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Artificial intelligence affordances for urban mobility

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Abstract

Purpose – Artificial intelligence (AI) has been touted as one of the viable solutions to address urban mobility issues. Despite a growing body of research on AI across various sectors, its use in the mobility sector remains underexplored. This study addresses this limitation by investigating AI applications and identifying the AI material properties and use cases that offer mobility-specific affordances.

Design/methodology/approach – Although AI applications in mobility are growing, academic research on the subject has yet to catch up. Therefore, we follow a systematic review and analysis of practitioner literature. We conducted a comprehensive search for relevant documents through Advanced Google and OECD databases and identified 173 sources. We selected 40 sources published between 2015 and 2022 and analysed the corpus of evidence through abductive qualitative analysis technique.

Findings – The analysis reveals that mobility organisations are implementing various AI technologies and systems such as cameras, sensors, IoT, computer vision, natural language processing, robotic process automation, machine learning, deep learning and neural networks. These technologies offer material properties for sensing mobility objects and events, comprehending mobility data, automating mobility activities and learning from mobility data. By exploiting these material properties, mobility organisations are integrating urban mobility management, personalising and automating urban mobility, enabling the smartification of infrastructure and asset management, developing better urban transport planning and management, and enabling automatic driving.

Originality/value – The study contributes a mid-range theory of the affordances of AI for mobility (AI4M) at the infrastructure, operation and service levels. This contribution extends the existing understanding of AI and offers an interconnected perspective of AI affordances for further research. For practitioners, the study provides insights on how to explore AI in alignment with organisational goals to collectively transform urban mobility to be affordable, efficient and sustainable.

Keywords Artificial intelligence, AI, Urban mobility, Transport, Affordances, Grey literature review, Material properties, Use cases

Paper type Research paper

1. Introduction

Urban mobility involves the movement of goods and people from one spot to another in cities and towns, regardless of the mode of transportation or the purpose of the journey (Lyons, 2018). Urban areas, unlike rural ones, have a higher population density and more complex transport infrastructures. These areas feature motorways, bus, tram, train, and bike lanes and tunnels, providing various transportation options including personal automobiles, mass transit systems, buses, trains, trams, ride-sharing services, cycle paths and e-scooters. As a result, urban mobility faces significant traffic congestion, inefficiency, accidents, high prices and pollution (Abduljabbar *et al.*, 2019; Davidsson *et al.*, 2016). To address these issues and create affordable, effective and sustainable mobility aligned with the United Nations (UN) sustainable development goals (SDGs), transformative digital solutions that leverage artificial

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intelligence (AI) are being implemented in mobility operations, products and services (Nikitas *et al.*, 2020).

AI is a class of technologies that interpret and learn from data to perform cognitive functions, roles and tasks generally associated with humans in the workplace and broader society (Feuerriegel *et al.*, 2024; Kaplan and Haenlein, 2019). AI is embedded in vehicles to enhance their ability to navigate and respond to traffic conditions without human intervention (Li *et al.*, 2018). Emerging mobility service innovations such as ride-sharing, car-sharing and bike-sharing increasingly rely on AI (Willing *et al.*, 2017). AI also offers opportunities to overcome the inefficiencies of single mobility services by integrating them into intermodal services (Schulz *et al.*, 2020; Willing *et al.*, 2017). These innovations are not only changing how people move from one place to another and the use of resources but also ushering in a new mobility era (Nikitas *et al.*, 2020; Duan *et al.*, 2022) that is reshaping the mobility service landscape from private ownership to a shared one (Dlugosch *et al.*, 2020; Molla *et al.*, 2024).

Despite the practical applications of AI in mobility, information systems (IS) studies have largely focused on AI use cases in manufacturing (Chen *et al.*, 2024), education (Van Slyke *et al.*, 2023), finance (Yang *et al.*, 2023) and healthcare (Amin *et al.*, 2024; Grüning *et al.*, 2023). A use case refers to a specific context or scenario in which a technology, in this case AI, is applied to achieve a defined goal or outcome. It outlines the interactions between users and the AI solution, detailing how the technology can solve a problem or enhance a process. In the mobility context, there are only limited studies such as Abduljabbar *et al.* (2019) and Nikitas *et al.* (2020), which provide overviews of the current landscape of AI applications. This lack of attention of AI use cases in mobility is surprising given the context-specific nature of AI affordances, the critical role of mobility for social and economic wellbeing, and its importance for achieving SDGs. While AI is being leveraged to advance urban mobility solutions and services, there is little research on how mobility organisations overcome the challenges in aligning AI's capabilities with organisational and SDG mobility goals and realise the full potential. Hence, it is important to address this oversight by exploring the AI material properties and use cases from practical applications of AI in the mobility sector.

Unravelling material properties of AI and its use cases is essential to explaining AI affordance perception and actualisation (Melville *et al.*, 2023). Material properties refer to *"features of IT, including hardware devices, software interfaces and applications, and communication services"* (Robey *et al.*, 2012, p. 218). They represent the AI artifact innovation and have no intrinsic values until applied in specific context. On the other hand, affordances refer to *"the possibilities for goal-oriented actions afforded to specific user groups by technical objects"* (Markus and Silver, 2008, p. 622). These action potentials arise from the interaction between technology features and the use context (Chemero and Turvey, 2007). In a specific context, such as mobility, a technical object affords goal-directed actions through its material properties (Robey *et al.*, 2012). Since the functionality AI designers initially intended could be different from the social meaning it acquires across different use cases, it is essential to understand how mobility organisations apply AI material properties to achieve goals. Use cases offer practical deployment and utilisation of the material properties within a specific context.

To develop a nuanced understanding of AI affordances in the context of mobility, it is important to unpack the material properties of AI and determine the techniques, technologies, and algorithms that afford mobility actors the ability to address organisational and societal challenges and goals. Thus, this study aims to address two key questions.

RQ1. what are the AI properties that offer mobility-specific action potentials?

RQ2. what AI for mobility use cases and affordances can be identified from practical applications of AI?

To address these questions, a systematic review and analysis of practitioner publications was conducted. We adopt this approach because (1) there is a lack of mobility domain-specific AI case studies to conduct a systematic academic literature review, (2) it offers diverse and real-world applications that may not be covered in academic literature and (3) it aligns with evidence-based practice, providing valuable insights for both practitioners and researchers, including areas that require further exploration. The results show that AI offers action potentials for sensing mobility objects and events, comprehending and learning from mobility data and automating mobility activities. Mobility organisations are exploiting these possibilities to integrate urban mobility operations, personalise and automate services, smartification of infrastructure and asset management and develop better urban transport planning to achieve organisational and societal goals. Based on these findings, we contribute a mid-range theory of the affordances of AI for mobility (AI4M) at the infrastructure, operation and service levels. This contribution extends the existing understanding of AI and offers an interconnected perspective of AI affordances for further research.

The remainder of the paper is structured as follows: background literature, research method, presentation of findings, theorisation of AI for mobility affordances, and conclusion and implications for future research.

2. Background literature

To address the research questions, we use the affordances theory as an overarching framework for our study. The concept of affordances, which originates from ecological psychology, explains the action potentials that an object affords a goal-oriented actor (Gibson, 1977). Markus and Silver (2008) expand the notion of affordances within the IS field, highlighting that affordances extend beyond mere technological features. They include purposefully designed capabilities that shape how actors perceive and interact with the technology, enabling them to take actions to achieve specific goals. Therefore, an actor and an object cannot be separated, as an actor is always required as a frame of reference to investigate affordances (Markus and Silver, 2008). According to Markus and Silver (2008), four key elements are crucial for comprehending affordances: (1) the feature of the technical object, (2) the actor, (3) the goal that the actor aims to achieve and (4) the action possibility that the technical object affords to achieve the goal. Material properties are system-related, whereas action potentials pertain to users with specific goals and are reflected in use cases. To provide related background to the research, we first review the literature on AI capabilities to understand the generic material properties, followed by an analysis of studies on AI use cases and affordances in different contexts.

