Article | Received 4 December 2024; Accepted 13 January 2025; Published 20 January 2025
https://doi.org/10.55092/sc20250001

Development of A Trustworthy AI-supported Digital Twin Framework for Road Operation and Maintenance

Linjun Lu, Mengtian Yin, Yue Xie, Yuandong Pan*, Mudan Wang, Ioannis Brilakis

Department of Engineering, University of Cambridge, 7a JJ Thomson Avenue, Cambridge CB3 0FA, UK

*Correspondence author; E-mail: yp296@cam.ac.uk.

Highlights:

- Digital twins (DTs) are a promising technology for effective infrastructure management.
- A multitier, modular, and interoperable DT framework was developed for road O&M.
- A trustworthy AI-supported module was developed to assist users in making informed decisions.
- The developed DT framework was piloted on three major UK roads for vegetation maintenance.

Abstract: Digital twins (DTs) are emerging as a promising technology for effective infrastructure management by continuously capturing the dynamic and comprehensive state of physical systems. However, their adoption for managing road infrastructure during the operation and maintenance (O&M) phase remains limited, which is otherwise the most prolonged and critical phase of the asset life cycle. This study proposed a multitier DT framework specifically tailored for road O&M, which is designed to be flexible, modular, interoperable, and, importantly, trustworthy. A core component of this framework is a trustworthy AI-supported module that assists users in making informed decisions that align with their preferences and expectations, thereby fostering user trust and satisfaction in the road DT system. The framework was piloted on three major roads in the United Kingdom, demonstrating its effectiveness through the implementation of vegetation control. This study aims to actively promote the development and deployment of DT technologies and trustworthy AI within advanced road infrastructure management.

Keywords: digital twins; trustworthy AI; interoperability; road infrastructure management; operation and maintenance; multi-objective optimization; large language model

1. Introduction

Roadways constitute part of the economic foundation of a country, playing a critical role in improving business productivity and providing an important link in the supply chain construction. Beyond this, they also serve a crucial social role in connecting communities, strengthening interpersonal bonds, and bridging geographical divides. For instance, a report from the American Society of Civil Engineers (ASCE) [1] revealed that the United States has over 4 million miles of highways, which transported 72%, or equivalently $16.8 trillion, of the nation's goods between cities in 2021. In the United Kingdom, roads are pivotal for personal mobility, with 96% of all journeys and 88% of total distances traveled occurring on them [2]. The importance of roads extends to businesses and domestic freight as well, where roads carry more than three times the goods moved by rail and water domestically combined. As of 2022, China's extensive highway network spans approximately 110 thousand miles, witnessing an average daily traffic of 14,993 vehicles and facilitating the transport of 37.12 billion tons of cargo and 3.55 billion passengers annually [3]. Therefore, a roadway system is not an end in and of itself, rather it is the means for individuals and businesses to thrive and achieve their ambitions.

In fact, the successful service of roadways hinges on more than their functionality; it also depends upon their sustained performance over a long-lasting time. However, as economic activities expand and travel increases, roadways around the world are expected to withstand an ever-increasing traffic volume in the coming years [4,5]. Unfortunately, the growing wear and tear, compounded by delayed or inadequate maintenance, accelerates the deterioration of already-aging roadway systems, leaving them sometimes in poor or mediocre condition. According to the same report released by [1], over 40% of the highways in the United States are in need of significant repair or reconstruction. These deteriorating highways may subsequently lead to a series of problems regarding escalating greenhouse gas emissions, a surge in traffic accidents, increased congestion and delays, and additional costs for vehicle repairs and operations. In response to this challenge, governments worldwide have been prioritizing strategic investments in advanced technologies dedicated to improving and preserving roadway conditions, with the ultimate goal of ensuring roadway systems continue to fulfill their role of efficiently and safely meeting the growing and shifting transportation demands in future generations [2,6].

Digital twins (DTs) have been recognized as a promising technology to create opportunities for effective and whole-lifecycle management of road systems. Essentially, a road DT is a digital replica of an actual road system created in a virtual space with right-time two-way information flows, which mimics the physical counterpart in most of its aspects, ultimately to timely monitor, analyze, evaluate, and optimize the physical entity in the real world [7]. On the way forward, the DTs can benefit and leverage new emerging technologies such as the Internet of Things (IoT) for data collection, advanced telecommunication technology for data transmission, machine learning (ML) and artificial intelligence (AI) for data analysis and decision-making, and virtual reality (VR) and augmented reality (AR) for better data visualization and immersive viewing experience, all of which can provide more comprehensive decision support for managing road infrastructure. However, current research efforts related to DTs in road infrastructure applications are still at an early stage with less attention being paid to the operation and maintenance (O&M) phase, which is otherwise the longest time span in the road asset life cycle. On the other hand, as AI plays an ever more important role in DT technology, it becomes essential to make the adopted AI reliable and trustworthy. If infrastructure operators do not trust the proposed results from the AI, it is unlikely that they will follow the recommendations, even if the recommendations are more optimal than those made from practical experience and may increase societal and environmental well-being. Therefore, it is imperative to design and deploy trustworthy AI within road DTs, from which the road stakeholders have confidence that the DTs they deploy behave trustily and are aligned with their values and expectations across a range of dimensions.

