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The effects of infrastructure quality on the usefulness of automated vehicles: A case study for Leeds, UK

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ABSTRACT

With rapid advancements in automated driving technologies, there is a growing emphasis on enhancing physical and digital infrastructure to ensure safe and efficient integration of Automated Vehicles (AVs) into road networks. This study conducts the first exploratory analysis of the impact of heterogeneity in road infrastructure readiness on the usefulness of AVs for urban commuting, with a focus on Leeds, UK. Employing a hypothetical scenario where current car commuters have access to AVs for their daily trips, this research explores possibility of replacing commuting trips by AVs, given the existing levels of infrastructure readiness. Through the evaluation of various road network configurations and AV capabilities, the study evaluated the usefulness of AVs for such journeys. The findings reveal that infrastructure readiness levels significantly impact AV performance and usefulness, potentially necessitating infrastructure upgrades to facilitate future AV deployment. The analysis indicates that relatively less challenging paths for AVs tend to be longer than those typically used by human-driven vehicles, with an increase of approximately 5 miles (8 km) in travel distance for some origin-destination pairs. Despite only 20 % of road links being classified as extremely challenging within the network, their dispersed distribution resulted in significant connectivity barriers, rendering a considerable number of trips infeasible for AV navigation. The research findings can provide valuable insights to help understand the integration of AVs into road networks and assist decision-makers and transport planners in developing informed and forward-looking policies, regulations and guidelines.

1. Introduction

Automated Vehicles (AVs) are expected to bring transformational changes in transport and society by transferring some or all of driving responsibilities from human drivers to computer based systems. This paradigm shift is promising an array of potential benefits, including enhanced road safety and efficiency, improved accessibility and productivity for individuals, and a reduction in energy consumption (Fagnant and Kockelman, 2015; Harb et al., 2021; Milakis et al., 2017; Wadud et al., 2016). However, the realisation of these benefits crucially hinges on the safety assurance of the Automated Driving System (ADS), which manages the dynamic driving tasks at Level 3 automation and above (SAE International, 2021). As underlined by Madadi et al. (2021), many studies have examined the impacts of AVs under the scenario where the entire vehicle fleet is fully automated (Level 5), with an unlimited Operational Design Domain (ODD).[1] As such the primary benefits are derived from the ability of Level 5 AVs to navigate the entire road network under all conditions without human intervention. Nonetheless, achieving a high market penetration rate of fully automated vehicles is expected to be a gradual process, potentially spanning several decades (Bishop, 2024; Litman, 2023; Saeed et al., 2021).

The successful integration of AVs into road systems necessitates comprehensive preparation across multiple fields, including transport infrastructure, policy and legislation, technological innovation and consumer acceptance (Rashidi et al., 2020; Tengilimoglu et al., 2023a). Among these, the role of infrastructure in facilitating automated

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[1] Broadly, the ODD is characterised as the specific operational conditions under which a particular driving automation system is designed to function. This encompasses factors like environmental constraints, geographical boundaries, time-of-day limitations, and specific traffic or road attributes (SAE International, 2021).

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driving[2] has been underestimated in the last decade (Farah et al., 2018; Tafidis et al., 2021). The main effort in the domain has largely been vehicle-centric, with safety and reliability concerns predominantly assessed from the perspective of the vehicle itself. Nonetheless, there is an emerging consensus among stakeholders on the critical role of infrastructure, especially digital infrastructure, in paving the way for the deployment of highly automated (Level 4) vehicles,[3] i.e. vehicles that do not require fallback to a human driver (Tengilimoglu et al., 2023b). Similarly, empirical studies examining current AV trials (Klauer et al., 2023; Ramanagopal et al., 2018) and analyses of AV-involved accidents or disengagement reports from AV manufacturers (Ye et al., 2021) underscore that AVs require road infrastructure that is conducive to their operational needs.

On the other hand, the operation of AVs to date has largely been confined to testing and piloting initiatives within specific geographical areas, characterised by well-defined road types and relatively less complex driving environments under a certation weather conditions (Erdelean et al., 2019). This strategic limitation has been instrumental in fostering repeated experiences crucial for learning and continuous improvement, essential for unlocking automation benefits. However, it has concurrently constrained the geographical spread of automated services offered by developers (International Transport Forum, 2023a). As AVs become more prevalent across a broader section of the road network, identifying the types of infrastructure that could enhance their safety-critical functions becomes important (International Transport Forum, 2023a). Addressing these questions will likely be vital for acquiring essential insights into AVs' safe and efficient integration into the roadway ecosystem, including connected and intelligent systems.

In response, road authorities and safety organisations globally are exploring the potential infrastructure upgrades or adjustments that will likely accelerate the deployment of AV operations effectively (Gopalakrishna et al., 2021; Huggins et al., 2017; PIARC, 2021; Santec and ARA, 2020). Additionally, many studies have provided extensive lists of possible infrastructure modifications to support the safe integration of AVs, drawing on comprehensive literature reviews (Farah et al., 2018; Liu et al., 2019; Tengilimoglu et al., 2023c) and expert opinions (Lu et al., 2019; Tengilimoglu et al., 2023b; Wang et al., 2022). Implementing these infrastructure adjustments, however, presents complex challenges that demand substantial resources and financial investment. Therefore, many studies have attempted to use optimisation or cost-benefit analysis to determine the most cost-effective network-wide plan for the deployment of AVs. Such research has led to the proposition of various policies and infrastructural strategies tailored to AV-compatible road systems (Madadi et al., 2021; Manivasakan et al., 2021), including the establishment of dedicated AV lanes (Razmi Rad et al., 2020), designated AV zones (Conceição et al., 2017), and AV-ready subnetworks that facilitate mixed traffic or hybrid configurations (Madadi et al., 2019, 2021).

However, to minimise the cost of infrastructure investment, evaluating the readiness level of current road sections is also critical in order to formulate a more economical plan. This consideration is particularly relevant given the financial constraints faced by infrastructure owners and operators in maintaining their roads to a certain quality standard (Tengilimoglu et al., 2023a). To this end, recent research efforts have focused on developing and applying assessment frameworks to evaluate the readiness of both physical and digital road infrastructure for supporting the safe operation of AVs (Cucor et al., 2022; Soteropoulos et al., 2020; Tengilimoglu et al., 2024). These studies have uncovered significant diversity within the road network, ranging from highly structured environments with robust infrastructure support to those less structured, with limited or no support. Yet, to date, no study empirically assessed the impact of infrastructure readiness levels on the usefulness and performance of AVs.

This research aims to fill this gap by focusing on the variations in the readiness of road sections in the network. To the best of the authors' knowledge, this study represents the first exploratory research evaluating the potential impact of heterogeneity in road infrastructure readiness on the use of AVs within a city network.[4] Understanding how variations in road quality and features affect potential AV use can enable the development of targeted strategies to upgrade and optimise the road network for future travel demand in the city. As such this investigation is crucial for identifying key areas requiring infrastructure improvements and for planning future developments to facilitate the widespread adoption of AV technology. Thus, the aim of this study goes beyond simply enriching the understanding of infrastructure readiness; it seeks to provide empirical insights for policymakers and road agencies as they prepare for the broader adoption of highly automated vehicles.

The organisation of the remainder of this paper is as follows: **Section 2** provides a brief overview of the assessment framework utilised for evaluating the readiness level of roads for automated driving. In **Section 3**, the practical application of this framework is explored, with an emphasis placed on the selected case study area. Additionally, this section presents the findings from the evaluation of the network based on various network configurations and AV capability scenarios. **Section 4** investigates the impact of heterogeneity in road infrastructure readiness levels on AV usage for commuting trips within the study area. The findings are discussed by means of comparison with trips made by human-driven vehicles. The final **Section 5** summarises the conclusions drawn from this research and offers recommendations for future studies in this field.

2. Framework utilised to evaluate the readiness of roads for AV operation

Currently, there is no established official standard or benchmark for authorities to assess the readiness or compatibility of roads for AVs, primarily due to limited knowledge in the field. Despite this, there is a growing body of research aimed at developing a framework applicable across various contexts for evaluating the suitability of road networks for Level 4 AV operation. Initial studies in this area have taken a broad approach, often focusing on national (KPMG International, 2020) or city-wide indices (Jiang et al., 2022; Khan et al., 2019), which typically compare the rankings of various parameters to ascertain their readiness for AVs. Another prominent research approach involves using the definition of vehicles' Operational Design Domains (ODDs) as a baseline for identifying road sections suitable for automated driving. This approach is grounded in the understanding that various infrastructure and environmental conditions significantly influence an AV's ability to interpret its environment, thus affecting its operational capabilities (Mehlhorn et al., 2023). Within this context, several studies have developed classification schemes to categorise the capabilities of road infrastructure in supporting AVs and informing them about the functionalities provided by different road facilities (Carreras et al., 2018; García et al., 2021; Poe, 2020).

[2] In this study, the term "automated driving" is used to describe the technology that integrates automation of the driving task, vehicle connectivity, and data management. Additionally, the terms "automated driving" and "automated vehicles" are used interchangeably.

[3] In this study, the automated driving system (ADS) is responsible for controlling L4 AV and performs the entire dynamic driving task (DDT) while the system is engaged. The ADS continuously monitors all relevant ODD attributes; if any attribute falls outside its specified range, the ADS can no longer autonomously operate the vehicle. In such scenarios, the vehicle occupant must take control, or the ADS will execute a minimal risk manoeuvre, such as a safe stop. If the occupant takes control, the journey may continue, but the vehicle will no longer be under ADS operation. We specifically refer to scenarios where the occupant remains a passenger, and the ADS is solely responsible for completing the trip.

[4] The term of usefulness can be described from various perspectives, such as reducing driving stress during vehicle use. However, in this study, commuting trip completion rates serve as the metric for assessing usefulness.

However, there is a noticeable research gap in specifically addressing urban roads within cities, attributed to the existing uncertainties in the field of automation. A limited number of studies so far have collected detailed data with special equipment from certain road sections, such as highways in a road network (Carter et al., 2019; FTIA, 2021; Konstantinopoulou et al., 2020; Somers, 2019) or public transit route (Cucor et al., 2022) to assess the level of readiness of roads. As an alternative to these limitations, some research has proposed frameworks relying on publicly available data to assess the complexity of road conditions and the surrounding environment for automated driving (Soteropoulos et al., 2020). Similarly, Tengilimoglu et al. (2024) have introduced an assessment framework, scoring segments of physical and digital infrastructure based on their characteristics to facilitate the deployment of AVs. This framework acknowledges the uncertainties in automated driving technologies and considers various scenarios of AV capability and supporting digital technologies in road networks. In this way, it helps explore different perspectives of technological advancement and their impact on the suitability of the current road network for AV use. Therefore, the Road Readiness Index (RRI) proposed by Tengilimoglu et al. (2024) was utilised for the current study. This section provides a concise overview of this framework.