2.1 AI material properties

The beginning of modern AI can be traced to the 1950s (Anyoha, 2017). However, there is no consistent understanding of AI, which complicates the understanding of AI's material properties. Depending on the context, AI has been regarded as a concept instead of an artifact (McCarthy, 2007) or as a property of a system or a set of systems collaborating together to execute specific tasks such as speech recognition and decision-making support in ways like human beings or as a general-purpose technology that offers organisations the potential for wide-ranging improvements and new business opportunities (Holmstrom, 2021; Jöhnk *et al.*, 2021). Despite such differences, researchers identified five generic properties, often referred to as capabilities, of AI: sensing, comprehending, acting, learning and generating (Bawack *et al.*, 2021).

Sensing refers to the ability of AI to perceive and detect changes within a specific operating environment (Bawack *et al.*, 2021). AI has properties for understanding the status of operating environments and recognising the underlying input/output patterns and configurations (Bawack *et al.*, 2021). For instance, while object-detecting cameras in autonomous vehicles offer the ability to "see" object images and videos, ALexa in Amazon Echo speakers can "listen" and process sounds. To equip AI with sensing capabilities, image and video recognition, speech recognition, sensors and biometrics technologies have to be deployed.

Comprehending is another property of AI and refers to AI's capability for recognising underlying patterns, forming hypotheses, inferring and extracting ideas, and generating meaning from unstructured and structured data in a manner consistent with how a human brain works (Silver *et al.*, 2016). For example, advancements in computer vision enable AI to analyse visual content from camera footage or medical images, identify unexpected events or diagnose diseases with precision comparable to human experts (Leone *et al.*, 2020). Similarly, natural language processing (NLP) can analyse text and extract key metadata, such as entities, relationships, concepts, sentiment and context (Bawack *et al.*, 2021). AI's comprehension property mimics the cognitive functions of the human brain and is a key capability that distinguish AI from other technologies (Bawack *et al.*, 2021).

Acting property of AI refers to the ability to perform actions in response to the changing environment in which it operates (Bawack *et al.*, 2021). Although many technologies can execute autonomous actions, AI differs from other technologies because of its ability to respond to environmental changes dynamically, based on the perception and comprehension capabilities, rather than merely adhering to pre-programmed routines (Bawack *et al.*, 2021). In addition to interactive interfaces like conversational chatbots and virtual agents, AI can also act through automation technologies, including robotic process automation (RPA) and robotics, which are designed to automate data entry, transaction processing, customer queries and manufacturing routine tasks.

Learning is the ability to develop, enhance and adapt expertise (Bawack *et al.*, 2021). AI learns from experience and training data (Bawack *et al.*, 2021). For instance, AI-powered intelligent transport systems can predict traffic conditions based on historical data from previous traffic flows, time of day, seasonal variations, weather conditions and major disrupting events such as sports and road closures (Abduljabbar *et al.*, 2019). With advancements in machine and deep learning the learning capabilities of AI have significantly enhanced (Bawack *et al.*, 2021).

Generating refers to the ability to autonomously generate new and meaningful text, audio, images, videos, or other media from training data in response to prompts (Benbya *et al.*, 2024; Feuerriegel *et al.*, 2024). It expands the realm of AI properties in both the workplace and broader society. For example, recent generative AI applications built on large language models can understand the meaning of textual inputs and generate precise responses, effectively handling nuances and complexities of human language (Benbya *et al.*, 2024). The AI capabilities and underlying technologies offer a foundation for different AI use cases which we review next.

2.2 AI use cases and affordances

An increasing number of IS studies have explored the AI use case in various sectors such as manufacturing, education, finance and healthcare. For example, Chen *et al.* (2024) explore the impact of the generative AI online platform on operational and environmental performance of organisations within the Taiwanese manufacturing industry. Van Slyke *et al.* (2023) examine the challenges and potential future scenarios of generative AI tools in the education industry. Yang *et al.* (2023) analyse the differences between classic IT and AI artifacts in the auditing industry, offering insights to enhance human–AI collaboration in auditing. Grüning *et al.* (2023) explore the integration of AI systems into clinical practice in a lab-in-the-field experiment, emphasising the power dynamics between AI and physicians and its impact on technostress and work outcomes. There is, however, a lack of applied research investigating the use of AI in the mobility context.

Instead, literature on AI in mobility has predominantly been from computer science and focused on testing AI algorithms to solve singular mobility problems. For example, Cohen and

Jones (2020) apply an AI approach to understand travellers' mobility behaviours and recommend customised journeys based on travellers' preferences. Goswami *et al.* (2021) propose a protocol for implementing AI with neural networks (NN) for energy-efficient routing in intelligent transport systems. Halim *et al.* (2016) demonstrate how road accidents can be prevented with AI-powered unsafe driving pattern analysis. Mallouk *et al.* (2021) propose a supervised megalitre approach for the predictive maintenance of transport systems. These studies explore AI's potential applications and impacts without addressing the practical material properties of AI that can actively be used by organisations.

Despite the limitations, the extent literature offers the context-specific AI use cases and affordances that leverage different AI capabilities and material properties. In education, AI material properties are used to customise educational content according to individual learning styles and needs (Van Slyke *et al.*, 2023), enhance learning experiences (Brunnbauer *et al.*, 2021) and automate administrative, grading and scheduling tasks to free educators to focus more on educational pedagogy innovation (Alsheibani *et al.*, 2020). AI use cases in finance include risk management, fraud detection and automated trading. AI algorithms analyse large datasets to identify patterns and anomalies improving the accuracy of fraud detection and risk assessment (Yang *et al.*, 2023). Automated trading systems leverage AI to make rapid trading decisions based on real-time market data, optimising investment strategies and maximising returns (Alsheibani *et al.*, 2020, Alshahrani *et al.*, 2022).

In the healthcare, AI-powered diagnostic tools are used to analyse medical images and synthesise patient data for disease detection and diagnosis (Grüning *et al.* (2023). AI algorithms are also used to develop personalised treatment plans based on individual patient profiles. Furthermore, AI is used to accelerate drug discovery by identifying potential drug candidates and predicting their efficacy (Lou and Wu, 2021). In retailing and marketing, emerging AI use cases include analysis of consumer behavioural data to deliver personalised product recommendations and targeted advertising (Wang *et al.*, 2020) and optimisation of pricing strategies to enhance customer satisfaction and operational efficiency (Öksüz and Maass, 2020). In manufacturing, AI material properties have been deployed in inventory and product development, quality and facilities management (Chen *et al.*, 2024) and in predictive maintenance to reduce downtime and costs (Zhou *et al.*, 2023).

The review of literature reveals both industry specific and cross-industry AI use cases and affordances such as personalisation, prediction, automation and optimisation. While these studies have been useful in identifying AI's potential application areas, they do not inform if mobility organisations are actualizing the potentials to resolve real-world problems, the differences among organisations in appropriating AI and the emerging affordances of AI in the context of mobility. Table 1 summarises the implications of the literature review for our study.

