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Are current roads ready for highly automated driving? A conceptual model for road readiness for AVs applied to the UK city of Leeds

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ABSTRACT

The emergence of Automated Vehicles (AVs) promises a transformative impact on future travel patterns and consequently on the design of urban spaces. Despite the revolutionary prospects, the integration of AVs into existing and near-future road infrastructures presents a complex and unexplored challenge. This paper addresses this critical gap by introducing a novel and comprehensive assessment framework designed to evaluate the readiness of road networks for highly automated vehicles (Level 4 AV) operation. Recognising the uncertainties in automated driving technologies, the study defines two distinct AV capability levels and adopts three potential network scenarios to explore varied technological advancement perspectives and their impact on the suitability of current road network for their use. This multi-scenario approach offers a holistic viewpoint on the prospective circumstances and potential strategies to AV deployment. The proposed framework was empirically applied in a specific area in Leeds, United Kingdom, demonstrating its practical applicability. The findings of this research offer vital insights that contribute to the understanding of AV integration into road networks and support decision-makers and transport planners in developing informed and future-oriented policies, regulations, and guidelines.

1. Introduction

Over the past decade, Automated Vehicles (AVs) have transitioned from a conceptual possibility to an actual presence on public roads because of significant investments and advances in machine learning, sensor technology and computing (International Transport Forum, 2023a). AVs offer various potential benefits, including enhancing road safety, increasing people's accessibility, and reducing energy consumption (Milakis et al., 2017; Wadud et al., 2016). However, realising these benefits hinges on ensuring the safety of the Automated Driving Systems (ADS), typically referenced when discussing Level 3 automation and above. AVs are often described by SAE automation levels, which describe the capabilities of the vehicle in terms of its ability to perform some or all of the driving tasks without human intervention (SAE International, 2021). Levels 1 and 2 of driving automation, which include driver assistance features such as lane centring and/or adaptive cruise control, have been commercially available for several years. More recently, many automakers have introduced Level 3 vehicles, which offer partial automation under certain conditions (Bishop, 2024). At this level, the

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ADSs take over all driving tasks when engaged, reducing the need for continuous human supervision. However, the higher levels of automation, where human intervention is required only in certain situations (Level 4, hereafter L4) or is not required at all (L5), are still in the early stages, with widespread adoption expected to take decades (Litman, 2023).

Highly automated vehicles are undergoing extensive trials in numerous developed nations globally. Major automobile manufacturers, alongside tech giants and promising startups, have embarked on a race to achieve the pinnacle of vehicle automation. While the design concepts differ, all these vehicles rely on the use of a set of sensors to perceive the environment, advanced software to process inputs and decide the vehicle's path, and a set of actuators to act on decisions (Wevolver, 2020). Yet, their automation capabilities differ considerably based on their Operational Design Domain (ODD) due to variations in the type of service they provide or the specific sensors they are equipped with. 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).

In practical terms, the ODD is instrumental in delineating where an AV's automated functionalities can be effectively employed. Therefore, there is a growing interest in the scientific community to develop ODD taxonomies that define the conditions under which ADSs might operate (AVSC, 2020; BSI, 2020; Mendiboure et al., 2023; Thorn et al., 2018). In this context, there is an emphasis on exploring which factors have an impact on the functioning of AVs. This exploration can be done through empirical investigations of AV trials (Klauer et al., 2023; Ramanagopal et al., 2018) or by analysing AV-involved accident or disengagement data provided by AV manufacturers (Boggs et al., 2020; Ye et al., 2021). Furthermore, significant strides have been made in recent years towards developing risk assessment and safety verification methods for automated driving systems. Among these advancements, scenario-based strategies stand out; they evaluate the safety of AVs by testing individual traffic situations through virtual simulations against a variety of variables (Riedmaier et al., 2020). Apart from this, few studies have introduced models that evaluate the complexity of driving environments or scenarios of traffic based on sensory data of AVs (Cheng et al., 2022; Li et al., 2019; Wang et al., 2018).

On the other side, there is an expectation that AVs require a compatible road infrastructure that provides them with an environment fit for their use (Tsigdinos et al., 2021). However, current specifications lack information on the necessary infrastructure to support each level of automation or service model. The main efforts to date predominantly adopt a vehicle-centric perspective, with safety and reliability issues primarily viewed from the vehicle's standpoint. The role of infrastructure in the deployment of automated driving has often been relegated to the background (Tengilimoglu et al., 2023a). In practice, the road network is a mosaic of varied road types with various conditions, and AVs must transition between them seamlessly during their operation (Chen et al., 2023). It is therefore important for authorities and road agencies to know how ready their current road infrastructure is for safe automated driving.

In addition, for AVs to truly emerge as viable mobility options, they must operate not just in regions where their advanced capabilities have been rigorously tested, but also beyond. Therefore, developing and implementing an assessment framework to measure the readiness of the infrastructure for AVs can assist authorities in identifying areas that need to be addressed, as well as planning for the necessary infrastructure upgrades. This is pivotal as L4 AVs can only achieve full operational capability under specific and limited conditions, which requires a clear understanding of the infrastructure required. Realising this objective, however, is not straightforward, requiring significant effort and financial support (Saeed, 2019; Tengilimoglu et al., 2023b).

Various road categories, their specific design requirements, traffic loads and complexities should be evaluated separately and from different angles to prepare the roads for AVs (Ulrich et al., 2020). However, studies to date have tended to focus on the potential infrastructure requirements for automated driving based on experts' views (Tengilimoglu et al., 2023a) and presented these as a desirable infrastructure characteristic rather than analyse in detail the relationship between road infrastructure and the risk to performance of AVs (Carreras et al., 2018). This is mainly due to the lack of sufficient data to establish an empirical model for this relationship and differences in the technologies adopted in AVs. Therefore, there is currently very limited research on the assessment side of road infrastructure for AVs (Konstantinopoulou and Ljubotina, 2020) and therefore the suitability of road networks for the operation of AVs. Particularly, few studies have been conducted to systematically evaluate the suitability of road networks in urban areas for L4 AV operation and the potential impact of road infrastructure on the travel demand and network performance side. Most of the prior studies have predominantly focused on motorways in relation to automated driving.

Therefore, this study seeks to address the existing gaps in the field. The primary objective is to establish an assessment framework to determine the readiness of urban road infrastructure for the safe deployment of L4 AVs. Moving beyond prior research approaches that overlooked variations in AVs, considering uncertainties in automated driving technologies, this study highlights two distinct AV capability levels. Additionally, it adopts three potential network scenarios, depending on the technical capability of the AV. This approach moves beyond the current literature on presenting infrastructure requirements, instead leveraging expert opinions to critically evaluate the importance of various infrastructure elements for AV operations, and thereby determining the suitability of specific road sections for such technologies. To the best of the authors' knowledge, this study is the first exploratory research that evaluates the compatibility of road infrastructure and the surrounding environment for automated driving based on the opinions of key stakeholders and experts in the field. In the absence of actual AV trials, which can be resource-intensive, such an assessment framework might offer a starting point for authorities to assess road segment suitability within the network. In addition, through the visualisation of assessment outputs, potential operational zones for initial AV deployments can be identified to prioritise road user safety. As such the aim of this study is not only to deepen the understanding of infrastructure readiness but also to provide guidance for policymakers and road agencies as they navigate the impending transformation in transport: the broader adoption of L4 AVs.

The organisation of the rest of this paper is as follows: Section 2 summarises prior studies regarding road assessment and classification concepts. Section 3 introduces the concept of an assessment framework for evaluating the readiness level of roads for automated driving. It also offers a brief review of the current literature, addressing the basic principle of AVs and the challenges and factors that impact their performance. In Section 4, the practical application of this framework is explored, with a focus placed on the selected case study area. This section provides an in-depth description of the utilised data and methodological approaches for subcomponents. Then, it presents insights from this implementation as well as recommendations for future AV infrastructure development. The final section presents the conclusions drawn from this research, coupled with recommendations for prospective studies in this arena.

2. Literature review

In the existing literature, one can find infrastructure-related frameworks designed for pedestrian and bicycle traffic. These frameworks guide the identification of optimal locations for investment, with the aim of maximising societal benefits. These studies often construct walkability (e.g. Zhao et al., 2019; Su et al., 2019) or bike-ability indices (e.g. Winters et al., 2013; Krenn et al., 2015; Arellana et al., 2020). Within these frameworks, various components are calculated for specified reference spaces, such as grid cells or street segments. These are then merged into a singular value, commonly referred to as an "index", which represents the area's suitability for cycling or walking. In a similar context, this approach can be applied to the road network in a given area to assess its suitability for the operation of AVs considering different use cases or levels of automation (Soteropoulos et al., 2020; Tsigdinos et al., 2021).

While several indices have been introduced in the literature to assess the readiness of countries (KPMG International, 2020) or cities (Jiang et al., 2022; Khan et al., 2019) for AV operations, they primarily offer aggregated insights. There is a lack of research investigating which roads are relatively suitable for AVs within an urban network. To achieve this, a more detailed, disaggregated analysis is essential. At such a level, road assessment programs have been already developed worldwide (e.g. the iRAP Star Rating of roads for safety). These protocols often assign ratings to roads based on the presence or absence of key safety-related design features and are validated by recorded accident databases. Such protocols can be adapted to rate the ability of roads to support AVs (Konstantinopoulou and Ljubotina, 2020). However, there is currently an insufficient amount of data on AVs to build an empirical model for this relationship.

As such, early research in this domain has largely relied on the opinions of experts, seeking to chart the unknown terrain of AVs. For example, Nitsche et al. (2014) pioneered the concept of an evaluation framework of road infrastructure for AVs. The study outlined infrastructure-related requirements for highly automated driving, focusing on 14 factors that impact the efficacy of three specific ADS groups: lane assistance, collision avoidance, and speed control systems. Among these factors, the complexity of the urban road environment, quality of lane markings, their visibility and harmonization, temporary road work zones, and discontinuous or damaged road edges or kerbs have been identified as the main challenges by experts. Similarly, Madadi et al. (2018) have attempted to predict potentially challenging road and intersection scenarios for automated driving, as well as the pertinent factors involved. This endeavour was grounded in workshops with experts. They presented experts with images of specific locales, prompting direct questions. Based on the experts' feedback, the authors discerned correlations between certain road attributes and their appropriateness for L3-4 AVs.

Another relevant research strategy has been to use the definition of the vehicles' ODDs as a starting point for defining the suitable road sections for automated driving. This is because various infrastructure and environmental conditions significantly impact an AV's interpretation of its environment, exposing it to operational limitations. Within this framework, a couple of studies have proposed classification schemes that categorise the capabilities of road infrastructure to support and inform AVs about the functionalities offered by different road facilities (Carreras et al., 2018; García et al., 2021; Poe, 2020). These classifications, called Level of Service for Automated Driving, range from "A" (indicating a road segment is compatible with most vehicle ODDs) to "E" (signifying the road segment has minimal compatibility with most automation systems). However, a notable limitation in these classification systems is the tendency to assign existing road infrastructures a uniform low score, neglecting the diverse characteristics and distinctions between them.

On a more detailed scale, a few initiatives have pioneered inspection criteria for assessing the readiness of motorways and arterial roads for automated driving. Among them, for example, the Saving Lives Assessing and Improving TEN-T Road Network Safety (SLAIN) project evaluated the physical road infrastructure of certain road sections across four European countries: Croatia, Greece, Italy and Spain (Konstantinopoulou et al., 2020). Similarly, Austroads, which is a road transport agency, carried out an extensive field audit of Australian and New Zealand highways to assess their readiness for active safety systems and automated driving (Somers, 2019). These studies, grounded in experimentation, aimed to identify the performance characteristics of traffic signs and road markings that might influence machine-vision systems' recognition capabilities. Additionally, in 2021, the Finnish Transport Infrastructure Agency initiated a project focusing on infrastructure support and classification for automated driving on Finnish motorways (FTIA, 2021). The project assessed the suitability of a motorway section for operating L3 and L4 AVs. In a separate study by Carter and Quick (2019), certain operational issues with AVs were identified as risk factors and accordingly, potentially hazardous locations along the Route 65 Corridor, which is representative of regional highway corridors, located outside the City of Pittsburgh, USA.

Regarding the readiness index for urban roads, Soteropoulos et al. (2020) have developed a framework to assess the suitability of roads in the network of Vienna for L4 AVs from a technological standpoint. This framework, mainly relying on publicly available data, combines the challenges faced by ADSs in their current technical state and considers diverse street space contexts. The study found that urban motorways and expressways have relatively high values of the automated drivability index. On the other hand, the lowest values of the index were observed in the central districts of the city, where often complex intersections, narrow streets as well as pedestrian crossings or non-structural separated bicycle infrastructure on the roadway are present. For a similar purpose, Cucor et al. (2022) have recently introduced an assessment framework to score segments of physical and digital infrastructure based on their features to expedite the deployment of AVs. This framework is elucidated through its application on a public transport route in Zilina, Slovakia. Utilising both connectivity and positioning data alongside image data, the study identified infrastructure readiness and challenges.

In summarising the literature, current research is still evolving in terms of a generally applicable framework for assessing the suitability of the road network for L4 AV operations. Most prior studies have taken either a broad approach, typically centring on national or city-wide indices, or a more specific one, with a predominant focus on motorways. There is a notable scarcity of research specifically targeting urban roads within cities due to the uncertainties in the automation domain. Additionally, studies commonly provide insights based on the present technological capabilities of AVs, rather than delving into the complex relationship between road infrastructure and the risks associated with AV operation.