The RRI framework integrates various components identified from relevant literature and stakeholder expertise in road vehicle automation (see Table 1). The weighting of these components (Wci) was derived from a 5-point Likert scale survey with 160 experts from various sectors in the automation domain. However, it should be noted that the current RRI rating is based on the aggregate views of several experts, whose experience is derived from current knowledge acquired through pilots of AVs, simulation or modelling studies and sometimes anecdotal media coverage. The framework also includes subcomponents, selected based on their relevance and the feasibility of data collection, with most assigned equal weight (Wci,j). Measurement variables within these subcomponents are defined in binary or categorical forms, according to data availability. Due to the uncertain impact of individual parameters on AV performance, grading systems for these variables were established, considering UK specifications for road design, operation, and maintenance. Each measurement variable was then assigned a score ($Sc_{i,j}$), ranging from 0 to 1, indicating the challenging level of a particular road segment for AVs.[5] In this step, two different Level 4 automated driving capabilities within the same use-case model were considered for evaluating the measurement variables of the subcomponents.[6] These are:

- ***Low Capability of L4 Automated Vehicle (LC):*** Refers to a basic automated vehicle with limited perception capacities, slower computational processing, and lower intelligence. It relies heavily on its surroundings for driving tasks and might need human intervention in challenging situations such as adverse weather or unexpected road closures.
- ***High Capability of L4 Automated Vehicle (HC):*** This vehicle features advanced software, extensive sensor coverage, quick decision-making capabilities, and relatively higher intelligence - results of accumulating machine learning experiences from real-life driving and simulation of various traffic situations. It is less dependent on the environment and demands minimal human intervention, thanks to its use of AI neural networks and high computing power.

Table 1 presents an overview of the RRI structure and supplementary **Table S1** provides further details on performance grading for measurement variables (see **SM-1**). For an in-depth understanding of each component, subcomponent, and measurement variable in the assessment framework, readers are referred to Tengilimoglu et al. (2024).

The Road Readiness Index (RRI) is calculated for a road link in the network as follows:

$$\mathrm{R}RI_{lm} = \sum_{i=1}^{14} \sum_{j=1}^{n} \left[Wc_i \times \left(Wc_{i,j} \times Sc_{i,j,m} \right) \right] \tag{1}$$

where l represents the road link in the network, m is the type of L4 automated driving capability level, i is component number in the index, j is the subcomponent number in the corresponding component, n is the total number of subcomponents in the corresponding component, $\mathrm{Wc_i}$ and $\mathrm{Wc_{i,j}}$ are the corresponding weight of components and subcomponents, and $Sc_{i,j,m}$ is a score of measurement variables in a certain subcomponent. The weights attributed to the components and indicators are subject to the following constraints:

$$\sum_{i=1}^{14} Wc_i = 1, \sum_{j=1}^{n} Wc_{i,j} = 1 \tag{2}$$

RRI values range from 0 to 1, where a low score indicates that road infrastructure quality and the surrounding environment are unlikely to be suitable for automated vehicles to safely operate. On the other hand, a high score indicating that the infrastructure quality and condition of a road section is very likely to be suitable for automated driving. However, if the result of any component score in the analysis of a road link is zero $\left(i.e. \sum_{j=1}^{n} Wc_j \times Sc_{j,m} = 0\right)$, it is assumed that the RRI_{lm} for that link is also zero. This assumption is made because the zero result suggests that the road situation is extremely challenging for AVs. This implies that the road link poses such difficulties and risks that the other framework components alone are not sufficient to ensure safe and reliable operations for AV. Therefore, a zero RRI is assigned to signify the severity of road conditions, indicating the likely need for additional measures or improvements before AVs can navigate that road link effectively.

However, it is important to note that several dynamic factors, such as weather conditions, traffic, accidents, and the time of day, significantly influence the safe operation of AVs. Since these factors can change within seconds, incorporating them into the evaluation of road segments across the network is challenging. Therefore, the utilised RRI primarily focuses on relatively static factors and road environment attributes. Nonetheless, some dynamic factors and operational attributes of the road infrastructure can be indirectly captured in various subcomponents of the framework.

3. Application of the road readiness index to road network

3.1. Study area and road network

This research examines the integration of Level 4 Automated Vehicles (L4 AVs) within the road network of Leeds, a city in the United Kingdom. Leeds is the second largest Metropolitan district in England with a population of 812.00 and has witnessed considerable economic growth in the last decades (ONS, 2021). The city is divided into 33 wards or alternatively 107 census Middle Layer Super Output Areas (MSOAs) with an average population of just over 8000 each (ONS, 2021). The selection of Leeds for the application of RRI is grounded in several factors. Leeds exemplifies a variety of urban forms that mirror the historical development patterns common to many UK cities, as discussed in a government document focusing on urban form and infrastructure

[5] The measurement variables in the subcomponents are scored according to the level of difficulty for automated driving: 1 = Least challenging, 0.75 = Slightly challenging, 0.50 = Moderately challenging, 0.25 = Highly challenging, and 0 = Extremely challenging.

[6] The AV industry is rapidly advancing with a focus on developing diverse automated driving technologies for different service models, each with unique capabilities (Shladover, 2022). This development is characterised by a spectrum of operational features influenced by the varying hardware, software, and sensors in AVs, which create distinct operational domains. Notably, even within the same service model, discrepancies in technology levels and computing resources lead to diverse driving capabilities (Wevolver, 2020).

Table 1
Overview of the components, subcomponents, and corresponding scores of the Road Readiness Index, adopted from Tengilimoglu et al. (2024).

Ci	Wc_i	Framework components	Ci,j	$Wc_{i,j}$	Subcomponents	LC ($Sc_{i,j}$)	HC ($Sc_{i,j}$)
C1	0.0733	Road Geometric Challenges	C1,1	0.25	Horizontal curvature	(0, 0.5, 1)	(0.25, 0.75, 1)
			C1,2	0.25	Longitudinal gradient	(0.25, 0.75, 1)	(0.5, 1, 1)
			C1,3	0.25	Road width consistency	(0, 0.5, 1)	(0.25, 0.75, 1)
			C1,4	0.25	Digital mapping of road geometry	(0,1)	(0, 1)
C2	0.0653	Road Surface	C2,1	0.5	Road surface type	(0, 0.5, 1)	(0.25, 0.75, 1)
			C2,2	0.5	Road surface condition	(0, 0.5, 1)	(0, 0.75, 1)
C3	0.0731	Road Markings	C3,1	0.25	Digital mapping of road markings	(0, 1)	(0, 1)
			C3,2	0.25	Marking configuration	(0, 0.25, 0.50, 0.75, 1)	(0, 0.50, 0.75, 1, 1)
			C3,3	0.5	Marking condition	(0, 0.50, 1)	(0, 0.75, 1)
C4	0.0681	Road Boundaries	C4,1	0.5	Median type	(0, 0.25, 0.50, 0.75, 1)	(0.25, 0.50, 0.75, 1, 1)
			C4,2	0.25	Road edge condition	(0, 0.50, 1)	(0.25, 0.75, 1)
			C4,3	0.25	On-street vehicle parking	(0, 0.50, 1)	(0.25, 0.75, 1)
C5	0.0718	Traffic Signs Visibility	C5,1	0.5	Digital mapping of traffic signs	(0, 1)	(0, 1)
			C5,2	0.5	Traffic signs conditions	(0, 0.25, 0.50, 1)	(0, 0.50, 0.75, 1)
C6	0.0718	Special Road Section	C6,1	1.0	Special road sections	(0, 0.25, 0.50, 0.75, 1)	(0, 0.50, 0.75, 1, 1)
C7	0.0651	Road Lightning	C7,1	1.0	Lighting condition	(0, 0.25, 0.50, 1)	(0.25, 0.50, 0.75, 1)
C8	0.0707	Speed Limit	C8,1	1.0	Speed limit of road section	(0, 0.25, 0.50, 1)	(0, 0.25, 0.50, 1)
C9	0.0750	Number and Diversity of Road Users	C9,1	0.50	Road access	(0, 0.25, 0.50, 1)	(0.25, 0.50, 0.75, 1)
			C9,2	0.25	Counterflow	(0, 1)	(0.25, 1)
			C9,3	0.25	No. of lanes	(0,25 0.50, 1)	(0.25, 0.75, 1)
C10	0.0646	Roadside Complexity	C10,1	0.25	Presence of trees	(0, 0.50, 1)	(0.25, 0.75, 1)
			C10,2	0.25	Street furniture density	(0, 0.50, 1)	(0.25, 0.75, 1)
			C10,3	0.25	Proximity of buildings	(0, 0.50, 1)	(0.25, 0.75, 1)
			C10,4	0.25	Digital mapping of surrounding road environment	(0, 1)	(0, 1)
C11	0.0761	Facilities for Vulnerable Road Users	C11,1	0.25	Pedestrians crossing type	(0, 0.25, 0.50, 0.75, 1)	(0.25, 0.50, 0.75, 1, 1)
			C11,2	0.25	Pedestrian sidewalk	(0, 0.50, 0.75, 1)	(0.25, 0.75, 1, 1)
			C11,3	0.25	Cycling infrastructure	(0, 0.50, 1)	(0.25, 0.75, 1)
			C11,4	0.25	Public transit access point design	(0, 0.25, 0.50, 0.75, 1)	(0.25, 0.50, 0.75, 1, 1)
C12	0.0770	Precautions for Roadworks and Incidents	C12,1	1.0	Precautions for roadworks and incidents	(0, 0.25, 0.50, 0.75, 1)	(0.25, 0.50, 0.75, 1, 1)
C13	0.0779	Localisation Challenges	C13,1	0.5	Localisation challenges	(0, 0.25, 0.50, 0.75, 1)	(0, 0.50, 0.75, 1, 1)
			C13,2	0.5	Digital mapping of road environment	(0, 1)	(0, 1)
C14	0.0702	Communication Facilities	C14,1	1.0	Cellular network coverage	(0, 0.25, 0.50, 0.75, 1)	(0, 0.50, 0.75, 1, 1)

(Williams, 2014). The city's diverse road network, featuring both radial and grid patterns, along with its suburban growth, highlights the typical infrastructure challenges and opportunities present in many urban areas within the UK. Therefore, Leeds, with its substantial population, intricate urban structure, and surrounding suburbs, presents a representative view of both the potential benefits and complexities inherent in the deployment of AVs.

Leeds' road network, comprising approximately 4200 km (2610 miles) includes a variety of roads at different hierarchical levels.[7] The road is depicted by over 50,000 road links by Ordnance Survey, Great Britain's national mapping agency. For the purposes of this study, the analysis is concentrated solely on major roads, deliberately excluding local and access roads. This focus is informed by Tengilimoglu et al. (2024), which found that local and access roads generally have lower Road Readiness Index (RRI) values, indicating higher challenges for the operation of automated vehicles. Therefore, local and access roads were excluded from the network. After this omitting, the remaining sections of the network amount to about 1300 km (808 miles), represented by over 13,000 links.

