2050 (European Commission, 2019).

Similar policy interventions for drastic road fatality and serious injury reductions are being implemented in cities in the United States (Evenson et al., 2018). ITS is helping to shift the road safety focus from minimizing road crash consequences (through vehicle safety measures) to the use of technology to reduce the severity of traffic crashes through the use of IoT and communication technologies to quicken emergency response times and provide driver assistance for crash mitigation (Tatari et al., 2012). ITS within road safety management and emergency systems can collect data to be used to predict crash likelihoods, detect and verify incidents, improve accident response times and provide timely warnings for the traveling public in case of crashes on traveling routes (Kaiser, 2021). Another application of big data and IoT within ITS is the concept of musical roads, trialed by countries like Japan, the US, Denmark, Netherlands, Taiwan and Korea. (Toh et al., 2020). The idea is for these roads to produce music when cars drive past them, with the music tempo quickening in parallel with the travelling speed of the moving car. This technology is aimed at hazard warning, road safety and to help drivers keep within the speed limits necessary for the music to play at a normal tempo while providing a form of entertainment. (Toh et al., 2020). The future for ITS promises more innovations for traffic management systems, whether to reduce the latency of emergency services for ambulances and response vehicles (Djahel et al., 2013) through a combination of vehicle-to-vehicle and vehicle-to- infrastructure (Martinez et al., 2010), or decision support systems for emergency management on major roads and tunnels (Alvear et al., 2013) and data analytics on accidents trends for prediction and prevention (Agarwal et al., 2015).

3.4.4 Smart Parking Management System

Smart Parking Management Systems are one of the ways ITS is helping smart cities to optimize parking spaces. These intelligent parking systems provide information on vacant parking spaces to drivers (Kalašová et al., 2021), using a combination of information and communication technologies, big data and location technologies (Barriga et al., 2019), object detection sensors, infrared sensors, neural networks, and machine vision (The Guardian, 2018). Smart parking systems are in use currently in many European cities, as well as in other parts of the world (El-Seoud et al., 2016), helping to transform smart cities and make them more livable (Danilina and Slepnev, 2018), ensure less pollution, optimize space usage and safety (Karsten, 2018). With advances in AI, several big-data driven smart parking solutions have been developed and researched, like counter-based systems which use sensors to count the number of vehicles entering and leaving the parking area, giving indication on free parking spaces to authorities and drivers (Soegoto et al., 2018). A similar magnetic and vision sensor based system was researched and tested by Alam et al., (2018), based on a decentralized intelligence architecture, like that of ZigBee (Shim et al., 2006), a popular wireless parking system. Other examples of smart parking systems are based on a combination of technologies like fuzzy logic, vehicular to infrastructure communication, computer vision and RFID to identify and recommend free parking spaces for drivers (Fraifer and Fernström, n.d.) Park-sharing, a similar model to the ride and bike sharing service is becoming popular in Europe and in other parts of the world, offering users peer- to-peer and business-to-consumer parkin solutions (Civitas, 2020). Applications like ParkNShare, EasyPark, ParkNow, ParkAlot, Parkamo are leveraging data analytics and algorithms to give users even more options to choose from when travelling.

3.4.5 Smart Road and Pavement Management System

Within the application of ITS, the possibility for smart roads and pavements to complement other "smart" transportation systems is being experimented with by researchers worldwide. The world's first electrified road was launched in Sweden in 2018, as part of the eRoad Arlanda project, aiming to provide dynamic charging for vehicles while in motion instead of using roadside charging posts (The Guardian, 2018). Similarly, electrified road initiatives are being pursued in Korea (Hoster, 2017) and the UK, with other countries expected to follow suit (Kottasova and Petroff, 2015). Concerning the concept of the smart road, smart pavement management systems have emerged as key applications within smart cities in recent times. Smart pavement refers to roadways that have been designed to support 21st- century information technology-enabled features, like radio sensors embedded in the roads to constantly monitor and report on the pavement's condition in addition to charging electric cars as they drive on these roads (Careless, n.d.). Smart pavements give city authorities real- time data on road conditions and enhance connectivity to vehicles on the road, connecting cities and communities through seamless data processing and transfer (Integrated Roadways, n.d.; Sylvester, 2019).

4. Applications of AI in Intelligent and Smart Mobility Design

As a phenomenon in transition, mobility today is being bettered with artificial intelligence (Omar, 2015). With the large amounts of data associated with artificial intelligence, from geospatial data to weather data, to social media data to user traveling data, the possibilities for better and personalized mobility solutions powered by artificial intelligence are endless. AI presents designers and developers with the ability to integrate a variety of capabilities into real-world user-facing systems (Alsamhi et al., 2020), with features such as pattern recognition accuracy opening even bigger possibilities for speech recognition, translation, and objection recognition (Amershi et al., 2019). The automotive industry has been applying AI-like functions for various mobility-related services like predictive maintenance (Cornet et al., 2017). But the anticipated disruption AI can bring to the automotive industry to improve smart and intelligent is yet to be fully embraced (Cornet et al., 2017; Dai et al., 2019) with emerging possibilities for improved user experience backed by AI driven systems (Wallach et al., 2020). This section will share highlights on how AI is being deployed in intelligent transportation systems and smart mobility around the world, as gathered from the literature.

Presently, AI and machine learning have been applied in smart and intelligent mobility solutions, to solve various challenges transportation brings to cities (Li et al., 2018). For instance, Uber uses machine learning to give riders a personalized user experience in areas such as route optimization, cutback in the expected time of arrival, fraud detection, and risk estimation (Sharma, 2021; Tyagi, 2020).

Ride-hailing platforms these days feature AI conversational agents, for customer service. Grab also uses passenger AI, driver AI, traffic AI, and location AI to better understand its users and deliver a better user experience for both commuters and drivers (Grab, n.d.) Waymo's robo-taxi also uses AI to deliver smart and user-centered mobility services (Wilmot, 2020). In the area of goods transport, several robot prototypes that deliver necessities to homes are being used in cities around the world

(Paiva et al., 2021), with the shift from process automation to smarter automation being the latest direction for logistics movement (Chmielewski et al., 2021; Karabegović et al., 2015).

Another key area where artificial intelligence can help improve mobility is for the visually impaired. Brazil's CittaMobi for instance uses AI and IoT to give visually impaired people personalized and smart mobility assistance, with features such as real-time vehicle scheduling, best route planning, and other customizable services to improve the quality of life for that demographic, who are mostly unable to use traditional mobility solutions with ease, and often require human guidance (Sobnath et al., 2020). Rapp et al. (2017) conducted a study to make cities accessible and mobility friendly for people with cognitive disabilities, particularly support for people with Alzheimer's disease of spatial agnosia.

Roulland et al., (2014) proposed a new approach for public transport simulation based on machine learning algorithms to model user choices and demand for public transport using transport fare collection data. Though AI has various applications and use-cases in mobility, this report identified the key areas for it's application as smart city management, predictive maintenance, crisis management, insuretech, autonomous vehicles, driver and passenger monitoring. Traffic management and personalized mobility solutions (*see Figure 8*).

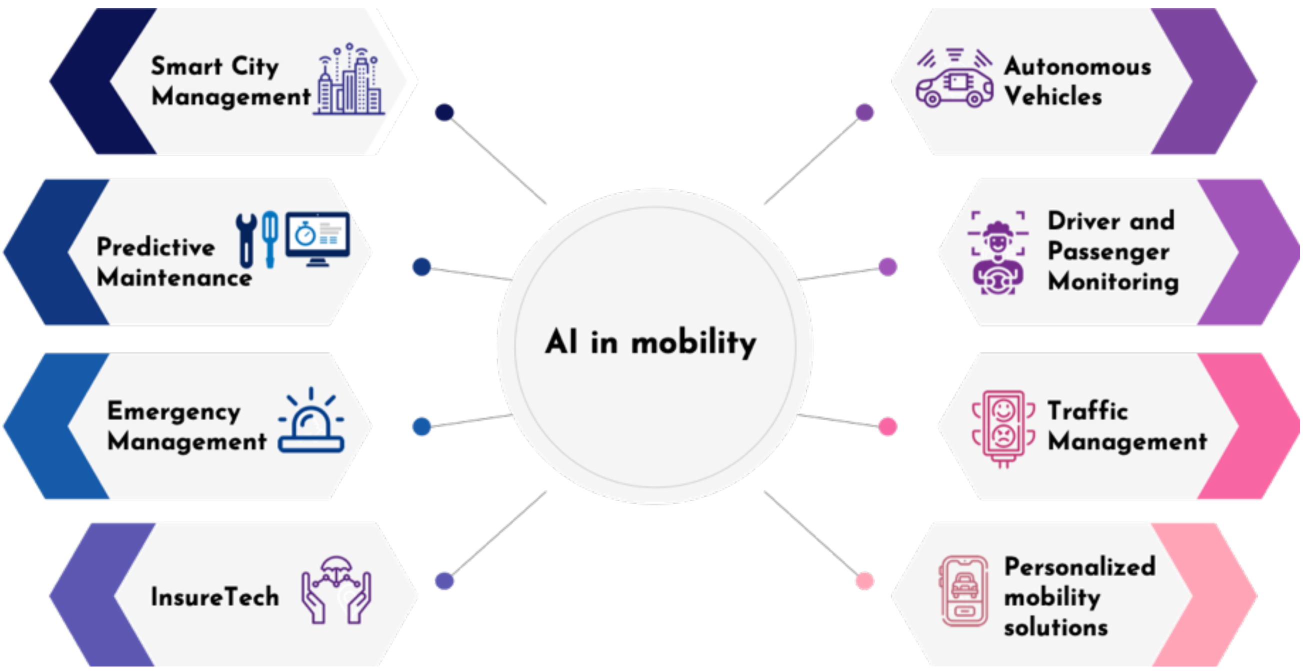

Figure 9: Some applications of AI in Smart mobility

4.1 Smart City Management

Cities are getting smarter today thanks to AI and other modern technologies (Impedovo and Pirlo, 2020). AI is being deployed in various use-cases to make cities more livable, sustainable, and progressive. A smart city can be described as an urban space that aims at improving the lives of its citizens through a combination of intelligent and smart solutions in various use-cases (Trivedi et al., 2017). An overview of some of these use cases, concerning smart mobility, both from real-life scenarios and conceptual (from research projects and studies) are highlighted in this section. In cities like New York, London, Paris, Beijing, Berlin, and Seoul, various smart mobility initiatives are currently in use, as part of a broader sustainable smart city agenda (Asiag, 2021).

In China, over 300 smart city projects are underway, with strong participation from industry and government, while India is also reported to have allocated a large chunk of development budgets to the building of over 100 cities (Toh et al., 2020). In Europe, the smart city phenomenon is prominent, with many cities implementing initiatives like care-free zones, pedestrianized streets, and no parking spaces near new developments (BusinessMaaS, 2017) aimed at promoting more environmentally friendly transport means, livable spaces, and sustainability; especially in the Nordic countries, which are considered the most digitized within the region (Borges et al., 2017). Some specific use cases of AI-driven smart city solutions are covered in Table 3. Even more interesting solutions for managing smart cities are being researched. For instance, Zhang et al.,(2016) proposed a deep learning algorithm called ST-ResNet, to forecast crowd inflow and outflow in cities. A similar traffic forecast model was proposed in a study by Zhao et al., (2017), using deep learning technologies to aid in crowd and traffic management in urban areas. Impedovo et al., (2019) also proposed an urban vehicular traffic prediction model using deep learning algorithms. Bus traffic flow prediction algorithms for smart city management has also been proposed in a study by Liu et al., (2019).

4.2 Predictive Maintenance

One of the widely known uses-cases for AI in mobility settings has been predictive maintenance of vehicles. Vehicle manufacturers today use several forms of AI to improve vehicle equipment longevity through predictive maintenance, condition-based maintenance (Ran et al., 2019), preventive maintenance (Werbińska-Wojciechowska, 2019), reactive maintenance, operation and maintenance, and fault diagnosis (Lei et al., 2020). Applied algorithms use predictive diagnostics to analyze and recognize patters within delivered data and forecast failure probabilities, allowing Original Equipment Manufacturers (OEM's) to schedule servicing in advance to improve customer experiences (Nowakowski, n.d.)

Predictive maintenance presents OEM's and vehicle owners with key insights on vehicle performance and improve maintenance time (Hessler, 2020). The potential for cost saving for both vehicle owners and OEM's is a key benefit from AI-backed predictive maintenance and remote diagnostics. The World Economic Forum projects that remote diagnostics enabled by telematics will add $60 billion worth of profits to OEM's suppliers and telematics service providers (World Economic Forum, 2016). McKinsey estimates that by 2025 predictive maintenance will save OEM's up to $627 billion annually (McKinsey Global Institute, 2015).

4.3 Crisis Management and InsureTech

An overview of applications of crisis management and emergency services using AI within the smart city context is looked at in this section. InsureTech involves the use of information technology to deliver specific solutions within the insurance sector (Stoeckli et al., 2018). In the insurance industry, AI and big data is driving a revolution, giving players within the sector efficient use-cases from the intersection of insurance and technology (Wang, 2021). Automation of insurance processes have been in existence and in use by insurance companies, in the areas such as conversational agents, customer onboarding, claims management and risk assessment (TechBullion, 2021). In the area of AI and big data, the insurance sector is relatively in the early stages, but with enormous potential to revolutionize the sector in many areas, including mobility (OECD, 2020).