3. Research method

Enterprise application of AI in mobility is on the rise, with a number of public and private enterprises adopting AI and embedding AI-based solutions to create a smart infrastructure, intelligent transport operations and automated and personalised services (Abduljabbar *et al.*, 2019; Nikitas *et al.*, 2020). In addition, the mobility sector also faces pressing challenges, which demand transformative digital solutions (Abduljabbar *et al.*, 2019; Davidsson *et al.*, 2016). Furthermore, mobility plays a vital role in advancing SDGs. These include SDG 3.6 on road safety, SDG 9.1 on infrastructure, and SDG 11.2 on providing access to safe, affordable, accessible and sustainable transport systems for all while expanding public transport (UnitedNations, 2015). Despite this significance, empirical research on AI for mobility remains limited, with few studies like Abduljabbar *et al.* (2019) and Nikitas *et al.* (2020) offering overviews of AI applications. To address this, we required a method that facilitates knowledge production in an academic landscape where scholarship is lagging. Therefore, like Bawack *et al.* (2021), we follow a systematic review and analysis of practitioner literature to explore the AI technologies being used in the mobility sector, their material properties and use

Table 1. Implications of background literature

Area of literature	Sample references	Implications for this study
AI conceptions and technologies	Anyoha (2017), Holmstrom (2021), Jöhnk *et al.* (2021), Knowles (2006), McCarthy (2007)	Sensitize us to different representation of AI, which is used in defining keywords
AI material properties and capabilities	Bawack *et al.* (2021), Benbya *et al.* (2024), Feuerriegel *et al.* (2024)	Inform us about different AI technologies and generic capabilities laying the foundation for conceptualizing the AI for mobility material properties
AI use cases and affordances in different contexts	Chen *et al.* (2024), Grüning *et al.* (2023), Leone *et al.* (2020), Van Slyke *et al.* (2023), Yang *et al.* (2023)	The industry and goal specific and cross-industry AI use cases and affordances are used as inputs in informing our data analysis to identify AI in mobility use cases and theorizing affordances
AI in mobility	Abduljabbar *et al.* (2019), Cohen and Jones (2020), Goswami *et al.* (2021), Halim *et al.* (2016), Li *et al.* (2018), Mallouk *et al.* (2021), Nikitas *et al.* (2020)	Sensitize us to specific AI technologies tested in mobility and anecdotal application areas which is used as input in defining search terms and data analysis

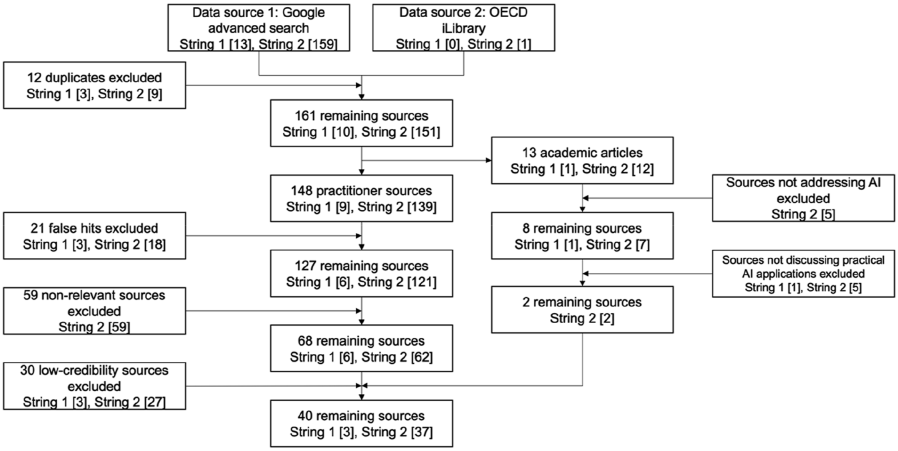
Source(s): Authors' own creation

cases to bridge the lag in present academic studies. This helps to capture current and practical uses of AI in the mobility sector and bridge the lag in present academic studies that mainly discuss potential applications and hypothetical impacts (Adams *et al.*, 2017).

Practitioner literature is a form of grey literature that includes company reports, policy briefs, news articles and white papers produced by professionals and government bodies (Adams *et al.*, 2017). As a secondary source of data, it is less influenced by recollection bias and is useful for exploring emerging innovations and reaching the views of difficult-to-access stakeholders (Adams *et al.*, 2017; Molla and Biru, 2023). These sources can offer detailed accounts of how organisations implement AI technologies to address urban mobility challenges. They often encompass case studies practical applications and experiential knowledge (Adams *et al.*, 2017), which are invaluable for understanding the material properties of AI in practice. Focusing on practitioner literature ensures timeliness and relevance in the rapidly evolving field of AI. It provides actionable insights and case studies that are often missing in academic sources. Additionally, it offers access to a diverse range of materials, enhancing breadth and representativeness while reducing publication bias. The method has been used in identifying AI capabilities (Bawack *et al.*, 2021) and allows a reasonable snapshot of the industry-specific AI implementations, application areas and use cases. Consistent with prior systematic grey literature review guidelines (Adams *et al.*, 2017) and applications (Bawack *et al.*, 2021; Molla and Biru, 2023), we follow the protocol described in Figure 1.

3.1 Source identification and search

3.1.1 Database selection. Since there is no dedicated database for AI and mobility practitioners, we follow an iterative approach in selecting the search database. Initially, we explored several data sources that focus on transport or mobility, including Intelligent Transport Systems Australia (https://its-australia.com.au/), iMove https://imoveaustralia.com/), the European Commission Mobility and Transport (https://transport.ec.europa.eu/index); the Organisation for Economic Co-operation and Development (OECD) (https://www.oecd-ilibrary.org/), Advanced Google (https://www.google.com.au/advanced_search). We tested these potential data sources for providing real-world AI case studies and advanced search functions using



Source(s): Authors' own creation

Figure 1. Process of searching, screening and selection

Boolean algorithms that matched our search terms and strategy. Only Advanced Google and OECD database met these criteria, and were selected.

Advanced Google was selected because it provides access to a wide range of sources (e.g. government websites, industry portals, organisational publications and news outlets) across the Internet with advanced searching options. Likewise, OECD database is a renowned international organisation dedicated to promoting policies offering a comprehensive collection of policy papers, working papers and research reports.

3.1.2 Search strings and delimiters. The definition of the search keywords follows an iterative approach, going back and forth and experimenting with different terms. There are a wide variety of AI technologies and systems. Based on the background review of key material properties in section 2.1, AI technologies such as deep learning, machine learning, neural networks, computer vision, speech recognition and automation are identified (Bawack *et al.*, 2021). To ensure inclusivity, these terms were used to construct the AI-related search strings. Additionally, in the literature on mobility, the terms "mobility" and "transport" are often used interchangeably (e.g. Abduljabbar *et al.*, 2019; Nikitas *et al.*, 2020). Consequently, we incorporated both terms alongside AI-related keywords to define our search strings. Moreover, mobility covers urban and rural aspects.

Urban mobility presents unique characteristics and *t* challenges that differ significantly from those in rural areas (Abduljabbar *et al.*, 2019; Molla *et al.*, 2024). Cities are hubs of economic activity and social interaction, leading to high population densities and increased demand for transportation. This concentration results in complex mobility issues (Abduljabbar *et al.*, 2019; Davidsson *et al.*, 2016). SDGs place a strong emphasis on sustainable urban development. Specifically, SDG 11 aims to "make cities and human settlements inclusive, safe, resilient, and sustainable", with a target to "provide access to safe, affordable, accessible and sustainable transport systems for all" (UnitedNations, 2015). This underscores the global priority given to addressing urban mobility challenges. Besides, urban areas are at the forefront of technological innovation and infrastructure development, making them ideal settings for implementing advanced technologies like AI compared to rural settings (Abduljabbar *et al.*, 2019). As a result, we focus on urban mobility over rural mobility. Therefore, two separate search strings were defined:

> Search string 1: ("AI" OR "artificial intelligence" OR "deep learning" OR "machine learning" OR "neural network" OR "computer vision" OR "speech recognition" OR "automation") AND ("urban mobility")

Search string 2: ("AI" OR "artificial intelligence" OR "deep learning" OR "machine learning" OR "neural network" OR "computer vision" OR "speech recognition" OR "automation") AND ("transport")

In addition, we define search delimiters such as the language to be English and the time period to include 1 January 2015 to 28 February 2022. 2015 was chosen as a cut-off year because the United Nations adopted the 2030 agenda for Sustainable Development, i.e. UN SDG goals. These goals emphasized the importance of sustainable urban mobility and the need for innovative solutions to address transportation challenges, making it a crucial year for mobility discussions. Furthermore, the year 2015 marked notable developments in AI in mobility including Google's Waymo project that introduced a driverless ride on public roads [1] and Tesla's Autopilot, a semi-autonomous driving system, signalling a shift in the automotive industry's embrace of AI [2].