However, implementing the index across such an extensive road network presents challenges in terms of data collection and evaluation since individually assessing each link requires intensive resources. Therefore, the case study area was narrowed down to cover the north-western part of the city (consisting of 44 MSOAs and representing over 40 % of the population). The selected area is a mosaic of different urban forms such as: the central business district, offices and shops, residential areas, suburbs, and rural areas. Moreover, it covers key locations such as universities, hospitals, the city centre, and the main transport hubs such as central train station and airport. The choice of focusing on the northern area of Leeds is mainly based on its demographic characteristics. This region is distinguished by relatively higher income levels and lower scores on the Index of Multiple

[7] Ordnance Survey classifies the UK's road hierarchy according to their function. These are: 1) *Motorway*, which is a multi-carriageway public road connecting important cities. 2) *A Road*, which is a major road intended to provide large-scale transport links within or between areas. 3) *B Road*, which is a road intended to connect different areas, and to feed traffic between A roads and smaller roads on the network. 4) *Minor Road*, which is a public road that provides interconnectivity to higher classified roads or leads to a point of interest. 5) *Local Road*, which is a public road that provides access to land and/or houses, usually named with addresses. Generally, not intended for through traffic. 6) *Local Access Road*, which is a road intended for the start or end of a journey, not intended for through traffic but will be openly accessible. 7) *Restricted Local Access Road*, which is a road intended for the start or end of a journey, not intended for through traffic and will have a restriction on who can use it. 8) *Secondary Access Road*, which is a road that provides alternate/secondary access to property or land not intended for through traffic.

Deprivation (IMD)[8] compared to other areas in Leeds.[9] Such demographic attributes suggest that residents in this area might be early adopters of AV technology, primarily for commuter trips (Rahman and Thill, 2023; Wadud and Mattioli, 2021). Additionally, this area serves as an appropriate case study for early AV buyers, considering that the cost of AVs is likely to be higher than that of vehicles in the current mass automotive market (International Transport Forum, 2023b; Transport Systems Catapult, 2017). Fig. 1 illustrates the selected 44 Middle Layer Super Output Areas (MSOAs) (shown in yellow) in the northwest part of the city boundary and selected major roads for analysis (depicted in red) within the road network of Leeds.

The road network data for Leeds were obtained from the Ordnance Survey MasterMap Highway for the year 2023. After data cleaning for road segments that are restricted to traffic (e.g. bus gates), dead-end roads, or do not have street views data, 5456 road links were obtained for analysis in selected study area. The average length of road links is calculated approximately as 74.3 m, resulting in a total road network length of 405.2 km. The Motorway network spans 9.76 km, accounting for 2.41 % of the total. The A Road Primary network extends over 118.29 km (29.19 %), while the A Road network measures 29.55 km (7.29 %). The B Road network covers 16.45 km (4.06 %). The Minor Road network is the largest, with a length of 227.85 km, constituting 56.24 % of the network. Lastly, the Local Road[10] network encompasses 3.27 km, making up 0.81 %.

3.2. Data collection and score assignment for road sections

This section provides a concise overview of the method for assigning scores to real-world road networks, following the conceptual framework introduced in **Section 2**. As previously highlighted, evaluating the various (sub)components of the Road Readiness Index (RRI) heavily relies on extensive field survey data, encompassing both physical and digital infrastructure information. The process of data collection, demanding significant time, labour, and financial resources, complicates the frequent updating of this information across the network. As a result, current data that are relevant to the components of the RRI are often limited in availability and accessibility. This scarcity poses challenges to the objective assessment of the suitability of road sections for automated vehicle operations.

Despite these challenges, street view imagery has been widely used in both quantitative and qualitative research to analyse built environments and urban landscapes (Arellana et al., 2020). Adopting a similar approach, this study primarily sourced data on road infrastructure conditions through visual inspections using aerial or satellite imagery and street view services such as Google Street View.[11] The approach also involved on-site observations for some locations that has limited information. Additionally, secondary data from variety of sources (see supplementary material **SM-2**) was utilised to accurately reflect the specific requirements of (sub)components. This collected secondary data was categorised based on the scoring system and subsequently integrated into the corresponding road links using QGIS, an open-access Geographic Information System (GIS) platform. Following this, the visual inspection data was compiled into the measurement variables in the scoring systems. Thus, each link in the road network was characterised by scores, in detailed spatial dimensions.

Briefly, the authors utilised diverse sources (see **Table S2**) to collect data representing each measurement variable within the sub-components, this comprehensive evaluation of each road link spanned four months. Additionally, this study examines two potential scenarios within the network based on the anticipated advances in the information, communication, and vehicle industries. These are:

- ***Network Scenario 1*** represents the study area's existing road conditions, which currently lack High Definition (HD) maps due to the anticipated costs of digitalising the road network in the near future, as well as Roadside Units (RSUs) for information exchange. In this scenario, AVs must depend solely on onboard sensors to navigate road sections without a prior detailed map, and use the existing cellular networks for external connectivity. The detection of roadworks or construction sites around the roadway were considered as a challenge for AVs.
- ***Network Scenario 2*** introduces advanced surveying techniques to produce detailed city maps, providing HD maps for all roads in the study area through third-party services or authorities. However, due to cost and implementation challenges, RSUs are absent in the road network, even though established Vehicle-to-Infrastructure (V2I) communication standards and initiatives are in place to guide the deployment and interoperability of these systems. This is also due to the absence of an agreement between the AV industry and road authorities on any system for implementation. Consequently, AVs in this scenario rely exclusively on the existing cellular network for information exchange. Also, this scenario assumes the absence of roadworks or incidents in the area.

The scoring of the components in the index was adjusted to align with these scenarios. **Table S2** in the supplementary materials (see **SM-1**) provides a detailed view of the data sources and assesses the quality and representativeness of the data for each component.

3.3. Results and interpretation of road assessment

The evaluation results for each measurement variable within the components of Road Readiness Index (RRI), reflecting the near-time conditions of the road network, are visually detailed in the figures found in the supplementary materials (see **SM-2**). These results are integrated according to Eq. 1, contributing to the final calculation of RRI values for road links. Fig. 2 displays the mapping of these integrated assessment outcomes for selected roads within the study areas. This mapping takes into account both low capability (LC) and high capability (HC) automated vehicles and the two different scenarios for the road network. In the figure, the index scores are divided into five distinct groups, each representing a different level of difficulty for automated driving. These levels range from extremely challenging to least challenging. This categorisation is essential as it highlights the varying degrees of suitability of different road sections for the facilitation of AVs. Such an approach provides a comprehensive understanding of how well different parts of the road network in Leeds can accommodate AVs, considering the specific capabilities of the vehicles and the complexities of the road environment. This categorisation serves as a critical tool in identifying areas that might need improvement or are already well-suited for the introduction of automated vehicle technology.

In Scenario 1, considered the base case scenario, a substantial portion of road sections in the case study area are classified as extremely challenging for the operation of both LC and HC AVs. Approximately 20 % of the selected road links for LC AVs and 18 % for HC AVs fall into this

[8] The Indices of Multiple Deprivation (IMD) are utilised in the UK as a comprehensive tool for identifying areas that are subject to various forms of deprivation. This index consists of data from diverse domains to formulate an overall relative measure of deprivation experienced by individuals within a specific area. More detailed information about the IMD, including its methodology and applications, can be found at the Consumer Data Research Centre (CDRC). Source: https://data.cdrc.ac.uk/dataset/index-multiple-deprivation-imd

[9] https://www.plumplot.co.uk/Leeds-salary-and-unemployment.html

[10] The inclusion of 56 local roads in the case study network ensures consistency with the previously established travel demand model, which utilised here for analysis.

[11] The visual inspection is generally based on satellite images dated March 24, 2022 and April 26, 2023. However, the assessment of many road sections, primarily major roads, is based on the latest Google Street View images from the second half of 2023.

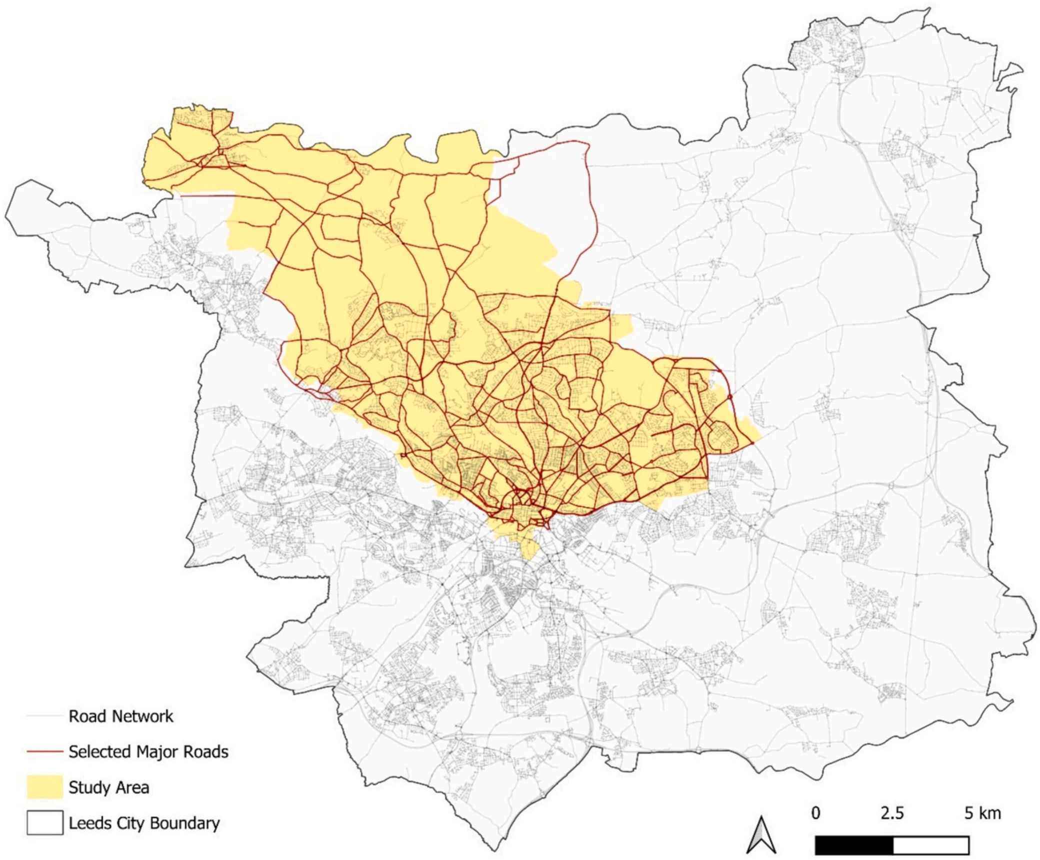

Fig. 1. Location map indicating study areas of Leeds, UK and select road sections in the network. MasterMap Highway © Crown copyright and database rights "2023" Ordnance Survey (AC0000851941).

category, indicated by the colour red in the visual outputs (see Fig. 2). This situation is mainly attributed to factors such as poor-quality road infrastructure and the complexity of the surrounding driving environment, which result in the index score being penalised. Notably, the lowest RRI values are typically observed in rural areas in the northern parts of the study area. Common issues in these regions include the absence of road markings, detectable road edges, pedestrian sidewalks and consistent road widths, as well as poor road surface conditions. Additionally, factors such as high vegetation coverage surrounding the roads, a lack of street lighting, and poor cellular coverage further contribute to the challenges faced by AVs in these areas. Similarly, some residential areas also exhibit low RRI values due to lacking road markings, having narrow streets with on-street vehicle parking, poor road surface conditions, and traffic signs obstructed by trees bushes or obstructed by graffiti.