In the near future, AI will play a major role in personalizing insurance for end users and vehicle companies, shifting the regular operations of "detect and repair" to "predict and prevent", using insights and data collected through sensors on and within vehicles (Balasubramanian et al., 2021). Other use cases of AI in InsureTech like AI-based computer vision system for examining and appraising damaged vehicles to facilitate shortened processing times, fraud detection, accident assessment and prevention are being used by leading insurance companies like Tokio Marine, Sompo Aviva, AXA, Zurich Insurance, GEICO, among many others (Tractable, 2021; Zarifis et al., 2019). AI use cases for crisis and safety management is reviewed in section 3.4.3. A similar application of AI in mobility crisis feature a smartphone-based application designed to help commuters get access to emergency services during a commute, and also provide warnings and alerts on road conditions to prevent accidents (K V et al., 2020). Such features often come with vehicle navigation systems, mobile-phone based navigation systems, and weather updates. Incorporating these into bundled services will likely give commuters more personalized experiences particularly in providing early and timely disaster warnings and access to emergency services.

4.4 Autonomous Vehicles

Predicted to be a major player in sustainable mobility solutions in the coming decade, autonomous vehicles (AV's) use AI in several ways to optimize mobility while giving drivers and passengers a personalized user experience. So far, AV's rely on AI primarily for localization and mapping, decision making and perception, and context-aware prediction systems (Ma et al., 2020). AV's use several AI techniques, including artificial neural networks, machine learning, deep neural network, recurrent neural network, and convolution neural networks in some cases (Kumer et al., 2021). Advanced Driver Assistance Systems (ADASs) are some of the AI-based applications used in autonomous vehicles to ensure safety (Nascimento et al., 2020; Benalla et al., 2020; Tenison et al., 2019; Taie et al., 2016) for driver and other commuters (Shadrin et al., 2017).

4.5 Driver and Passenger Monitoring

Various forms of driver and passenger monitoring is made possible through AI technologies (Sambana and Ramesh, 2020) in gauging driving cognition (Lin et al., 2009) as well as in other use cases. A wireless AI system capable of identifying authorized drivers based on radio biometric information, and able to monitor a driver's current state, the passenger count, and detect incidents of children left in the car has been proposed in a study by Xu et al., (2020). A similar driver monitoring system was proposed by Vaca-Recalde et al., (2020), based on image processing and convolutional neural networks, aimed at analyzing drivers' distraction and drowsiness while on the road. The datasets involved in this project were trained using the aforementioned algorithm, using facial features, blinking rate, and head positioning to make accurate predictions on the state of the driver (Vaca-Recalde et al., 2020). Another study proffered a driver drowsiness monitoring system to ensure safe driving (Vasudevan et al., 2017), using vehicle telemetry data in a driver-in-loop simulation. A driver alertness monitoring application based on computer vision is also proposed by González-Ortega et al., (2012), through eye state detection. Another for detecting driver mirror-checking behaviors and driver maneuvering is proposed by Li and Busso, (2016). As many possibilities for personalizing user experiences in automobiles and getting cars more connected to users arise, AI will feature prominently in new mobility solutions. Swedish auto technology services provider WirelessCar plays a pioneering role in supporting automakers like Volvo, Jaguar, Land rover and many others with connected vehicle technologies including driver behavior monitoring (WirelessCar, 2021).

Another interesting AI use-case gaining traction these days is in the area of Emotion AI. For mobility use-cases, the possibility of deploying emotion AI into semi and fully autonomous vehicles is being researched, aimed at gathering relevant insights on drivers and passengers based on their facial expressions and emotion indicators to aid decision making for the vehicles (X. Liu et al., 2020; Wachter, 2019). An emotion tracking technology was launched by Affectiva in the US in 2018, aimed at giving a better understanding of what happens inside a vehicle (Johnson, 2018). Affectiva's deep-learning-based technology uses in- vehicle cameras to measure driver and cabin occupant emotions and cognitive states like drowsiness, distraction, object and child seat detection in real-time, to aid OEMs and mobility service providers in providing optimized services and safety (Affectiva, n.d.).

4.6 Personalized Mobility Solutions

Due to its ability to process large volumes of data, AI offers service designers several possibilities for user-centered mobility solutions. MaaS has so far been designed to deliver personalized multi-modal mobility solutions for society (Esztergár-Kiss et al., 2020), in various forms, including ride, bike, and scooter sharing, ride sharing, bus, tram, and train booking services among many others. Beyond providing ticketing and booking options for commuters, the creation of personalized mobility solutions within any of the AI use-cases will help advance the MaaS cause further, providing more access to demographics who may not be able to access mobility solutions in the current state, like older residents and people living with varying forms of disabilities. Such AI-backed mobility solutions will also give MaaS operators more data sources to fuel more personalized transport solutions for users.

Some of these personalized mobility solutions were uncovered in the literature search, some of which have been highlighted in the ensuing paragraphs. It is interesting to note however that more possibilities for AI-backed mobility are being studied and churned out, in grey literature and traditional scientific scholarly works. The future of service-dominant logic within mobility looks even brought with these possibilities.

A gamified sustainable mobility habit promoter was proposed in a study by Khoshkangini et al., (2017). Powered by machine learning, the game can automatically generate and recommend personalized mobility challenges based on user preferences, within an urban mobility setting, to encourage sustainable mobility habits (Khoshkangini et al., 2017). Another interesting application of AI to promote sustainable mobility is a tracking system proposed in a study by Ferreira et al., (2016), which works by giving users updates on their carbon footprints based on their various mobility choices. A similar personalized sustainable mobility behavior modification application was proposed in the work of Anagnostopoulou et al., (2020), by leveraging pervasive mobile sensing to uncover users' mobility patterns and transportation choices and using the collected data to generate personalized interventions to remind users to adopt more sustainable transportation habits.

In designing mobility options for people with health conditions and disabilities, Rapp et al., (2017) conducted a study to make cities accessible and mobility friendly for people with cognitive disabilities, particularly support for people with Alzheimer's disease of spatial agnosia. A bicycle-sharing version of the car-sharing mobility type has been proposed in a study by Yang and Lee, (2019), aimed at introducing an intelligent mobility service that enables millennials to be able to share bicycles as part of a larger MaaS service. Though the service is yet to be piloted at the time of this study it offers insights into the possibilities of user-centered smart mobility design for a rapidly evolving mobility landscape. A smartphone application for carpooling with user location tracking and traffic anomaly detection features powered sensing algorithms was proposed by Binu and Viswaraj, 2016)

An overview of some interesting AI application in designing personalized mobility solutions are featured in Table 3

Use Case	Description	Application Area	Reference
Personalized mobility for visually impaire	Provides users with voice prompts on bus departure times, proximity to bus stations, itinerary updates, and more.	CittaMobi Accessibility – Brazil	(Mourato et al., 2015)
Personalized mobility for people with low vision	Developed in the UK mainly for people suffering from low vision, consists of a bus tracking system, among other functionalities, to locate the nearest bus stop, read aloud the bus stop name every time the bus stops, and indicate bus arrival schedule.	Mobi+ project – Clermont-Ferrand, FRANCE	Zhou et al., (2012)
AI-backed transportation crime prediction	Prediction of high crime risk transportation areas in urban environments using transportation and GPS data.	Experimental	Kouziokas, (2017)
Transport mode recommendation	A Smartphone-based System for Comfortable Public Transport Recommendation.	ComfRide – Experimental	V erma et al., (2018)

Table 3: Some AI-driven personalized mobility use-cases in research and real-life

Table 3 continued

Use Case	Description	Application Area	Reference
Personalized Interactive Urban Maps for Autism (PIUMA) Project	Provides personalized interactive maps for People with Autism Spectrum Disorder.	Experimental	Cena et al., (2017)
A multimodal route recommender system using commuter's smartphones	A service aimed at predicting the Spatio-temporal bus demands in real- time from mobility data generated by smart-card-based trip information of public bus commuters in Singapore city.	BuStop – Singapore City (Experimental)	Mandal et al., (2021)
Ubiquitous Intermodal	Service aimed at providing route assistance to commuters and guide them through chosen journeys.	Experimental	Samsel, (2019)
Personalized multi-modal route recom	Personalized route recommender service using algorithms and live traffic data.	RouteMe	Herzog et al., (2017)
Smart Wheelchair	Peronsliazed smart wheek chair for disabled commuters, with sensors analyzing data to deliver indoor environment map, tracking the relative angular position of the wheelchair, distance to obstacles and physical distance traveled.	Experimental	Gomez Torres et al., (2019)
Personalized route recommendation	A smartphone software application processing large amounts of historical and live mobility-related data to give users information and updates on potential threats and accidents, best practices reduce carbon emissions, etc.	Experimental	Papageorgiou and Maimaris, (2017)
User-preference-based mobility matching	Matching users to mobility options based on pre-defined preferences.	Experimental	Basile et al., (2020)
eMaaS	An approach for collecting, aggregating, processing and provisioning of data originating from sources to improve electric mobility in smart cities.	Experimental	Bokolo et al
Personalized ride sharing based on rider characteristics and user threshold time	A Machine Learning Recommender Model for Ride Sharing Based on Rider Characteristics and User Threshold Time.		Yatnalkar, (2019)
Ride-hailing service prediction	Predicting ride-hailing trends and probabilities using ConvLSTM networks.	Didi Chuxing, China (Experimental)	(Tan et al., 2022)
Passenger, driver, traffic AI and location AI	AI for tracking passenger and driver in commute, traffic situations, and location.	Grab	(Grab, n.d.)

Table 3 continued

Use Case	Description	Application Area	Reference
Emotion AI for passenger and in-vehicle management	Digital service able to read drive and passenger emotions using embedded sensors in the vehicles.	Affectiva – US	(Affectiva, n.d.; X. Liu et al., 2020)

(Cena et al., 2017) proposed a smartphone-based application, ComfRide, aimed at giving commuters comfortable route options based on personal preferences and real-time environmental data, by relying on crowdsourced GPS and inertial sensor data backed by artificial intelligence. With commuter comfort as it's the main goal, Comfride makes suggestions for single or multiple breakpoints during a journey, with the study reporting a 30% average better comfort level than Google navigation based on recommended routes after its two-year field trial of over 28 different bus routes (Verma et al., 2018).

5. Towards an AI-driven, service-dominant smart mobility design

In the previous chapters, the report described how AI has been applied in different mobility contents around the world. In this current chapter, the report will look at how mobility can be approached from a service perspective as against from a technological perspective as discussed in the earlier chapters. Approaching mobility from a service perspective is important because it provides a deeper understanding of user-mobility needs and how to leverage service innovation to think about new and personalized mobility services, and how to create and capture value in this area. A framework that speaks to service from a business perspective is the service-dominant logic (S-D Logic), a framework that has been a significant highlight of service innovations in recent times, powering competition and constant innovation in service delivery (Lusch et al., 2007). This is evident by the design of various digital services in areas like e-commerce, logistics, transport, dating, entertainment, and so on.

For a constantly evolving service like smart mobility, S-D logic has fueled the shift to several multi-modal mobility services in urban areas around the world, leveraging the latest technologies to deliver bundled mobility options for users (Turetken et al., 2019). For instance, logistics providers are offering integrated, end-to-end logistics solutions involving multiple service providers and actors, instead of simply offering vehicles for transportation (Turetken et al., 2019). The same can be said about multi-modal mobility services, where various actors collaborate to deliver bundled mobility options for commuters, often with a single payment for all the services (BusinessMaaS, 2017; Esztergár-Kiss et al., 2020; Ho et al., 2018).

Despite these service-focused innovations in mobility however, private cars remain the dominant form of transportation in many developed countries (Schulz et al., 2020), partly due to identified broader MaaS adoption barriers like "anti-new mobility", issues with car- sharing, (Alonso-González et al., 2020), and issues of access for people with disabilities (Zhou et al., 2012) and the aged (Payyanadan and Lee, 2018). To solve the inclusivity challenge, participatory design (co-creation with various users groups, employees, customers, etc) (Auernhammer, 2020) will play a significant role, to ensure smart mobility services improve user experience and covers many users to a large extent, driven by AI (Wallach et al., 2020). In previous sections, various forms of AI-driven mobility solutions which have been conceptualized and developed, focusing on leveraging various data sources to deliver relevant, real-time multimodal mobility solutions was highlighted.

ICT today enables real-time information on traveling schedules from one point to another, intending to reduce uncertainty and increase the efficiency of a trip for travelers (Väänänen et al., 2016). As Maas continues to evolve, presenting innovations that could potentially transform the transport ecosystem for both passenger and goods transportation (Sochor et al., 2018), designers have the chance to innovate and come up with new models to make AI a key component of mobility service design. So far, demand models within the state of the art mobility solutions distinguish the main modes of mobility to include walking, cycling, public transport, and car (car driver and car passenger) (Friedrich et al., 2018). Design choices could focus on specific AI-driven services for these forms of mobility use cases. AI is expected to transform and impact transportation in many ways, and it is therefore important for public transport stakeholders and service designers to proactively consider the opportunities AI presents to help to build the mobility of the future (UITP, 2021). The opportunity for key players within the mobility ecosystem to optimize operations, simplify journey planning and customize travel experiences for citizens is huge. leveraging artificial intelligence and IoT, for MaaS - a user-centric, integrated mobility service driven by data, with keen focus on satisfying user expectations and providing customized journeys for commuters (Yinying and Csaba, 2018).

Designing AI-driven digital services will likely mean the task of solving personalized mobility challenges will largely be dependent on using the right design principles to aptly train algorithms to address complex problems, and iterate where necessary (Verganti et al., 2020). AI is revolutionizing various industries including mobility continually, and most developed economies are focusing on leveraging the advantages of data-driven predictions for improving smart communities (Østergaard et al., 2019).