3. Framework for the assessment of road readiness for L4 AVs operation

This section details the methodology and approach employed to develop an assessment framework that can evaluate the readiness level of roads for automated driving, specifically at L4. The task of identifying which road segments are more suitable in a road network for automated driving is complex due to the numerous criteria that affect the operation of AVs. Moreover, as mentioned earlier, there is limited data available on AV-involved traffic accidents or disengagement reasons of automated driving systems, which makes it difficult to explicitly define criteria for assessing road suitability. Furthermore, the available data predominantly originates from countries leading in vehicle automation, such as the USA, and may not represent regional differences. For these reasons, reviewing relevant literature and consulting experts about the capabilities and limitations of automated driving can be viewed as supplementary or alternative ways to establish evaluation criteria for the early stages of this emerging mobility service. To this end, the authors build upon their recent studies (Tengilimoglu et al., 2023a, 2023c), which identify limitations that certain road infrastructure features may impose on automated driving. Additionally, updated literature is reviewed to gather the latest knowledge on the identified components and corresponding subcomponents of the index. Fig. 1 depicts the steps undertaken to develop the assessment framework, along with the corresponding subsections.

3.1. Identifying the components of the assessment framework

Understanding what a typical automated driving system consists of and how it works is crucial to identifying the components of the framework. As a brief overview, the operation principle of automated driving systems (Level 3 and above) can be broadly categorised into three main subsystems: perception, planning, and control (Eskandarian et al., 2021; Pendleton et al., 2017; Tas et al., 2016). Fig. 2 shows the general overview of typical automated vehicle architecture. The perception layer refers to the ability of an AV to collect meaningful information from the sensing data and extract relevant knowledge from the environment. This data can be obtained either directly from on-board sensors such as cameras, lidars, and radars or through sensor fusion techniques or remote data sources such as roadside communication units. The perception layer calculates the global and local location of the ego-vehicle and builds a map of the environment (Van Brummelen et al., 2018). In other words, this layer refers to the understanding of the environment, such as where obstacles are located, detecting road signs/markings, and categorising data by their semantic meaning (Pendleton et al., 2017).

In the planning layer, functions such as action prediction, path planning, and obstacle avoidance are combined to generate an effective plan in a real-time manner. The planning layer determines the best global route from its current position of the world to the requested destination based on the remote map data of road and traffic information. Then, based on real-time vehicle states and the current environment provided by the perception layer, the planning layer computes a locally optimal trajectory through decision-making and trajectory planning (Eskandarian et al., 2021). Also, with vehicle connectivity, the perception layer can share its perception data with other road users, and the planning layer is able to perform cooperative driving with other road users (Guanetti et al., 2018). Finally, to follow the optimal route decision (e.g. lane change, right turn, or another manoeuvre), the control layer governs the longitudinal and lateral motions of the vehicle by calculating the appropriate command to control the actuators in the

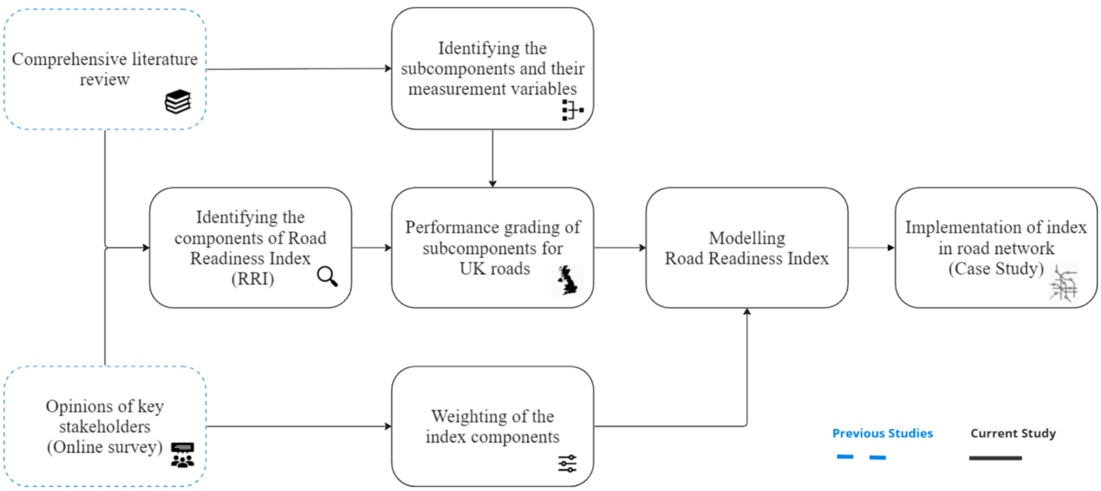


Fig. 1. Process for developing road readiness index for L4 AV operation.

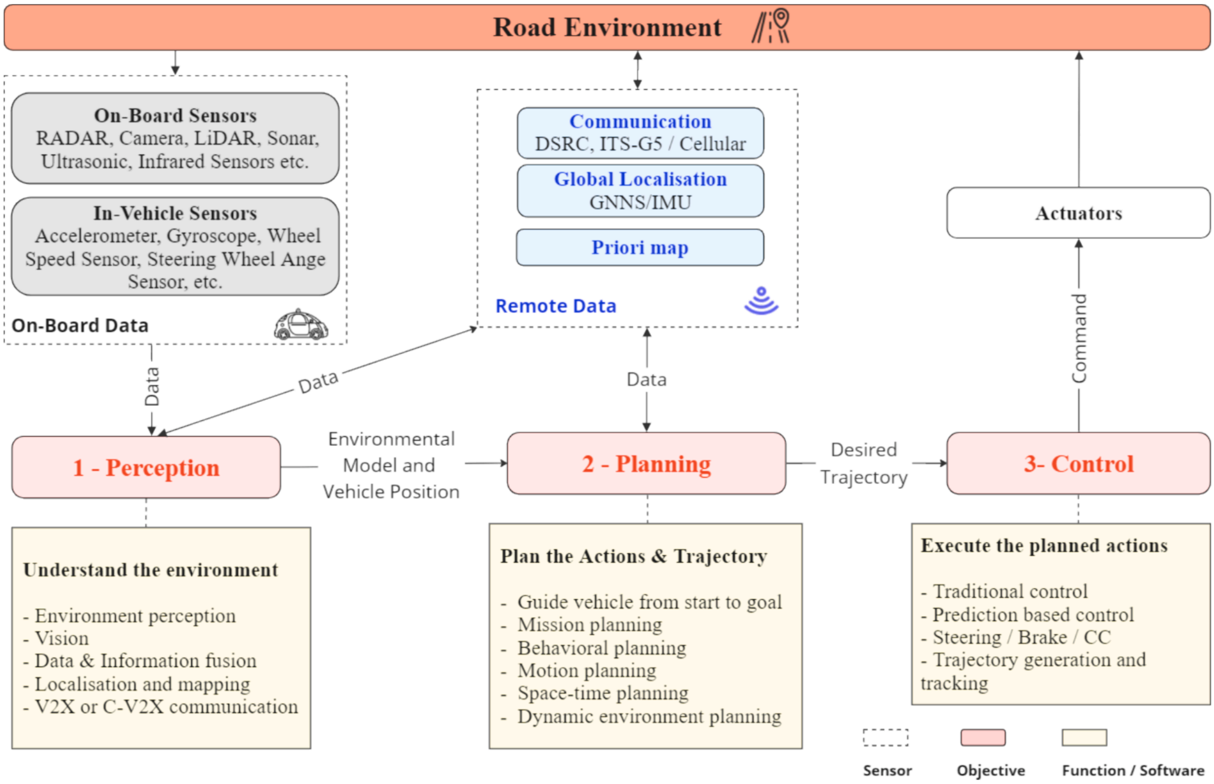


Fig. 2. The architecture of automated vehicles, adapted form (Eskandarian et al., 2021; Khan et al., 2023).

vehicle (Meneguette et al., 2018).

A thorough review of existing studies reveals numerous factors related to the requirements and limitations of the primary functions, as well as the auxiliary hardware and software integral to automated driving. These factors form a broad set of criteria to assess the operational design domains of emerging technologies (Thorn et al., 2018). From this comprehensive list, 15 pivotal factors have been identified for the proposed Road Readiness Index (RRI). These are: road geometry challenges, road surface conditions, road marking conditions, road boundaries, traffic signs visibility, special road sections, road lighting, speed limit, number and diversity of road users, precautions for roadworks and incidents, localisation challenges, communication supports, and intersections and roundabouts.

A brief description of these index components and their associated literature references is presented in Table 1. Further details about these framework components are presented in **Supplementary materials** (see **SM-1**), including the rationale behind their selection and their impact on the capabilities of AVs. However, it is essential to note that there are several dynamic factors such as weather and traffic conditions, accidents, and time of day that significantly influence the safe operation of AVs. As these dynamic factors may change in seconds, it is challenging to incorporate them into the evaluation of road segments in the network. Therefore, this study concentrates primarily on relatively static factors and road environment attributes. Nonetheless, some dynamic factors can be indirectly captured in various subcomponents in the framework.

3.2. Weighting of the components according to the opinions of experts

In the previous subsection, components of the index that can affect the performance of automated driving systems (ADS) in relation to road infrastructure and the surrounding road environment were presented. However, it is essential for policy makers and road authorities to understand the significance and relevance of each component in the framework to evaluate their road infrastructure or prioritise their investment. To achieve this, advanced weighting methods, such as the Analytic Hierarchy Process (AHP), have been applied in the literature to generate reliable weights for the parameters from decision-makers or expert judgments (Odu, 2019). However, in the absence of evidence-based sources to determine such measures, an expert weighted score method can be implemented in exploratory research by averaging the weights for each parameter. In addition, indexes consisting of many parameters without hierarchical structures require great effort in terms of computation (i.e. pairwise comparisons by experts).

Therefore, this study drew upon findings from the authors' previous research (Tengilimoglu et al., 2023c) to determine the

Table 1
Overview of components of the road readiness index for automated driving.

(Ci)	Framework Components	Description	References
C1	Road Geometry Challenges	Road geometric design challenges resulting from alignment and cross-section conditions that can affect the driving tasks or capabilities of AVs	(Amelink et al., 2020; Eskandarian et al., 2021; FTIA, 2021; García et al., 2021; Johnson, 2017; Konstantinopoulou and Ljubotina, 2020; Marr et al., 2020; Martínez-Díaz et al., 2019; Soteropoulos et al., 2020; Thorn et al., 2018; Wang et al., 2020)
C2	Road Surface Condition	Appearance and quality of road surfaces ensure safe driving for road users and are less challenging for the perception systems of AVs.	(Amelink et al., 2020; BSI, 2020; FTIA, 2021; Johnson, 2017; Konstantinopoulou and Ljubotina, 2020; Soteropoulos et al., 2020; Thorn et al., 2018)
C3	Road Marking Condition	Conditions and configuration of road markings that AVs need to detect and read rules of the road segment.	(Cucor et al., 2022; FTIA, 2021; Huggins et al., 2017; Konstantinopoulou et al., 2020; Lawson, 2018; Marr et al., 2020; Somers and Jones, 2019)
C4	Road Boundaries	Continuous and detectable road boundaries that AVs may not struggle with positioning themselves on the road section.	(Suleymanov et al., 2021; Transport Systems Catapult, 2017; Wang et al., 2022; Waykole et al., 2021)
C5	Traffic Signs Visibility	Conditions of traffic signs that AVs may not struggle to read and understand the rules of traffic.	(Cucor et al., 2022; Konstantinopoulou et al., 2020; Mihalj et al., 2022; PIARC, 2021; Poe, 2020; Roper et al., 2018)
C6	Special Road Section	Road sections or structures that require additional attention and may present challenges for AVs.	(Farah et al., 2018; FTIA, 2021; Huggins et al., 2017; Lu, 2018; Lyon et al., 2017; Manivasakan et al., 2021; Paulsen, 2018; PIARC, 2021; Rios-Torres and Malikopoulos, 2017)
C7	Road Lightning	The lighting conditions of the road segment so that AVs can detect and read the road infrastructure and surrounding elements.	(Amelink et al., 2020; BSI, 2020; Chen et al., 2020; FTIA, 2021; Gopalakrishna et al., 2021; Huggins et al., 2017; Johnson, 2017; Konstantinopoulou and Ljubotina, 2020; Liu et al., 2019; Soteropoulos et al., 2020; Thorn et al., 2018)
C8	Speed Limit	The maximum legal operating speed limits of road sections that AVs can stop within their detection range or conventional vehicles can travel along priority junctions safely.	(Cucor et al., 2022; Easa et al., 2021; Magyari et al., 2021; Pendleton et al., 2017; Soteropoulos et al., 2020)
C9	Number and Diversity of Road Users	The number and diversity of road users on the road segment that AVs must detect and respond to.	(Soteropoulos et al., 2020; Tabone et al., 2021; Thorn et al., 2018; Wang et al., 2020)
C10	Roadside Complexity	The level of roadside complexity may affect the performance of AVs, due to street furniture, trees, or commercial facilities.	(Ebrahimi Soorchaei et al., 2022; Huggins et al., 2017; Koopman and Fratrik, 2019; PIARC, 2021; Shladover, 2018; Soteropoulos et al., 2020; Ulrich et al., 2020).
C11	Facilities for Vulnerable Road Users	Infrastructure-related facilities to reduce interaction between AVs and VRUs (e.g. pedestrians and cyclists).	(Johnson and Rowland, 2018; Lu et al., 2019; Madigan et al., 2019; Manivasakan et al., 2021; Nitsche et al., 2014; Rasouli and Tsotsos, 2020; Tabone et al., 2021)
C12	Precautions for Roadworks and Incidents	Measures to reduce the risks that AVs may face in the roadwork area or incident scene.	(Amelink et al., 2020; Gopalakrishna et al., 2021; Lytrivis et al., 2018; PIARC, 2021; Thorn et al., 2018; Transport Systems Catapult, 2017;Wang et al., 2022).
C13	Localisation Challenges	Road sections on the network that may have difficulty receiving a strong GNSS signal due to the surrounding built environment or nature.	(Cucor et al., 2022; Eskandarian et al., 2021; Godoy et al., 2015; Huggins et al., 2017; Kuutti et al., 2018; Martínez-Díaz et al., 2019; Meng et al., 2018; Reid et al., 2019)
C14	Communication Facilities	Digital infrastructure facilities that support critical information transfer or communication between road users and the surrounding road environment so that AVs can operate safely.	(Cucor et al., 2022; Eskandarian et al., 2021; FTIA, 2021; Huggins et al., 2017; Lytrivis et al., 2019; Martínez-Díaz et al., 2019; Meng et al., 2018; Mihalj et al., 2022; PIARC, 2021; Poe, 2020; Somers, 2019)
C15	Intersections and Roundabouts	Types of intersections and roundabouts that reduce conflict between road users and ensure the safe operation of AVs.	(Amelink et al., 2020; BSI, 2020; Chen et al., 2020; FTIA, 2021; Gopalakrishna et al., 2021; Huggins et al., 2017; Johnson, 2017; Konstantinopoulou and Ljubotina, 2020; Liu et al., 2019; Soteropoulos et al., 2020; Thorn et al., 2018)

importance ratings of components. A 5-point Likert scale was utilised in a survey with experts, aiming to evaluate the factors that might influence the safe operation of L4 AVs in the foreseeable future. This survey gathered responses from a total of 168 experts spanning 29 countries, who specialised in the vehicle automation domain. These experts were divided into three groups: Agency (comprising local/regional authorities (9), national authorities (12), road agency/administration/operators (27), consultancy/engineering (24)); Industry (consisting of vehicle industry (15), technology developers (9), service providers and suppliers (4), research and development companies (3), insurance companies (1)); and Academia (encompassing universities (39), research institutes and organisations (25)). Among them, 160 experts assessed factors that were pinpointed from the current literature. Only those factors that were directly related to the components of the index were considered. The weight of each component (Wc_i) was then calculated based on their mean values, as shown in Table 2.