In searching the two databases, we follow procedures specific to each data source. For instance, Advanced Google searches stopped when *"In order to show you the most relevant results, we have omitted some entries very similar to the [N] already displayed"* was displayed. From both Google and OECD, 173 sources were initially identified and exported to excel capturing the year, title, length of document, source, type of document, author, author position (see example in Table 2).

3.2 Screening and selection

For practitioner literature, to screen the quality and relevance, the norm established by relevant studies was followed (Adams *et al.*, 2017; Molla and Biru, 2023). The process involved removing duplicates, false hits, non-relevant sources, and low-credibility sources. While credible sources, i.e. from major news outlets, organisational publications, and government reports were included, others such as undergraduate student written blogs, social media posts, personal and organisational profiles, presentation slides and sources less than one page long were excluded. Non-relevant sources, including those that do not offer a substantive discussion of AI in mobility, were also excluded.

Our search (Advanced Google) has identified 13 academic sources. We screened these academic sources based on two criteria: their focus on AI and the inclusion of case studies demonstrating practical AI applications in mobility. 5 sources do not focus on AI, and 6 sources discuss only hypothetical AI applications in mobility. They were therefore excluded, resulting in 2 academic sources included in the final sample.

Overall, as a result of the screening process, 40 references remained for further analysis, of which one were from OECD, and 2 were academic, and exported to NVivo (See Appendix 1).

3.3 Analysis and interpretation

The analysis commenced with reading the 38 documents and familiarising with the content. Afterwards, an open coding procedure (Gioia *et al.*, 2013) was followed by labelling relevant statements as open codes guided by the two research questions. The abductive approach to qualitative data analysis was adopted to ensure structure and theme from the beginning of coding, while still enabling an inductive exploration of the data cycling back and forth between empirical data and background literature (Linneberg and Korsgaard, 2019). First, the various digital artifacts and technologies such as cameras, sensors, Internet of Things (IoT), computer vision, data analytics, NLP, RPA, robotics, ML, DL and NN, identified from the background literature were searched within the source text and coded. In addition, the names of industry-specific artifacts associated with each of these technologies such as "road cameras", "intelligent traffic control system", "IBM Watson", "Microsoft Azure" were coded as open codes related to the first research question. Statements that depict practical applications of AI technologies such as "counting passenger numbers", "predicting vehicle arrival time", "digitising asset information" and "monitoring transport assets" were identified as open codes

Table 2. An example of the source database

Title	Length (pages)	Source	Type	Author	Author position
Journeys in big data and AI across the transport networks of London and Paris	7	https://www.diginomica.com/	Article	Phil Wainewright	Analyst and consultant
IoT and AI: Transforming Transport Management	4	https://www.iotforall.com/	Article	Manoj Kumar	IoT Expert
Artificial intelligence in transport: Current and future developments, opportunities and challenges	12	https://www.europarl.europa.eu/	Government report	European Parliament	Government
AI Barometer Part 4 – Transport and logistics	10	https://www.gov.uk/	Government report	UK Government	Government
Artificial Intelligence and Road Transport: the beginnings of a fruitful relationship?	6	https://www.girteka.eu/	News	Pavel Kveten	Chief Operating Officer
BusTech Group and SAGE Automation Announce Partnership	6	https://its-australia.com.au/	News	Damian Hewitt	General Manager for Transport
AI business models for travel and transport	9	https://en.acatech.de/	White paper	Susanne Boll	Professor
Machine learning in transport and logistics	13	https://monstar-lab.com/	White paper	Anders Skjøt Kongsbak and Tobias Morville	Strategy Consultant and Head of Machine Learning

Source(s): Authors' own creation

related to the second research question. Appendix 2 provides examples of open codes. As a result of this process, 43 open codes were generated for AI technologies and 71 open codes were created for AI use cases.

To analyse open codes, Lawrence and Tar (2013) and Gioia *et al.* (2013) suggest that the codes be grouped into more abstract categories based on patterns and similarities. These categories become the axes that connect open codes together. This process, known as axial coding, allows for elevating the data to higher degrees of abstraction (Lawrence and Tar, 2013). To identify AI material properties, for example, open codes such as "environmental condition sensors" referred to 3 times, "in-vehicle sensors" referred to 16 times, "traffic monitoring sensors" referred to twice, "transport asset monitoring sensors" referred to 3 times were categorised into a sub-category named "perceiving mobility object conditions". This is because of the shared focus on the sensor-based feature of mobility cognition. Open codes such as "diagnosing asset defects", "digitising asset information" and "monitoring transport assets", led to the formulation of a mid-level category called "mobility asset condition awareness" use case.

Finally, sub-categories with similar themes were grouped into higher-level overarching themes (Gioia *et al.*, 2013). For example, to identify the mobility-specific AI material properties, we draw on the literature reviewed in section 2.1. For instance, the sub-categories that describe the technical features of AI, including "capturing mobility-related visual data", "perceiving environmental changes", and "extracting information from connected devices in transport networks", were combined to derive an overarching material property category named "sensing mobility data". Through this process, four material properties were identified. AI use cases were also conceptualised by combining mobility-specific AI applications in similar areas. For example, the sub-categories that describe AI applications in asset management, including "mobility asset condition awareness" and "mobility asset maintenance scheduling", were aggregated into a higher-level use case called "undertaking smart infrastructure and asset management". Figure 2 shows the findings.

4. Findings

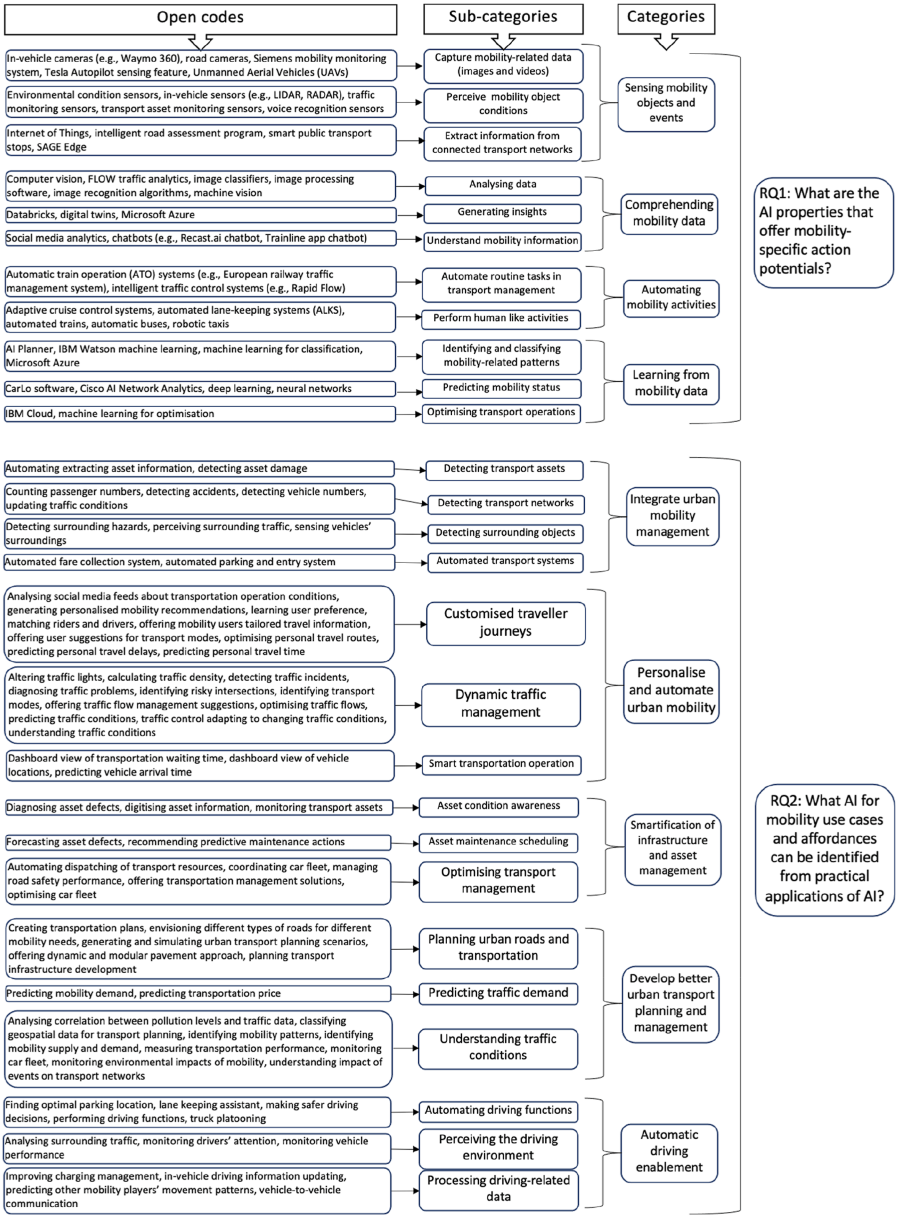
4.1 Mobility-specific AI material properties