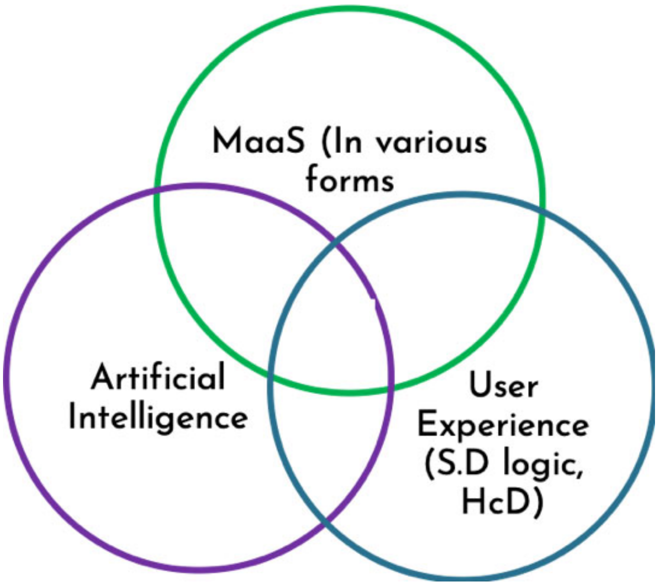

Figure 10: The intersection between AI, MaaS and User Experience

The intersection between service-focused design (human-centered service design, S-D logic and user experience) artificial intelligence, and mobility opens up a world of opportunities to provide a truly user-centered and intelligent mobility solution (Dai et al., 2019) for various modes of transport. These technologies can supply real-time useful insights on user behavior and provide even more opportunities to have a human-centered mobility solution design, backed by machine learning (Gutierrez, 2016). AI-based smart mobility is expected to improve the speed and convenience of traveling, and in-turn contribute positively to the development of smart tourism (Liberato et al., 2018). For MaaS service designers, AI presents an even better opportunity to give users and other relevant ecosystem players truly personalized mobility and travel experience through actionable data insights, participatory design and a better understanding of each user group and what their mobility needs are or could be (Schroener et al., 2020). As the binder that holds MaaS together, AI can give real- time and historical insights that city authorities and platform providers can use to personalize the journey experiences for every customer segment. For service designers, the possibility of designing either a simple travel assistant with route incident updates for commuters as a complementary service for existing ride-sharing applications, or a simple, gamified carbon emission tracker application to give commuters a real-time update on the effects of their travel activities on the environment is something worth looking at.

Even for electric vehicles, embedded sensors and in-cabin tracking services driven-by AI are projected to become the main agenda for the European Automotive industry in the quest for carbon reduction (Tschiesner et al., n.d.). The golden pot between Maas, AI and UX intersection is big enough for various mobility innovations, and will only get bigger as mobility patterns evolve worldwide. One of the obvious questions designers will have to grapple with is how to marry the plethora of mobility capabilities, evidenced by the keen competition within multi-modal smart mobility solutions, the wealth of possibilities AI can present for personalization and competitive edge, and human-centered, responsible design.

The answer to this question might be in the form of novel business models or the improvement of already existing ones, focusing on better service delivery as against goods delivery. Another possible answer could be that the sweet spot between the intersection of Maas, AI and service design might be the differentiator and the game changer for platform and solution providers. Already, ride sharing service providers are leveraging AI to deliver personalized experiences, and OEM's are partnering with ride sharing service providers to create and capture value. It will be interesting to see how various actors within the smart mobility ecosystem co-create and collaborate to ensure consistent value capture. The future of smart mobility is increasingly moving from just getting commuters from point A to B, to more personalization, data driven recommendations, and other complimentary services which will in more ways benefit the user beyond just commuting.

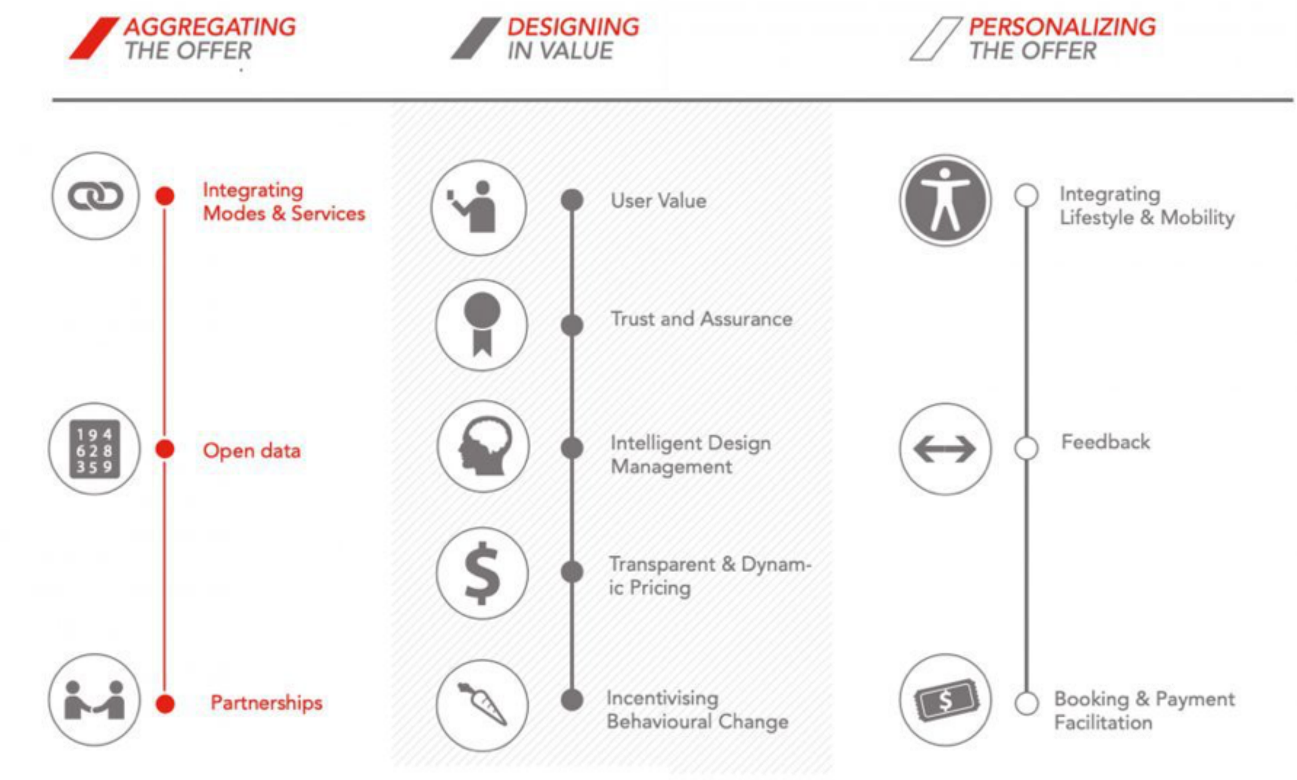

Figure 11: Human-centered smart MaaS model adapted from Snook (2019)

An interesting human-centered smart MaaS model used for a MaaS project by Snook, (2019) in *Figure 11* presents a framework for designing with a data-driven user-centered approach, with three main pillars: aggregating the offer, designing in value and personalizing the offer.

Aggregating the offer covers integrating various mobility modes and services, from scooters to trains, giving users more options to choose from. Integrating different modes will however rely on data, and open data for that matter. Open data sharing will play an important role in shaping the design and integration of various mobility services. This can be achieved through partnerships and collaborations from every player within the ecosystem, ticketing service providers, transport administrations, logistics service providers, platforms, traffic information providers, and much more, through API's and an openness approach to standards and systems to give innovators enough tools to deliver connected service offerings to users.

In designing in value, designers must look to fully understand various user journeys, what their mobility itches are and how to literally scratch them, to gain their trust and assurance using a user-first approach. Intelligent design focuses on the modelling and automating of cognitive processes and knowledge representations which can applied to solve design problems within service systems (Tung and Yuan, 2007). Service systems comprise a large network of interactions between users, producers and other actors who co-create value (Tung and Yuan, 2007). Intelligent design within smart mobility service systems gives designers the possibility of using algorithms and the abundance of available data to identify customer issues before they occur, ensuring the users get personalized and context-relevant solutions (BBVA, 2019; Behe and Meyer, 2018). Managing the intelligent design of a possible mobility solution will involve a combination of anticipatory and participatory design principles to deliver real value to the users. With intelligent design giving a clear picture of what the user needs now and, in the future, designers may incorporate incentivization of behavioral change into the design of smart mobility, as part of personalization. The Snook model is an interesting example of how understanding various users plays an important role in solving their mobility challenges, leveraging AI and S-D logic.

6. Challenges with Designing AI-drive smart mobility services

Designing user-centered, AI-driven digital services is an exciting prospect for service designers and users alike. Data driven services will play a huge role in delivering the best user experiences. Designing with AI however presents new challenges, especially in this era of shared data and services. AI and machine learning models has significant benefits, but the possibility of enforcing biases among other challenges like privacy, security, responsibility and control make these technologies potentially harmful to users (Leong, 2019). For designing smart mobility, challenges like data security, privacy, control, ethics and sustainability were identified within this research scope as some of the challenges mobility service designers are likely to grapple with when looking to design AI-driven mobility services. The ensuing section overviews these challenges in brief detail.

6.1 Data Security

Designing data-driven mobility solutions means a wealth of data is likely to be used, whether it's traffic information, passenger preference data, travel itineraries, driver information, road information, vehicle condition information, and much more. With autonomous vehicles for instance, the possibility of security bug exploitation by hackers is a real threat, with possibilities like remotely applying brakes, shutting down the vehicle and steering control (Cui et al., 2018). Other security threats within smart mobility and smart city contexts can be based on observable data (data acquired by eavesdropping on wireless and wired communication), repurposed data (data being collected for specific purpose but is used for another. These forms of attacks could be from service providers (who profile users or from location-based services), published data (includes statistical data from government platforms as well as individuals) (Eckhoff and Wagner, 2018). Sharing and analyzing these huge volumes of data securely is a challenge service designer will have to consider, particularly with the possibility of leveraging data from mobile phones, social media, health, etc. to personalize travel experiences for commuters. In order to be effective and reliable, AI systems need to de designed to be resilient, secure and safe, for users and platform providers (PWC, n.d.).

6. 2 Privacy

Privacy challenges with designing AI-driven services have gained significant attention in recent times. With intelligent mobility, the privacy threats are equally worrying. Analyzing the amounts of mobility data presents possibilities for nefarious purposes, particularly for location stamps which are usually specific to individual users (Matheson, 2018). Kitchin (2016) identified some possible privacy challenges with smart city and mobility technologies to include identity privacy, bodily privacy, territorial privacy, locational and movement privacy, communications privacy and transactions privacy. Eckhoff and Wagner (2018) classified some of the privacy forms to include privacy of location, privacy of state of body and mind, privacy of social life, and privacy of behavior and action. Possible breaches of all these privacy forms will pose a significant challenge to mobility service designers. Although many smart applications these days try as much to adhere to data protection regulations, the trade-off between privacy and utility is a cause for concern, as privacy-enhancing technologies are often not adopted for fear that they will degrade the data quality to a point where the service quality will be affected (Eckhoff and Wagner, 2018).

Magazanik (2020) identified specific privacy risks with smart mobility, as recommended by the Israeli Privacy Protection Authority Guide. The risks cover shared travel, vehicle sharing, shared autonomous vehicles, smart taxi services, smart transportation stations, real- time transpiration information, multi-channel smart travel ticketing systems, smart parking, shared parking among other mobility use-cases, rating these risks between potential high and low severities (Magazanik, 2020). Given a few randomly selected points in mobility datasets, sensitive information of individuals can easily be identified, even though the data is often anonymized. The possibility is even surer with merged mobility datasets, as anonymized data from one dataset could be matched with deanonymized data for another to unmask the anonymized data. (Matheson, 2018). A recent study by MIT researchers found out that the growing practice of compiling massive , anonymized datasets of the movement patterns of people is on one hand a good opportunity to provide deep insights into human behavior and on the other could put people's private data at risk (Matheson, 2018).

6.3 Trust and Collaboration

Trust and collaboration can be a significant challenge in the design of smart mobility services. Particularly in the case of AV's and self-driving cars, the need to develop systems which engender trust from the users as well as authorities is key. Further, because data will

likely be accessed from various sources in order to personalize offerings, the ability to easily gain access to these data in real time might be a challenge, in cases where every source will seek to protect their data. Getting users to trust the platforms powering the digital services within smart city contexts will be key to getting the needed participation and collaboration from the users. General anxiety and aversion for AI, partly due to recent AI failures and the portrayal of dangers with possible rogue AI has made trusting such systems a challenge for designers. The aversion generally covers the unknown capabilities of the AI and how dangerous systems can become as they get more intelligent and might spiral out of control, and whether AI could replace humans in the near dystopian future (Schmelzer, 2019). Other factors that influence trust in AI include user education, past experiences, biases, perceptions towards automation and intelligent systems, as well as the AI's properties (Schmelzer, 2019). Yes, AI can give designers more room to innovate and personalize mobility services, but do people trust AI enough to completely cede their mobility responsibility to a software or system? Big question. Possible ways to ensure trust and collaboration in designing AI are discussed in the mitigation section.