In urban areas, sections that are particularly challenging for AVs are often found in links with traffic islands designated for pedestrian crossings. These areas are characterised by a high density of street furniture and a noticeable lack of road markings that are important as a primary or secondary input for AV detection and lane localisation. Similar challenges are observed at many single or two-lane roundabouts, particularly due to their curvature forms, resulting in sections that are extremely challenging for AVs. Additionally, road segments passing through tunnels or longer underpasses tend to receive lower RRI scores, primarily due to localisation and illumination challenges inherent in automated driving. Moreover, road sections adjacent to roadworks or construction sites are also marked with lower scores, as they present complex and frequently changing layouts that pose navigation challenges for AVs.

On the other hand, as expected, the majority of road sections in the selected area demonstrate relatively high RRI values, with about 76 % for LC AVs and 81 % for HC AVs. These sections are classified as slightly challenging for AVs. This is primarily because these selected major roads form the main skeleton of the city's transport system, are maintained frequently, and meet certain safety standards for road users. One notable finding is that road links adjacent to the areas such as the central business district, offices, and shops, despite their complex surrounding environments, have received relatively high RRI values. The main reason for this is that these areas typically have a well-defined separation between Vulnerable Road Users (VRUs) and main traffic flows. Furthermore, they possess high-quality physical infrastructure, including lower speed limits and specifically designed parking bays and public transit access points. These features facilitate the detection of road edges by AVs, making navigation less challenging. Nevertheless, there are noticeable gaps, indicated by lower RRI values, among the road links with higher RRI scores.

In Scenario 2, which assumes the availability of HD maps for the entire road network and the absence of roadworks, there is a significant expansion in the operational areas for both LC and HC AVs compared to the base case scenario. The majority of road links in the network fall into the slightly and least challenging categories of the RRI for LC AVs. Notably, for HC AVs, this distribution has a predominance of links in the least challenging category due to their having advanced automated driving systems, encompassing sophisticated sensors and computational capacity. This shift highlights the vital role of HD maps in facilitating automated driving, as digital mapping of environment is linked to many components within the index. HD maps are vital for road sections with poor markings, traffic signs, challenging geometries or localisation, as they provide crucial supplementary information for navigating difficult driving conditions.

Scenario 2 utilises static map layers to complement onboard sensors, aiding in precise localisation, enhancing perception beyond the

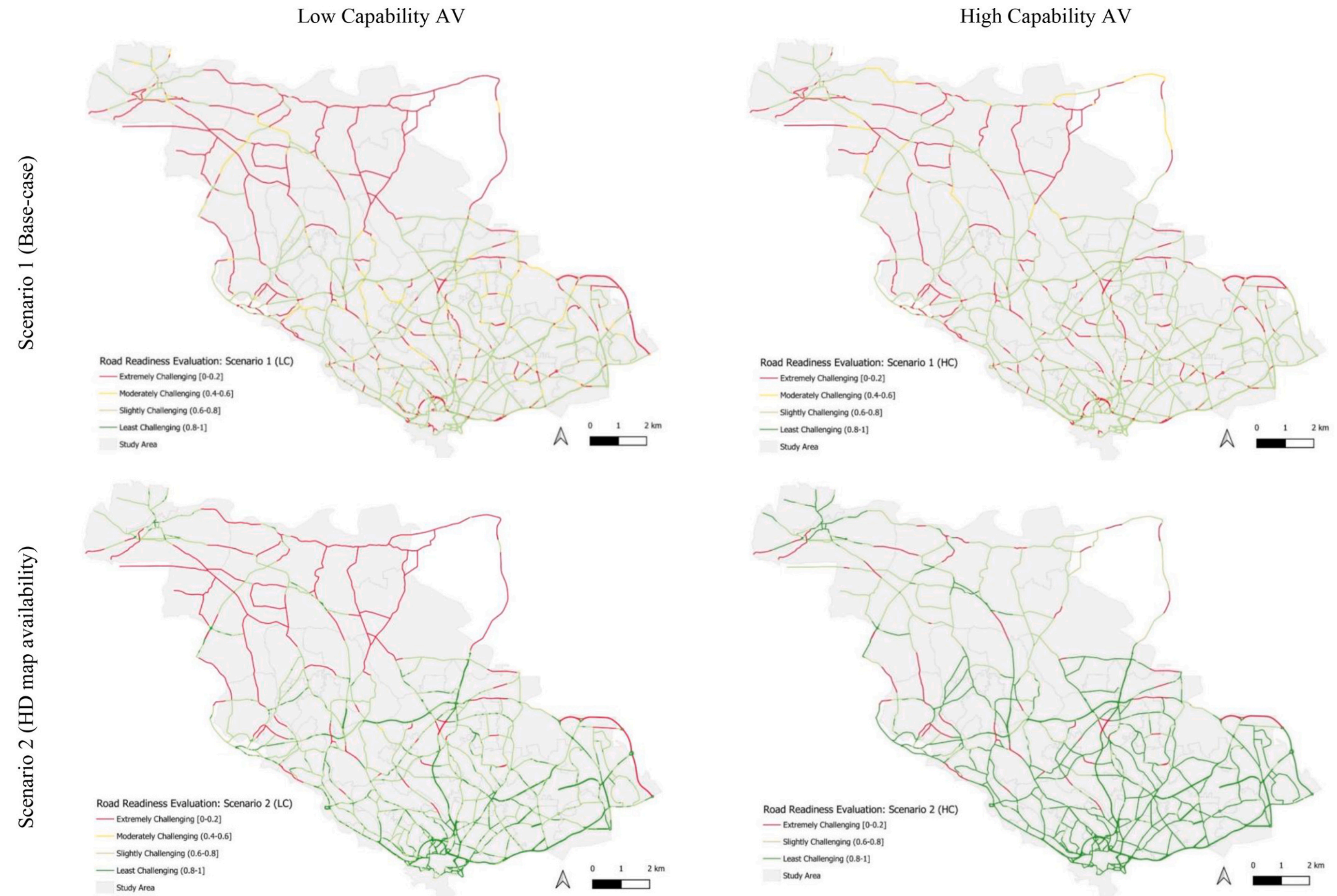

Fig. 2. Overview of the assessment of the readiness of roads in Scenario 1–2, comparing low capability AV (left) and high capability AV (right). MasterMap Highway © Crown copyright and database rights "2023" Ordnance Survey (AC0000851941).

immediate visual range, and facilitating more accurate path planning. This integration of HD maps significantly boosts the operational efficiency of AVs by addressing key information gaps. However, it is important to note that the provision of HD maps alone does not fully mitigate all the challenges in the road network. A considerable proportion of road links still present significant obstacles for AVs, mainly due to issues such as limited cellular coverage. This indicates that while HD maps are a significant step forward, they are part of a broader ecosystem of technologies and infrastructure improvements needed to fully facilitate effective and safe AV operations.

Table 2 details the distribution of road links in the case study area by road hierarchy and RRI category for both scenarios. Interestingly, the table shows that motorways have a relatively higher proportion of low RRI values compared to other road types, contrary to expectations. This is predominantly due to sections of motorways in the case study area that traverse long tunnels in the university region of the city centre, posing significant challenges in terms of lighting and localisation for AVs, particularly in the absence of HD maps.

4. Analysis of AV usefulness in a heterogeneous road network

The implementation of the RRI on selected major roads in the case study area reveals a remarkable heterogeneity in terms of infrastructure and road conditions. This diversity primarily stems from variations in the quality and consistency of the infrastructure within the road environment. Such heterogeneity highlights the potential need for improvements in specific road segments, where existing conditions are less conducive to the safe operation of AVs. This situation also gives rise to the hypothesis that without specific modifications or upgrades to the infrastructure to meet automated driving requirements, seamless operation of AVs across the existing road network might be unlikely. As such this section investigates the effect of heterogeneity in road readiness levels within a network on the use of AVs.

4.1. Commuting trips within the study area

In examining the impact of existing road infrastructure on AV usefulness, the study focused on understanding the network's travel demand characteristics, mainly represented by origin-destination (OD) data. This data, capturing movement through geographic space from an origin to a destination, is crucial for understanding travel patterns. This study utilised open access data from the UK Census 2011, which contains aggregate statistics on number of commuters between administrative zones - Middle layer Super Output Areas (MSOA), by mode of travel (ONS, 2011).[12] The dataset provides 2011 estimates, classifying usual residents aged 16 to 74 in England and Wales by their method of travel to work.

Within the scope of this study, the focus is specifically on car or van driving as the mode of travel to work. This approach is taken to

[12] Since the study focused solely on major roads within the network, using a Lower Layer Super Output Area (LSOA) level Origin-Destination (OD) matrix for this analysis is not suitable. This is primarily because many LSOA boundaries do not encompass major road links. Consequently, the LSOA-level OD matrix may not accurately reflect the traffic patterns and flows that are specifically relevant to the major roads being studied.

Table 2
Distribution of road links by road hierarchy and RRI category for Scenarios 1,2.