The findings show that AI offers mobility organisations at least four material properties including sensing mobility objects and events, comprehending mobility data, automating mobility activities and learning from mobility data, as shown in Appendix 3.

4.1.1 Sensing mobility objects and events. Sensing mobility objects and events refers to the material property of AI in capturing, perceiving and extracting mobility-related information. This involves using cameras, sensors and connected devices that record various types of data (image, audio, video, temperature, etc.). First, visual recognition AI captures and processes visual data from the environment. This includes various technologies and systems, such as UAVs, in-vehicle and road cameras, image recognition technologies, the Siemens mobility monitoring system, and the Tesla autopilot sensing feature. Visual recognition AI can *"differentiate 2D images such as road signs and markings that LIDAR and RADAR cannot discern and cameras coupled with image processing software use convolutional neural networks for object detection"* (Ricardo, 2018).

Second, sensor-based mobility object condition offers a comprehensive understanding of the mobility operating environment. The sensors include environmental condition sensors, in-vehicle sensors, traffic monitoring sensors, transport asset monitoring sensors and voice recognition sensors. The most notable example of this feature is the connected and autonomous vehicle (CAV) that can sense its surrounding objects – *"a CAV has the opportunity to far exceed our ability to perceive the surroundings due to the sensing technologies employed in its "sensor suite". This includes cameras, radars, ultrasonic sensors, and for Level 3 and beyond, LIDARs"* (Ricardo, 2018). Finally, the AI feature of extracting information facilitates the continuous acquisition of mobility-related data through interconnected devices and systems in transport networks. Examples include FLOW, the Intelligent Road Assessment Program, IoT databases, SAGE Edge and smart public transport stops. The captured information is afterwards transmitted to the AI system's reasoning part for further processing.

4.1.2 Comprehending mobility data. The material property of AI in comprehending mobility-related data is reflected in the features of analysing visual data pertinent to mobility, generating insights from such data, and understanding and responding to mobility information presented in human language. First, mobility visual data analysis contains extracting meaningful information from images, videos, and other visual inputs. There is a large amount of visual data streaming through various dimensions of the mobility sector, for example, road cameras, IoT devices and CAVs (Docherty *et al.*, 2018). AI can obtain specific patterns from visual data. For example, *"Machine Vision can be used to classify geospatial data, automatically identifying different types of land use or property, improving map data"* (UK Government, 2021).



Source(s): Authors' own creation

Figure 2. Data structure

Second, the feature of generating and visualising insights from mobility-related data is offered by data analytics tools. One example is digital twins that create a digital representation of transport assets, infrastructure and systems to enable operators to "*assess the overall condition of the systems through their entire lifecycle (degradation of assets, failure, customer behaviour)*" (European Parliament, 2019). Third, the feature of understanding human language and responding to conversational prompts naturally has been utilised to extract mobility-related feeds from social media and interact with users via chatbots.

4.1.3 Automating mobility activities. Automating mobility activities refer to the material property of AI in automating repetitive and routine tasks in transport management, as well as performing driving activities. For example, Automatic train operation (ATO) systems exemplify this feature by automating the control of train movements with optimal speeds: "*ATO technology has been developed to enable trains to operate even without a driver in a cab, either with an attendant roaming within the train or with no staff on board*" (Chatzimichailidou and Dunsford, 2021). Traffic signal control systems, like Rapid Flow and AI are used "... *to manage large amounts of information analyse data about traffic flow, weather patterns, and road conditions in order to optimise signal timing and make quick decisions, g*" (Kuruvilla, 2022).

AI is also taking on the role of a driver with no or limited human intervention, mimicking human decision-making and actions on the road. In addition, vehicular robotics automate vehicle operations including adaptive cruise control systems, automated lane-keeping systems, automated trains, automatic bus and robotic taxis.

4.1.4 Learning from mobility data. Learning from mobility data refers to the material property of AI in learning from experience without being explicitly programmed. This is reflected in the features of identifying mobility-related patterns, predicting mobility status, and optimising transport routes and operations. Identifying mobility-related patterns involves uncovering hidden patterns from mobility data and grouping this information to generate insights for transport operation and management. For example, Microsoft Azure, a megalitre application, has been used by Transport for NSW (TfNSW) to "*flag potentially dangerous intersections and reduce road accidents*" (Chanthadavong, 2021). AI such as NN create deep and complex models of large amounts of previous mobility-related data points and detect nonlinear relationships to "*predict traffic conditions*" (Shivani, 2021). Furthermore, "*ANN models are used in public transport to help predict arrival times for buses at stop areas*" (Conde and Twinn, 2019). AI also offers the ability to optimise transport routes and operations through the analysis of large volumes of mobility data: "*machine learning is being used in the optimisation of routes in real time to avoid congestion*" (Trudgian, 2021).

4.2 AI use cases in mobility

Our result shows that the exploitation of the in-context material properties of AI and AI-enabling technologies is making possible five mobility-specific AI use cases: (1) integrating urban mobility management, (2) personalising and automating urban mobility, (3) smartification infrastructure and asset management, (4) developing better urban transport planning and management and (5) enabling automatic driving, presented in Appendix 4.

4.2.1 Integrate urban mobility management. The urban mobility management use case focuses on the detection of transport assets, networks and vehicles' surrounding objects to offer a comprehensive urban transportation landscape. Mobility organisations are exploiting the AI material property of sensing mobility objects and events to monitor transport assets and networks, and technologies such as cameras, sensors, and computer vision to detect objects around vehicles. Public transport infrastructure operators in Australia and the European Union (EU) employ computer vision-based applications to automatically detect transport infrastructure assets (e.g. roads, tunnels, and bridges) and understand and manage the existing transportation infrastructure effectively thus enhancing safety. For example, VicRoads, a transport infrastructure operator of Victoria, Australia, employs "*Asset Vision that uses footage captured by vehicle-mounted cameras to automatically detect, categorise, and assess the condition of road assets, including signs, line marking, trees, and safety barriers, as well as the road surface itself*" (Hamid, 2022).

Organisations such as BusTech Group, Transport for London and Bengaluru Transport Authority, Alibaba are gathering and using data to map transportation networks to improve traffic flow.

> In Bengaluru, India, where traffic jams are common, Siemens Mobility built a monitoring system that uses AI through traffic cameras that detect vehicles and calculate the density of traffic on the road and then alter traffic lights based on real-time road congestion. Alibaba, China's e-commerce giant, launched "City Brain" to minimize road congestion, utilizing data from traffic lights, CCTV cameras, and video recognition to make suggestions for traffic flow management. (Shivani, 2021).