2. Background

2.1. State of research in digital twin-enabled road infrastructure applications

With the recent advancements and innovations in industrial technologies, digital transformation is set to revolutionize the Architecture, Engineering, and Construction (AEC) industry and the DTs play a critical role in this major transformation. Recognizing this potential, some researchers have been exploring the usage of DT-based solutions for different phases of road infrastructure management. In the planning and design phase, the road DTs are initially created by digitalizing existing road infrastructures (if applicable), site topography, environment conditions, and surroundings using online maps, LiDAR data, design documents, and other relevant data sources [8]. These DT models can be transferred across all stages of planning and design and bring together road planners and designers onto a unified platform, facilitating the sharing of insights, allowing for real-time modifications, and fostering an environment where all parties are harmoniously aligned. Specifically, through incorporating various analytical models, such as graph-based path modeling [9] and multi-criteria decision making [10], road DTs can support planners in designing sustainable and multifunctional road network that accounts for a broad spectrum of demands and constraints. Planners are thus equipped to offer clear task clarifications that inform future design directions. Moreover, DTs help direct the design of projects that focus on widening, reconstructing, and expanding existing road infrastructures [11]. Designers can leverage road DTs to reconstruct every metric from a physical structure and experiment digitally in a virtual environment, and subsequently examine the expected results before making any modifications that would impact the existing road infrastructure. This way, the design can be effectively updated, revised, improved, and verified with less resource expenditure.

In the construction phase, the road DTs finalized at the design stage can be handed over to the construction managers to help support upcoming project management and enhancement efforts. As the construction progresses, these DTs constantly update and maintain synchronization with their physical counterparts through the integration of BIM and 3D modeling software (e.g., Autodesk Revit and InfraWorks), onsite scanning and surveying data, and any number of IoT sensors and devices that transmit data back to the twins in real-time [11,12]. At this stage, the DTs serve as a central hub for data integration and management, information visualization, construction activity arrangement, and scenario-based planning. With the aid of DT capabilities, the construction supervisors are able to keep a close eye on the road construction progress and performance, ensuring that the actual build aligns with the planned design [13]. By utilizing data from various sensors deployed on both workers and machinery, road DTs offer a holistically live view of construction activities and the quality of work being done on-site. When supported by AI and ML, these spatial-temporal insights allow for more efficient allocation of resources [14], intelligent pavement compaction [15], and optimal machinery and material usage [7], and the improvement of quality control measures [13]. Moreover, road DTs enable construction teams to virtually simulate potential safety risks and formulate preemptive safety measures. They can also serve as an innovative tool for training personnel within a safe and virtual environment, reducing the risk of accidents and enhancing overall project safety.

In the O&M phase, the road DTs mark a paradigm shift towards more advanced traffic and road infrastructure management. By aggregating and analyzing granular traffic data collected from different traffic locations through radars, cameras, UAVs, and other IoT-related sensors, road DTs allow for dynamic analysis and simulation of traffic patterns at both the microscopic and macroscopic levels [16,17]. This empowers traffic management to take proactive measures to alleviate congestion, optimize traffic light sequences, and improve overall road safety [18]. Additionally, DTs serve as a pivotal tool in the continuous health monitoring of road infrastructure. By leveraging mobile mapping technologies and an extensive IoT sensor network embedded within the infrastructure, a road DT can provide right-time insights into the condition of road assets [19,20]. Such timely monitoring is critical for identifying early signs of wear and tear, damage, or other deterioration, paving the way for a proactive maintenance strategy. This capability ensures maintenance and repairs are systematically planned before minor issues evolve into significant challenges, thus avoiding costly and intrusive repairs [21]. Despite the transformative potential of DTs in road O&M, existing literature has only discussed the challenges, limitations, and advantages of these technologies, without offering a detailed and programmatic DT framework for real-world implementation. While there have been initiatives to develop DTs for road infrastructure management, these efforts remain in the digital modeling stage, leaving a gap between current practices and the comprehensive realization of a fully developed road DT.