It is worth noting that different mobility models may require different considerations and infrastructure requirements based on their functionalities (Aigner et al., 2019). For this reason, the ranking of the factors was based on generic driving tasks of highly automated vehicles, rather than focusing on specific use-case scenarios. Nonetheless, each subcomponent representing components of the index was evaluated based on the two different driving capability levels of L4 automated vehicles, which is explained in the next section. In brief, the weights of the framework components are assumed to be valid for all L4 automated vehicles, but the performance

Table 2
Weightings of the components of the Road Readiness Index (RRI) based on experts' views (N = 160), adapted from (Tengilimoglu et al., 2023c).

Item (Ci)	Framework Components	Mean*	S.D.	Weight (Wc_i)
C1	Road Geometry Challenge	4.280	0.838	0.0733
C2	Road Surface Condition	3.813	0.979	0.0653
C3	Road Markings Condition	4.269	0.979	0.0731
C4	Road Boundaries	3.974	0.917	0.0681
C5	Traffic Signs Visibility	4.194	1.088	0.0718
C6	Special Road Sections	4.194	0.940	0.0718
C7	Road Lighting	3.800	1.003	0.0651
C8	Speed Limit	4.129	0.978	0.0707
C9	Number and Diversity of Road Users	4.381	0.914	0.0750
C10	Roadside Complexity	3.773	0.987	0.0646
C11	Facilities for Vulnerable Road Users	4.446	0.804	0.0761
C12	Precautions for Roadworks and Incidents	4.494	0.746	0.0770
C13	Localisation Challenging	4.547	0.733	0.0779
C14	Communication Facilities**	4.101	0.903	0.0702
				1.0000

* Where: 1 = Not At All Important, 2 = Low Importance, 3 = Importance, 4 = Very Important and 5 = Extremely Important.
** For this component, the highest average of communication related parameters is taken into account in the study.

grading of the subcomponents may vary according to the capability levels of the vehicles as their response to measurement variables can differ.

3.3. Identifying the subcomponents of the components and their performance grading in the context of UK road configuration

This step entails the identification of subcomponents that can represent components within the assessment framework. It also involves assigning performance grades to their measurement variables based on the scoring system. Although each component identified from the literature and the views of experts has an impact on the safe operation of AVs, there is currently no official standard or benchmark to be used by authorities to assess the level of readiness or compatibility of roads for AVs. Similarly, it is challenging to propose objective and proven thresholds for each component since the level of impact of individual subcomponents on the performance of AVs is not entirely clear yet. For this reason, grading systems were established for components to be evaluated quantitatively or qualitatively for road environment compatibility for automated driving. These scoring systems mainly were proposed by considering the current UK specifications and manuals regarding road design, operation, and maintenance.

In this process, first, subcomponents that can represent the framework components have been selected based on current literature insights. The feasibility of gathering data with current technology also played an important role in these selections. Subsequently, the weight of these subcomponents within the components ($Wc_{i,j}$) was determined, with most being assigned an equal weight. In the next step, the measurement variables of the subcomponents were defined in binary or categorical form depending on data availability. Following this, each measurement variable in the subcomponents was assigned a score ($Sc_{i,j}$) ranging between 0 and 1 to signify the grade of a particular road segment, with 0 being the lowest and 1 being the highest.[1] According to the selected grading criteria, a higher score denotes road characteristics that are more suitable for the safe operation of AVs.

However, the current AV industry focuses on developing automated driving technology for different service models with different capabilities (Shladover, 2022). For example, an automated bus and an urban robo-taxi will likely have different automated driving hardware, software, and sensors and thus have different operational domains. Even in the same use case model of AVs, some vehicles may be capable of self-driving on roads where other AVs may not operate, depending on their technology levels and computing budgets. For this reason, the study considered two different automated driving capability levels of L4 AVs for the same use-case model when scoring the measurement variables of subcomponents. These are:

- ***Low Capability of L4 Automated Vehicle (LC):*** refers to a vehicle equipped with basic software and hardware that has limited perception range, needs more time for computation and response and is more dependent on the surrounding road environment to perform driving tasks. In other words, low-capability L4 vehicles have basic sensors and decision-making algorithms that can handle numerous simple tasks, but they may struggle to navigate through more complex environments due to constrained computing budgets. These vehicles may require human intervention in certain situations, such as adverse weather conditions or unexpected road closures.
- ***High Capability of L4 Automated Vehicle (HC):*** refers to a vehicle equipped with advanced software and hardware that has a long perception range with multiple sensors, has advanced decision-making algorithms and processing power, needs less time for computation and response, and is relatively less dependent on the surrounding road environment in order to perform driving tasks.

[1] The measurement variables in the subcomponents of the components 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.

They require less human intervention compared to low-capability AVs due to the heavy use of AI neural networks, high computing budget, and power draw.

After that, the weight of the subcomponents ($Wc_{i,j}$) and the score of the measurement variables in each subcomponent ($Sc_{i,j}$) were finalised in the light of the literature and the collective insights of the authors. Table A1 presents a summary of performance grading for each subcomponent and measurement variable within the component, based on UK road configurations (see **Appendix A**). Detailed information on each component in the assessment framework, along with their corresponding subcomponents and measurement variables, is provided in the **Supplementary materials** (see **SM-1**). It is worth mentioning that most of the measurement variables are not only UK-specific, so they can be applied in other countries. However, the subcomponents chosen to evaluate each component and the corresponding assessment system may change and need to be regularly reviewed in response to more precise and specific criteria that are identified.

3.4. Modelling of the road readiness index for the road network

The preceding subsections provided an overview of the assessment framework, including the weights assigned to its components, the chosen subcomponents, and the scoring scheme for each subcomponent. After these steps, the Road Readiness Index (RRI) can be modelled separately for road links and intersections/roundabouts. For road links, the RRI calculation is as follows:

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

where l is road link in the network and m is the type of L4 automated driving based on the 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, Wc_i and $Wc_{i,j}$ 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 subcomponents are subject to the following constraints:

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

For intersections/roundabouts, which are commonly illustrated as nodes in between road links, the RRI calculation is as follows:

$$RRI_{nm} = \sum_{j=1}^{n=4}(Wc_{15,j} \times Sc_{15,j,m}) \tag{3}$$

where n is node in the network and m is the type of L4 automated driving based on the capability level, j is the subcomponent number in the component ($i = 15$), n is the total number of subcomponents in the corresponding component, $Wc_{i,j}$ is the corresponding weight of subcomponent, and $Sc_{i,j,m}$ is a score of measurement variables in a certain subcomponent.

Note that the value range of the road readiness index is set to be RRI $\in [0, 1]$. That is 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. This suggests that road links or intersections require substantial investment to facilitate automated driving. A high score can be considered as indicating that the infrastructure quality and condition of a road section is very likely to be suitable for automated driving.

On the other hand, if the result of any component score in the analysis of a road link is zero ($i.e.\sum_{j=1}^{n} Wc_j \times Sc_{j,m} = 0$), 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. The literature indicates that many components in the framework are essential for the proper operation of AVs. Consequently, if the calculated result is zero, it 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 the road conditions and the need for additional measures or improvements before AVs can navigate that particular road link effectively.

4. Application of the road readiness index to a road network

4.1. Study area and road network

This section presents a case study that provides an evaluation of a real-world road network through the conceptual framework introduced in **Section 3**. The presented analyses of roads regarding the integration of AVs utilise a region in the city of Leeds, United Kingdom. Multiple factors prompted the choice of Leeds for this study. The city embodies a mosaic of urban forms, echoing the historical evolution of urban development patterns found in many UK cities, as outlined in the government document on urban form and infrastructure (Williams, 2014). Its blend of radial and grid patterns, combined with its peripheral developments, mirrors the infrastructure challenges and opportunities present in many urban areas in the UK. Furthermore, Leeds, with its sizable population and multifaceted urban morphology, showcases both the potential and challenges for AV operations. Given the representative nature of Leeds's road network and urban structure, findings from this case study could hold broader implications for several cities across the UK and Europe.

The road network data for Leeds Metropolitan District were obtained from the Ordnance Survey MasterMap Highway for the year 2021. This dataset includes all road categories based on eight different levels of hierarchy (N = 53,609 road links).[2] However, conducting a comprehensive evaluation of the entire road network in Leeds poses certain difficulties. The sheer size of the road network presents challenges in terms of data collection, analysis, and evaluation. Moreover, assessing each link individually is resource intensive. Due to these limitations, the study focuses on the Chapel Allerton region, an inner suburb in the northeast of Leeds. This is because focusing on a specific region like Chapel Allerton allows for a more targeted and manageable assessment while still capturing the essential characteristics and challenges of the broader road network in Leeds (see Fig. 3).

The selected area is one of the dense wards in the Leeds Metropolitan District. According to the UK Office for National Statistics, based on the 2021 census, the population of Ward is 24,963 and 5.144 km^2 area with having 4,853/km^2 population density. The Chapel Allerton area was chosen as the case study area for several reasons. Firstly, its proximity to the city centre, being just 2 miles away, and population density make it an ideal location to assess the feasibility and suitability of AVs in an urban setting. It is considered that users can either own or lease AVs or are served by a shared model of AVs that are circulating in the system. So, this closeness to the city centre suggests that the area could potentially benefit from the implementation of different AV use cases. Secondly, what makes Chapel Allerton an interesting case study area is the presence of different types of urban forms within the area (see Fig. 3). The area encompasses various types of urban structures, ranging from residential zones comprising terrace houses and a mix of detached houses, to local commercial hubs, parks, industrial sectors, multiple educational institutions, a hospital, shopping centres, and more. By evaluating the road infrastructure in an area with diverse urban characteristics, it becomes possible to understand how the heterogeneity of the environment affects the suitability of roads for automated driving. Additionally, the study area includes various road types, the distribution of which is detailed in footnote 4. This diversity is crucial for assessing the broader implications of AV integration and providing indications for infrastructure planning decisions. Thus selected area can be a good example for evaluating the road infrastructure and plans for the introduction of L4 AVs.

4.2. Data collection and score assignment

The framework is data-driven; however, the availability and accessibility of data related to the components of the RRI are often limited. This constrains research on evaluating the suitability of road sections for automated driving. This is because many of the subcomponents heavily depend on extensive field survey data, encompassing both physical and digital infrastructure data, which entails substantial time, labour, and financial resources (Konstantinopoulou and Ljubotina, 2020). This also makes the rapid update of data difficult for authorities. Therefore, a limited number of studies so far have collected detailed data with special equipment only from certain road sections, such as highways in a road network, to assess the level of readiness of roads (FTIA, 2021; Somers, 2019). In response to these limitations, some research has alternatively proposed a framework that relies on publicly available data to assess the complexity of road conditions and the surrounding environment for automated driving (Soteropoulos et al., 2020).

On the other hand, street view images have been widely employed in quantitative and qualitative research on built environments and urban landscapes (Arellana et al., 2020). In a similar strategy, for this study, most of the data for road infrastructure conditions were gathered from visual inspection using either aerial photography/satellite imagery or street view services such as Google Street View.[3] The approach also involved on-site observations and the utilisation of secondary data to accurately identify the specific requirements of the study area. Then, the proposed methodology involves implementing the index on a road network using a Geographic Information System (GIS) platform. Therefore, the values computed for the measurement variables should be compiled on such a platform. The road network is structured as a set of links and nodes representing the city's streets. While open-source platforms like Open Street Maps can be utilised for this purpose, in this study, road network data were sourced from the Ordnance Survey MasterMap Highway due to having more detailed information in spatial dimensions. So, each link in the road network can be characterised by the evaluated factors and components. That is, using the measurement variables collected from different sources and weights obtained from the experts' opinions, the estimated RRI can be mapped across the city or case study area. Briefly, various sources were utilised to gather data that could represent each measurement variable, and each road link and intersection was evaluated by the authors, and such a task required two months. Table A2 provides an overview of the data sources used and evaluates the quality and representativeness of the collected data for each component (see **Appendix A**).

[2] According to Ordnance Survey, the road hierarchy in the UK can be categorised based on road 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 forthrough traffic.