Transport authorities and operators are also using computer vision-based visual recognition software to enhance traffic management systems by diagnosing traffic problems. For instance, *"Alibaba, China's e-commerce giant, launched 'City Brain' to minimise road congestion, utilising data from traffic lights, CCTV cameras, and video recognition to make suggestions for traffic flow management"* (Shivani, 2021). Based on that, cities like Xi'an Transport Authority maps and analyses the correlation of specific mobility patterns with traffic data from video cameras, and incorporates megalitre into traffic signal and management systems to detect and forecast traffic problems:

> The Chinese city of Xi'an is implementing intelligent traffic management services, using a network of surveillance cameras to monitor traffic violations, predictively identify potential traffic events before they happen using large volumes of road condition and camera data, and dynamically alter the timing of signal lights to optimise the flow of vehicles. (UK Government, 2021)

4.2.2 Personalise and automate urban mobility. Mobility organisations are also using AI in personalising and automating urban mobility to offer customised travel recommendations and manage traffic and transportation operations dynamically. For example, organisations such as the Geneva Administrative Council and Kentkart are embedding cameras and sensors to automate transport systems to process charges.

> Geneva boasts a very efficient smart parking system, deployed through a network of sensors, lowering the number of vehicles searching for a place to park by 30%. (EuropeanParliament, 2021)

Others such as Klaxit, SEAT, Transport for London, Google, Linde, Uber, Lyft, BusTech Group, Via and Soloplan are building on integrating urban mobility management by exploiting AI's material properties such as comprehending mobility data, automating mobility activities, and learning from mobility data to provide personalised travel recommendations through mobile apps, websites and social media. Urban mobility solution providers, such as Uber and Lyft *"use AI in multiple ways to provide reliable pickup and drop-off times for their routes"* (Conde and Twinn, 2019). Trainline, a rail booking service provider in Britain, uses AI to

> . . .generate personalised alerts about travel disruption to users of its mobile app [. . .] with analysis of the Twitter feeds published by all of the UK's various train operating companies. Using natural language processing, AI automatically works out which tweets are important, and then analyses where the disruption is having an effect. The next step is to match that analysis to individual journeys. This then feeds through to the Trainline voice app, which is designed for use by travellers on the move (Wainewright, 2018).

In another example, SEAT, a Spanish passenger car company has partnered with IBM to launch "Mobility Advisor", a new AI-powered solution designed to help urban citizens identify patterns, generate insights and make informed decisions *"about their daily transportation options: from cars, to scooters, to bikes and public transport"* (Volkswagen, 2019).

Furthermore, organisations such as Xi'an Transport Authority, Rapid Flow Technologies, Alibaba, Bengaluru Transport Authority, Google, Linde, BusTech Group, Alstom, Transport for NSW (TfNSW) and Uber are exploiting the material properties associated with predictive analytics and AI algorithms for dynamic traffic management and efficient operation of transport networks to improve traffic congestion and reduce emissions. One example is:

> Surtrac from Rapid Flow Technologies, a Carnegie Mellon University spinoff, provides solutions for intelligent traffic signal controls. It has coordinated traffic flows at a network of nine traffic signals on three major roads in Pittsburgh. Rapid Flow helped reduce travel times by over 25 percent on average

> and wait times declined by an average of 40 percent. It also reduced emissions by 20 percent. (Shivani, 2021)

Besides, organisations are using advanced AI solutions to provide operators with a dashboard view of vehicle locations and real-time travel plans including optimised routing and transport resource allocation, based on real situations and predictions of incidents and travel demand. An example is that a program jointly developed by SAGE and BusTech Group:

> SAGE's IoT data capture device, SAGE Edge, has been installed onto buses and vehicle infrastructure such as bus stops. Data captured by the device provides a range of information to benefit drivers, operators and passengers alike, such as real-time traffic condition updates and traffic event notifications. Transport network operators will obtain a dashboard view of vehicle placement on the grid, real-time and trend data on passenger numbers on services and waiting time at bus stops. (ITSAustralia, 2020)

4.2.3 Smartification of infrastructure and asset management. The third use case of AI is the smartification of infrastructure and asset management. Mobility organisations that manage assets are exploiting the AI material property of sensing mobility objects and events, comprehending mobility data and learning from mobility data to understand transport asset conditions and schedule maintenance.

To support asset condition awareness, organisations such as Laing O'Rourke, Transport for NSW, AtkinsRéalis, and BusTech Group are using AI including sensor technologies, computer vision and digital twins, combined with *UAV or drones* to detect "roads, tunnels, and bridges infrastructures" (EuropeanParliament, 2021). In addition, organisations are creating digital twins of transport infrastructure to digitise asset information. For example, Laing O'Rourke, an international engineering company, uses AI to

> create a railway clone, integrating IT, operational and engineering technologies to assess the overall condition of the systems through their entire lifecycle (degradation of assets, failure, customer behaviour), including information on possible design and manufacturing enhancements and . . . scheduling maintenance work (EuropeanParliament, 2019).

Other organisations such as SNCF, and BusTech Group are exploiting the AI material property of learning from mobility data for maintenance scheduling. Specifically, they use DL for *"damage detection, damage prediction, damage classification, damage localisation, condition assessment, and lifetime prediction"* (EuropeanParliament, 2021). Furthermore organisations, such as the French operator SNCF, have employed AI technologies such as ML and DL for predictive maintenance:

> apply predictive maintenance enabled by deep learning to pantographs that can become fragile due to the wear effect... predictive maintenance also allowed incidents involving train switches to be reduced by 30%, and this technology has been applied to many train systems and subsystems (EuropeanParliament, 2019).

4.2.4 Develop better urban transport planning and management. AI is also used to develop better urban transport planning and management with a deep understanding of traffic conditions, plan urban roads and transportation, predict traffic demand and optimise transport management.

To start with, organisations such as Linde, Girteka, BusTech Group, Transport for NSW, AtkinsRéalis and Uber are exploiting the AI material property of learning from mobility data to understand and predict traffic support planning and design process and redistribute resources to match the transport supply with the mobility demand. Particularly, by identifying both transit mobility patterns and local urban function information transport authorities such as the TfNSW make informed decisions. The TfNSW has employed Cisco's AI Network Analytics to *"investigate vehicle supply and customer demand, and performance in a real-time view, which guide future network decisions"* (Chanthadavong, 2021). Transport Malta applies *"AI and data analytics in transportation planning to provide an adequate* *infrastructure for pedestrians and cyclists to safely travel from one destination to the other"* (Lubrano, 2021).

Moreover, mobility organisations are leveraging the forecasting feature of AI to predict mobility demand and thus adaptively allocate transport resources to accommodate mobility needs. For instance, Transport for London employs the "GrowthPlanner" tool to *"understand demand, trends, and flow of transport infrastructure usage, using ticketing and geolocation data and predictive analytics to identify future system needs"* (UKGovernment, 2021). Urban mobility service providers like Uber have gathered *"masses of data to make predictions about market demand and find optimal routes for drivers"* (VerdictAI, 2017). Alstom provides transport operators such as Dubai Transport Authority, with AI solutions for adaptive transport resource distribution:

> By compiling data from technology such as signalling systems, flow management systems and centralised operational control centres, operators see the impact of certain events from the pandemic to daily influences such as weather, sports matches and traffic on passenger flows. Advanced AI solutions then suggest solutions to operators for reducing congestion and redistributing resources during these events.. (ALSTOM, 2021)

In order to solve transport underutilisation and enable efficient use of transport resources, transport operators are employing AI technologies to *"improve fleet effectiveness and thus allow the use of fewer vehicles on the ground and less CO2 emissions"* (Kentkart, 2021). One instance is that *"Dubai boasts a long list of smart mobility solutions enabled by deep learning, including a bus on-demand service, in selected areas of the city, which success has been proved by a trial assessing response time, transit time, passenger accessibility, affordability, convenience, safety, resident opinions, and user experiences"* (EuropeanParliament, 2021).