Scenarios & AV types	Road hierarchy*	Road Readiness Index category					Total
		Extremely Challenging [0–0.2]	Highly Challenging (0.2–0.4]	Moderately Challenging (0.4–0.6]	Slightly Challenging (0.6–0.8]	Least Challenging (0.8–1]	
S1 – LC	Motorway	73	0	0	77	2	152
	A Road Primary	280	0	24	1088	0	1392
	A Road	108	0	6	283	0	397
	B Road	35	0	10	334	0	379
	Minor Road	596	0	166	2318	0	3080
	Local Road	8	0	9	39	0	56
	Total # of links	1100	0	215	4139	2	5456
	Percentage (%)	20.16	0.00	3.94	75.86	0.04	100.0
S2 – LC	Motorways	0	0	0	20	132	152
	A Road Primary	115	0	0	326	951	1392
	A Road	56	0	0	141	200	397
	B Road	6	0	0	215	158	379
	Minor Road	260	0	0	1622	1198	3080
	Local Road	0	0	1	45	10	56
	Total # of links	437	0	1	2369	2649	5456
	Percentage (%)	8.01	0.00	0.02	43.42	48.55	100.0
S1 – HC	Motorway	73	0	0	74	5	152
	A Road Primary	260	0	6	1124	2	1392
	A Road	84	0	9	302	2	397
	B Road	35	0	0	344	0	379
	Minor Road	529	0	9	2536	6	3080
	Local Road	8	0	0	48	0	56
	Total # of links	989	0	24	4428	15	5456
	Percentage (%)	18.13	0.00	0.44	81.16	0.27	100.0
S2 – HC	Motorway	0	0	0	5	147	152
	A Road Primary	96	0	0	85	1211	1392
	A Road	34	0	0	34	329	397
	B Road	6	0	0	18	355	379
	Minor Road	149	0	0	339	2592	3080
	Local Road	0	0	0	16	40	56
	Total # of links	285	0	0	497	4674	5456
	Percentage (%)	5.22	0.00	0.00	9.11	85.67	100.0

* For further details about the road hierarchy please refer to footnote 2.

concentrate on how AVs could potentially replace existing trips made by human-driven vehicles. To maintain this focus, other modes of transportation, such as public transit and active transport (walking or cycling), are excluded from the analysis. Additionally, the study omits intra-zonal trips, which are trips that both start and end within the same zone (MSOA). These trips are typically shorter and may not significantly contribute to understanding the potential for AV usefulness. Some inter-zonal trips, particularly those that either start or end outside of the defined study area, are also excluded. This exclusion helps to maintain the relevance of the data by focusing on trips that are wholly contained within the study area.

The analysis resulted in a total of 27,187 trips across 1715 OD pairs within 44 MSOAs −134 OD pairs did not include any car or van trips for commuting. The number of these trips varied, ranging from 1 to 401. As expected, the main destinations of these trips are the city centre areas, where the main business district and transport hubs are situated. Fig. 3 illustrates the number of trips made by car drivers increases with distance from the city centre. Additionally, the distribution of Origin-Destination (OD) pairs exhibits homogeneity and encompasses nearly the entire network within the study area, making it an appropriate framework for analysing AV usage within the system (see Fig. 4).

4.2. Converting spatial road network into a graph system for routing

After establishing the travel patterns within the study area, the subsequent stage involved transforming the spatial road network into a graph format for routing analysis. Street networks, a specific type of spatial network, possess unique characteristics and can be abstractly represented in various ways (Marshall et al., 2018). The prevalent method, and the one adopted for this study, involves representing each road as an edge within a graph, while intersections, typically found at road junctions, serve as vertices. This approach might also include vertices at points other than junctions, depending on the network's complexity (Gilardi et al., 2020). For this conversion, the study utilised the "igraph" package in R, a fast and open-source library for graph and network analysis (Csardi and Nepusz, 2006). In conjunction with "igraph", the "sf" (simple features) package (Pebesma, 2018) was employed for handling and manipulating spatial data.

The transformation of a three-dimensional road network, with overpasses, underpasses, and varied intersection types, into a two-dimensional graph system presents certain challenges (Gilardi et al., 2020). To address these, related nodes at these intersections were duplicated and assigned new identifiers, ensuring accurate link and node representation, and reducing potential routing errors. In addition, the graph system of the road network was constructed considering the traffic direction provided in the OS MasterMap Highway. However, due to its complexity, turn restriction rules at some junctions were not incorporated into the routing analysis. Then, the closest nodes to each MSOA centroid were identified to represent the origin and destination points in routing. The analysis assumed an unlimited capacity for traffic volume on road links, simplifying the approach by excluding the potential for congestion. This assumption also implies that vehicles travel at the speed limit of each road section. Furthermore, time spent at junctions was not included in the analysis, as junctions were not a focus

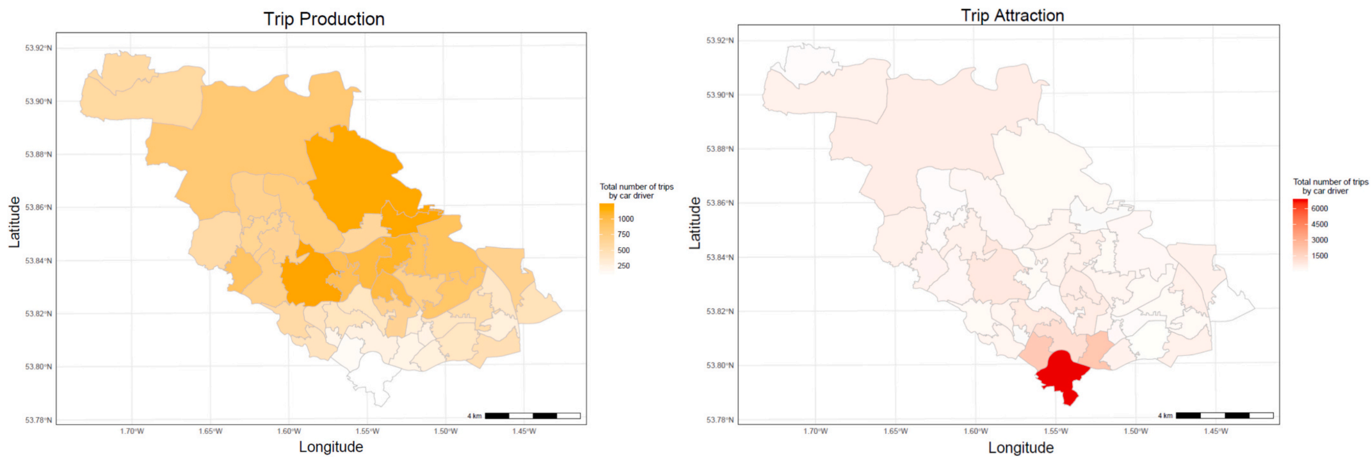

Fig. 3. Trip production (left) and attraction (right) of MSOAs in selected study area for commuting trips made by car drivers only based on 2011 census data.

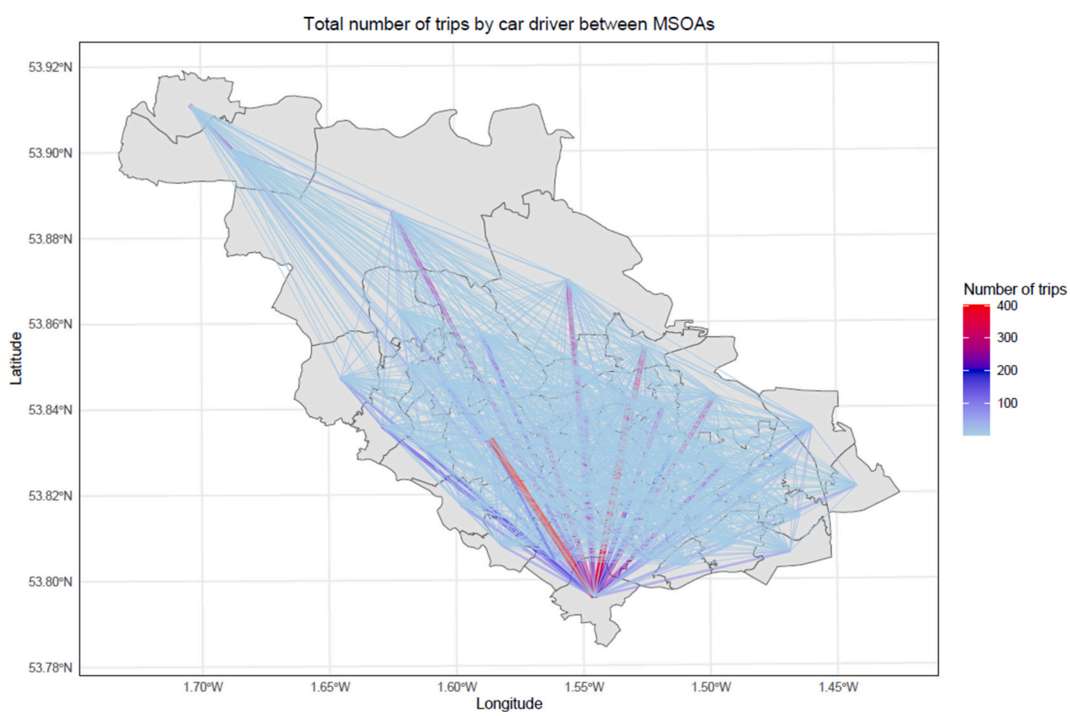

Fig. 4. Distribution of commuting trips made by car drivers, illustrated by desire lines between centroids of MSOAs.

of this study, and the primary emphasis was on distance-based comparisons. The objective is not to find a precise result, but rather to demonstrate the potential impacts of heterogeneity in road infrastructure on AV usefulness.

Shortest path algorithms such as Dijkstra's or the A* search algorithm are designed to find the path with the lowest cumulative cost (or weight) between two nodes in a graph. In most cases, these algorithms are used to find the shortest distance or the least time-consuming path, where lower values are preferable. In the igraph package for R, the default method used for finding the shortest path is Dijkstra's algorithm (Dijkstra, 1959).[13] Moreover, when calculating shortest paths, the default behaviour the package is to consider the unweighted shortest path. This means that each edge in the graph is considered to have the same weight (usually a weight of 1), so the shortest path is determined based on the number of edges (i.e. road links). However, some links might be very short (a few meters) while others could be much longer (several miles). Therefore, the length of each edge was normalised by dividing it by the maximum length found in the graph. This puts all lengths on a scale from (0–1]. In this way, the algorithm balance between finding the fewest number of edges and the shortest total distance.

4.3. Results and interpretation of routing of commuting trips

The following subsections present the findings and interpretation of shortest path analysis of OD pairs based on varying scenarios in network and vehicle capability.

4.3.1. Base case scenario: Human-driven vehicle (HDV)

In this study, the base case scenario is defined by trips made by car drivers, representing human-driven vehicles (HDVs) in the network. The

[13] The algorithm works by iteratively selecting the node with the smallest distance from a starting point, then exploring its neighbours, updating their distances if a shorter path is found. This process is repeated until the shortest path to the destination node is determined.

routing results for each OD pair in the weighted and directed road network are illustrated in Fig. 5. This figure presents a heatmap showing the travel distance in miles for each shortest path of HDV trips. The average trip length is found to be 4.4 miles, with the shortest trip being 0.6 miles and the longest reaching 14 miles.