6.4 Accountability, Control and Bias

Designing mobility services with AI means the intended services will most likely have less human intervention in operationalization. The likelihood of false positives (when the algorithm wrongly predicts a positive outcome) and false negatives (when the algorithm wrongly predicts a negative outcome) (Google, n.d.) mean that ensuring accountability and preventing biases are not represented in the AI model is crucial for the design of smart mobility service. Designers have to provide design answers to questions like 'who is accountable for failures and errors of the algorithm?', 'what controls need to be put in place to track the performance of the algorithm and pinpoint problems?' and 'how explainable are the AI's decision systems to the users' ((PWC, n.d.). When it comes to bias, AI's propensity to enforce stereotypes is real (Siau and Wang, 2020). Some of the biases designers must consider include dataset biases (where the dataset used to train the AI does not cover all possible users expansively), association biases (when the data used to train the AI model reinforces and multiplies cultural biases), automation biases (where automated decisions and predictive systems override social and cultural considerations), interaction biases (where the AI is tampered with to produce biased results), and confirmation bias (where the AI interprets information in a way that confirms misconceptions) (Chou et al., n.d.)

6.5 Sustainability

A challenge with designing intelligent mobility solutions is the issue of how sustainable these technologies can be for companies, users and the long-term effect on the environment. The need to significantly reduce emissions within the transport sector is a challenge most governments are faced with today, and many initiatives are underway to address greenhouse house gas reduction (European Commission, 2020). The European Union's goal of a -55% greenhouse gas reduction target by 2030 and a climate neutrality by 2050 (European Commission, 2020) is one of such initiatives. In designing smart mobility services, sustainability and a green mobility agenda must be considered at the very stage of ideation, to aptly manage the design vision with the possibility of affecting the environment negatively and how to mitigate these effects. If the smart mobility that designers envisage is poised to negatively affect the environment in the use of the digital services, the fine line between innovation and sustainability becomes a cause for concern. Ensuring that the impacts of the designed smart transport activities do not threaten the long-term ecological sustainability (Jeekel, 2017). In the same sphere, planning for obsolescence is key, in the design of smart mobility systems. With newer models of smart vehicles and AV's being developed, it remains to be seen how older, no-longer functional and in vogue models of vehicles will be disposed off and whether older models could be upgraded to newer ones to help curb the potential environmental challenge with disposing older models.

7. Mitigations

A number of mitigations for the identified challenges were examined in the course of the research, within both academia and industry. Regulation and policy play a key role in ensuring some of these identified challenges are prominent on the agenda of the relevant mobility ecosystem players, and it remains to be seen how designers will navigate these challenges in the quest for smart, data-drive mobility solutions.

7.1 Data Security and Privacy

Kitchin (2016) proposed a two thronged market and technology approach to dealing with privacy challenges within smart city contexts. The first is a contention that the market will likely adapt to self-regulate privacy and data security in response to societal demand, for fear of losing market share to companies that make privacy protection a priority. The second is for industry players to see consumer privacy and data security as a completive advantage, developing privacy and security protocols that will make them more attractive to customers (Kitchin, 2016).

At the core of this proposal is that contention that privacy will likely be the differentiator between service providers which will then force service providers to strengthen their platforms in order to stay ahead and continue to capture value. While this may not be adequate to aptly allay the privacy concerns of users and authorities alike, it is an interesting way of thinking about responsibility in using user data. Within the reviewed literature, some state-of-the-art technology solutions for mitigating privacy challenges include data masking (Provazza, 2017), strong end-to-end encryption, strong passwords and access controls, firewalls, latest malware checkers, security certificates, audit trails; isolating trusted resources from non-trusted; disabling unnecessary functionality; ensuring that there are no weak links between components; isolating components where possible from a network; implementing fail safe and manual overrides on all systems; ensuring full backup of data and recovery mechanisms; and automatically installing security patch updates on all components, including firmware, software, communications, and interfaces (Kitchin, 2016). Another is the use of privacy enhancing technologies in the design of smart mobility systems. These could include homomorphic encryption, secure multi-party computation, pseudonymization, communication anonymizers, synthetic data generation and federated learning (Dilmegani, 2020).

A design solution to privacy was proposed by Cavoukian (2009), who introduced the Privacy by Design principles as a possible solution to the privacy challenges inherent within information and communication technologies, with the view "that the future of privacy cannot be assured solely by compliance with regulatory frameworks; rather, privacy assurance must ideally become an organization’s default mode of operation”. These principles aim to make privacy a part of the design process rather than an afterthought. The principles include being proactive not reactive (preventive not remedial), privacy as the default setting, embedding privacy into design, full functionality, end-to-end security, full lifecycle protection, visibility and transparency, keeping it open, respect for user privacy, and keeping the design user-centric. These principles have been cited by many researchers and will definitely come in handy for any smart mobility design. In mitigating privacy challenges, some of these solutions will extend to ensuring the security and integrity of the data and the platform as whole. Similarly, to mitigate security challenges with smart systems, proposed a complementary “security by design” method, with the view to making security approach to design a proactive and preventive rather than reactive and remedial. Other direct technological security risk mitigation solutions include the use of foggy dummies, an idea that involves generating smart dummies to protect the privacy and data of the users (Abi Sen et al., 2018).

7.2 Trust and Collaboration

For smart city systems and projects to last and be successful, engendering trust from citizens is a key (Glasco, 2017). More information about the smart systems powering the various innovations including mobility must be made known to the users, together with the risks and security mitigations put in place to avert attacks. Collaboration and open data sharing will give stakeholders greater opportunities for personalization (Näslund and Strömberg, 2017). Because a number of smart city solution providers which covers smart mobility equate trust with cyber security (Chan, n.d.), it is important to focus on delivering services that give city dwellers and users the confidence of the security of the platforms. By being tangible, transparent and reliable, AI systems contribute to developing cognitive trust among citizens (Glikson and Woolley, 2020).

Other ways of building trust in AI systems include representation (making the AI systems more representative of humans, to make it easier for the systems to be trusted), transparency and explainability (giving justifications and explanations for why the AI does what it does), tribality (making the AI systems available for others to try and test the systems before adoption), usability and reliability (the competence of the AI to complete tasks consistently and reliably), collaboration and communication (seamless collaboration to ensure AI performs tasks independently) (Siau and Wang, 2018).

7.3 Accountability, Control and Bias

Addressing accountability control and bias in AI systems will go a long way to ease some of possible risks in the identified challenges. Governance will play a key role in ensuring accountability in AI systems, and must be as iterative as AI processes are (Ada Lovelace Institute, 2021). Ada Lovelace Institute (2021) identifies some algorithmic accountability policies which are aimed towards ensuring that algorithms are answerable for their impacts. The report details key learnings to aid governments in ensuring algorithms are more accountable and responsible. A proposed mitigation for control in AI development is the incorporation of human-in-the- loop into smart systems. Human-in-the-loop (HITL) describes a process where a human intervenes in both the training and testing stages of the algorithm design, when a machine or computer system is unable to solve a problem, thus creating a continuous feedback loop to make the algorithm better (Mazzolin, 2021). HITL ensures that the AI system is more transparent, incorporates human judgement in more effective ways, makes the algorithms better and shifts the pressure away from building "perfect" algorithms, ultimately giving relevant control over the system to avert any errors or nefarious possibilities.

For mitigating biases, a number of suggestions have been proposed by researchers and industry alike. Microsoft (n.d.) for instance proposed the inclusive design methodology, aimed at drawing on the full range of human diversity and learning from people with a range of perspectives in the design of smart services. By leveraging participatory design principles (Pobiner and Murphy, 2018), a broader view of all users and their needs will help to reduce possibilities of bias and harmful discriminatory effects (Microsoft, n.d.). Google (n.d)'s People + AI guidebook details several principles for designing human-centered AI systems, including designing to mitigate bias and discrimination. Other proposed mitigations for algorithmic bias include regular audits on to check against biases and widespread algorithmic literacy to give users of these systems knowledge on how the system functions (Amershi et al., 2014; Lee et al., 2019)

7.4 Sustainability

Sustainable mobility has become one of the popular buzzwords these days. For designers, the responsibility to design services that deliver value to users while reducing harm on the environment is key. The European Green Deal calls for a reduction in the emission of greenhouse gasses from transport, towards a 2050 climate-neutral economy (European Commission, 2020). This broad vision gives mobility ecosystem players a clear picture of what to include in designing and delivering mobility services. The responsibility of ensuring that sustainability principles are embedded alongside wider considerations of AI safety, ethics governance falls to companies, service providers, governments and virtually every relevant player in the mobility ecosystem (PWC, n.d.). Just like privacy by design and security by design, sustainability by design is one of the ways designers can make their smart mobility innovations more responsible. By planning for obsolesce and end-of-life use- cases for instance, the life cycle of the mobility solutions, whether they are semi or fully autonomous vehicles, scooters, e-bikes, trains, trams, and so on will be managed well to deal with possible environmental waste and pollution from their continuous use.

8. Discussion and Conclusion

Will the mobility of tomorrow be more AI driven and data-reliant? Possibly. As user needs continue to change constantly, the need for design to be at pace with users is key, and could probably be the differentiator between service providers. Significant interest and investments into AI-driven mobility solutions are being looked at by vehicle manufacturers, major cities, and economies around the world. In the Nordic-Baltic region for instance, a collective project is underway to promote the use of AI to serve humans better through skills development, enhancing data access, and enhancing ethical values and standards for various industries including mobility and transport (Lee et al., 2019). New ways of looking at mobility will no doubt improve city dwelling and give city authorities around the world more opportunities to build the cities of the future. With the wealth of data available through AI , an interesting perspective will be how designers can leverage various data sources, like health data, social media, data, user- itinerary data, weather, and traffic conditions to deliver well-coordinated mobility solutions for traveling within cities and metropolitan areas.

In this report, several use-cases for AI in the MaaS context have been looked at, highlighting various experimental and real-life applications within smart mobility and ITS. A literature review of various conceptualizations of MaaS, ITS, smart mobility and AI have also been highlighted, as well as thoughts on the intersection between MaaS, AI and user experience. Towards an AI-driven multi-modal mobility service design, the report exposes several opportunities for designers to leverage AI and big data from connected devices and other digital services to serve mobility needs.

9. Future Research

Future research into mobility may be in the areas of electric and autonomous mobility, personalized travel experiences driven by data, IoT and context aware mobility, AL for sustainable mobility behavior and new business models. How OEM's and other actors within the mobility ecosystem can create, capture and deliver relevant value in the face of new developments and trends like sharing will be interesting for both future research and practice. For instance, could OEM's explore a ride sharing and pooling service that connects idle cars to mobility demand at personalize times? This could a way for both vehicle owners and users to earn some money from the times their vehicles are not in use. Other areas for future research and practice, in areas like electric and autonomous mobility, personalized travel experiences IoT and context-aware mobility, AI for sustainable mobility behavior and emerging business models within new mobility are discussed briefly in the ensuing sections. This list is however not fully exhaustive as new research areas within mobility could emerge in the future.

9.1 Electric and Autonomous Mobility

Already, electric cars are contributing to a shift towards greener mobility, and it remains to be seen how the future of mobility will be shaped by cleaner energy powering the vehicles of tomorrow. Future research may look at how fully autonomous mobility solutions can be leveraged into other transport modes, jot just personal cars. Could we perhaps have autonomous scooters and bicycles powering the mobility of tomorrow? It will be interesting to discover what research findings will be in this area in the near future and how various actors within the mobility ecosystems could leverage autonomy to deliver faster and user- centered mobility solutions.

9.2 Personalized Travel Experiences driven by data

Research into how travel experiences can be personalized for users leveraging historical and real time data will be an interesting focus for further insights. Data from mobile phones, fitness applications, social media applications, eating habits, health data and much more could give insights into possible personalization for user mobility. Further research into these possibilities will be an interesting addition to existing research in this area. A few of these researches were cited in this study, and with interest in personalized mobility considerably high, the best is obviously yet to come, for researchers and end-users alike.

9.3 IoT and Context Aware Mobility Design

Will the mobility of tomorrow be able to make timely decisions in various contexts? Further research could look at various contexts and scenarios for the application of AI to avert disasters, suggest solutions to possible situations of delay, and other use-cases which current smart mobility solutions are yet to deliver.

9.4 AI for sustainable mobility behavior

Research into how AI can be leveraged to improve sustainability practices for users will be an interesting contribution to this body of knowledge. Future research could look at how awareness of a user's carbon emissions could help shape their mobility behaviors, and perhaps investigate how various forms of multi-modal mobility solution could be carefully selected towards a greener agenda.

9.5 Emerging business models for AI-driven mobility

Another interesting area for further research could be the new business models emergent with AI-drive mobility, in line with developments with SD-logic. Already, some OEM's are partnering ride-hailing solution providers to jointly deliver better services to consumers. How value is created, delivered, captured and defended will be an interesting research focus, especially with the new possibilities of AI and smart mobility.

References

Abi Sen, A. A., Eassa, F. A., and Jambi, K. (2018). Preserving Privacy of Smart Cities Based on the Fog Computing. In R. Mehmood, B. Bhaduri, I. Katib, and I. Chlamtac (Eds.), Smart Societies, Infrastructure, Technologies and Applications (Vol. 224, pp. 185–191). Springer International Publishing. https://doi.org/10.1007/978-3-319-94180-6_18

Ada Lovelace Institute, AI Now Institute and Open Government Partnership. (2021). Algorithmic Accountability for the Public Sector. Available at: https://bit.ly/3zfCtQh

A. M. Nascimento, L. F. Vismari, C. B. S. T. Molina, P. S. Cugnasca, J. B. Camargo, J. R. d. Almeida, R. Inam, E. Fersman, M. V. Marquezini, and A. Y. Hata. (2020). A Systematic Literature Review About the Impact of Artificial Intelligence on Autonomous Vehicle Safety. IEEE Transactions on Intelligent Transportation Systems, 21(12), 4928–4946. https://doi.org/10.1109/TITS.2019.2949915

Affectiva. (n.d.). Affectiva Automotive AI: Redefining the occupant experience and improving road safety with In-Cabin Sensing. Affectiva. Retrieved July 25, 2021, from http://go.affectiva.com/auto

Agarwal, P. K., Gurjar, J., Agarwal, A. K., and Birla, R. (2015). Application of Artificial Intelligence for Development of Intelligent Transport System in Smart Cities. International Journal of Transportation Engineering and Traffic System, 1(1), 24.