4.2.5 Automatic driving enablement. Enabling automatic driving is one of the most pertinent uses of AI in mobility. Traditional automotive manufacturers like BMW, new entrants like Tesla, technology companies like Google, and new-age mobility service providers such as Uber and Didi Chuxing that aim to establish their own fleets are exploring AI technologies to develop CAVs. Based on visual and vehicle performance telematics data collected from IoT and an array of sensors these organisations are enabling vehicles to sense and analyse their location and other objects around them, interpret traffic signs and signals, and monitor vehicle performance. For example, *"a self-driving electric shuttle by an American company is being powered by IBM's Watson and its Internet of Things database to analyse the surrounding traffic and make decisions based on that data"* (Lubrano, 2021). The collected data are processed to understand other mobility players' intentions and predict movement patterns, *"including predicting the behaviour of other vehicles and pedestrians"* (UKGovernment, 2021). Furthermore, using AI software and megalitre and DL techniques, these organisations are enabling vehicles to simulate human thoughts, make safe driving decisions and perform driving functions with appropriate speeds and directions. For example, *"Tesla has used AI in its Autopilot feature, which monitors things like road lines; other vehicles; and the cars around it to keep drivers alert and make safer decisions"* (Kuruvilla, 2022). This approach works by teaching the vehicle how to drive while maintaining safe headways, lane discipline and control.

5. Discussion: theorising affordances of AI for urban mobility

This study explores AI's material properties that afford mobility-specific action potentials and unravels use cases from practical AI applications. The findings reveal specific technologies and systems that are applied in the mobility sector, including cameras, sensors, IoTs, computer vision, data analytics, NLP, RPA, robotics, ML, DL, NN. These AI and AI-enabling technologies present mobility-specific material properties including sensing mobility objects and events, comprehending mobility data, automating mobility activities and learning from mobility data. These features align with Bawack *et al.* (2021)'s categorisation of AI capabilities.

The findings also show that a wide variety of organisations are using AI technologies and systems. These organisations include urban transport infrastructure authorities (e.g. Transport for London and Bengaluru Transport Authority), urban transport operators (e.g. SEAT and SNCF), urban mobility solution providers (e.g. Uber and Lyft) and automotive manufacturers (e.g. BMW and Tesla). To pursue their goals, some shared and some organisation specific, these organisations are deploying AI's material properties in five areas of applications that were historically either impossible, costly or difficult to achieve by traditional digital artifacts (Yang *et al.*, 2023). Overall, at the time of the study, mobility organisations were exploring and exploiting AI's material property for integrating urban mobility management to offer a comprehensive urban transportation landscape. While AI's features to sense, comprehend and learn mobility data are helping mobility organisations to personalise their services, the automating and sensing features of AI are deployed in enabling automatic driving. On the other hand, relatively, the organisations were yet to fully explore the different material properties of AI to develop better urban transport planning and management.

Based on these observations, we offer a theorisation of the affordances of AI for mobility (AI4M affordances). The theory of affordances refers to the potential actions or possibilities that an environment offers to an *organism*, often highlighting the interaction between the organism (goal-seeking actor) and the environment (Gibson, 1977). Technology affordances in particular are action potentials that a technological artifact affords an actor in pursuit of the goal through its material properties (Robey *et al.*, 2012).

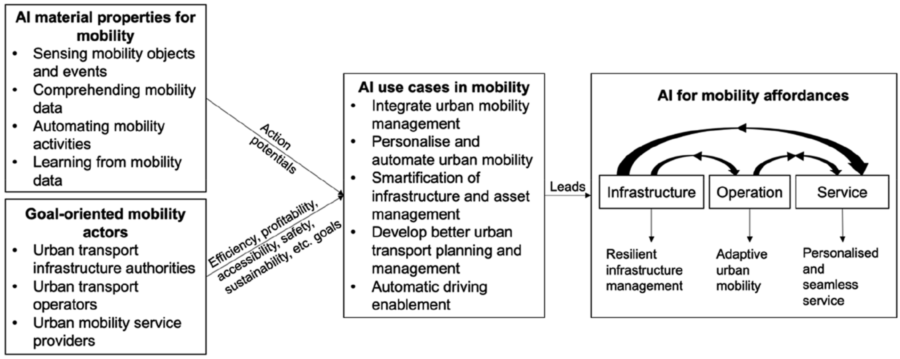
The various urban mobility organisations highlighted in the findings are "organisms", i.e. goal oriented actors. These organisations pursue a range of goals. Some of these goals such as efficiency, customer retention, profitability are specific to the line of business and their role in the mobility ecosystem (Nikitas *et al.*, 2020). Other goals are shared across different mobility organisations and aligned to the UN SDGs goals to make urban mobility accessible, efficient, safe and sustainable (UnitedNations, 2015).

The various AI technologies and material properties can be considered as the features of the "environment". The data analysis shows several AI technologies that possess four material properties in the urban mobility context. Mobility actors' goals and the AI4M material properties shape the five key areas of AI applications in urban mobility.

By combining the "organism" and the "environment" three high-level and hierarchically interconnected AI4M affordances emerge: at the infrastructure, operation and service levels as (1) potential for resilient mobility infrastructure management, (2) potential for adaptive urban mobility operations and (3) potential for personalised and seamless mobility service. At each of these levels, specific AI material properties need to be perceived by mobility actors in alignment with organisational and SDG goals. Since affordances are action potentials for goal-oriented actors, the three affordances do not pre-exist in AI itself but emerge through mobility actors' evaluation of AI's material properties to achieve their goals. This perspective aligns with the emergent view of affordances (Markus and Silver, 2008). Furthermore, the affordances at the infrastructure level facilitates the actualisation of operational and service level affordances. Likewise, the affordance actualized at the service level facilitates the actualisation of affordances at the operation and infrastructure levels. Figure 3 presents our theorisation of AI4M affordances.

5.1 AI potential for resilient mobility infrastructure management

This affordance emerges from the application of AI's properties of sensing mobility objects and events, comprehending mobility data, and learning from mobility data for smartification of infrastructure and asset management and integrating urban mobility management. It reflects a mobility organisation's ability to exploit AI's property to sense and understand real-time conditions of the urban mobility environment to manage and maintain urban mobility infrastructure efficiently and resiliently through predictive maintenance and smart asset management. The concept of predictive maintenance has been discussed in the literature



Source(s): Authors' own creation

Figure 3. Theorisation of AI4M affordances

(Mallouk *et al.*, 2021; Zonta *et al.*, 2020). Transport infrastructure organisations can exploit AI's ability to sense and comprehend mobility data to predict the maintenance needs of infrastructure and assets. By doing so, these organisations can proactively address potential issues, reduce downtime and improve the safety and efficiency of urban mobility systems (Mallouk *et al.*, 2021; Zonta *et al.*, 2020).

5.2 AI potential for adaptive urban mobility management

This affordance emerges from AI's features of sensing, comprehending, automating and learning from mobility data in the integration of urban mobility management, development of urban transport planning and automatic driving enablement. It reflects a mobility organisation's ability to analyse and comprehend large volumes of mobility data for strategic decision-making and proactively manage urban mobility through predictive insights in real-time. To improve the efficiency of operations, mobility organisations can exploit AI's material properties to gain insights from transport assets, networks and services. They also can leverage AI's material property of automating mobility activities to automate repetitive and routine tasks in transport management and operation such as driving in public or controlled environments. Urban transport authorities can exploit the material properties associated with predictive analytics and AI algorithms for dynamic traffic management and efficient operation of transport networks to optimise traffic flow and improve traffic congestion (Ali *et al.*, 2019; Goswami *et al.*, 2021). Transport operators and service providers can use AI for efficient management of transport resources, which helps to achieve not only operational efficiency but also sustainability goals.