Adopting a similar approach to the concept of "*edge betweenness*", which refers to the number of shortest paths that pass through each edge (link) in a network (Lovelace et al., 2019), all 27,187 car trips for commuting across 1715 OD pairs were allocated to corresponding road links. Fig. 6 visually represents the total number of car trips passing each road section within the network. This illustration is based on the shortest path calculations for each of the OD pairs, providing a clear depiction of the flow patterns on different road segments. It also provides an insight into the most frequented routes in the network and helps in understanding the spatial distribution of HDV trips in the study area.

4.3.2. Network scenario 1 (base case): Automated vehicle (AV)

In the base case scenario, HDVs are assumed to travel all roads without restrictions, except for traffic directions, as access-controlled sections such as bus gates and bus-only roads were excluded from the analysis. However, for AVs, their operation may be limited to roads meeting certain readiness criteria. Roads with low RRI scores are likely unsuitable or unsafe for AVs. Thus, by excluding edges (links) with an RRI score of 0 in the graph system, the model focuses on road segments more appropriate for AVs, creating a network that better aligns with realistic operating conditions for these vehicles. Moreover, the weighted road network is structured by combining normalised road lengths and inverted RRI scores (i.e., 1-RRI, where a low RRI score implies a higher cost) into a combined weight for each road segment. Normalising road lengths ensures that the algorithm accounts for physical distance, while inverted RRI scores introduce a weighting factor that represents each road's suitability for AVs. This weighting scheme balances the importance of road length and readiness, ensuring that the shortest paths calculated for AVs are not only the shortest in distance but also the least challenging and most suitable according to their readiness scores. This approach facilitates a meaningful comparison between current HDV road usage and potential AV usage, offering insights into possible changes in traffic patterns and road utilisation with AV integration. The adopted weighting strategy for road links is formulated as:

$$\text{Weight of edges (road links)} = \alpha(l_i/l_{max}) + (1-\alpha)(1-RRI_i) \tag{3}$$

Where: l_i represents the length of road link i in the network, l_{max} is the maximum length of any link in the network, RRI_i is the assessment value of the index corresponding to road link i, α is the coefficient adopted for weighting the importance of the parameters, which is taken as 0.5 in this study.

The differences in routing results for each OD pair between HDVs and AVs within an adapted weighted and directed network were presented using heatmaps. Fig. 7a compares the travel distances in miles for the shortest path of each LC AV trip with its HDV counterpart. This visual representation effectively highlights the variations in travel patterns and efficiency between HDVs and AVs, indicating how AV capabilities could potentially alter road usage across the network. Among the 1715 OD pairs evaluated, the network only allows for the successful completion of 100 OD pairs by LC AVs. A significant majority of trips were deemed infeasible due to the presence of roads that are extremely challenging for AV navigation. Despite approximately 20 % of road links receiving penalties (see Table 2), their dispersed distribution resulted in significant barriers to connectivity between MSOAs. Out of a total of 27,187 trips analysed, only 1799 corresponding to those 100 OD pairs could potentially be replaced by LC AVs in this scenario. An in-depth analysis of these trips revealed that the average trip length is 2.3 miles, with the shortest trip being 0.6 miles and the longest reaching 5.5 miles.

High Capability (HC) AVs exhibit only slightly better performance, with the network accommodating successful completion for 120 OD pairs. Similar to LC AVs, the majority of potential trips were hindered by the challenging nature of certain road sections. From the total of 27,187 trips analysed, only 2018 corresponding to those 120 OD pairs could potentially be replaced by HC AVs in Scenario 1. For HC AVs, the

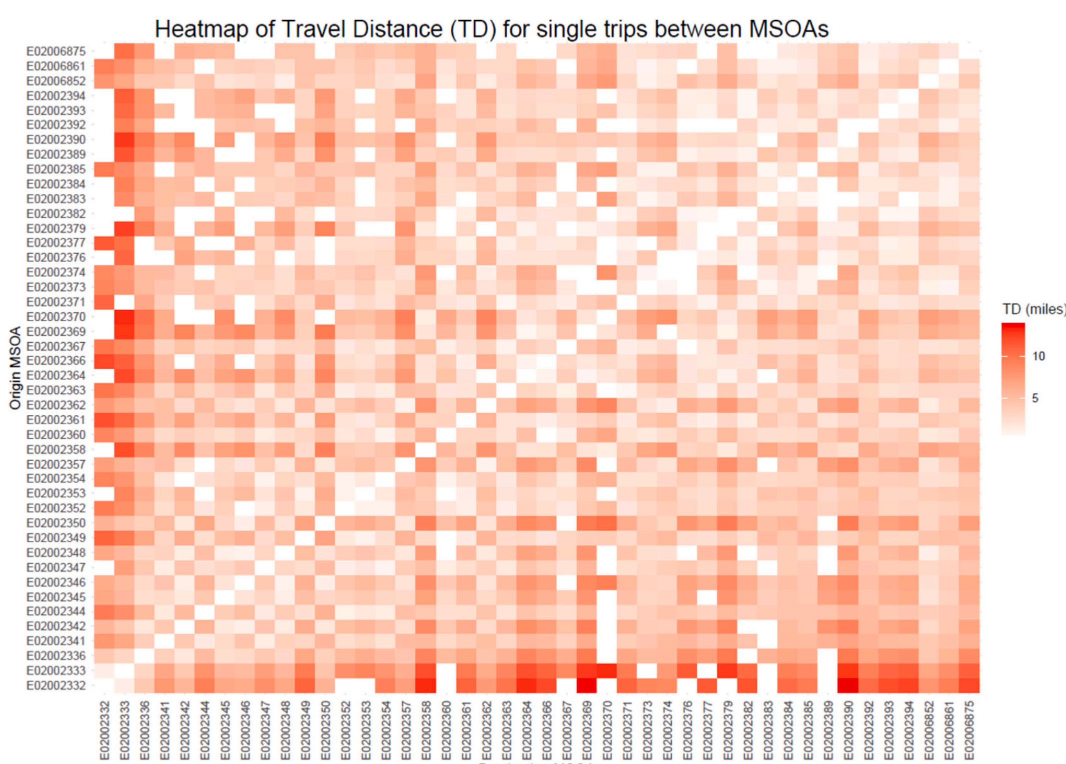

Fig. 5. Heatmap illustration of travel distance for a single trip of 1715 OD pairs within 44 MSOAs.

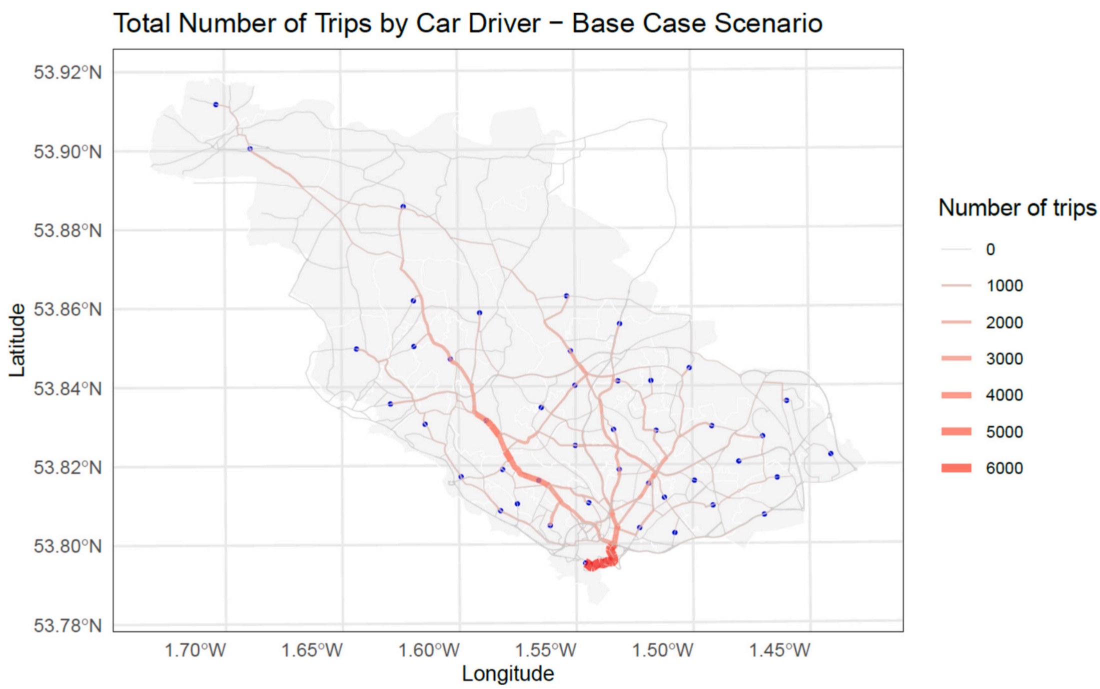

Fig. 6. Visual representation of the total number of car trips passing through each road section, based on the shortest paths of each OD pair.