Alam, M., Moroni, D., Pieri, G., Tampucci, M., Gomes, M., Fonseca, J., Ferreira, J., and Leone, G. R. (2018). Real-Time Smart Parking Systems Integration in Distributed ITS for Smart Cities. Journal of Advanced Transportation, 2018, 1–13. https://doi.org/10.1155/2018/1485652

Allström, A., Barceló, J., Ekström, J., Grumert, E., Gundlegård, D., and Rydergren, C. (2017). Traffic Management for Smart Cities. In V. Angelakis, E. Tragos, H. C. Pöhls, A. Kapovits, and A. Bassi (Eds.), Designing, Developing, and Facilitating Smart Cities: Urban Design to IoT Solutions (pp. 211–240). Springer International Publishing. https://doi.org/10.1007/978-3-319-44924-1_11

Alonso-González, M. J., Hoogendoorn-Lanser, S., van Oort, N., Cats, O., and Hoogendoorn, S. (2020). Drivers and barriers in adopting Mobility as a Service (MaaS) – A latent class cluster analysis of attitudes. Transportation Research Part A: Policy and Practice, 132, 378–401. https://doi.org/10.1016/j.tra.2019.11.022

Al-Rahamneh, A., Astrain, J. J., Villadangos, J., Klaina, H., Guembe, I. P., Lopez-Iturri, P., and Falcone, F. (2021). Enabling Customizable Services for Multimodal Smart Mobility With City-Platforms. IEEE Access, 9, 41628–41646. https://doi.org/10.1109/ACCESS.2021.3065412

Alsamhi, S. H., Ma, O., and Ansari, Mohd. S. (2020). Convergence of Machine Learning and Robotics Communication in Collaborative Assembly: Mobility, Connectivity and Future Perspectives. Journal of Intelligent and Robotic Systems, 98(3–4), 541– 566. https://doi.org/10.1007/s10846-019-01079-x

Alvear, D., Abreu, O., Cuesta, A., and Alonso, V. (2013). Decision support system for emergency management: Road tunnels. Tunnelling and Underground Space Technology, 34, 13–21. https://doi.org/10.1016/j.tust.2012.10.005

Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., and Horvitz, E.
(2019). Guidelines for Human-AI Interaction. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–13. https://doi.org/10.1145/3290605.3300233

Anagnostopoulou, E., Urbančič, J., Bothos, E., Magoutas, B., Bradesko, L., Schrammel, J., and Mentzas, G. (2020). From mobility patterns to behavioural change: Leveraging travel behaviour and personality profiles to nudge for sustainable transportation. Journal of Intelligent Information Systems, 54(1), 157–178. https://doi.org/10.1007/s10844-018-0528-1

Andersson, P., and Torstensson, J. (2017). Exploring the role of blockchain technology in Mobility as a Service: Towards a fair Combined Mobility Service [Chalmers University of Technology]. Retrieved August 2, 2021 from https://bit.ly/3k1maAZ

Asiag, J., Joseph. (2021, April 18). 8 Smart Cities Lead the Way in Advanced Intelligent Transportation Systems. Otonomo. Retrieved August 10, 2021 from https://bit.ly/37OaLin

Aswin Kumer, S. V., Kanakaraja, P., Sairam Nadipalli, L. S. P., Ramesh, N. V. K., and Kotamraju, S. K. (2021). The Categorization of Artificial Intelligence (AI) Based on the Autonomous Vehicles and Its Other Applications. In V. Goyal, M. Gupta, A. Trivedi, and M. L. Kolhe (Eds.), Proceedings of International Conference on Communication and Artificial Intelligence (pp. 411–421. Springer Singapore.

Balasubramanian, R., Libarikian, A., and McElhaney, D. (2021, March 12). Insurance 2030—The impact of AI on the future of insurance. McKinsey and Company. Retrieved August 15, 2021, from https://mck.co/3ySGGdj

Ballester, O. (2021). An Artificial Intelligence Definition and Classification Framework for Public Sector Applications. DG.O2021: The 22nd Annual International Conference on Digital Government Research, 67–75. https://doi.org/10.1145/3463677.3463709

Barriga, J. J., Sulca, J., León, J. L., Ulloa, A., Portero, D., Andrade, R., and Yoo, S. G. (2019). Smart Parking: A Literature Review from the Technological Perspective. Applied Sciences, 9(21), 4569. https://doi.org/10.3390/app9214569

Basile, S., Consonni, C., Manca, M., and Boratto, L. (2020). Matching User Preferences and Behavior for Mobility. Proceedings of the 31st ACM Conference on Hypertext and Social Media, 141–150. https://doi.org/10.1145/3372923.3404839

BBVA. (2019, March 18). Anticipating user needs with intelligent design. BBVA. https://bbva.info/3Admi7f

Behe, M., J., and Meyer, S., C. (2018, May 10). What is Intelligent Design? Discovery Institute. https://www.discovery.org/v/what-is-intelligent-design/

Benalla, M., Achchab, B., and Hrimech, H. (2020). Improving Driver Assistance in Intelligent Transportation Systems: An Agent-Based Evidential Reasoning Approach. Journal of Advanced Transportation, 2020, 4607858. https://doi.org/10.1155/2020/4607858

Biknevicius, E. (2015, February 10). GeorgiePhone Apps for blind and visually impaired. Etalinq. Retrieved August 3, 2021 from https://bit.ly/37RmFYM

Binu P.K and Viswaraj, V.S. (2016). Android based application for efficient carpooling with user tracking facility. 2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 1–4. https://doi.org/10.1109/ICCIC.2016.7919536

Boreiko, O., Teslyuk, V., Kryvinska, N., and Logoyda, M. (2019). Structure model and means of a smart public transport system. The 16th International Conference on

Mobile Systems and Pervasive Computing (MobiSPC 2019),The 14th International Conference on Future Networks and Communications (FNC-2019),The 9th International Conference on Sustainable Energy Information Technology, 155, 75– 82. https://doi.org/10.1016/j.procs.2019.08.014

Borges, L. A., Nilsson, K., Tunström, M., Dis, A. T., Perjo, L., Berlina, A., Costa, S. O. e, Fredricsson, C., Grunfelder, J., Johnsen, I., Kristensen, I., Randall, L., Smas, L., and Weber, R. (2017). White Paper on Nordic Sustainable Cities. Nordregio. http://www.nordregio.se/nordicsustainablecities

BusinessMaaS. (2017, December 21). Mobility-as-a-Service and overcoming the issues to get Critical MaaS. Businessmaas.Com. Retrieved August 2, 2021 from https://bit.ly/3snbG2K

Butler, L., Yigitcanlar, T., and Paz, A. (2020). How Can Smart Mobility Innovations Alleviate Transportation Disadvantage? Assembling a Conceptual Framework through a Systematic Review. Applied Sciences, 10(18), 6306. https://doi.org/10.3390/app10186306

Butler, L., Yigitcanlar, T., and Paz, A. (2021). Barriers and risks of Mobility-as-a-Service (MaaS) adoption in cities: A systematic review of the literature. Cities, 109, 103036. https://doi.org/10.1016/j.cities.2020.103036

C. Lin, L. Ko, and T. Shen. (2009). Computational intelligent brain computer interaction and its applications on driving cognition. IEEE Computational Intelligence Magazine, 4(4), 32–46. https://doi.org/10.1109/MCI.2009.934559

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira, J., and Ratti, C. (2013). Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. Transportation Research Part C: Emerging Technologies, 26, 301–313. https://doi.org/10.1016/j.trc.2012.09.009

Careless, J. (n.d.). The possibilities are endless with smarter pavements. Asphalt Magazine. Retrieved August 9, 2021, from http://asphaltmagazine.com/smarterpavements/

Cavoukian, A. (2009). Privacy by Design: The 7 Foundational Principles. https://bit.ly/3AdgYB3

Cena, F., Rapp, A., Tirassa, M., Boella, G., Calafiore, A., and Keller, R. (2017). Personalized interactive urban maps for autism: Enhancing accessibility to urban environments for people with autism spectrum disorder. Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers, 9–12. https://doi.org/10.1145/3123024.3123148

Civitas. (2020). Smart choices for cities Cities towards Mobility 2.0: Connect, share and go! Civitas. https://civitas.eu/sites/default/files/civ_pol-07_m_web.pdf

Chan, B. (n.d.). The Smart City is Enabled and Sustained by Trust. Meeting of the Minds. https://meetingoftheminds.org/the-smart-city-is-enabled-and-sustained-by-trust- 30051

Chou, J., Ibars, R., and Murillo, O. (n.d.). In Pursuit of Inclusive AI. Microsoft. Retrieved September 8, 2021, from
https://www.microsoft.com/design/assets/inclusive/InclusiveDesign_InclusiveAI.p
df

Chmielewski, J., Daher, M., and Ghazal, O. (2021, March 16). The journey toward a
touchless network through intelligent automation: The future of movement of goods. Deloitte Insights. Retrieved July 30, 2021 from https://bit.ly/3gd4YY2

Cledou, G., Estevez, E., and Soares Barbosa, L. (2018). A taxonomy for planning and designing smart mobility services. Government Information Quarterly, 35(1), 61– 76. https://doi.org/10.1016/j.giq.2017.11.008

Cornet, A., Kässer, M., Müller, T., and Tschiesner, A. (2017). The Road to Artificial Intelligence in Mobility—Smart moves required (McKinsey Centre for Future Mobility). McKinsey and Company. Retrieved July 29, 2021 from https://mck.co/37P5S8D

Cruz, C. O., and Sarmento, J. M. (2020). “Mobility as a Service” Platforms: A Critical Path towards Increasing the Sustainability of Transportation Systems. Sustainability, 12(16), 6368. https://doi.org/10.3390/su12166368

Cui L, Xie G, Qu Y, Gao L, and Yang, Y. (2018). Security and Privacy in Smart Cities: Challenges and Opportunities. IEEE Access, 6, 46134–46145. https://doi.org/10.1109/ACCESS.2018.2853985

Dai, Y., Xu, D., Maharjan, S., Qiao, G., and Zhang, Y. (2019). Artificial Intelligence Empowered Edge Computing and Caching for Internet of Vehicles. IEEE Wireless Communications, 26(3), 12–18. https://doi.org/10.1109/MWC.2019.1800411

Dilmegani, C. (2020, July 21). Top 10 Privacy Enhancing Technologies (PETs) in 2021. AI Multiple. https://research.aimultiple.com/privacy-enhancing-technologies/

Danilina, N., and Slepnev, M. (2018). Managing smart-city transportation planning of "Park-and-ride" system: Case of Moscow metropolitan. IOP Conference Series: Materials Science and Engineering, 365, 022002. https://doi.org/10.1088/1757- 899x/365/2/022002

Djahel, S., Salehie, M., Tal, I., and Jamshidi, P. (2013). Adaptive traffic management for secure and efficient emergency services in smart cities. 2013 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), 340–343. https://doi.org/10.1109/PerComW.2013.6529511

Eckhoff, D., and Wagner, I. (2018). Privacy in the Smart City—Applications, Technologies, Challenges, and Solutions. IEEE Communications Surveys and Tutorials, 20(1), 489–516. https://doi.org/10.1109/COMST.2017.2748998

Elsagheer Mohamed, S. A., and AlShalfan, K. A. (2021). Intelligent Traffic Management System Based on the Internet of Vehicles (IoV). Journal of Advanced Transportation, 2021, 4037533. https://doi.org/10.1155/2021/4037533

El-Seoud, S., El-Sofany, H., and Taj-Eddin, I. (2016). Towards the Development of Smart Parking System using Mobile and Web Technologies. https://doi.org/10.1109/IMCTL.2016.7753762

Esztergár-Kiss, D., Kerényi, T., Mátrai, T., and Aba, A. (2020). Exploring the MaaS market with systematic analysis. European Transport Research Review, 12(1), 67. https://doi.org/10.1186/s12544-020-00465-z

European Commission. (2019). EU Road Safety Policy Framework 2021-2030—Next steps towards "Vision Zero." European Commission. Retrieved July 28, 2021 from https://bit.ly/3xZ9bod

European Commission. (2020). Sustainable and Smart Mobility Strategy – putting European transport on track for the future. European Commission.

European Commission. Joint Research Centre. (2020). AI watch: Defining Artificial Intelligence : towards an operational definition and taxonomy of artificial intelligence. Publications Office. https://data.europa.eu/doi/10.2760/382730

Evenson, K. R., LaJeunesse, S., and Heiny, S. (2018). Awareness of Vision Zero among United States' road safety professionals. Injury Epidemiology, 5(1), 21–21. PubMed. https://doi.org/10.1186/s40621-018-0151-1

Fraifer, M., and Fernström, M. (n.d.). Investigation of Smart Parking Systems and their technologies. 14.

Ferreira, J. C., Monteiro, V., Afonso, J. A., and Afonso, J. L. (2016). Tracking Users Mobility Patterns Towards CO2 Footprint. In S. Omatu, A. Semalat, G. Bocewicz, P. Sitek, I. E. Nielsen, J. A. García García, and J. Bajo (Eds.), Distributed Computing and Artificial Intelligence, 13th International Conference (pp. 87–96). Springer International Publishing.