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

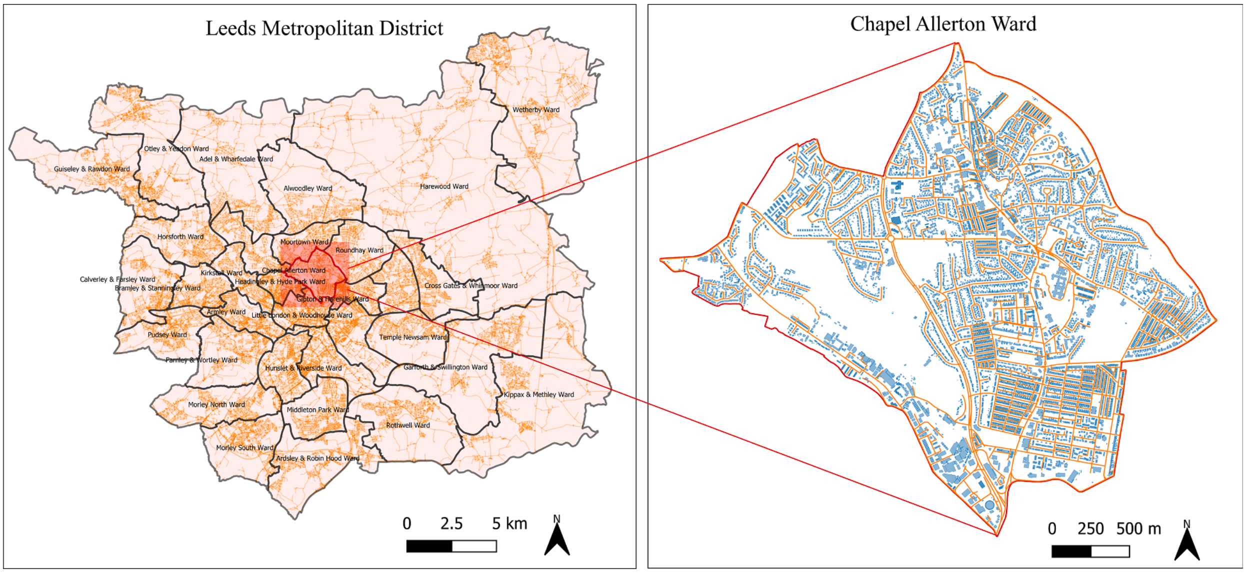


Fig. 3. Location description of the case study area: Leeds Metropolitan District (left), Chapel Allerton Ward (right).

Regarding the study area, road network data for Chapel Allerton Ward encompass all road categories except motorways, comprising a total of 1,553 road links. After data cleaning for road segments that are restricted to traffic or do not have street view data, 1,495 road links were obtained for analysis. The average length of road links is calculated at approximately 65 m, resulting in a total road network length of 96.8 km.[4] It should be noted that the physical attributes and amenities may vary within a road link or intersection. However, considering that any issues or conditions present on a road link may affect the performance of automated vehicles, it is essential to maintain the integrity of the link conditions in the data representation. As such, any challenging issues on road attributes or environment along the road link were assigned to represent the whole link. For example, if there is a pothole on one small segment of the road surface or damaged traffic signs on the side of the road, this can pose a risk for AVs to operate through this road link. This hypothesis is grounded in the rationale that authorities and societies are likely to adopt a cautious approach and exhibit increased vigilance towards AVs and the road links designed to accommodate them during the initial phases of deployment. On the other hand, small segment sizes for road links would produce a large amount of noise in the analysis. For these reasons, road links were not split into small sizes for the scope of this study.

4.3. Scenarios of road network evaluation

The case study focuses on three scenarios, taking into account two distinct automated vehicle capabilities. Considering the potential technological development in the information and communication and vehicle industry foreseeable future, these scenarios can be explained as:

- ***Network Scenario 1*** concerns the current conditions of the road network in the study area as the base case scenario. It is assumed that the study area does not have High Definition (HD) map and Roadside Units (RSUs) providing connectivity to exchange information between AVs and infrastructure. In this scenario, AVs have to rely solely on onboard sensors to understand the road environment and respond appropriately to surrounding road users. If a connection is required to obtain information, only the current cellular network quality can be used for connection to the outside world. Also, it is assumed that there is no presence of roadwork or incident in the study area.
- ***Network Scenario 2*** considers the incorporation of cutting-edge surveying technology and techniques that allow for the creation of a highly detailed map of cities. Consequently, it is assumed that HD maps are accessible for all roads within the study area. However, the absence of RSUs in the road network can be attributed to the challenges associated with implementation and management costs. Furthermore, the establishment of protocols and standards for vehicle-to-infrastructure (V2I) communications between the vehicle industry and road authorities has not yet been mutually agreed upon. If there is a need for a connection to obtain information, the current cellular network is the only available option, relying on its existing quality and coverage.

[4] The length of A Road network is 6.7 km (6.95%), the length of the B Road network is 4.3 km (4.44%), the length of the Minor Road network is 14.2km (14.63%), the length of the Local Road network is 59.2km (61.16%) and the length of the Access Road network is 12.4 km (12.84%).

- ***Network Scenario 3*** depicts a highly desirable scenario for the AV industry. It envisions the availability of HD maps for the entire road network and widespread coverage of 5G service with at least average quality, ensuring consistent and reliable connectivity across the entire area. Moreover, like the previous scenarios RSUs and roadworks are not present in the road network.

4.4. Results and discussion

4.4.1. Key findings and their implications

The evaluation results of road links and nodes for each subcomponent in the index components, derived from the existing conditions of the road network, are illustrated in the Figures provided in **Supplementary materials** (see **SM-2)**. Subsequently, the final Road Readiness Index values were computed by integrating these subcomponents, which reflect the measurement values of the road links and nodes, as per Equation (1). Fig. 4 illustrates the mapping of the outcomes obtained from integrating the assessment components for the Chapel Allerton region in Leeds, considering low-capability (LC) and high-capability (HC) automated vehicles. The index scores in the figure were divided into five groups to represent different difficulty levels for automated driving, ranging from extremely challenging to least challenging. Essentially, this categorisation demonstrates the suitability of road sections in facilitating AVs in terms of both road infrastructure and the surrounding environment.

The figure clearly indicates that the majority of road sections in the case study area are categorised as extremely challenging (represented by the colour red) for the safe operation of both AV capabilities. This is mainly due to factors such as poor-quality road infrastructure and the complexity of the surrounding driving environment, resulting in the index score being penalised. In general, the lowest value of RRI can be observed in residential areas, where often the absence of road markings, clear and detectable road edges or pedestrian sidewalks, narrow streets with on-street vehicle parking, poor road surface conditions, the presence of obstructions such as trees or bushes. Similarly, the low RRI values can be also observed in mixed-use with commercial facility areas, where the road environment is complex, no clear segregation between VRUs and public transit.

On the other hand, certain road sections (approximately 23.5 % and 26.2 % of total road links for LC and HC, respectively) in the network demonstrate relatively high RRI values, which are classified as either slightly or least challenging for AVs. However, there are significant gaps (i.e. lower RRI value sections) among these road links, primarily arising from variations in the quality and consistency of infrastructure and the road environment. As a result, the road network in the case study area demonstrates a marked heterogeneity in terms of its infrastructure and road conditions. Therefore, without modifications or upgrades in the infrastructure regarding the automated driving requirements, it is unlikely that AVs can operate seamlessly throughout the existing road network.

Regarding the evaluation results of nodes, which include intersections and roundabouts, a distinct pattern emerges. Unlike road links, a substantial proportion of these nodes (approximately 66.1 % and 85.7 % of total nodes for LC and HC, respectively) in the network were classified as either slightly or least challenging for AVs. One key factor behind this is that many junctions in the case study area are priority-controlled, three-armed, and feature a regular layout. These attributes generally offer a less challenging driving environment for AVs compared to other complex types of junctions. However, this trend can also be attributed to the smaller number of criteria used in the assessment framework for nodes, which reduces the likelihood of the index being penalised. Additionally, when assessing road links, larger areas are considered compared to nodes, thus making them more susceptible to penalties. Furthermore, the observed variations in the performance between different AV capabilities within the network can be linked to the distinct advantages of high-capability AVs, which enable them to mitigate drawbacks or navigate through complexities within the road network. These advantages are typically associated with advanced automated driving systems, encompassing sophisticated sensors and computational capacity. However, some junctions along the links with high RRI values are categorised as having low scores, indicating a high level of challenge for the operation of AVs. This implies that even if the road links themselves are suitable without any upgrades, AVs are likely to encounter difficulties in crossing junctions and may become stuck within the link. Additional consideration will likely be necessary for extending the operational areas of AVs, taking into account the challenges posed by intersections.

In Scenario 2, which assumes an HD map is available for the entire road network, it is observed that the operation areas of both AV capabilities extend significantly compared to the base case scenario (Fig. 5). For instance, for low-capability AVs, around 68.8 % of all road links in the network exhibit RRI values greater than the moderately challenging category, an increase of 45 % compared to Scenario 1. This change highlights the critical role HD maps play in facilitating automated driving, as these maps are linked to many components within the index. Especially for local roads and certain major roads suffering from poor road markings and traffic signs, challenging geometry and complex roadside environments, HD maps can potentially provide AVs with important additional details about the driving environment. Additionally, this scenario yielded higher index values for junctions, predicated on the assumption that HD maps can mitigate risks associated with poor delineation of markings at these locations. Briefly, this scenario utilises static map layers to provide redundancy for onboard sensors, aiding in precise localisation, enhancing perception beyond the sight range, and facilitating more accurate path planning.

Nonetheless, the provision of HD maps alone does not resolve all the challenges inherent in the road network. A substantial proportion of road links pose considerable obstacles for AVs, primarily due to factors such as limited cellular coverage. This is especially pronounced in densely populated areas where road links consistently exhibit low values due to the poor quality of communication services provided by telecom operators. This phenomenon could be rationalised by the direct correlation between population density and the requisite number of base stations; higher population density necessitates a larger number of base stations. Therefore, variances in cellular service quality across the case study area inevitably impact the suitability of roads for AV operation.

Scenario 3 undertakes an assessment of how advancements in cellular technology can influence the operational areas of AVs within the road network. As illustrated in Fig. 6, the findings demonstrate that, given the availability of 5G cellular network coverage coupled with HD maps, most road sections in the network present less of a challenge for automated driving. Furthermore, it is observed that the

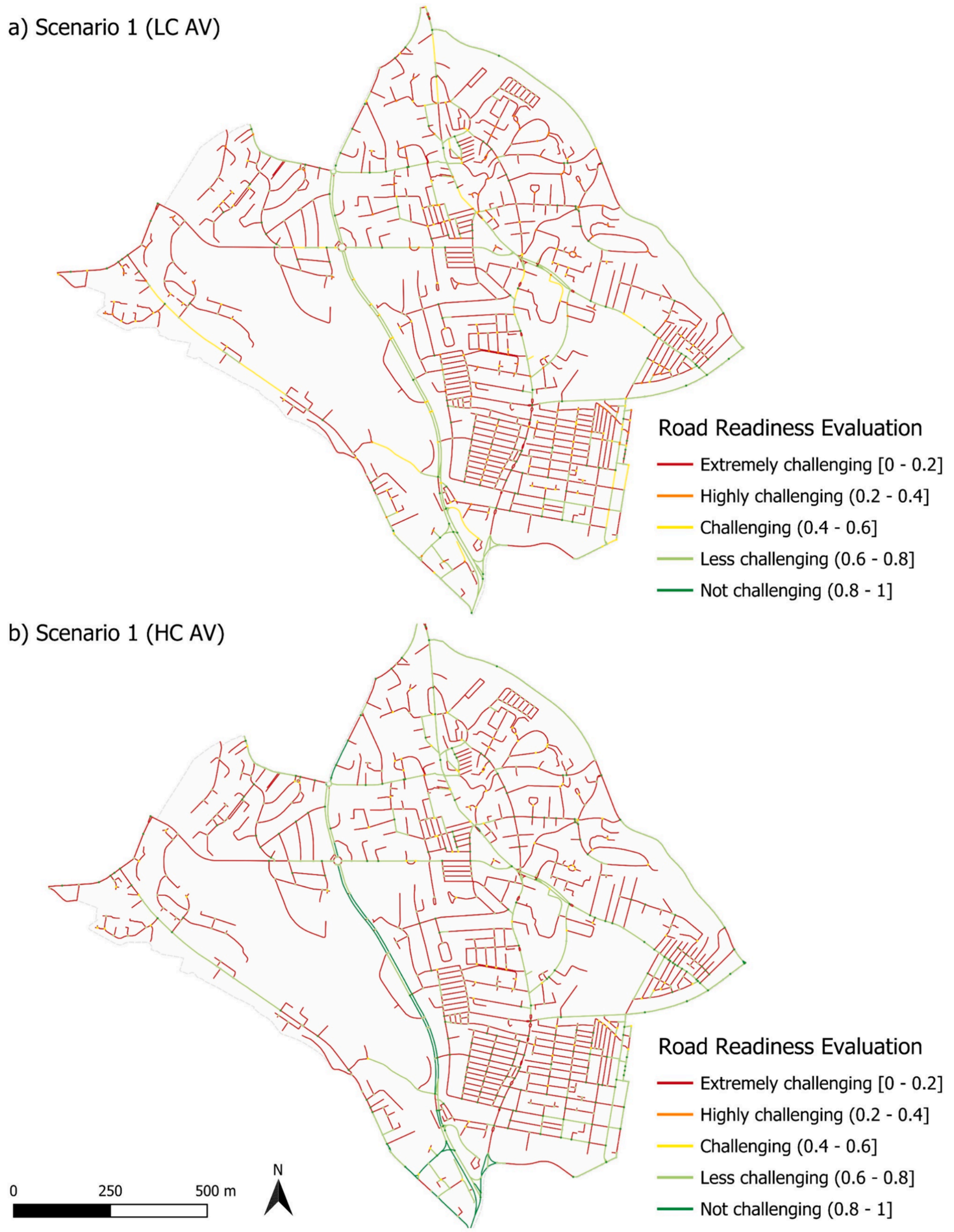


Fig. 4. Overview of the assessment of the readiness of roads and intersections in Scenario 1, comparing low capability AV (a) and high capability AV (b).

gaps previously present between main roads in earlier scenarios were largely bridged in this scenario. This highlights the vital role of digital infrastructure in partially compensating for the challenges caused by the physical road environment that AVs are likely to face.