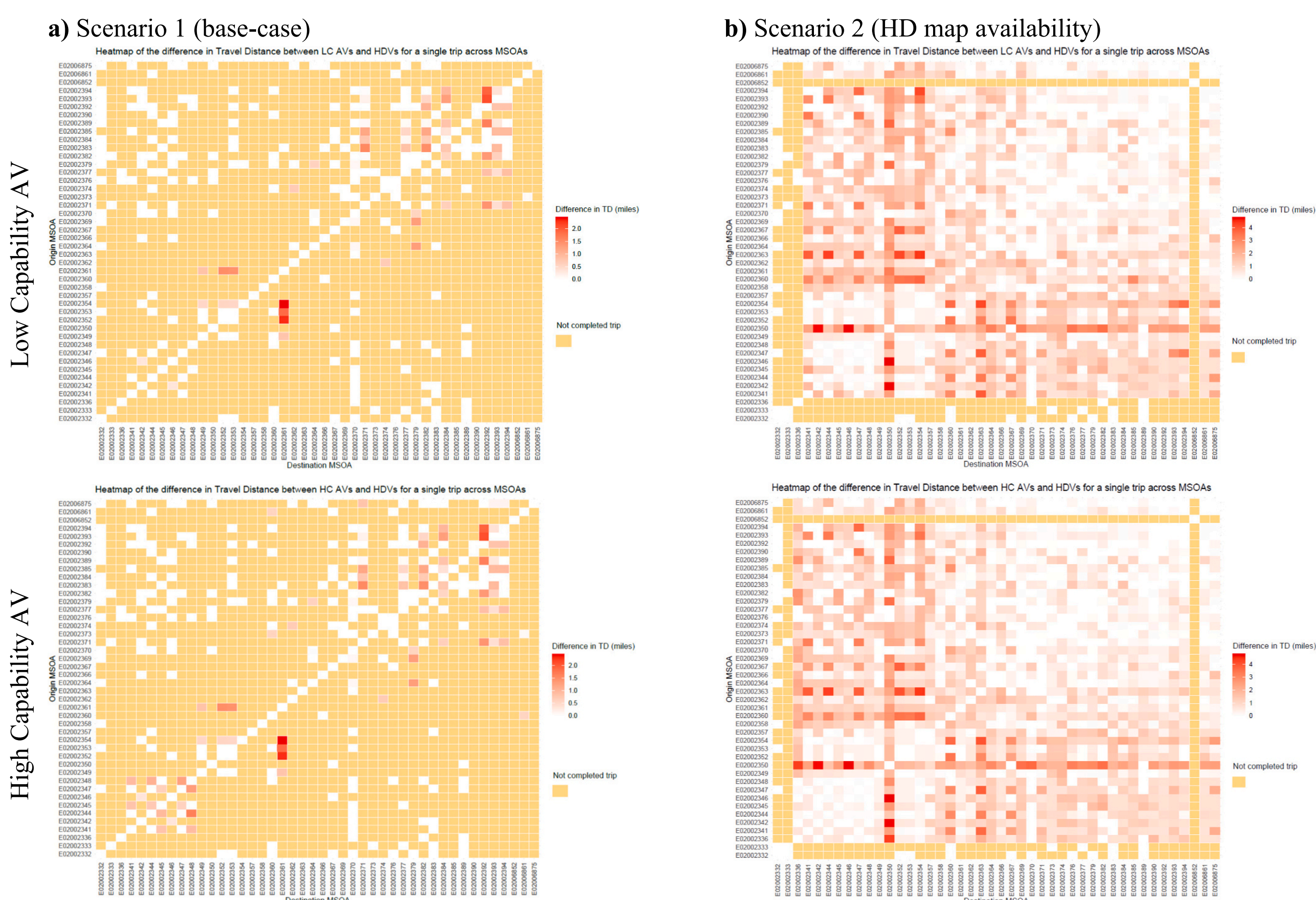

Fig. 7. Heatmap illustration of the difference in travel distance for a single trip between AVs and HDVs across 1715 OD pairs within 44 MSOAs, based on AV capabilities in Network: a) Scenario 1, and b) Scenario 2.

average trip length is slightly longer at 2.5 miles, with the shortest and longest trips being 0.6 miles and 5.8 miles, respectively. This is primarily due to the ability of HC AVs to make trips over slightly longer distances within the network for additional OD pairs compared to LC AVs.

When analysing AV trips within the network, it was observed that relatively less challenging paths designated for both AVs tend to be longer than those typically used by HDVs. As can be seen from the Fig. 7a, there is an increase of approximately 2.5 miles in the travel distance for certain OD pairs. The analysis revealed that trips made by LC AVs are, on average, 28 % longer than those made by human-driven vehicles. Similarly, trips made by HC AVs in the analysed 120 OD pairs are on average 27.2 % longer than those of HDVs.

Lastly, the spatial distribution of feasible AV trips is illustrated in Fig. 8a, offering valuable insights into how the integration of AVs might transform the existing transportation landscape within the study area. The figure reveals that most of these trips occur between MSOAs that are geographically closer to each other. This implies a lower likelihood of encountering extremely challenging road sections along shorter routes compared to longer ones. Thus, without physical and digital infrastructure modification or upgrades in the network, LC AVs will likely not serve most of the travel needs within the urban environment.

4.3.3. *Network scenario 2 (HD map availability): Automated vehicle (AV)*

As previously mentioned, in Scenario 2 most road links in the network are categorised into the slightly and least challenging categories of the Road Readiness Index (RRI) for AVs. As such, compared to the previous scenario, the operation areas of AVs expand significantly, enabling the completion of most trips. Fig. 7b displays a heatmap comparing the differences in travel distances (in miles) for the shortest paths of AV trips and HDVs. Out of 1715 OD pairs, the network allows LC AVs to successfully complete 1423 OD pairs. This significant increase in feasible trips is attributed to the advantages of High Definition (HD) maps for AV navigation and the assumption of the absence of road work in the network. The analysis of 22,670 trips corresponding to the 1423 OD pairs revealed an average trip length of 4.8 miles, with the shortest trip being 0.6 miles and the longest being 12.9 miles.

In contrast, High Capability (HC) AVs demonstrate slightly better performance, with the network facilitating the successful completion of 1498 OD pairs. This represents an 87 % coverage of the existing road network for vehicle-based commuting trips, marking an almost 80 % increase compared to the previous scenario. In the analysis of 23,847 trips associated with the 1498 OD pairs for HC AVs, the average trip length remains consistent at 4.8 miles (compared to trips completed by LC AVs), with a range from 0.6 miles to 14.1 miles. However, when the trips completed by both AV capabilities were analysed, it was observed that HC AVs generally completed the trips in shorter distances. This is attributed to their ability to navigate challenging network sections more effectively due to their advanced capabilities.

As with scenario 1, it was observed that the least challenging paths for both AV capabilities tend to be longer than those typically used by HDVs. Specifically, Fig. 7b indicates that for certain OD pairs, there is an increase of approximately 5 miles in travel distance for both AV capabilities. The analysis revealed that trips made by LC AVs in 1423 OD pairs are, on average, 24.9 % longer than those made by HDVs. Similarly, trips made by HC AVs in the analysed 1498 OD pairs are on average 22.6 % longer than those of HDVs. This implies that AVs will likely to navigate alternative routes compared to HDVs, which could result in additional distance being travelled within the city. Such deviations from the shorter HDV routes have potential implications for energy consumption and environmental impact, underscoring the need to consider the broader effects of integrating AVs into urban traffic systems.

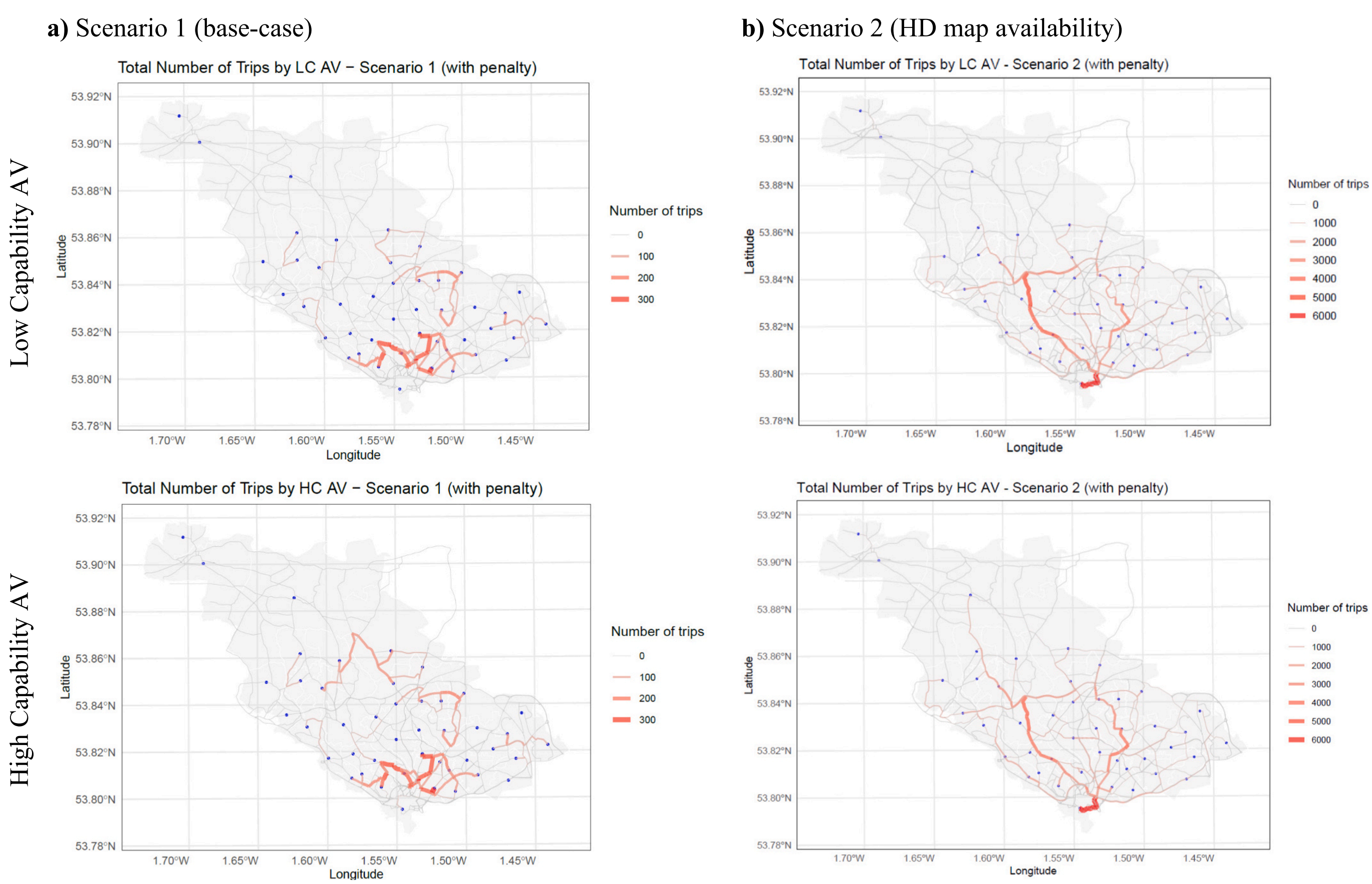

Fig. 8. Visual representation of the total number of car trips passing through each road section, based on the shortest paths of each OD pair in Network: a) Scenario 1, and b) Scenario 2.

In this scenario, out of a total of 27,187 trips analysed, 22,670 could potentially be accommodated by LC AVs, and 23,847 by HC AVs. Despite the integration of HD maps, a notable number of trips remained infeasible due to challenges on approximately 8 % and 5 % of road sections for LC and HC AVs, respectively, which were deemed extremely challenging for AV navigation. The spatial distribution of these feasible AV trips, as illustrated in Fig. 8b, offers valuable insights into the potential transformation of the transportation landscape within the study area through AV integration. The figure shows that, with the presence of HD maps and advancements in AV capabilities, the distribution of total completed trips in the network becomes more similar to that of HDVs.

Overall, the findings showed that the dispersed distribution of extremely challenging road segments within the analysed network led to significant barriers for both AV capabilities to complete their journeys. Therefore, broadly similar trends were observed in the spatial distribution characteristics of completed journeys for both AV capabilities. Moreover, it is observed that AVs tend to follow slightly different paths compared to HDVs, resulting in variations in the total number of cars passing through certain links in the network. This deviation underscores the possible necessity of adapting road networks to better support AV navigation and potentially enhance overall traffic flow. However, it should not be overlooked that today's current ADS technologies may already be capable of overcoming some challenges posed by road infrastructure, but most AV manufacturers have yet to share or verify such data. This required a holistic perspective in the assessment of the road network for these technologies.