Francini, M., Chieffallo, L., Palermo, A., and Viapiana, M. F. (2021). Systematic Literature Review on Smart Mobility: A Framework for Future "Quantitative" Developments. Journal of Planning Literature, 36(3), 283–296. https://doi.org/10.1177/0885412221994246

Franco, P., Johnston, R., and McCormick, E. (2020). Demand responsive transport: Generation of activity patterns from mobile phone network data to support the operation of new mobility services. Transportation Research Part A: Policy and Practice, 131, 244–266. https://doi.org/10.1016/j.tra.2019.09.038

Friedrich, M., Hartl, M., and Magg, C. (2018). A modeling approach for matching ridesharing trips within macroscopic travel demand models. Transportation, 45(6), 1639–1653. https://doi.org/10.1007/s11116-018-9957-5

Georgakis, P., Almohammad, A., Bothos, E., Magoutas, B., Arnaoutaki, K., and Mentzas, G. (2020). Heuristic-Based Journey Planner for Mobility as a Service (MaaS). Sustainability, 12(23), 10140. https://doi.org/10.3390/su122310140

Giesecke, R., Surakka, T., and Hakonen, M. (2016). Conceptualising Mobility as a Service. 2016 Eleventh International Conference on Ecological Vehicles and Renewable Energies (EVER), 1–11. https://doi.org/10.1109/EVER.2016.7476443

Glasco, J. (2017). Building Trust in Smart Cities: The Importance of Clarity, Communications and Civic Engagement.

Glikson, E., and Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. Academy of Management Annals, 14(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Gomez Torres, I., Parmar, G., Aggarwal, S., Mansur, N., and Guthrie, A. (2019). Affordable Smart Wheelchair. Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems, 1–6. https://doi.org/10.1145/3290607.3308463

González-Ortega, D., Díaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., and Perozo-Rondón, F. J. (2012). Driver Drowsiness Monitoring Application with Graphical User Interface. In J. Bravo, D. López-de-Ipiña, and F. Moya (Eds.), Ubiquitous Computing and Ambient Intelligence (pp. 359–366). Springer Berlin Heidelberg.

Google. (n.d.). People + AI Guidebook. Google Research.

Grab. (n.d.). How AI Will Power Smarter Transport in Southeast Asia. Grab. Retrieved July 20, 2021, from https://bit.ly/3xRDyNr

Griffiths, J. (2019). A new age of artificial intelligence applications. The Record. Retrieved July 28, 2021 from https://bit.ly/3gamfkM

Gutierrez, D. (2016, December 21). Making Mobility as a Service a Reality with Artificial Intelligence. Inside Bigdata. Retrieved July 30, 2021 from https://bit.ly/2W3hS3Z Handte, M., Foell, S., Wagner, S., Kortuem, G., and Marron, P. J. (2016). An Internet-of-

Things Enabled Connected Navigation System for Urban Bus Riders. IEEE Internet of Things Journal, 3(5), 735–744. https://doi.org/10.1109/JIOT.2016.2554146

Hannon, E., McKerracher, C., Orlandi, I., and Ramkumar, S. (2016, October). An- integrated-perspective-on-the-future-of-mobility-article.pdf. Mckinsey.Com. Retrieved June 25, 2021 from https://mck.co/3yUELot

Hao, K. (2018, November 10). What is AI? We drew you a flowchart to work it out. MIT Technology Review. Retrieved June 30, 2021 from https://bit.ly/3xUobE2 Hensher, D., Mulley, C., and Ho, C. et al. (2020). Understanding MaaS: Past, Present and

Future (p. 15). The University of Sydney. Retrieved June 29, 2021 from

https://bit.ly/3jZ55I1

Herzog, D., Massoud, H., and Wörndl, W. (2017). RouteMe: A Mobile Recommender

System for Personalized, Multi-Modal Route Planning. Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization, 67–75. https://doi.org/10.1145/3079628.3079680

Hessler, M. (2020, March 11). Real-time in-vehicle data and AI technologies provide the key to predictive maintenance. Capgemini. https://www.capgemini.com/us- en/2020/03/real-time-in-vehicle-data-and-ai-technologies-provide-the-key-to- predictive-maintenance/#

Hietanen, S. (2014). Mobility as a Service. The New Transport Model, 12(2), 2–4. Hilmani, A., Maizate, A., and Hassouni, L. (2020). Automated Real-Time Intelligent

Traffic Control System for Smart Cities Using Wireless Sensor Networks. Wireless Communications and Mobile Computing, 2020, 8841893. https://doi.org/10.1155/2020/8841893

Ho, C. Q., Hensher, D. A., Mulley, C., and Wong, Y. Z. (2018). Potential uptake and willingness-to-pay for Mobility as a Service (MaaS): A stated choice study. Transportation Research Part A: Policy and Practice, 117, 302–318. https://doi.org/10.1016/j.tra.2018.08.025

Horn, G., and Schönefeld, K. (2020). AI for Future Mobility: What Amount of Willingness to Change Does a Society Need?: Proceedings of the 9th International Conference on Smart Cities and Green ICT Systems, 38–43. https://doi.org/10.5220/0009577500380043

Hoster, H. (2017, February 8). Wired-up roads will soon charge your electric car – while you're driving. The Conversation. Retrieved July 28, 2021, from https://bit.ly/3mf50CD

I. Tenison, R. P. Bharathan, D. Kurian, J. S. Rajan, A. T. P. Imthias, and S. K. Muhammedali. (2019). Feynman Machine: A Cortical Machine Intelligence for Path Detection in Advanced Driver-Assistance Systems. TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), 246–250. https://doi.org/10.1109/TENCON.2019.8929604

Impedovo, D., Dentamaro, V., Pirlo, G., and Sarcinella, L. (2019). TrafficWave: Generative Deep Learning Architecture for Vehicular Traffic Flow Prediction. Applied Sciences, 9(24). https://doi.org/10.3390/app9245504

Impedovo, D., and Pirlo, G. (2020). Artificial Intelligence Applications to Smart City and Smart Enterprise. Applied Sciences, 10(8). https://doi.org/10.3390/app10082944

Integrated Roadways. (n.d.). SMARTER ROADS BEGIN WITH SMART PAVEMENT. Integratedroadways. Retrieved August 7, 2021, from https://integratedroadways.com

Jakhar, D., and Kaur, I. (2020). Artificial intelligence, machine learning and deep learning: Definitions and differences. Clinical and Experimental Dermatology, 45(1), 131–132. https://doi.org/10.1111/ced.14029

Jasanoff, S. (2016). The Ethics of Invention: Technology and the Human Future (First Edit). W.W. Norton and Company.

Jeekel, H. (2017). Social Sustainability and Smart Mobility: Exploring the relationship. World Conference on Transport Research - WCTR 2016 Shanghai. 10-15 July 2016, 25, 4296–4310. https://doi.org/10.1016/j.trpro.2017.05.254

Jittrapirom, P., Caiati, V., Feneri, A.-M., Ebrahimigharehbaghi, S., González, M. J. A., and Narayan, J. (2017). Mobility as a Service: A Critical Review of Definitions, Assessments of Schemes, and Key Challenges. Urban Planning, 2(2), 13–25. https://doi.org/10.17645/up.v2i2.931

Johnson, K. (2018, March 21). Affectiva launches emotion tracking AI for drivers in autonomous vehicles. Retrieved June 28, 2021, https://bit.ly/3smlyK4 K V, G. L., Sait, U., Kumar, T., Bhaumik, R., Shivakumar, S., and Bhalla, K. (2020).

Design and development of a smartphone-based application to save lives during accidents and emergencies. International Conference on Computational Intelligence and Data Science, 167, 2267–2275. https://doi.org/10.1016/j.procs.2020.03.279

Kaiser, V. (2021, April 27). Improve Mobility and Road Safety With Intelligent Transportation Systems. Rsandh.Com. Retrieved July 2, 2021 from https://bit.ly/3iS3l3J

Kalašová, A., Čulík, K., Poliak, M., and Otahálová, Z. (2021). Smart Parking Applications and Its Efficiency. Sustainability, 13(11), 6031. https://doi.org/10.3390/su13116031

Kallet, R. H. (2004). How to Write the Methods Section of a Research Paper. RESPIRATORY CARE, 49(10), 4.

Kamargianni, M., and Matyas, M. (2017). The Business Ecosystem of Mobility-as-a- Service. 8–12. Retrieved July 5, 2021, from https://bit.ly/3yXCCZ8

Kanafani, A., Khattak, A., and Dahlgren, J. (1994). A planning methodology for intelligent urban transportation systems. Transportation Research Part C: Emerging Technologies, 2(4), 197–215. https://doi.org/10.1016/0968-090X(94)90010-8

Kaplan, A., and Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Karabegović, I., Karabegović, E., Mahmić, M., and Husak, E. (2015). The application of service robots for logistics in manufacturing processes. Advances in Production Engineering and Management, 10(4), 185–194. https://doi.org/10.14743/apem2015.4.201

Karlsson, I. C. M., Sochor, J., and Strömberg, H. (2016). Developing the 'Service' in Mobility as a Service: Experiences from a Field Trial of an Innovative Travel Brokerage. Transportation Research Procedia, 14, 3265–3273. https://doi.org/10.1016/j.trpro.2016.05.273

Karsten, J. (2018, May 12). What is Smart Parking? Parkeagle.Com. https://www.parkeagle.com/2018/05/12/what-is-smart-parking/

Khayyam, H., Javadi, B., Jalili, M., and Jazar, R. N. (2020). Artificial Intelligence and Internet of Things for Autonomous Vehicles. In R. N. Jazar and L. Dai (Eds.), Nonlinear Approaches in Engineering Applications (pp. 39–68). Springer International Publishing. https://doi.org/10.1007/978-3-030-18963-1_2

Khoshkangini, R., Marconi, A., and Valetto, G. (2017). Machine Learning for Personalized Challenges in a Gamified Sustainable Mobility Scenario. Extended Abstracts Publication of the Annual Symposium on Computer-Human Interaction in Play, 361–368. https://doi.org/10.1145/3130859.3131321

Kim, S., Park, H., and Lee, H. (2020). The Diffusion Barriers of AI Mobility Service: The Case of TADA. 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), 666–670. https://doi.org/10.1109/ICAIIC48513.2020.9065038

Kitchin, R. (2016). Getting smarter about smart cities: Improving data privacy and data security.

Kottasova, I., and Petroff, A. (2015, August 18). These roads will charge cars as they drive. CNN Business. Retrieved July 6, 2021, from https://cnn.it/3mbsmsI

Kouziokas, G. N. (2017). The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban environment. Transportation Research Procedia, 24, 467–473. https://doi.org/10.1016/j.trpro.2017.05.083

Lee, N. T., Resnick, P., and Barton, G. (2019). Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms. https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation- best-practices-and-policies-to-reduce-consumer-harms/

Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., and Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. Mechanical Systems and Signal Processing, 138, 106587. https://doi.org/10.1016/j.ymssp.2019.106587

Leong, B. (2019, February 20). Artificial intelligence: Privacy promise or peril? Future of Privacy Forum. https://fpf.org/blog/artificial-intelligence-privacy-promise-or-peril/

Li, M., Hua, G., and Huang, H. (2018). A Multi-Modal Route Choice Model with Ridesharing and Public Transit. Sustainability, 10(11), 4275. https://doi.org/10.3390/su10114275

Li, Y., May, A., and Cook, S. (2019). Mobility-as-a-Service: A Critical Review and the Generalized Multi-modal Transport Experience. In P.-L. P. Rau (Ed.), Cross- Cultural Design. Culture and Society (pp. 186–206). Springer International Publishing.

Liberato, P., Alen, E., and Liberato, D. (2018). Smart tourism destination triggers consumer experience: The case of Porto. European Journal of Management and Business Economics, 27(1), 6–25. https://doi.org/10.1108/EJMBE-11-2017-0051

Liu, P., Zhang, Y., Kong, D., and Yin, B. (2019). Improved Spatio-Temporal Residual Networks for Bus Traffic Flow Prediction. Applied Sciences, 9(4). https://doi.org/10.3390/app9040615

Liu, X., Wang, J., Zhang, W., Zheng, Q., and Li, X. (2020). EmotionTracker: A Mobile Real-time Facial Expression Tracking System with the Assistant of Public AI-as-a- Service. Proceedings of the 28th ACM International Conference on Multimedia, 4530–4532. https://doi.org/10.1145/3394171.3414447

Lusch, R. F., Vargo, S. L., and O'Brien, M. (2007). Competing through service: Insights from service-dominant logic. Journal of Retailing, 83(1), 5–18. https://doi.org/10.1016/j.jretai.2006.10.002

Ma, Y., Wang, Z., Yang, H., and Yang, L. (2020). Artificial intelligence applications in the development of autonomous vehicles: A survey. IEEE/CAA Journal of Automatica Sinica, 7(2), 315–329. https://doi.org/10.1109/JAS.2020.1003021

MaaS Alliance. (2017). Guidelines and recommendations to create the foundations of a thriving MaaS ecosystem. MaaS Alliance. Retrieved July 6, 202, from https://bit.ly/3g7JCeU

Magazanik, L., Shmerling. (2020, September 30). Privacy Protection for Smart Mobility Organizations in the Digital Age. Israel Tech Policy Institute. https://techpolicy.org.il/blog/privacy-protection-for-smart-mobility-organizations- in-the-digital-age/

Majster, M., Van Audenhove, F.-J., Ninane, O., Cattoir, F., Pilot, O., Blondel, M., Schmitz, K., Eiden, M., and Eagar, R. (2021). Artificial intelligence in mobility (p. 4). Arthur D. Little. Retrieved July 8, 2021 https://bit.ly/2UqCuTb

Maldonado Silveira Alonso Munhoz, P. A., da Costa Dias, F., Kowal Chinelli, C., Azevedo Guedes, A. L., Neves dos Santos, J. A., da Silveira e Silva, W., and Pereira Soares, C. A. (2020). Smart Mobility: The Main Drivers for Increasing the Intelligence of Urban Mobility. Sustainability, 12(24), 10675. https://doi.org/10.3390/su122410675

Mandal, R., Karmakar, P., Chatterjee, S., Spandan, D. D., Pradhan, S., Saha, S., Chakraborty, S., and Nandi, S. (2021). Exploiting Multi-modal Contextual Sensing for City-bus's Stay Location Characterization: Towards Sub-60 Seconds Accurate Arrival Time Prediction. ArXiv:2105.13131 [Cs]. http://arxiv.org/abs/2105.13131

Mandhare, P., Kharat, V., and Patil, C. Y. (2018). Intelligent Road Traffic Control System for Traffic Congestion A Perspective. International Journal of Computer Sciences and Engineering, 6, 908–915. https://doi.org/10.26438/ijcse/v6i7.908915

Manning, K. (2020, August 21). Intelligent Process Automation (IPA) vs Robotic Process Automation (RPA). ProcessMaker. Retrieved July 9, 2021, from https://bit.ly/2XEboJD

Martinez, F., Toh, C.-K., Cano, J.-C., Calafate, C., and Manzoni, P. (2010). Emergency Services in Future Intelligent Transportation Systems Based on Vehicular Communication Networks. IEEE Intell. Transport. Syst. Mag., 2, 6–20.