5.3 AI potential for personalised and seamless mobility services

This affordance refers to the ability to integrate various modes of transport to offer seamless mobility services tailored to individual user needs and changing conditions. It emerges from the application of AI for personalising and automating urban mobility and enabling automatic driving. Personalisation is key in service delivery (Docherty *et al.*, 2018). For instance, similar to education and retailing, where AI enables educators and retailors to customise learning experiences and customer interactions (Van Slyke *et al.*, 2023), AI affords that ability to personalise travel plans and recommendations. Urban mobility service providers can deploy AI in integrating urban mobility management to understand users' mobility patterns and preferences and predict traffic conditions to offer customised travel recommendations across various mobility options.

6. Contribution and conclusion

AI is regarded as a promising solution for addressing urban mobility challenges. Despite a growing body of research on AI applications across various sectors, its use in the mobility sector remains underexplored. This study investigates AI applications in the urban mobility sector to identify the in-context material properties and use cases that offer mobility-specific affordances. Based on the findings, we have theorised AI for mobility affordances.

6.1 Contributions

The study makes both theoretical and empirical contributions that advance the understanding of AI. Theoretically, the study extends the affordance theory by proposing hierarchically interconnected affordances, adding to the notions of cascading affordance (Zeng *et al.*, 2020). Similar to Zeng *et al.*' (2020) conception of cascading affordances, the research reveals that the emergence of some affordances depends on the emergence of other affordances. Transport infrastructure is essential in any transport system. It supports transport operation and allows the provision of mobility services to customers. Likewise, insight from mobility service and behaviour is essential to create an adaptive transport operation and enhance the resilience of the infrastructure. Therefore, while the AI affordance at the service level relies on infrastructure and service level affordances, it, in return, contributes to actors' comprehension and subsequent actualisation of lower-level affordances. By demonstrating such hierarchy and interconnectedness among affordances, we extends IS studies (Du *et al.*, 2019; Leidner *et al.*, 2018; Trocin *et al.*, 2021) that conceptualised second-order affordances through the aggregation of first-order affordances but not the inter-dependencies.

The hierarchical conception of AI for mobility affordances lays the foundation for ongoing scholarly research on AI and mobility. It is crucial for managers, both individual executives and collective top management teams (TMTs), to understand how AI technologies can enhance critical internal and external processes while exploring and exploiting these technologies. Using the affordances identified in this paper, researchers can examine how mobility managers and TMTs perceive valuable areas for applying AI to achieve goals that would otherwise be difficult or impossible without such technologies. However, it is important to note that affordances do not guarantee results, they represent possibilities for action rather than actual actions or outcomes (Strong *et al.*, 2014). Many mobility organisations face challenges such as resource reorganisation delays, limited technological capabilities and a lack of AI leadership. These issues can hinder the renewal of their organisational capabilities and processes. Our theorisation of AI affordances for mobility can be used to advance the understanding of the affordance actualisation challenges that mobility organisations must overcome to benefit from AI fully.

Beyond the mobility context, our conceptualisation of hierarchically interconnected AI affordances holds significant value. As environmental, social and governance (ESG) pressures continue to increase, many organisations strive to leverage AI to enhance efficiency, decarbonize operations and improve social impact. According to the balanced scorecard perspective, organisations can be viewed as interconnected systems comprising hard and soft infrastructure, business processes and customer experience (Kaplan and Norton, 2001; Molla, 2013). Researchers interested in exploring AI affordances within organisations and in the context of ESG can adapt our hierarchically interconnected conception of affordances to investigate AI's opportunities for managing both hard (such as digital platforms) and soft (human resources) infrastructure, enhancing business processes, and improving service delivery. This approach offers a comprehensive understanding of the application and value of AI in these contexts, ultimately contributing to ESG performance and sustainable development.

Empirically, our findings add to existing understanding of the use of AI in various industries taking the urban mobility context. Unlike existing literature on AI in mobility, which is predominantly discussing either potential or experimental applications, we offer an empirical insight from the practical applications of AI. Specifically, we present a theoretical understanding of four AI material properties and five use cases. Our contribution shows that, AI use cases in mobility exhibit uniqueness and similarities to those in other sectors. The uniqueness primarily stems from the necessity to perceive mobility objects, assets and infrastructure. This requirement is more pronounced in the mobility sector compared to other sectors since it serves as a prerequisite for other use cases. On the other hand, the use of AI for customisation and personalisation of travel plans and recommendations is similar to other sectors such as education, healthcare and retail. Other researchers can build on this contribution to identify the unique material properties and use cases of AI for informed decision making.

We also contribute to extending the existing understanding of the effective use of AI in the context of urban mobility through the affordance perspective, thereby contributing to the limited IS studies on AI in this field. In this study, we theorised three AI affordances that can potentially transform urban mobility and contribute to the achievement of SDGs. This structured approach can guide other researchers in exploring the role of AI in mobility and SDGs.

Finally, by providing empirical evidence and a theoretical framework grounded in practical AI applications, we lay the groundwork for future scholarly research on AI in mobility. By connecting AI properties and use cases with mobility-related SDGs from an affordance perspective, our study avoids deterministic views of technologically induced urban mobility transformations while also preventing an overemphasis on social determinism that overlooks the material properties of AI technology itself. Future research investigating AI in mobility can be conceptualised through our hierarchical AI4M affordances framework to identify important features of AI and how they can be strategically leveraged by specific actors to achieve goals, address the challenges of urban mobility and advance SDGs. In addition, this study emphasises that mobility actors must perceive AI material properties in alignment with organisational and SDGs. This insight highlights the need for future research to examine how mobility actors perceive AI affordances for mobility, the factors influencing their perceptions and the consequences of these perceptions. Furthermore, affordances do not guarantee results, as they represent potentials for action rather than actual actions or final outcomes (Strong *et al.*, 2014). Therefore, to convert possibilities into results, goal-oriented mobility actors must engage in purposeful actions to utilise AI for desired outcomes. This necessitates research into how mobility actors adapt and develop their capabilities to actualise AI affordances.

6.2 Implication to practice

For practitioners, the insights from this study underline the importance of reviewing and investigating practical features of specific AI technologies and systems that have been applied in the mobility sector to set realistic expectations for AI deployments. The empirically grounded findings offer mobility organisations actionable guidance to explore viable AI technologies that align with their operational needs and strategic goals to collectively transform urban mobility to be affordable, efficient and sustainable.

6.3 Limitations and future research

Despite its contributions, the study has limitations that open opportunities for further research. First, the reliance on practitioner literature, while valuable for gaining practical insights, might introduce biases due to the non-peer-reviewed nature of some sources. Besides, the evidence included in this study is derived from limited databases. Expanding the range of databases and incorporating more primary sources can be beneficial. Second, the study does not target any particular country. Future studies can select a specific region to ensure a consistent socio-political, regulatory, policy and market environment. Moreover, the rapid evolution of AI technologies means that the findings might be temporal and require further research to remain relevant. Furthermore, the generalisability issue arises because the findings and theoretical insights are derived exclusively from the context of mobility. Consequently, additional research is needed to explore other contexts beyond mobility. Future studies can adopt this approach to conceptualise hierarchical AI affordances in various sectors like healthcare where AI is implemented.

6.4 Conclusion

This study analysed the practical applications of AI and contributes to the understanding of the AI properties, use cases and affordances that offer mobility-specific action potentials. Future research investigating this topic can be conceptualised through our three-level AI for mobility affordances framework to identify important features of AI and how they can be leveraged by specific actors to achieve strategic goals, address the challenges of urban mobility and advance SDG goals. This study provides a foundation for future scholarly research on AI in mobility and highlights areas where further inquiry is needed, such as AI affordances perception and actualisation in mobility organisations, the role of organisational actions in leveraging AI and the impact of AI on urban mobility outcomes.

Notes

1. https://waymo.com/intl/zh-cn/waymo-driver/
2. https://teslamotorsclub.com/tmc/threads/historical-timeline-for-autopilot-and-fsd-development.295292/

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Supplementary material

The supplementary material for this article can be found online.

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