However, certain road sections, including dead-end streets and numerous local and access roads, continue to pose significant challenges for both types of AVs. This challenge can be attributed to the infrequent oversight of these road sections due to their limited traffic. Such roads typically fall at the lower echelons of the road hierarchy. As a result, the quality of their infrastructure and control over their surrounding environments often lags behind that of other road types. These findings underline the point that road links in the network will not be AV-compatible by the implementation of digital infrastructure alone. To fully support AV operation, significant changes are needed in the physical design and conditions of the infrastructure.

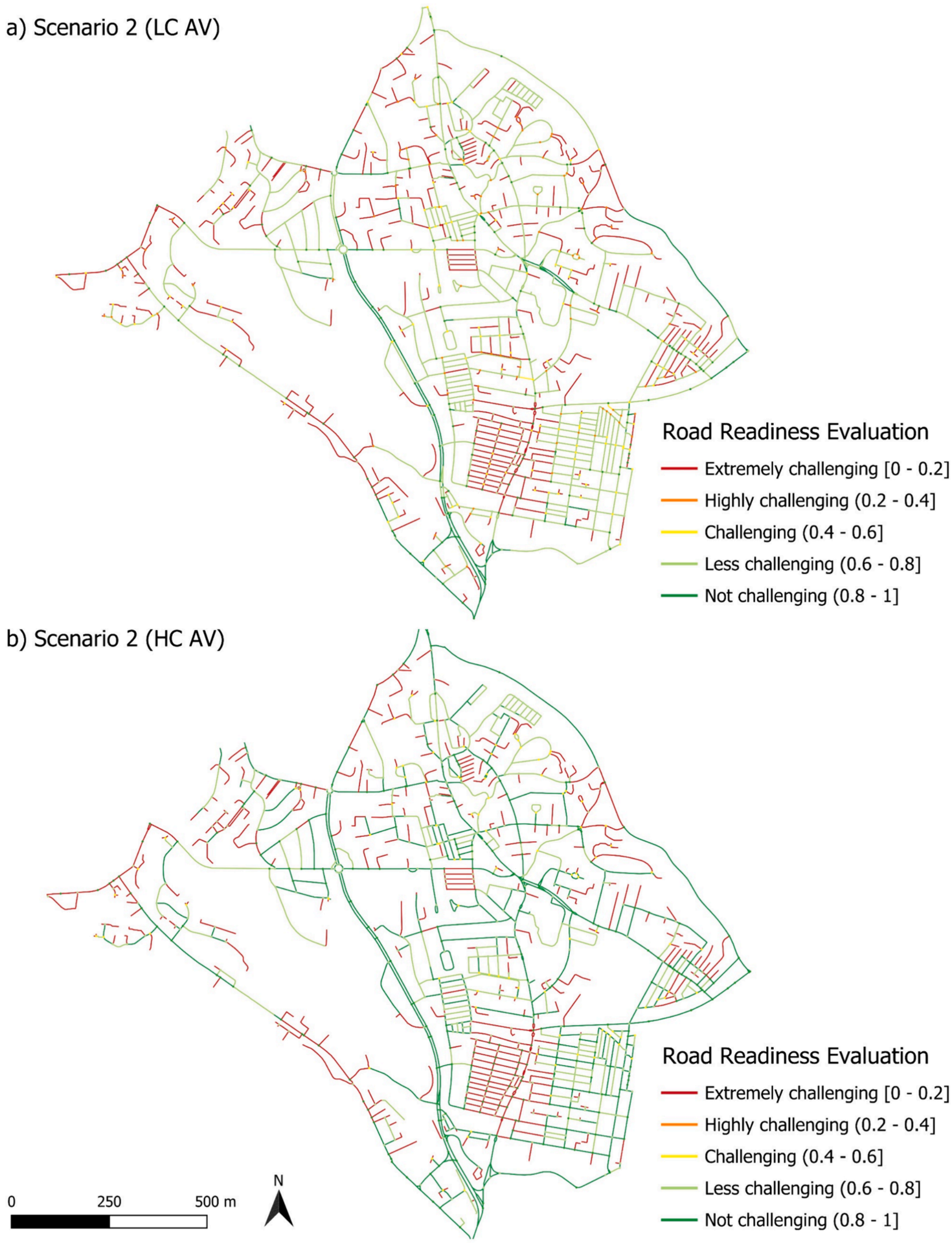


Fig. 5. Overview of the assessment of the readiness of roads and intersections in Scenario 2, comparing low capability AV (a) and high capability AV (b).

4.4.2. Correlations of road hierarchy and deprivation with RRI

Overall, the outcomes from the assessment, in conjunction with the scenarios, highlight the variability in road readiness for automated driving. A significant factor behind this variability is the diversity in the road infrastructure conditions across the network. However, a clear correlation emerges between the road hierarchy and the RRI value. Main roads, including A, B, and Minor Roads (for further details, refer to footnote 2), typically exhibit relatively high RRI values, even with higher speed limits and a greater variety and number of road users. Table 3 presents the distribution of road links in the case study area by road hierarchy and RRI category for Scenarios 1–3. The data shows that most sections classified as Local and Access roads pose significant challenges for automated driving across both AV capability levels. This is primarily because main roads employ comprehensive safety measures for road users and undergo frequent maintenance, making them comparatively well-prepared to accommodate the integration and operation of automated vehicles effectively.

Fig. 6. Overview of the assessment of the readiness of roads and intersections in Scenario 3, comparing low capability AV (a) and high capability AV (b).

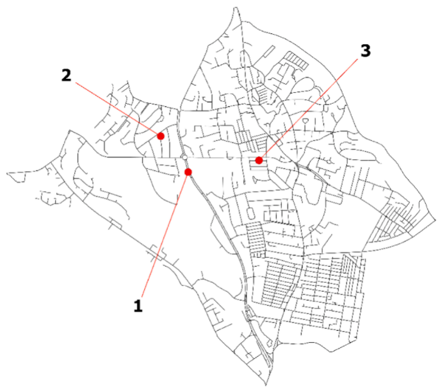
In addition, this study further explored whether road links in economically disadvantaged areas might exhibit lower RRI values. To this end, the Index of Multiple Deprivation (IMD)[5] was employed to assess the deprivation levels of sub-areas within the case study area (Chapel Allerton Ward). Pearson correlation tests were subsequently performed to determine if there was any correlation between IMD scores (where a higher score signifies more deprivation) and RRI values. The results showed no significant correlation in Scenarios 1

[5] The Indices of Multiple Deprivation (IMD) are measures used in the UK to identify areas facing multiple types of deprivation. The IMD combines data from various domains to create an overall relative measure of deprivation experienced by individuals in a given area. This measure is determined for each Lower Layer Super Output Area (LSOA) in England. Further information can be found in Consumer Data Research Centre (CDRC). Source: https://data.cdrc.ac.uk/dataset/index-multiple-deprivation-imd.

Table 3
Distribution of road links by road hierarchy and RRI category for Scenarios 1–3.

Scenario (S)	Road hierarchy*	Road Readiness Index category (HC)					–	Road Readiness Index category (HC)					Total
		Extremely Challenging	Highly Challenging	Moderately Challenging	Slightly Challenging	Least Challenging		Extremely Challenging	Highly Challenging	Moderately Challenging	Slightly Challenging	Least Challenging	
S1	A Road	17	0	1	65	0		17	0	0	30	36	83
	B Road	23	0	3	51	0		23	0	0	54	0	77
	Minor Road	87	0	13	120	0		86	0	0	113	21	220
	Local Road	829	0	8	114	0		823	0	0	123	5	951
	Access Roads	161	0	1	2	0		155	0	0	9	0	164
	Total # of links	1117	0	26	352	0		1104	0	0	329	61	1495
	Percentage (%)	74.7	0.0	1.7	23.5	0.0		73.8	0.0	0.0	22.0	4.1	100.0
S2	A Road	3	0	0	28	52		3	0	0	1	79	83
	B Road	13	0	0	46	18		13	0	0	3	61	77
	Minor Road	50	0	0	121	49		50	0	0	7	163	220
	Local Road	377	0	1	533	40		351	0	0	182	418	951
	Access Roads	122	0	2	40	1		86	0	0	62	16	164
	Total # of links	565	0	1	768	160		503	0	0	255	737	1495
	Percentage (%)	37.8	0.0	0.1	51.4	10.7		33.6	0.0	0.0	17.1	49.3	100.0
S3	A Road	0	0	0	21	62		0	0	0	0	83	83
	B Road	0	0	0	30	47		0	0	0	1	76	77
	Minor Road	0	0	0	105	115		0	0	0	1	219	220
	Local Road	240	0	0	600	111		212	0	0	72	667	951
	Access Roads	102	0	0	60	2		60	0	0	59	45	164
	Total # of links	342	0	0	816	337		272	0	0	133	1090	1495
	Percentage (%)	22.9	0.0	0.0	54.6	22.5		18.2	0.0	0.0	8.9	72.9	100.0

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



RRI values: Scenario 1 0.6848 (LC) / 0.8038 (HC)
Scenario 2 0.8124 (LC) / 0.9153 (HC)
Scenario 3 0.8299 (LC) / 0.9328 (HC)

RRI values: Scenario 1 0.0000 (LC) / 0.0000 (HC)
Scenario 2 0.6863 (LC) / 0.7669 (HC)
Scenario 3 0.7214 (LC) / 0.8020 (HC)

RRI values: Scenario 1 0.0000 (LC) / 0.0000 (HC)
Scenario 2 0.0000 (LC) / 0.0000 (HC)
Scenario 3 0.0000 (LC) / 0.7776 (HC)

Fig. 7. An overview of road sections with different RRI values in the case study area.

and 2. Yet, a distinct correlation emerged in Scenario 3. In this context, the IMD score and RRI demonstrated a positive correlation, with $r(1493) = 0.108$ and $p \leq 0.001$ for LC AVs, and with $r(1493) = 0.083$ and $p = 0.001$ for HC AVs.

A possible explanation for this finding in Scenario 3 lies in the unique street typologies of Chapel Allerton Ward's less deprived areas. Predominantly, these are low-density zones marked by a significant number of dead-end streets. Such streets usually act as access routes and are not used as primary thoroughfares. Due to this specific urban structure, many streets lead to residential vehicle parks and often lack comprehensive traffic control measures like pedestrian sidewalks or road markings. As a consequence, these areas frequently receive low RRI values, primarily because of their corresponding lower scores of subcomponents. On the other hand, this indicates that with the necessary investments in digital infrastructure within the study areas, more deprived neighbourhoods could stand to benefit significantly from AV service in the case study area, owing to their urban forms being more conducive to AV operation. However, it should be noted that this correlation might not be reflected in other areas of Leeds, due to the variety in street topology.

4.4.3. Sensitivity analysis

The accuracy and robustness of an index are paramount when it serves as a decision-making tool or evaluative metric. In the context of the Road Readiness Index (RRI), the outcomes may vary based on the components it includes and their respective weights. Thus, an extensive sensitivity analysis was performed to understand how variations in the RRI outcomes arise due to different weighting strategies, penalty strategies, and the removal of certain components. This investigation provided insights regarding which components greatly impact the RRI and how the distribution of its values across the road network shifts when specific components are omitted.

Firstly, the impact of uniform weights in comparison to expert-determined weights for each component on the overall index was evaluated. Table A3 displays the distribution of road links according to categorised RRI values, reflecting the challenging levels for AVs (see **Appendix A**). Despite the varying weighting strategies, there is no remarkable difference in the share of different categories of road links across the network. This can largely be attributed to the consensus among experts that almost all components are of equal importance for automated driving. Additionally, when comparing the perspectives of industry participants to those of all stakeholders combined, a very slight shift was noticed from the least challenging to slightly challenging road categories. This observation suggests a nuanced difference in perception regarding the readiness of road links for AV operation between these groups. However, in general, there is no statistically significant difference in attitudes towards parameters between stakeholder groups—for detailed information please refer to (Tengilimoglu et al., 2023c).

When penalties in the RRI are removed, a noticeable redistribution occurs across the challenge levels. Many road links, which were previously designated as extremely challenging under both the expert-weighted and equal-weighted approaches, transition to slightly challenging or moderately challenging categories. This indicates that, within the standard RRI, penalties are pivotal for a conservative assessment of road link suitability for automated driving. This further implies that the majority of road links in the case study area either fail to meet current road safety standards or have technological limitations, creating a complex environment for AVs. Another observation is that the presence of HD maps (see results of scenario 2) mitigates numerous penalties within the network, a result stemming from the structural nuance of the assessment framework. Conversely, road links categorised as least challenging largely retain a consistent presence across the network, regardless of penalty adjustments.

Lastly, the omission of certain components from the RRI was examined to understand their individual impact on the overall index. In all scenarios, the proportion of road links classified as extremely challenging remained unchanged. This suggests that the index incurred penalties because multiple components exhibited poor performance in scoring the measurement variables. However, it is evident that some components, when omitted, influence the distribution more than others. For instance, removing the condition of road markings, road boundaries, and facilities for vulnerable road users resulted in noticeable fluctuations in both the slightly challenging and least challenging categories, especially in Scenario 3. Similarly, in Scenario 2, communication facilities and the number and diversity of road users components were observed as critical factors in determining the suitability of road links for automated driving.

In summary, the sensitivity analysis of the RRI brings attention to the influence of certain components, the role of penalties, and the effects of weight adjustments. While the fundamental structure of the RRI is consistent, it is important to be aware of these sensitivities to ensure its effectiveness across various contexts. When utilising the RRI as a tool, these findings can provide valuable insights for those in decision-making roles.