Masoud, N., and Jayakrishnan, R. (2017). A real-time algorithm to solve the peer-to-peer ride-matching problem in a flexible ridesharing system. Transportation Research Part B: Methodological, 106, 218–236. https://doi.org/10.1016/j.trb.2017.10.006

Matheson, R. (2018, December 7). The privacy risks of compiling mobility data. MIT News. https://news.mit.edu/2018/privacy-risks-mobility-data-1207

Mazzolin, R. (2021, November 23). Artificial Intelligence and Keeping Humans "in the Loop." CIGI. https://www.cigionline.org/articles/artificial-intelligence-and- keeping-humans-loop/

McKinsey Global Institute. (2015). The Internet of Things: Mapping the Value Beyond the Hype. https://social-innovation.hitachi/en-us/think-ahead/transportation/future- of-mobility/

McCarthy, J. (1959). PROGRAMS WITH COMMON SENSE. 15.

Microsoft. (n.d.). Inclusive Design. Microsoft. Retrieved September 3, 2021, from https://www.microsoft.com/design/inclusive/

Minchin, J. (2021, June 10). Maas North America 2021: A sneak preview. Intelligent Transport. Retrieved July 12, 2021, from https://bit.ly/3gtLIWH

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., and Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data and Society, 3(2), 1–21. https://doi.org/10.1177/2053951716679679

Morgan, J. (2019, August 21). AI Stems From Our Desire To Forge The Gods. Medium. Retrieved July 15, 2021, from https://bit.ly/3jV76ow

Mourato, P., Lima, H., Luna, C., Rocha, T., and Ferraz, F. (2015). Analysis and Proposed Improvements in the Support for the Visually Impaired in the Use of Public Transportation. 4.

Murati, E. (2020). Mobility-as-a-service (MaaS) digital marketplace impact on EU passengers' rights. European Transport Research Review, 12(1), 62. https://doi.org/10.1186/s12544-020-00447-1

Näslund, E., and Strömberg, F. (2017). Open Data within a Smart City Initiative [Umeå University]. https://umu.diva- portal.org/smash/get/diva2:1113129/FULL TEXT01.pdf

N. Li and C. Busso. (2016). Detecting Drivers' Mirror-Checking Actions and Its Application to Maneuver and Secondary Task Recognition. IEEE Transactions on Intelligent Transportation Systems, 17(4), 980–992. https://doi.org/10.1109/TITS.2015.2493451

Nam, K., and Lee, N. H. (n.d.). Typology of Service Innovation from Service-Dominant Logic Perspective. 15.

Nichols, J. A., Herbert Chan, H. W., and Baker, M. A. B. (2019). Machine learning: Applications of artificial intelligence to imaging and diagnosis. Biophysical Reviews, 11(1), 111–118. PubMed. https://doi.org/10.1007/s12551-018-0449-9

Nikitas, A., Michalakopoulou, K., Njoya, E. T., and Karampatzakis, D. (2020). Artificial Intelligence, Transport and the Smart City: Definitions and Dimensions of a New Mobility Era. Sustainability, 12(7), 2789. https://doi.org/10.3390/su12072789

Nilsson, N. J. (1998). Artificial intelligence: A new synthesis (5th print). Kaufmann. Nowakowski, C. (n.d.). Predicting and diagnosing potential incidents in the Automotive sector is becoming increasingly critical to stay competitive. Bearingpoint. Retrieved August 3, 2021, from https://www.bearingpoint.com/en/our- success/insights/predictive-diagnostics-insight/

Öberg, J., Ribe, J., Glaumann, M., Gjelstrup, A., and Berntsson, G. L. (2017). SMART PUBLIC TRANSPORT New digital ecosystems unlock the growth potential of the smart city.pdf. Telia. https://www.teliacompany.com/globalassets/telia- company/documents/news/connected_things-publictransport.pdf

OECD. (2020). The Impact of Big Data and Artificial Intelligence (AI) in the Insurance Sector. www.oecd.org/finance/Impact-Big-Data-AI-in-the-Insurance-Sector.htm.

Ojala, A., and Lehner, O. (2018). The Building Blocks of Academic Writing in the Field of Information Systems. Scandinavian Journal of Information Systems, 21.

Olszewski, R., Pałka, P., and Turek, A. (2018). Solving "Smart City" Transport Problems by Designing Carpooling Gamification Schemes with Multi-Agent Systems: The Case of the So-Called "Mordor of Warsaw." Sensors, 18(2), 141. https://doi.org/10.3390/s18010141

Omar, H. (2015). Intelligent Traffic Information System Based on Integration of Internet of Things and Agent Technology. International Journal of Advanced Computer Science and Applications, 6(2). https://doi.org/10.14569/IJACSA.2015.060206

Østergaard, H., Bughin, J., Andersen, J. R., Rugholm, J., Poulsen, M., and Chui, M. (2019). How artificial intelligence will transform Nordic businesses. McKinsey and Company. Retrieved July 10, 2021, from https://mck.co/2VVfegp

Paiva, S., Ahad, M., Tripathi, G., Feroz, N., and Casalino, G. (2021). Enabling Technologies for Urban Smart Mobility: Recent Trends, Opportunities and Challenges. Sensors, 21(6), 2143. https://doi.org/10.3390/s21062143

Pangbourne, K., Mladenović, M. N., Stead, D., and Milakis, D. (2020). Questioning mobility as a service: Unanticipated implications for society and governance. Transportation Research Part A: Policy and Practice, 131, 35–49. https://doi.org/10.1016/j.tra.2019.09.033

Papageorgiou, G., and Maimaris, A. (2017). Towards the development of Intelligent Pedestrian Mobility Systems (IPMS). 2017 International Conference on Electrical Engineering and Informatics (ICELTICs), 251–256.
https://doi.org/10.1109/ICEL TICS.2017.8253267

Payyanadan, R. P., and Lee, J. D. (2018). Understanding the ridesharing needs of older adults. Travel Behaviour and Society, 13, 155–164. https://doi.org/10.1016/j.tbs.2018.08.002

Pobiner, S., and Murphy, T. (2018, December 11). From smart products to smart systems: The importance of participatory design in the age of artificial intelligence. Deloitte Insights. https://www2.deloitte.com/us/en/insights/focus/cognitive- technologies/participatory-design-artificial-intelligence.html

Polydoropoulou, A., Pagoni, I., Tsirimpa, A., Roumboutsos, A., Kamargianni, M., and Tsouros, I. (2020). Prototype business models for Mobility-as-a-Service. Transportation Research Part A: Policy and Practice, 131, 149–162. https://doi.org/10.1016/j.tra.2019.09.035

Porru, S., Misso, F. E., Pani, F. E., and Repetto, C. (2020). Smart mobility and public transport: Opportunities and challenges in rural and urban areas. Special Issue: Modeling and Detecting Traffic Dynamics: Granular, Pedestrian and Vehicular Flow, 7(1), 88–97. https://doi.org/10.1016/j.jtte.2019.10.002

Provazza, A. (2017, May 26). Artificial intelligence data privacy issues on the rise. TechTarget.

https://searchmobilecomputing.techtarget.com/news/450419686/Artificial- intelligence-data-privacy-issues-on-the-rise

PWC. (n.d.). A practical guide to Responsible Artificial Intelligence (AI). PWC. Retrieved August 31, 2021, from https://www.pwc.com/gx/en/issues/data-and- analytics/artificial-intelligence/what-is-responsible-ai/responsible-ai-practical- guide.pdf

Q. Xu, B. Wang, F. Zhang, D. S. Regani, F. Wang, and K. J. R. Liu. (2020). Wireless AI in Smart Car: How Smart a Car Can Be? IEEE Access, 8, 55091–55112. https://doi.org/10.1109/ACCESS.2020.2978531

Ran, Y., Zhou, X., Lin, P., Wen, Y., and Deng, R. (2019). A Survey of Predictive Maintenance: Systems, Purposes and Approaches. ArXiv:1912.07383 [Cs, Eess]. http://arxiv.org/abs/1912.07383

Randall, L., and Berlina, A. (2019). Governing the digital transition in Nordic Regions: The human element. Nordregio. https://doi.org/10.6027/R2019:4.1403-2503

Rapp, A., Cena, F., Tirassa, M., Boella, G., Calafiore, A., and Keller, R. (2017). Tracking personal movements in urban environments: Personalized maps for people with autism spectrum disorder. Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers, 883–886. https://doi.org/10.1145/3123024.3125507

Ribeiro, J., Lima, R., Eckhardt, T., and Paiva, S. (2021). Robotic Process Automation and Artificial Intelligence in Industry 4.0 – A Literature review. Procedia Computer Science, 181, 51–58. https://doi.org/10.1016/j.procs.2021.01.104

Roulland, F., Ulloa, L., Mondragon, A., Niemaz, M., and Ciriza, V. (2014). Learning mobility user choice and demand models from public transport fare collection data. 6. Retrieved July 12, 2021, from https://bit.ly/3y0LSuA

Russell, S., Moskowitz, I. S., and Raglin, A. (2017). Human Information Interaction, Artificial Intelligence, and Errors. In W. F. Lawless, R. Mittu, D. Sofge, and S. Russell (Eds.), Autonomy and Artificial Intelligence: A Threat or Savior? (pp. 71– 101). Springer International Publishing. https://doi.org/10.1007/978-3-319-59719- 5_4

Samsel, C. (2019). Ubiquitous Intermodal Mobility Assistance [PHD Dissertation, RWTH Aachen University]. Retrieved July 17, 2021, from https://bit.ly/3iTHlWp

Sambana and Ramesh. (2020). An Artificial Intelligence approach to Intelligent Vehicle Control and Monitoring System. 2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (ISSSC), 1–6. https://doi.org/10.1109/iSSSC50941.2020.9358811

Santos, G., and Nikolaev, N. (2021). Mobility as a Service and Public Transport: A Rapid Literature Review and the Case of Moovit. Sustainability, 13(7), 3666. https://doi.org/10.3390/su13073666

Schmelzer, R. (2019, October 31). Should We Be Afraid of AI? Forbes. https://www.forbes.com/sites/cognitiveworld/2019/10/31/should-we-be-afraid-of- ai/?sh=270aa75d4331

Schulz, T., Böhm, M., Gewald, H., Celik, Z., and Krcmar, H. (2020). The Negative Effects of Institutional Logic Multiplicity on Service Platforms in Intermodal Mobility Ecosystems. Business and Information Systems Engineering, 62(5), 417– 433. https://doi.org/10.1007/s12599-020-00654-z

Shadrin, S. S., Varlamov, O. O., and Ivanov, A. M. (2017). Experimental Autonomous Road Vehicle with Logical Artificial Intelligence. Journal of Advanced Transportation, 2017, 2492765. https://doi.org/10.1155/2017/2492765

Shim, S., Park, S., and Hong, S. (2006). Parking Management System Using ZigBee. 7. Schmidt, A. (2020). Interactive Human Centered Artificial Intelligence: A Definition and

Research Challenges. Proceedings of the International Conference on Advanced Visual Interfaces. https://doi.org/10.1145/3399715.3400873

Schroener, A., van Grinsven, A., Tol, E., Leestemaker, L., Schackmann, P.-P., Vonk Noordegraaf, D., Meijeren, J. van, and Kalisvaart, S. (2020). The impact of emerging technologies on the transport system (p. 173). Retrieved July 10, 2021, from https://bit.ly/3jZ7L8x

Schulz, T., Böhm, M., Gewald, H., Celik, Z., and Krcmar, H. (2020). The Negative Effects of Institutional Logic Multiplicity on Service Platforms in Intermodal

Mobility Ecosystems. Business and Information Systems Engineering, 62(5), 417–

433. https://doi.org/10.1007/s12599-020-00654-z

Schulz, T., and Überle, M. (2018). How Institutional Arrangements Impede Realization of

Smart Ecosystems: The Case of Door-To-Door Mobility Integrators.