4.3.4. Sensitivity analysis

This section examines how the routing results for OD pairs fluctuate based on the adopted α values in Eq. 3, reflecting the relative importance of the normalised length of links versus Road Readiness Index (RRI) values. Fig. 9 depicts the distribution of travel distances for OD pairs within the network for HC AVs in Scenario 2, considering different weighting coefficients. Each boxplot corresponds to a distinct α coefficient value, ranging from 0, highlighting the RRI, to 1, giving full priority to the length of the road link in determining the route. The figure indicates that the mean travel distance does not significantly change with different α values. Notably, while the average travel distances remain relatively stable across different α values, the total system-wide travel distance, which accounts for individual trips for each OD pair, exhibits considerable variation, ranging from 6813 to 7527 miles. Additionally, slight route changes are observed for some OD pairs. Nonetheless, the weighting scheme employed effectively balances the importance of road length and readiness levels without being overly sensitive to the selected α values, demonstrating its practical applicability for network analysis.

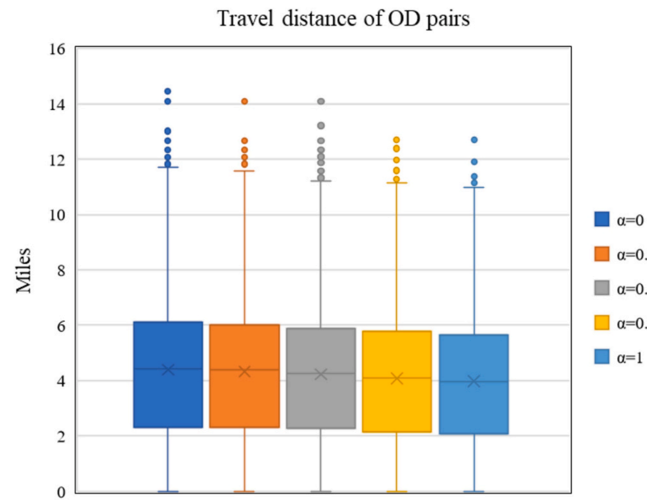

Fig. 9. Boxplot of Travel Distances for OD Pairs with varied weighting coefficients in Scenario 2 for HC AVs.

5. Conclusion and recommendations for further research

The current automated vehicles (AVs) have not yet reached a point where their automated driving systems can operate without fail across the entirety of regular road infrastructures (Bishop, 2024). This limitation underscores the role of importance of both the infrastructure and the surrounding environment in the initial phase of transitioning towards fully autonomous vehicles. However, preliminary research in this area has revealed considerable variation in the level of preparedness of road infrastructure in city networks (Soteropoulos et al., 2020; Tengilimoglu et al., 2024). This variability suggests that certain roads or zones may not be as conducive to continuous AV operations as others. As such, the present study carried out the first exploratory analysis to understand how heterogeneity in road infrastructure readiness may impact the utility of AVs for urban commuting, specifically focusing on the city of Leeds, UK.

A key conclusion is that automated vehicles will likely be required to travel more distance than human-driven vehicles when taking over control of the vehicle is not an option (i.e., utilised as a passenger mode only). Although the analysis was concentrated on road segments that constitute the main arteries of the road network, there remains significant variation in both their physical and digital infrastructure quality, and hence, in their readiness levels. This diversity in infrastructure quality will likely lead AVs to take different routes than human-driven vehicles to reach their destinations, which will potentially result in additional miles travelled within the city. The routing analysis of OD pairs revealed that relatively less challenging paths for both AV capabilities could be up to 5 miles (8 km) longer than those potentially utilised by HDV for some OD pairs. Importantly, the analysis revealed that AV trips are on average about 20–25 % longer than human-driven vehicle trips in the analysed OD pairs. This observed increase in total travel distance is consistent with the insights obtained from a study conducted in the Amsterdam metropolitan region (Madadi et al., 2021), suggesting potentially adverse implications for energy consumption and environmental impact. Moreover, with the likelihood of increased empty-vehicle travel and the relocation of parking spaces outside of the city centre, AVs are expected to contribute to a rise in travel distance (Milakis et al., 2018; Soteropoulos et al., 2019). Therefore, the broader implications of integrating AVs into urban traffic systems warrant thorough consideration.

The findings also highlighted that infrastructure, especially digital infrastructure, plays a more crucial role than AV capability in expanding operational areas and thus completing journey between OD pairs. When solely reliant on on-board sensors, without the aid of digital mapping, a substantial majority of commuting trips could not be facilitated by both AV capabilities due to the absence of suitable routes between origins and destinations. In this scenario, for instance, it was observed that only 7 % of OD pairs within the study area could be serviced by high-capability AVs as limited routes fully meet the requirements of AVs. This underscores the likelihood that substantial enhancements to both physical and digital infrastructure will be necessary to enable AVs to fulfil a significant portion of urban travel demands. Notably, the integration of digital mapping into the network—corresponding to a reduction in around 13 % of the penalised road sections—increased the number of accessible OD pairs to 87 %. This affirms the vital role of digital infrastructure in enhancing AV compatibility and demonstrates a marked improvement in AV network accessibility, facilitating connectivity for nearly an additional 80 % of OD pairs. Nonetheless, there is still a considerable amount of OD pairs that could not have connected. The primary obstacle appears to be the provision of communication support for AVs to exchange safety-critical information, which is notably challenging in rural areas and certain urban locations. This is crucial to achieving a more uniform level of readiness across the entire road network and enhancing the safety of AV operations across various environments.

In particular, catering to demand in rural areas poses a problem for AVs. For example, establishing connections between urban centres and rural areas or towns is not viable with the road sections analysed. In scenarios where AV ownership is personal, drivers may need to take control of the vehicle for these segments to make trips possible within the study area. However, this requirement could diminish the full potential benefits of AVs, particularly in terms of time value for users (Wadud, 2017). It could also lead to driver annoyance with the ADS. Similarly, in a shared AV model, such rural locations are likely to fall outside the geofenced service areas during the initial stages. Rural populations, which generally have a higher proportion of individuals aged 65 and over, may include some who are unable to drive (Department for Environment Food and Rural Affairs, 2024). Moreover, rural areas tend to have poorer quality and less frequent public transport services compared to urban areas, leaving residents with limited alternative transport options. A recent study indicated that, on average, rural bus services in England and Wales have declined by 52 % since 2008 (Friends of the Earth, 2023). Consequently, these communities might face increased challenges in accessing vital services, particularly healthcare. This situation underscores the critical need to enhance accessibility for rural populations, ensuring that they benefit equitably from advancements in AV technology. However, while AVs promise the convenience of door-to-door service, such service may be impractical in many parts of the urban network as lower-tier roads, such as access or local roads, often present significant challenges for automated driving (Tengilimoglu et al., 2024). Therefore, the implementation of AV-compatible drop-off and pick-up points on the main arteries of the network will likely be crucial in alignment with emerging technology to maximise the benefits of AVs (Bruck and Soteropoulos, 2022).

In addition, the findings underscore that, within the existing infrastructure, high capability AVs, such as advanced equipped robo-taxis, can efficiently meet short to medium distance commuting needs within urban areas. This efficiency primarily stems from the challenge of finding relatively fewer challenging routes for longer trips due to the heterogeneity in the quality of infrastructure. Furthermore, differences between the shortest and least challenging (i.e. most suitable) routes for AV trips across the network can be utilised by authorities to identify the critical road sections needing further investment to obtain optimal routes and facilitate broader AV adoption. This enables policymakers, city authorities, and third-party service providers, such as those offering communication services or digital mapping, to assess the network with a solid empirical basis. Therefore, the findings from this study may serve as useful indicators for guiding investment strategies and near-term planning, suggesting potential early operational routes to optimise benefits across the transportation system. However, these near-term actions should be implemented with “no regrets” and should benefit both road network operations and human-operated vehicles (Amelink et al., 2020). In this context, the activities and plans of vehicle automation industry towards improving ADS capabilities are also crucial for reducing heterogeneity in road readiness. Therefore, achieving readiness for automated driving in an safe and efficient manner will likely require coordinated efforts in improving ADS capabilities, as well as in upgrading infrastructure and its maintenance practice (Sauvaget et al., 2023; Somers, 2019).

Finally, there is a clear need for further research in specific areas. Firstly, limitations in the methodology of the source RRI (Tengilimoglu et al., 2024) are also applicable for this study since it followed a similar strategy. For example, incorporating environmental conditions and traffic flow-related factors into the index by evaluating them in real time could provide a more comprehensive and responsive assessment of road suitability for AVs. Furthermore, leveraging real-time AV sensor data could allow for dynamic modelling of parameters such as the number and diversity of road users in the index. Secondly, to mitigate the uncertainties in automated driving technologies, this study adopted a holistic approach to assessing the readiness levels of road sections by considering two distinct capabilities and two network scenarios. However, as AV technology continues to advance, there will be a need to continuously update and refine the assessment framework to keep pace with cutting-edge technology and the evolving requirements of road infrastructure, especially for the specific use case of Level 4 AVs. Thirdly, this study primarily examines scenarios of uncongested traffic, without any constraints on flow based on link capacity. Hence, incorporating RRI into traffic models could provide more detailed and nuanced insights. Furthermore, a significant barrier to AV adoption in urban road networks is the diversity of intersections and roundabouts, each with its unique rules and complexities. Intersections are critical as they directly influence trip routing. Just as some road sections pose challenges for AV operation, certain intersections also present difficulties, necessitating further analysis to include these interactions. Additionally, local access roads are omitted from the scope of this study. Future studies should consider including local roads to conduct a detailed analysis, especially from the perspectives of accessibility and equity related to AVs.

Regarding travel outcomes, the OD data utilised in this study, derived from the 2011 census, may not accurately represent the current network state. While offering valuable insights, this data might not capture changes in travel patterns or infrastructure developments since the census. This temporal discrepancy should be considered when assessing the study's findings and their relevance to contemporary and future transportation planning and policy formulation. Additionally, the analysis could be further enriched by integrating the effect of the built environment on interest in the ownership and use of self-driving vehicles (Nodjomian and Kockelman, 2019). Besides, exact numbers (e.g., increase in driving distance) presented in this study may not be reliable, as ADS capabilities change with technological enhancements, the increases in travel distance and emissions will also change. Similarly, a different readiness index may also change the numbers. However, the key is that there is a strong possibility of a remarkable increase in driving miles due to operational reasons. Despite these limitations, we believe this is the first study that demonstrates the usefulness of RRI in highlighting the need to incorporate infrastructure preparedness to fully understand the actual benefits of AVs on the roads.

CRediT authorship contribution statement

Oguz Tengilimoglu: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Conceptualization. **Oliver Carsten:** Writing – review & editing, Supervision. **Zia Wadud:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2024.104042.

Data availability

Data will be made available on request.

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