4.4.4. Recommendations for improving the road infrastructure for AVs

The implementation of the Road Readiness Index (RRI) in the case study area, complemented by the visualisation of its outputs, offers crucial insights for policymakers and road authorities. These insights highlight prevalent issues within the road network, indicating potential measures that could be proactively taken during the shift towards automated driving. Such measures can be considered to address anticipated equity and accessibility challenges due to the variation in road infrastructure. These issues can be briefly explained as follows:

- There is a common view that higher penetration of AVs may lower parking demand in residential areas and in business districts by reducing car ownership and increasing ridesharing. However, during the initial stages of AV deployment, there is a need to substantially modify parking layouts and rights-of-way to mitigate conflicts between AVs and their surrounding environment, as well as interactions with human-operated vehicles. To ensure the safe operation of AVs, particularly on local and minor roads (e.g. snapshot 2 in Fig. 7), reconsideration of on-street parking regulations might be essential. For narrow roads, measures such as implementing a one-way system or permitting parking only on one side may be worth considering. These approaches also necessitate clear markings of prohibited road sections and parking spaces.
- Another prevalent issue within the road network is the high number of dead-end streets. As it is not yet clear how AVs will navigate such roads, in this index, these road sections were considered as extremely challenging for both AV capabilities. However, not all dead-end streets will likely present high challenges. Some, due to the presence of well-designed turning points at their ends, may allow AVs to manoeuvre easily. Yet, it was observed that inconsistencies in turning points, both in terms of their layout and size, as well as vehicle parking at these locations, pose challenges for AVs to manoeuvre smoothly. Therefore, to facilitate door-to-door AV services, considerable effort needs to be made towards standardising turning points and enforcing restrictions on on-street parking at these points.
- While urban trees are crucial for reducing the impacts of climate change (Tan et al., 2016) and contributing to walkable, societally desirable streets within the urban road network (Su et al., 2019), they can potentially present challenges for automated driving from several perspectives. Beyond the challenges for localisation (Cucor et al., 2022), trees and bushes have been observed as one of the main challenging roadside objects that cause obstructions on vertical traffic signs, street lighting and line-of-sight at intersections. Moreover, the accumulation of leaves on road surfaces can pose difficulties in detecting road edges or line markings, particularly during the autumn season. Although, digital mapping can help for addressing this issue, more frequent maintenance of

physical road elements in areas with high greenspace coverage will likely be required, and removal or pruning of trees may be necessary to mitigate potential obstructions.

- Maintaining consistency in physical infrastructure features, aligned with AV requirements, will be critical for automated driving. Significant heterogeneity has been observed in the road network in terms of the quality of road surfaces, and traffic signs, as well as the condition and configuration of markings. Certain sections of roads, for instance, present visual challenges for vision-based systems due to the diversity of surface materials, the patching of potholes, and the presence of numerous manholes. To mitigate the potential risks for AVs, authorities need to consider regular maintenance schedules to enhance road infrastructure. This would also include adhering to a standardised and consistent methodology in the placement and maintenance of road markings and traffic signs. Furthermore, minimizing potential sources of confusion, such as numerous manholes and patches, can be achieved through comprehensive and organized planning during the stages of infrastructure development and repair. Therefore, there will likely be a need for advanced road assessment systems that can provide more accurate and precise data from the road network.
- While urban roads are often well-lit at night, object detection and recognition at night-time is a challenging task for AVs (Milford et al., 2020). As such, sufficient street lighting can significantly contribute to the perception systems of AVs by aiding in the detection of road markings, signs, and surrounding objects. Notably, it has been observed that some sections of the road network have limited lighting operation times due to energy saving strategies. However, with the introduction of AVs, there is a need to reevaluate these operational time restrictions, particularly around bus stops, pedestrian crossings, speed bumps, and intersections. There are other challenges like motion blur and glare that can cause failures under night-time conditions (Milford et al., 2020). Thus, AV developers must demonstrate that their systems can robustly handle challenges posed by inadequate lighting conditions.
- Wheelie bins exemplify objects that are neither static nor dynamic, yet frequently appear alongside roads in certain areas. They pose a unique challenge as they are not traditionally considered roadside furniture, yet their varying positions and outlines make their incorporation into a static world model difficult (AVSC, 2020). It was observed that wheelie bins often change position within many local roads (e.g. snapshot 3 in Fig. 7), occasionally even located on the roadway. To mitigate this issue and reduce roadside severity, one recommendation would be for local authorities to consider reducing the number of individual household bins by implementing larger, communal ones, or designating specific areas for bin placement. This could potentially result in a more predictable roadside environment conducive to the safe operation of automated vehicles.
- The outputs of scenarios indicate that HD maps can effectively expand the operational areas of AVs by providing either prior or real-time information about the road environment. However, some studies have argued that digital maps will likely not be available or not be at the desired level for many cities in the early stage of AV implementation due to the cost of the mapping and communication technologies (International Transport Forum, 2023a; Tengilimoglu et al., 2023c). Hence, to ensure a feasible and affordable investment in the early stages of implementation, initial efforts should be focused on major roads and crucial regions within the network that are expected to experience high travel demand. Policymakers and authorities need to develop incremental investment strategies for the digitisation of the road environment. However, most of the current initiatives come from the AV industry or service providers.
- Additionally, the digitalisation of infrastructure has the potential to support AVs by providing critical information (e.g. work zone, road closure, signal phase, speed limit) that can be used for their safe operations and allow potential improvements in real-time road monitoring and maintenance period scheduling (Mihalj et al., 2022). Communication technologies will also play a pivotal role in supporting the digitalisation of roads and the surrounding environment, where connectivity is deemed a key component. However, there are notable variations in the quality of cellular network services across the road network. Notably, lower quality of service was identified in densely populated areas of the road network, this can present a challenge for AV services aiming to maximise societal benefits. Similar to the strategy for HD maps, initial investments in high-quality cellular networks or short-range communication devices should be focused on major roads and crucial regions within the network.
- Intersections pose significant challenges for automated driving due to their dimensions, visibility issues and the complexity of traffic situations. Current AV trials in mixed traffic conditions reveal that intersections are the most challenging road sections for automated driving as most of the reported AV-involved accidents happened around the intersections. However, most of these accidents are rear-end crashes involving human-driven vehicles (Favarò et al., 2017). A recent report indicated that nearly all collision events involved one or more road rule violations or other errors by a human driver or road user (Schwall et al., 2020). At these locations, AVs need to detect, identify, and predict the actions of other road users, ensuring appropriate responses and trajectory planning. Although most signal-controlled intersections in the study area seem to pose relatively fewer challenges for automated driving, the diversity and configuration of lane markings might create difficulties, especially regarding lane detection and motion planning. As such, the role of advanced mapping technology becomes crucial. Road topological data for trajectory planning, or semantically enriched maps, can address these challenges. Otherwise changes to lane markings at such locations may be required.
- Last but not least, the performance of L4 AVs is expected to vary across different road environments (Chen et al., 2023). One of the likely key requirements to make automated driving technology work optimally in the UK will be the availability of large custom datasets gathered from urban streets that have been labelled in machine-learning-friendly ways with respect to markings, signage, streetlights and so forth. Such datasets will enable AV developers can improve their systems, while also assisting various AV service

providers in familiarising themselves with the specific road conditions. This is crucial, as most current AV trials rely on their own collected data, and often restrict their operational zones to legally permitted areas.

5. Conclusions and recommendations for future research

Automated Vehicles (AVs) are expected to profoundly influence various dimensions of mobility, ranging from passengers' behaviour to urban spaces' structure (Soteropoulos et al., 2019). However, the adoption and operation of AVs hinge on the readiness of today's existing or near-future road infrastructure and this challenge is yet to be fully addressed. This study sought to bridge this gap by proposing a comprehensive assessment framework to evaluate the readiness of road networks for highly automated vehicles (L4 AVs) operation. The framework was then put into practice in a specific area in Leeds, United Kingdom, as a case study to demonstrate its practicality. Following this application, the study provided key insights that can aid decision-makers and transport planners in shaping future policies, regulations, and guidelines for AV implementation on road networks. While the framework is primarily tailored to the UK context, the index can be applied to different geographical regions with subtle variations.

A key conclusion from this study is the significant heterogeneity in readiness levels throughout the road infrastructure network. The network exhibits substantial diversity, from highly structured environments with robust infrastructure support to less structured ones with limited or no support. As such, the potential benefits of AV services in urban areas - such as enhancing mobility for disabled or elderly individuals, and providing affordable and accessible transportation (Litman, 2023; Milakis et al., 2017) - may not be immediately achievable under current conditions. Similarly, door to door shared options of AVs, for example, robo-taxis, which are widely perceived to reduce reliance on personal vehicle ownership, may not be possible in the near term without significant infrastructural modifications or considerable advancements in AV technologies. This is largely due to the majority of road sections presenting a challenging environment for automated driving technologies, in terms of both digital and physical infrastructure. A common assumption among stakeholders is that AVs operate safely on high-quality roads, and cities or areas with poor road infrastructure are predicted to be slow to adopt AVs. Such a situation could precipitate equity issues within communities, as access to AV-based services may be limited to certain AV-compatible zones. This disparity could also influence property values, thereby exacerbating existing social inequalities.

Given the diverse nature of urban roads and their conditions, the advantages and disadvantages of the deployment of L4 AVs will vary from one urban area to another, leading to a selective deployment of AVs in certain areas. As highlighted by stakeholders in a recent report (International Transport Forum, 2023b), the introduction and management of AV-based services should be aligned with policy objectives such as enhancing safety, improving accessibility, increasing equity, mitigating environmental impact, and stimulating economic development. Despite the evident heterogeneity in road environments, the findings highlight that the main roads, those at the upper echelons of the network hierarchy, demonstrate a relatively high readiness value for AV operation. This observation is consistent with the insights obtained from a study conducted in Vienna, Austria (Soteropoulos et al., 2020). Therefore, a strategic approach that prioritises these segments for the initial investment for enhancement of road infrastructure and integration efforts for AVs seems sensible. Particularly, the digitisation of the road environment should commence from main roads to optimise societal benefits and financial viability. This initiative could further aid in the adoption of shared mobility services of AVs, such as shuttles or buses, that operate within specific subnets of the network. Nonetheless, actualising this vision necessitates proactive government backing facilitated through a well-designed regulatory framework for AV-based services (Tengilimoglu et al., 2023c).

Another critical issue is that the transition stage should be carefully managed, as technological advancements in the AV industry and modifications in physical and digital road infrastructure are likely to occur at different speeds. In this regard, authorities should be aware of the potential operational areas in their networks for these new technologies to effectively manage the transition phase. The framework presented in this study can serve as a valuable tool for such an undertaking. Implementing the readiness index can offer authorities preliminary insights into their road network without running actual AV trials. This approach is especially beneficial for cities yet to experience AV deployments, as waiting for real trials might result in substantial delays due to the barriers related to costs, technological limitations, supply chain issues, and local regulatory environments. Furthermore, city authorities have an opportunity to position their road networks attractively for AV developers. By identifying and promoting suitable operational areas, they not only ease the path for AV integration but also become an attractive spot for the emerging AV sector. Moreover, the insights derived from the assessment can be instrumental in refining AV control strategies. Utilising these outcomes to identify and anticipate highly challenging road sections enables AVs to proactively adjust their driving behaviours—for example, by decelerating earlier upon approach.

However, as AV technology continues to evolve, there would be a need to continuously adapt and revise the assessment framework to reflect the state-of-the-art technology and the emerging requirements for road infrastructure. Additionally, subsequent phases of this research should focus on examining the demand side of automated driving, specifically investigating how variations in the readiness level of road infrastructure could influence the accessibility of AV-based services, and in turn, alter traffic patterns within the network. The study conducted by Madadi et al. (2019) may serve as a valuable reference for this exploration. Furthermore, the integration of travel models into the readiness index can yield more comprehensive and nuanced insights. For example, this inclusion could enhance the understanding of the capacity of current road networks to accommodate AV-based services, and identify which areas or demographics may reap the most benefits. This enriched understanding could provide road authorities with valuable inputs for investment agendas, providing a basis for better optimisation of infrastructure.

Finally, as the current study is more of an exploratory and conceptual model than a descriptive index, it is clear that further research is needed in certain areas:

- Firstly, the proposed assessment framework was developed based on relevant literature and insights of experts, rather than empirical findings, due to the limitations associated with the availability of real-world AV data. As such, the importance level of the proposed index components was determined by experts based on a simple ranking technique. Moving forward, in-depth interviews or focus group discussions with stakeholders could potentially refine the index structure, particularly the scoring of measurement variables for specific use cases of L4 AVs. Such an approach may reduce the subjectivity inherent in the opinions of experts, leading to a more robust and universally applicable index.
- Secondly, the study has primarily focussed on relatively static factors and road environment attributes, due to the challenging nature of integrating rapidly changing dynamic factors into the road segment evaluation. With the ongoing advancements in intelligent transportation systems along with information and communication technologies, however, road and city authorities are gaining access to a myriad of dynamic data through sensors within the road network. Therefore, future iterations of this study should aim to develop a dynamic road readiness index incorporating the use of real-time data. For example, incorporating environmental conditions and traffic flow-related factors into the index by evaluating them in real-time could offer a more comprehensive and responsive assessment of road suitability for AVs. Furthermore, leveraging real-time AV sensor data allows for dynamic modelling of parameters, such as the number and diversity of road users. This also enables the integration of research (Cheng et al., 2022; Wang et al., 2018) focused on modelling environmental complexity into to framework.
- Thirdly, given that physical attributes and amenities can significantly vary within a single road link or at intersections, future research might aim to evaluate road segments of equal or smaller lengths to increase the granularity of data. Specifically, implementing the index at a lane-level detail could offer a more precise understanding of the road environment. This would provide authorities with more specific information, optimising decision-making, and investment strategies for the development of "AV-compliant" road links.
- Fourthly, most data used in this study was assessed via visual inspection, employing aerial photography, satellite imagery, and street view services. However, these images, being snapshots from the past, present a limited perspective and are updated irregularly. Additionally, the evaluation process is potentially susceptible to human errors and can be time-consuming. Future research could consider the use of digital image processing techniques for the evaluation of subcomponents. While this method may require more resources and effort, the resulting insights could significantly enhance the accuracy and relevance of the readiness index for AVs. This becomes particularly important when real AV data are available that could provide more up-to-date information about the road environment.
- Lastly, a critical future direction for this study involves focusing on the validation and feasibility of the proposed framework using real-world AV test data, especially within UK cities. An analysis of network locations where AVs encounter collision risks or necessitate disengagement of their automated driving systems could serve as a basis for verifying the factors adopted in the (sub) components. Additionally, exploring the correlations between the Road Readiness Index (RRI) scores at these locations will be instrumental. Further, the weights or impact coefficients of these factors could be refined using a Bayesian network approach. This method would help mitigate the subjectivity associated with expert insights, providing a more objective basis for evaluating the framework's components. The recent study by Tu et al. (2023), which focuses on evaluating the safety risks for AV road testing in China using iRAP attributes, could offer a valuable methodological reference for this verification process.