Shadrin, S. S., Varlamov, O. O., and Ivanov, A. M. (2017). Experimental Autonomous

Road Vehicle with Logical Artificial Intelligence. Journal of Advanced

Transportation, 2017, 2492765. https://doi.org/10.1155/2017/2492765 Sharma, S. (2021, February 15). How uber uses machine learning to reinvent

transportation? Retrieved June 30, 2021, from https://bit.ly/2UsuoJK Siau, K., and Wang, W. (2018). Building Trust in Artificial Intelligence, Machine

Learning, and Robotics. Cutter Business Technology Journal, 31, 47–53. Singh, B., and Gupta, A. (2015). Recent trends in intelligent transportation systems: A

review. Journal of Transport Literature. https://doi.org/10.1590/2238-

1031.jtl.v9n2a6

Singh, G., Bansal, D., and Sofat, S. (2014). Intelligent Transportation System for

Developing Countries A Survey. International Journal of Computer Applications,

85(3), 34–38. https://doi.org/10.5120/14824-3058

Skouby, K. E., Kivimäki, A., Haukipuro, L., Lynggaard, P., and Windekilde, I. (n.d.).

Smart Cities and the Ageing Population. 12.

Snook. (2019, November 11). Mobility as a service. Snook.

https://wearesnook.com/mobility-as-a-service/

Sobnath, D., Rehman, I. U., and Nasralla, M. M. (2020). Smart Cities to Improve Mobility

and Quality of Life of the Visually Impaired. In S. Paiva (Ed.), Technological Trends in Improved Mobility of the Visually Impaired (pp. 3–28). Springer International Publishing. https://doi.org/10.1007/978-3-030-16450-8_1

Sochor, J., Arby, H., Karlsson, I. C. M., and Sarasini, S. (2018). A topological approach to Mobility as a Service: A proposed tool for understanding requirements and effects, and for aiding the integration of societal goals. Research in Transportation Business and Management, 27, 3–14. https://doi.org/10.1016/j.rtbm.2018.12.003

Sochor, J. L. (2013). User perspectives on intelligent transportation systems [KTH Royal Institute of Technology]. Retrieved June 30, 2021, from https://bit.ly/3snN4XF

Soegoto, E. S., Pamungkas, V. Y., and Herdiawan, A. (2018). Designing Smart Parking Application for Car Parking Space Arrangement. IOP Conference Series: Materials Science and Engineering, 407, 012185. https://doi.org/10.1088/1757- 899x/407/1/012185

Stanford University, United States of America, and Auernhammer, J. (2020, September 10). Human-centered AI: The role of Human-centered Design Research in the development of AI. Design Research Society Conference 2020. https://doi.org/10.21606/drs.2020.282

Stoeckli, E., Dremel, C., and Uebernickel, F. (2018). Exploring characteristics and transformational capabilities of InsurTech innovations to understand insurance value creation in a digital world. Electronic Markets, 28(3), 287–305. https://doi.org/10.1007/s12525-018-0304-7

Stiglic, M., Agatz, N., Savelsbergh, M., and Gradisar, M. (2018). Enhancing urban mobility: Integrating ride-sharing and public transit. Computers and Operations Research, 90, 12–21. https://doi.org/10.1016/j.cor.2017.08.016

Su, H., Cong, G., Chen, W., Zheng, B., and Zheng, K. (2019). Personalized Route Description Based On Historical Trajectories. Proceedings of the 28th ACM

International Conference on Information and Knowledge Management, 79–88.

https://doi.org/10.1145/3357384.3357877

Sylvester, T. (2019, March 19). Smart Pavement: Connecting Smart Cars to Smart Cities.

Tim Sylvester. Retrieved July 1, 2021 from https://bit.ly/2VUi9Xf

Taie, M. A., Moawad, E. M., Diab, M., and ElHelw, M. (2016). Remote Diagnosis, Maintenance and Prognosis for Advanced Driver Assistance Systems Using

Machine Learning Algorithms. SAE International Journal of Passenger Cars - Electronic and Electrical Systems, 9(1), 114–122. https://doi.org/10.4271/2016-01- 0076

Tan, L., Zhang, Z., and Jiang, W. (2022). Ride-Hailing Service Prediction Based on Deep Learning. International Journal of Machine Learning and Computing, 12(1), 6.

Tatari, A., Khorasani, G., Yadollahi, A., and Rahimi, M. (2012). Evaluation of Intelligent Transport System in Road Safety.

TechBullion. (2021, April 16). How Is AI Revolutionizing Insurance? TechBullion. https://techbullion.com/how-is-ai-revolutionizing-insurance/

Tenison I, R. P. Bharathan, D. Kurian, J. S. Rajan, A. T. P. Imthias, and S. K. Muhammedali. (2019). Feynman Machine: A Cortical Machine Intelligence for Path Detection in Advanced Driver-Assistance Systems. TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), 246–250. https://doi.org/10.1109/TENCON.2019.8929604

The Guardian. (2018). World’s first electrified road for charging vehicles opens in Sweden. The Guardian.

https://www.theguardian.com/environment/2018/apr/12/worlds-first-electrified-road-for-charging-vehicles-opens-in-sweden

Toh, C. K., Sanguesa, J. A., Cano, J. C., and Martinez, F. J. (2020). Advances in smart

roads for future smart cities. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 476(2233), 20190439. https://doi.org/10.1098/rspa.2019.0439

Tractable. (2021, August 12). Sompo Japan is first Japanese insurer to use AI to calculate approximate repair costs. https://tractable.ai/blog/sompo-japan-is-first-japanese- insurer-to-use-ai-to-calculate-approximate-repair-costs/

Trivedi, J., Sarada Devi, M., and Dhara, D. (2017). Review Paper on Intelligent Traffic Control system using Computer Vision for Smart City. International Journal of Scientific and Engineering Research, 8, 14–17.

Tschiesner, A., Möller, T., Kässer, M., Schaufuss, P., and Kley, F. (n.d.). Mastering new mobility: Perspectives on navigating an uncertain future. McKinsey and Company. Retrieved August 3, 2021, from https://mck.co/3CSezgJ

Tung, W.-F., and Yuan, S.-T. (2007). iDesign: An Intelligent Design Framework for Service Innovation. 2007 40th Annual Hawaii International Conference on System Sciences (HICSS’07), 64–64.

Turetken, O., Grefen, P., Gilsing, R., and Adali, O. E. (2019). Service-Dominant Business Model Design for Digital Innovation in Smart Mobility. Business and Information Systems Engineering, 61(1), 9–29. https://doi.org/10.1007/s12599-018-0565-x

Tyagi, N. (2020, June 12). 5 ways ML helps in Uber Services Optimization. Retrieved June 28, 2021 from https://bit.ly/3yVJtm2

UITP. (2021, June 29). The Shift2MaaS project overcame barriers and borders to advance multimodal travel in Europe. UITP. Retrieved July 9, 2021, from https://bit.ly/3CUURRz

United Nations. (2018). World Urbanization Prospects: The 2018 Revision: Key facts. United Nations. Retrieved June 27, 2021, from https://bit.ly/3k5fi5s

United Nations. (2019). World Population Prospects 2019 (ST/ESA/SER.A/423). United Nations. Retrieved June 27, 2021, from https://bit.ly/3iSzMiw

United Nations. (2020). Transport Trends and Economics 2018–2019: Mobility as a Service. UN. https://doi.org/10.18356/84ff262a-en

Urban Mobility. (2021). Closer. https://closer.lindholmen.se/en/focus-areas/urban- mobility

Väänänen, K., Ojala, J., Hilden, E., Karlsson, M., Wallgren, P., and Turunen, M. (2016). Improving Attractiveness of Public Transportation with Interactive Experiences. Proceedings of the 9th Nordic Conference on Human-Computer Interaction, 1–2. https://doi.org/10.1145/2971485.2987677

Vaca-Recalde, M. E., Pérez, J., and Echanobe, J. (2020). Driver Monitoring System Based on CNN Models: An Approach for Attention Level Detection. In C. Analide, P. Novais, D. Camacho, and H. Yin (Eds.), Intelligent Data Engineering and Automated Learning – IDEAL 2020 (pp. 575–583). Springer International Publishing.

van der Aalst, W. M. P., Bichler, M., and Heinzl, A. (2018). Robotic Process Automation. Business and Information Systems Engineering, 60(4), 269–272. https://doi.org/10.1007/s12599-018-0542-4

Vasudevan, K., Das, A. P., B, S., and P, S. (2017). Driver drowsiness monitoring by learning vehicle telemetry data. 2017 10th International Conference on Human System Interactions (HSI), 270–276. https://doi.org/10.1109/HSI.2017.8005044

Verma, R., Ghosh, S., Saketh, M., Ganguly, N., Mitra, B., and Chakraborty, S. (2018). Comfride: A smartphone based system for comfortable public transport recommendation. Proceedings of the 12th ACM Conference on Recommender Systems, 181–189. https://doi.org/10.1145/3240323.3240359

Verganti, R., Vendraminelli, L., and Iansiti, M. (2020). Design in the Age of Artificial Intelligence. Harvard Business School. https://www.hbs.edu/ris/Publication%20Files/20-091_3889aa72-1853-42f8-8b17- 5760c86f863e.pdf

Wachter, F. (2019). Emotional driving in AI-powered Cars; Driver and traffic safety. [Chalmers University of Technology]. Retrieved July 26, 2021, https://bit.ly/3j00QwF

Wallach, D. P., Flohr, L. A., and Kaltenhauser, A. (2020). Beyond the Buzzwords: On the Perspective of AI in UX and Vice Versa. In H. Degen and L. Reinerman-Jones (Eds.), Artificial Intelligence in HCI (Vol. 12217, pp. 146–166). Springer International Publishing. https://doi.org/10.1007/978-3-030-50334-5_10

Wang, J., Yu, X., Liu, Q., and Yang, Z. (2019). Research on key technologies of intelligent transportation based on image recognition and anti-fatigue driving. EURASIP Journal on Image and Video Processing, 2019(1), 33. https://doi.org/10.1186/s13640-018-0403-6

Wang, Q. (2021). THE IMPACT OF INSURTECH ON CHINESE INSURANCE INDUSTRY. 2020 International Conference on Identification, Information and Knowledge in the Internet of Things, IIKI2020, 187, 30–35. https://doi.org/10.1016/j.procs.2021.04.030

Wärneståł, P. (2018). Designing the Future—Tools for AI-Powered Service Platforms. Good Audience.

Wilmot, S. (2020, December 2). Driverless Cars Are Coming, but Not Yet to Take Over. Wall Street Journal. Retrieved July 26, 2021, from https://on.wsj.com/3mbPpUA Wirtz, B. W., Weyerer, J. C., and Geyer, C. (2019). Artificial Intelligence and the Public

Sector—Applications and Challenges. International Journal of Public

Administration, 42(7), 596–615. https://doi.org/10.1080/01900692.2018.1498103 WirelessCar. (2021, March 24). WirelessCar's B2B solutions expand and enhance business

opportunities for car makers and car rental companies alike. https://www.wirelesscar.com/wirelesscars-b2b-solutions-expand-and-enhance- business-opportunities-for-car-makers-and-car-rental-companies-alike/

World Economic Forum. (2016). Digital Transformation of Industries: In collaboration with Accenture Automotive Industry. World Economic Forum. http://reports.weforum.org/digital-transformation/wp- content/blogs.dir/94/mp/files/pages/files/wef-dti-automotivewhitepaper-final-january-2016.v1.pdf

World Health Organization. Regional Office for Europe, Krug, E., Bettcher, D., Arnold, V., and Robinson, S. (2019). The role of cities in preventing noncommunicable diseases and road injuries. Public Health Panorama, 5(2–3), 336–340.

World's first electrified road for charging vehicles opens in Sweden. (2018). The Guardian. Retrieved July 29, 2021, from https://bit.ly/3ANEt3p.

Wu, Y. C., Wu, Y. J., and Wu, S. M. (2019). Chapter 15—An outlook of a future smart city in Taiwan from post–Internet of things to artificial intelligence Internet of things. In A. Visvizi and M. D. Lytras (Eds.), Smart Cities: Issues and Challenges (pp. 263–282). Elsevier. https://doi.org/10.1016/B978-0-12-816639-0.00015-6

Yang, W., and Lee, S. (2019). MaaS(Mobility-as-a-Service)기반 공유자전거 서비스 모델연구. 서비스연구, 9(4), 19–40. https://doi.org/10.18807/JSRS.2019.9.4.019

Yatnalkar, G. P. (2019). A Machine Learning Recommender Model for Ride Sharing Based on Rider Characteristics and User Threshold Time. Theses, Dissertations and Capstones, 93.

Yinying, H., and Csaba, D. C. (2018). In Information Management for Mobility-as-a- Service Based on Autonomous Vehicles (pp. 293–303). Retrieved July 28, 2021, from http://real.mtak.hu/78822/

Zarifis, A., Holland, C. P., and Milne, A. (2019). Evaluating the impact of AI on insurance: The four emerging AI- and data-driven business models. Emerald Open Research, 1, 15. https://doi.org/10.35241/emeraldopenres.13249.1

Zhang, J., Zheng, Y., and Qi, D. (2016). Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction. 7.

Zhao, Z., Chen, W., Wu, X., Chen, P. C. Y., and Liu, J. (2017). LSTM network: A deep learning approach for short-term traffic forecast. IET Intelligent Transport Systems, 11(2), 68–75. https://doi.org/10.1049/iet-its.2016.0208

Zhou, H., Hou, K.-M., Zuo, D., and Li, J. (2012). Intelligent Urban Public Transportation for Accessibility Dedicated to People with Disabilities. Sensors, 12(8), 10678– 10692. https://doi.org/10.3390/s120810678