CRediT authorship contribution statement

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

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.

Data availability

Data will be made available on request.

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Appendix A

Table A1
Overview of scoring scheme for subcomponents of the road readiness index for automated driving.*

# (C_i)	Framework Components	# ($C_{i,j}$)	Subcomponents	Weight ($Wc_{i,j}$)	Measurement variables	Score($Sc_{i,j,m}$) LC	HC
C1	Road Geometry Challenges	C1,1	Horizontal curvature	0.25	Straight or gently curving (Radius of curvature: R ≥ 400 m)	1	1
					Moderate curvature (150 ≤ R < 400 m)	0.5	0.75
					Sharp curvature or corners (R < 150 m)	0	0.25
		C1,2	Longitudinal gradient	0.25	Flat or gentle rise (0 % to < 4 %)	1	1
					Moderate rise (4 % to < 8 %)	0.75	1
					Steep rise (≥8%)	0.25	0.5
		C1,3	Road width consistency	0.25	Constant or slight change in road or lane width (road width change rate less than 15 %)	1	1
					Presence of moderate change (narrowing or widening) in road or lane width (road width change rate is 15 to 30 %)	0.5	0.75
					Presence of high change in road or lane width (road width change rate higher than 30 %)	0	0.25
		C1,4	Digital mapping of road geometry	0.25	Presence of digital map of road geometry	1	1
					No presence of digital map of road geometry	0	0
C2	Road Surface Condition	C2,1	Road surface type	0.5	Asphalt or concrete and has a homogeneous appearance	1	1
					Pavers, bricks, or presence of different colours or materials on the road surface (e.g. patching, ghost markings, presence of lots of manholes etc.)	0.5	0.75
					Unpaved road surface (e.g. gravel)	0	0.25
		C2,2	Road surface condition	0.5	No presence or low level of deterioration (e.g. potholes, cracks, rutting etc.) or RCI is Green	1	1
					Presence of moderate level of deterioration or RCI is Amber	0.5	0.75
					Presence of severe level of deterioration or RCI is Red	0	0
C3	Road Marking Condition	C3,1	Digital mapping of road markings	0.25	Presence of digital map of road markings	1	1
					No presence of digital map of road markings	0	0
		C3,2	Road marking configuration	0.25	Presence of both the centre lines and two edge markings	1	1
					Presence of centre lines and one-side edge markings	0.75	1
					Presence of only centre lines or two-sides edge markings	0.5	0.75
					Presence of only one-side edge markings	0.25	0.5
					No presence of road markings	0	0
		C3,3	Road marking wear condition	0.5	Wear score is 50 (no obvious wear) to 40 (very little wear) according to CS126 standard	1	1
					Wear score is 30 (some visible wear, larger bare sports) to 20 (visible but has randomly spaced small bare spots)	0.5	0.75
					Wear score is 10 (barely visible) to 0 (non-existent, residue only)	0	0
C4	Road Boundaries	C4,1	Median type	0.5	One-way road, or two-way road with concrete/metal safety barrier, kerb stone or grass median	1	1
					Wide or double centre line or central hatching (two-way road)	0.75	1
					Centre line (two-way road)	0.5	0.75
					Cable barrier or flexible posts (two-way road)	0.25	0.5
					No presence of median (two-way road)	0	0.25
		C4,2	Road edge condition	0.25	Continuous road edge (e.g. kerb stone, barriers, grass etc.) on both sides of roadway	1	1
					Discontinuous or damaged road edge (e.g. access points) on one-side of roadway	0.5	0.75
					Discontinuous or damaged road edge (e.g. access points) on both sides of roadway	0	0.25
		C4,3	On-street vehicle parking	0.25	Parking or limited time waiting is not permitted	1	1
					Presence of parking or limited time waiting zone on one side of roadway	0.50	0.75
					Presence of parking or limited time waiting zone on two sides of roadway	0	0.25
C5	Traffic Signs Visibility	C5,1	Digital mapping of traffic signs	0.5	Presence of digital map of traffic signs	1	1

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Table A1 (*continued*)

# (C$_i$)	Framework Components	# (C$_{i,j}$)	Subcomponents	Weight (Wc$_{i,j}$)	Measurement variables	Score(Sc$_{i,j,m}$) LC	HC
					No presence of digital map of traffic signs	0	0
		C5,2		0.5	Presence of visible and readable physical traffic signs (e.g. not obstructed, damaged, vandalised etc.) or absence of traffic signs on the roadway	1	1
					Presence of multiple signs in single unit	0.5	0.75
					Presence of electronic signs such as variable message signs	0.25	0.5
					Unreadable, damaged, or obstructed traffic signs (critical defects according to CS125)	0	0
C6	Special Road Section	C6,1	Special road sections	1.0	Not presence of any special road sections stated below	1	1
					Presence of grade-separated interchanges or slip roads/ ramps (e.g. merging or diverging sections)	0.75	1
					Presence of weaving areas (merging and diverging sections)	0.5	0.75
					Presence of toll plazas or gates on the roadway (e.g. chicane or road narrowing)	0.25	0.50
					Presence of dead-end roadway (with/out turning point)	0	0
C7	Road Lighting	C7,1	Lighting condition	1.0	Presence of road lighting systems and no obstacles around (e.g. trees in the surrounding)	1	1
					Presence of road lighting systems with obstruction around or short underpasses (L $<$ 20 m) on the roadway	0.5	0.75
					Presence of long underpasses (L $>$ 20 m) or tunnels	0.25	0.50
					No presence of road lighting systems or damaged lighting system	0	0.25
C8	Speed Limit	C8,1	Speed limit of road section	1.0	Speed limit $<$ 37 mph	1	
					37 mph $\leq$ Speed limit $<$ 42 mph	0.50	
					42 mph $\leq$ Speed limit $<$ 61 mph	0.25	
					61 mph $\leq$ Speed limit	0	
					Speed limit $<$ 47 mph		1
					47 mph $\leq$ Speed limit $<$ 53 mph		0.50
					53 mph $\leq$ Speed limit $<$ 76 mph		0.25
					76 mph $\leq$ Speed limit		0
C9	Number and Diversity of Road Users	C9,1	Road access	0.5	Access control roads: VRUs (e.g. pedestrians and cyclists) are not permitted	1	1
					Mixed traffic roads without any public transit facilities (bus, tram etc.)	0.5	0.75
					Mixed traffic roads with public transit facilities	0.25	0.5
					Shared space roads: access to all road users	0	0.25
		C9,2	Counterflow	0.25	No presence of counter flow traffic	1	1
					Presence of counter flow traffic	0	0.25
		C9,3	No. of lanes	0.25	Total number of lanes on the road section (N $\leq$ 2)	1	1
					Total number of lanes on the road section (2 $<$ N $\leq$ 4)	0.5	0.75
					Total number of lanes on the road section (N $>$ 4)	0.25	0.5
C10	Roadside Complexity	C10,1	Presence of trees	0.25	No presence of trees on two sides of roadway (or presence far from the road edges such as d $>$ 8–10 m)	1	1
					Presence of trees on one side of roadway	0.5	0.75
					Presence of trees on both sides of roadway	0	0.25
		C10,2	Street furniture density	0.25	Low density of street furniture (e.g. advertising display, benches, bicycle stands, billboards, bins, bus shelter, lamps, post boxes, etc.) on two sides of roadway	1	1
					High density of street furniture on one side of roadway	0.50	0.75
					High density of street furniture on two sides of roadway	0	0.25
		C10,3	Proximity of buildings	0.25	No presence of close buildings (e.g. commercial, industrial, educational etc.) on two sides of roadway (not far from the road edge d $<$ 2–3 m)	1	1
					Presence of close buildings on one side of roadway	0.50	0.75
					Presence of close buildings on both sides of roadway	0	0.25
		C10,4	Digital mapping of roadside environment	0.25	Presence of digital map of the roadside environment	1	1
					No presence of digital map of roadside environment	0	0
C11	Facilities for Vulnerable Road Users	C11,1	Pedestrians crossing type	0.25	Presence of pedestrian bridges or underpasses on the roadway	1	1
					Puffin, Toucan, Pegasus crossing on the roadway	0.75	1
					Pelican crossing on the roadway	0.5	0.75
					Zebra crossing or surface marked crossing on the roadway	0.25	0.50
					Unmarked or No provision for pedestrians crossing on the roadway	0	0.25

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Table A1 (*continued*)

# (C_i)	Framework Components	# ($C_{i,j}$)	Subcomponents	Weight ($Wc_{i,j}$)	Measurement variables	Score($Sc_{i,j,m}$) LC	HC
		C11,2	Pedestrian sidewalk	0.25	Physically segregated pedestrian sidewalk with barriers, buffer, or landscaping zones on the roadway	1	1
					Presence of sidewalk on both sides of the roadway	0.75	1
					Presence of sidewalk on one side of the roadway	0.50	0.75
					No presence of sidewalk for pedestrians on the roadway	0	0.25
		C11,3	Cycling infrastructure	0.25	Physically segregated cycle lane on the roadway	1	1
					Segregation with lane markings or painting on surface on the roadway	0.50	0.75
					No presence of segregation on the roadway	0	0.25
		C11,4	Public transit access point design	0.25	Not presence of bus route, stops, or Presence of dedicated bus lane on the roadway	1	1
					Presence of bus lay-by on the roadway	0.75	1
					Presence of bus shelter on the roadway	0.50	0.75
					Presence of bus stop with road marking and post on the roadway	0.25	0.5
					Presence of temporary bus stop or bus stop with a simple sign or post on the roadway	0	0.25
C12	Precautions for Roadworks and Incidents	C12,1	Precautions for roadworks and incidents	1.0	No presence of roadwork or incident on the roadway	1	1
					Presence of roadwork or incident with real-time layout level information, and standardised digital and physical warning signs and markings on the roadway	0.75	1
					Presence of roadwork or incident with standardised digital and physical warning signs and markings on the roadway	0.50	0.75
					Presence of roadwork or incident with only standardised physical warning signs and markings	0.25	0.50
					Presence of roadwork or incident without any precautions for AVs	0	0.25
C13	Localisation Challenges	C13,1	Localisation challenges	0.5	Presence of landmarks or magnetic road markings on the roadway	1	1
					Presence of low-rise development on both sides of the roadway	0.75	1
					Presence of high-rise development or high-vegetation cover on one side of the roadway	0.5	0.75
					Presence of high-rise developments (e.g. urban canyons) or valleys surrounding the roadway or high vegetation cover on both sides of the roadway or short underpasses ($L < 20$ m) on the roadway	0.25	0.5
					Presence of long underpasses ($L > 20$ m) or tunnels on the roadway	0	0
		C13,2	Digital mapping of road environment	0.5	Presence of digital map of road and surrounding environment	1	1
					No presence of digital map of road and surrounding environment	0	0
C14	Communication Facilities	C14,1	Roadside Units	1.0	Presence of Roadside Units (RSUs) along with the roadway (e.g. DSRC or ITS-G5)	1	1
		or			No presence of Roadside Units (e.g. DSRC or ITS-G5)	0	0
		C14,1	Cellular network coverage	1.0	Excellent or good 5G NR coverage in operation area for C-V2X	1	1
					Average 5G NR coverage in operation area for C-V2X	0.75	1
					Excellent or good 4G/LTE coverage in operation area for C-V2X	0.5	0.75
					Average 4G/LTE coverage in operation area for C-V2X	0.25	0.5
					Below average, poor, limited cellular coverage or Network blackspots	0	0
C15	Intersections and Roundabouts	C15,1	Intersection and roundabout type	0.25	Signal controlled intersections with protected turn lane	1	1
					Signal controlled intersections, or Priority-controlled intersections with protected turn lane	0.75	1

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Table A1 (*continued*)

# (Ci)	Framework Components	# (Ci,j)	Subcomponents	Weight (Wci,j)	Measurement variables	Score(Sci,j,m) LC	HC
					Priority-controlled intersections, or Mini or single-lane roundabouts	0.50	0.75
					Uncontrolled intersections, or Median crossing points	0.25	0.5
					Multi-lane roundabouts	0	0.25
		C15,2	Number of arms	0.25	N = 3 (e.g. T or Y intersections)	1	1
					N = 4 (e.g. Cross / staggered)	0.5	0.75
					N > 4 (e.g. multi-armed)	0	0.25
		C15,3	Regularity of layout	0.25	Regular form of intersection	1	1
					Irregular form of intersection	0	0.25
		C15,4	Delineation (marking) conditions	0.25	Clear visible marking or Availability of HD mapping	1	1
					Some visible wear on the markings	0.5	0.75
					Barely visible or non-existent markings	0	0.25

* Detailed information on each component in the assessment framework, along with their corresponding subcomponents and measurement variables, can be found in the **Supplementary materials (SM-1)**.

Table A2
Overview of the data collection method for representing the subcomponents of framework components and general assessment of the quality of collected data.

Ci	Framework components	Ci,j	Subcomponents	Source of data/ method of data collection	General assessment of collected data quality/ representation
C1	Road Geometric Challenges	C1,1	Horizontal curvature	It was initially calculated by using ROCA (ROad Curvature Analysis) toolbox in ArcGIS Pro developed by (Bíl et al., 2018). It was then revised by visual inspection using aerial photography/satellite imagery or street view services.	Fair
		C1,2	Longitudinal gradient	It was roughly estimated by using the data provided by the Ordnance Survey MasterMap. Elevation differences of road link ends were divided into the length of the road link. However, this method has limitations for long or non-straight road links and no precise gradient level is obtained. Also revised by visual inspection using street view services.	Fair
		C1,3	Road width consistency	It was initially calculated the change rate of width in road links using the data provided by the Ordnance Survey MasterMap. The difference between average road width and minimum road width was divided by average road width. A score of 1 was given if the ratio was less than 0.15, 0.5 if it was between 0.15 and 0.3, and 0 otherwise. Also, it was revised by visual inspection using aerial photography/satellite imagery or street view services.	Fair
		C1,4	Digital map of road geometry	An assumption was made according to scenarios (S1: no HD maps, S2-3: available for all network)	Poor
C2	Road Surface	C2,1	Road surface type	It was evaluated by visual inspection using street view services.	Fair
		C2,2	Road surface condition	The condition of the road surface was categorised based on the available RCI data provided by the Department for Transport. The data is available at: https://maps.dft.gov.uk/road-condition-explorer/index.html. Also, it was evaluated by visual inspections using street view services for places where automated inspection data collected by specialised vehicles is not available.	Fair
C3	Road Markings	C3,1	Digital map of road markings	An assumption was made according to scenarios (S1: no HD maps, S2-3: available for all network)	Poor
		C3,2	Marking configuration	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services.	Fair
		C3,3	Marking condition	It was roughly evaluated by visual inspection using street view services according to examples in Appendix C of the DMRB CS 126 standard.	Fair
C4	Road Boundaries	C4,1	Median type	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services.	Good

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Table A2 (*continued*)

Ci	Framework components	Ci,j	Subcomponents	Source of data/ method of data collection	General assessment of collected data quality/ representation
		C4,2	Road edge condition	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Also, the continuity of road edge conditions was controlled from: https://www.leedstraffweb.co.uk/main.html and Ordnance Survey MasterMap Topography Layer.	Fair
		C4,3	On-street vehicle parking	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Also, parking locations on the network were controlled from: https://www.leedstraffweb.co.uk/main.html	Fair
C5	Traffic Signs	C5,1	Digital map of traffic signs	An assumption was made according to scenarios (S1: no HD maps, S2-3: available for all network)	Poor
		C5,2	Traffic signs conditions	It was roughly evaluated by visual inspection using street view services according to examples in Appendix E of the DMRB CS 125 standard.	Fair
C6	Special road section	C6,1	Special road sections	It was evaluated by using the data provided by the Ordnance Survey MasterMap. In addition, it was checked by visual inspection using aerial photography/satellite imagery or street view services.	Good
C7	Road Lighting	C7,1	Lighting condition	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Detailed information on the location and unit type of streetlights is available at: https://datamillnorth.org/dataset/street-lights-unmetered. However, the limitation of this method cannot consider whether the lighting systems work properly at night.	Poor
C8	Speed Limit	C8,1	Speed limit of road section	It was evaluated based on the interactive map providing traffic orders of roads that are under the control of Leeds City Council. (https://www.leedstraffweb.co.uk/main.html). Also, it was roughly controlled by visual inspection of speed limit signs on the roadway using street view services. Alternatively, Open Street Map can be used for this subcomponent.	Fair
C9	Number and Diversity of Road Users	C9,1	Road access	It was initially evaluated by considering road hierarch. Also public transit (bus) route was controlled from: Open Streep Map, https://www.geopunk.co.uk/timetables/town/leeds. Then it was controlled by visual inspection using aerial photography/satellite imagery or street view services	Fair
		C9,2	Counterflow	It was evaluated by using the data provided by the Ordnance Survey MasterMap. Also, it was controlled by traffic orders data of the city from https://www.leedstraffweb.co.uk/main.html	Fair
		C9,3	No. of lanes	It was initially estimated by dividing the average road width by the approximate lane widths by type of road hierarchy. It was then revised by visual inspection using aerial photography/satellite imagery or street view services.	Fair
C10	Roadside Complexity	C10,1	Presence of trees	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Detailed analysis for this subcomponent can be done by using Tree Detection toolbox (deep learning model to detect trees in high resolution imagery) in ArcGIS Pro by aerial photography/satellite imagery.	Fair
		C10,2	Street furniture density	It was roughly evaluated by visual inspection using street view services.	Poor
		C10,3	Proximity of buildings	It was roughly estimated using data provided by Ordnance Survey MasterMap in QGIS. Also, commercial facilities control with visual inspection by using street view services.	Poor

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Table A2 (*continued*)

Ci	Framework components	Ci,j	Subcomponents	Source of data/ method of data collection	General assessment of collected data quality/ representation
		C10,4	Digital mapping of surrounding road environment	An assumption was made according to scenarios (S1: no HD maps, S2-3: available for all network)	Poor
C11	Facilities for Vulnerable Road Users	C11,1	Pedestrians crossing type	It was initially evaluated by using data provided by Data Mill North and Ordnance Survey MasterMap. It was then revised by visual inspection using aerial photography/satellite imagery or street view services.	Good
		C11,2	Pedestrian sidewalk	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Also, it was controlled from: https://www.leedstraffweb.co.uk/main.html	Good
		C11,3	Cycling infrastructure	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Also, it was controlled from: Google Maps Cycling and Open Street Map.	Good
		C11,4	Public transit access point design	It was evaluated by visual inspection using aerial photography/satellite imagery or street view services. Also public transit (bus) route was controlled from: Open Streep Map, https://www.geopunk.co.uk/timetables/town/leeds	Good
C12	Precautions for Roadworks and Incidents	C12,1	Precautions for roadworks and incidents	As this subcomponent requires a dynamic evaluation, it was assumed that no roadwork or incident on the network. Detailed information on live roadworks and incidents are available at https://one.network/uk/leeds.	Poor
C13	Localisation Challenges	C13,1	Localisation challenges	It was evaluated by visual inspection using street view services. Also estimated roughly by using the data provided by the Ordnance Survey MasterMap, such as building heights and average road width.	Poor
		C13,2	Digital mapping of road environment	An assumption was made according to scenarios (S1: no HD maps, S2-3: available for all network)	Poor
C14	Communication Facilities	C14,1	Roadside Unit or	There is no publicly available data for this subcomponent. Therefore, it was assumed that there were no roadside units on the network.	Poor
		C14,1	Cellular network coverage	It was simply evaluated by using service provider coverage maps or third-party webpages (e.g. https://mastdata.com/index.aspx). Only one service provider (EE Mobile) with widely available network coverage data in the study area was selected for the assignment. Then for the validation of the coverage map, the experimental data source was analysed. For places where automated inspection data collected by specialised vehicles is available, parameters related to the signal quality of the LTE service provided by Ofcom were categorized according to thresholds suggested by (Cucor et al., 2022). The data is available at: (https://www.ofcom.org.uk/phones-telecoms-and-internet/coverage/mobile-signal-strength-measurement-data).	Fair
C15	Intersections and Roundabouts	C15,1	Intersection and roundabout type	It was evaluated by using the data provided by the Ordnance Survey MasterMap. In addition, it was evaluated by visual inspection using aerial photography/satellite imagery or street view services.	Good
		C15,2	Number of arms	It was evaluated by visual inspection using aerial photography/satellite imagery.	Good
		C15,3	Regularity of layout	It was evaluated by visual inspection using aerial photography/satellite imagery.	Good
		C15,4	Delineation (marking) conditions	It was roughly evaluated by visual inspection using street view services according to examples in Appendix C of the DMRB CS 126 standard.	Fair

Table A3
Distribution of road links based on categorised RRI values in different index structures.

Scenario	Assessment of road links (N = 1,495)	Actual applied: Expert-weighted components (Wc_i)	Industry participants only weighted components (Wc_i)	Equal-weighted components (Wc_i)	Excluding penalties in RRI	Omitting a component from the Road Readiness Index													
						C1: Road Geometry Challenge	C2: Road Surface Condition	C3: Road Markings Condition	C4: Road Boundaries	C5: Traffic Signs Visibility	C6: Special Road Sections	C7: Road Lighting	C8: Speed Limit	C9: Number and Diversity of Road Users	C10: Roadside Complexity	C11: Facilities for Vulnerable Road Users	C12: Precautions for Roadworks and Incidents	C13: Localisation Challenging	C14: Communication Facilities
Scenario 1 (LC)	Extremely Challenging	74.7 %	74.7 %	74.7 %	0.0 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %	74.7 %
	Highly Challenging	0.0 %	0.0 %	0.0 %	1.3 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Moderately Challenging	1.7 %	1.7 %	1.5 %	48.0 %	1.5 %	2.3 %	0.6 %	1.1 %	1.1 %	4.7 %	3.8 %	4.3 %	1.0 %	1.3 %	0.8 %	5.1 %	0.5 %	1.1 %
	Slightly Challenging	23.5 %	23.6 %	23.7 %	50.6 %	23.7 %	23.0 %	24.7 %	24.1 %	24.0 %	20.6 %	21.5 %	20.9 %	24.2 %	23.9 %	24.4 %	20.2 %	24.7 %	24.2 %
	Least Challenging	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.1 %	0.0 %	0.0 %	0.0 %	0.1 %	0.1 %	0.1 %	0.0 %	0.1 %	0.0 %
Scenario 2 (LC)	Extremely Challenging	37.8 %	37.8 %	37.8 %	0.0 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %	37.8 %
	Highly Challenging	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Moderately Challenging	0.1 %	0.1 %	0.1 %	7.1 %	0.1 %	0.0 %	0.0 %	0.0 %	0.1 %	0.1 %	0.1 %	0.1 %	0.1 %	0.1 %	0.1 %	0.1 %	0.1 %	0.1 %
	Slightly Challenging	51.4 %	51.3 %	51.2 %	82.0 %	52.6 %	52.8 %	45.1 %	46.3 %	54.8 %	55.0 %	54.5 %	54.0 %	43.7 %	51.7 %	42.4 %	55.5 %	51.6 %	43.5 %
	Least Challenging	10.7 %	10.8 %	10.8 %	10.9 %	9.4 %	9.4 %	17.1 %	15.9 %	7.3 %	7.1 %	7.6 %	8.0 %	18.4 %	10.4 %	19.7 %	6.6 %	10.4 %	18.7 %
Scenario 3 (LC)	Extremely Challenging	22.9 %	22.9 %	22.9 %	0.0 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %	22.9 %
	Highly Challenging	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Moderately Challenging	0.0 %	0.0 %	0.0 %	3.5 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.1 %	0.1 %	0.1 %	0.0 %	0.1 %	0.0 %	0.1 %	0.0 %	0.1 %
	Slightly Challenging	54.6 %	54.7 %	54.3 %	73.9 %	58.0 %	56.9 %	34.2 %	37.3 %	61.1 %	61.3 %	61.4 %	60.5 %	41.5 %	55.7 %	38.4 %	61.9 %	56.2 %	53.4 %
	Least Challenging	22.5 %	22.4 %	22.8 %	22.5 %	19.1 %	20.2 %	42.9 %	39.8 %	16.0 %	15.7 %	15.7 %	16.5 %	35.6 %	21.3 %	38.7 %	15.1 %	20.9 %	23.6 %
Scenario 1 (HC)	Extremely Challenging	73.8 %	73.8 %	73.8 %	0.0 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %	73.8 %
	Highly Challenging	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Moderately Challenging	0.0 %	0.0 %	0.0 %	10.8 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Slightly Challenging	22.0 %	22.1 %	21.1 %	85.0 %	20.3 %	24.1 %	18.5 %	24.0 %	16.9 %	24.6 %	24.5 %	24.6 %	20.6 %	23.1 %	19.9 %	24.8 %	15.7 %	21.7 %
	Least Challenging	4.1 %	4.1 %	5.0 %	4.1 %	5.8 %	2.0 %	7.6 %	2.1 %	9.2 %	1.5 %	1.6 %	1.5 %	5.6 %	3.0 %	6.3 %	1.3 %	10.5 %	4.4 %
Scenario 2 (HC)	Extremely Challenging	33.6 %	33.6 %	33.6 %	0.0 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %	33.6 %
	Highly Challenging	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Moderately Challenging	0.0 %	0.0 %	0.0 %	0.7 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %

(*continued on next page*)

Table A3 (*continued*)

Scenario	Assessment of road links (N = 1,495)	Actual applied: Expert-weighted components (Wc_i)	Industry participants only weighted components (Wc_i)	Equal-weighted components (Wc_i)	Excluding penalties in RRI	Omitting a component from the Road Readiness Index													
						C1: Road Geometry Challenge	C2: Road Surface Condition	C3: Road Markings Condition	C4: Road Boundaries	C5: Traffic Signs Visibility	C6: Special Road Sections	C7: Road Lighting	C8: Speed Limit	C9: Number and Diversity of Road Users	C10: Roadside Complexity	C11: Facilities for Vulnerable Road Users	C12: Precautions for Roadworks and Incidents	C13: Localisation Challenging	C14: Communication Facilities
	Slightly Challenging	17.1 %	17.7 %	17.1 %	44.0 %	21.3 %	17.0 %	4.8 %	7.6 %	23.5 %	23.7 %	23.1 %	23.7 %	12.2 %	20.5 %	9.8 %	24.4 %	22.9 %	12.2 %
	Least Challenging	49.3 %	48.7 %	49.2 %	55.3 %	45.0 %	49.4 %	61.5 %	58.7 %	42.9 %	42.7 %	43.2 %	42.6 %	54.1 %	45.8 %	56.5 %	41.9 %	43.4 %	54.2 %
Scenario 3 (HC)	Extremely Challenging	18.2 %	18.2 %	18.2 %	0.0 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %	18.2 %
	Highly Challenging	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Moderately Challenging	0.0 %	0.0 %	0.0 %	0.1 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %
	Slightly Challenging	8.9 %	9.1 %	9.7 %	26.6 %	13.6 %	6.6 %	2.5 %	3.7 %	15.1 %	15.1 %	13.0 %	15.1 %	7.0 %	10.0 %	4.8 %	15.9 %	13.5 %	13.8 %
	Least Challenging	72.9 %	72.7 %	72.1 %	73.4 %	68.2 %	75.3 %	79.3 %	78.1 %	66.8 %	66.8 %	68.8 %	66.7 %	74.8 %	71.8 %	77.0 %	65.9 %	68.3 %	68.0 %
		100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2024.104148.

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