2.2. Needs and state of research in trustworthy AI-supported applications in AEC sector

Over the last two decades, the growing influence of AI across social and technical spheres has dramatically impacted almost all industrial and organizational workflows. However, the adoption of AI within the AEC sector lags significantly behind the rapid pace seen in other areas such as robotics and manufacturing [22,23]. Despite the considerable benefits that modern AI technologies can deliver, the AEC industry continues to prioritize antiquated and empirical methods for work scheduling and decision-making. This hesitation is partially brought out by trust issues as to AI's reliability, ethical decision-making, and safety, all of which are critical concerns in an industry where public safety and infrastructure integrity are paramount. Also, the algorithmic complexity and often obscure nature of AI models pose significant challenges in providing straightforward and comprehensive explanations for the actions or decisions made, leading to a common criticism of AI as a "black box" [22]. This opacity makes AI appear emotionally less trustworthy compared to traditional methods with transparent and interpretable operations. Moreover, the specific project requirements and inconsistent data quality in the AEC industry cast doubt on the efficacy and robustness of AI, which further impedes its wider implementation [24]. Thus, in order to fully harness the power of AI in the AEC applications, the need to build trust towards the adopted AI by their human counterparts has been becoming ever more pressing.

In response to these challenges, the field of trustworthy AI has been gaining increasing attention from the AEC community in recent years. For instance, to demystify the "black box" nature of AI models and improve their transparency, explainable tools like SHAP, LIME, and Grad-CAM have been adopted in some studies [25,26]. These tools are capable of highlighting and visualizing the most critical features that impact the final decisions made by AI, making the results more understandable to humans and thereby enhancing their credibility. Bias is another frequently encountered trust issue in AI applications because of the imbalanced dataset on which a model is trained. To address this hurdle and ensure fairness, one commonly employed strategy is to randomly discard samples from the majority classes or duplicate samples within the minority classes to equalize the class distribution in the training dataset [27]. Another alternative strategy to address the imbalance issue is to incorporate class penalties and weights into the loss function during model training [28]. Given the paramount importance of safety in AI applications on construction sites, the imperative for reliable, safe, and trustworthy AI becomes even more pronounced. One approach to this end is to rigorously test the AI algorithms within physically simulated environments, by which the potential weakness in reliability and safety can be identified and the corresponding functionalities can be improved. Additionally, the integration of predictive models that can predict and mitigate potential safety hazards represents another critical strategy towards enhancing the reliability and safety of AI applications [22]. Recently, researchers have explored the potential of integrating AI with blockchain technologies to increase data privacy and security so as to boost user trust in AI systems. Blockchain technology can promote peer-to-peer transaction management that offers a secure and transparent way to handle digital interactions. In simple words, it can add value to AI by explaining AI decisions, reducing risks, increasing efficiency, and improving data accessibility and decentralization [29].

As reviewed above, the existing studies have solely focused on singular and limited aspects of trust in the context of AI-enabled applications. Nevertheless, trustworthiness is a multifaceted requisite, for which different trust dimensions should act in harmony and push in synergistic directions toward the realization of trustworthy AI. According to the systematic literature review conducted by Emaminejad and Akhavian [22] and the EU Ethical Guidelines for Trustworthy AI [30], the critical dimensions of trust most applicable to the AEC domain are identified as transparency and interpretability, fairness and non-discrimination, reliability and safety, robustness and performance, data privacy and security. Recognizing the challenge of addressing all dimensions of trustworthiness in a single study, an AI-supported decision module was developed in this study with focusing on three key trust dimensions: transparency, interpretability, and fairness. In addition, this developed module is designed to be human-centered, allowing users to actively participate in the decision-making process and provide insights for AI adjustments as needed. Such interactive engagement is aimed at bolstering user cognitive trust in the AI-based module, illustrating a forward-thinking approach to integrating trust dimensions into AI applications for the AEC domain.

3. Problem statement and research objective

The deployment of DTs offers a promising solution for physical system management by providing a dynamic and comprehensive representation thereof in a virtual environment. However, current activities related to DTs in road infrastructure applications are still at an early stage with less attention being paid to the O&M phase, which is however the longest time span in the road asset life cycle. As reviewed previously, the existing DT frameworks for road infrastructure exhibit certain strengths, such as their ability to integrate heterogeneous datasets, enable real-time monitoring and data visualization, and simulate real-world scenarios. However, they fall short of supporting multi-objective decision making, lacking modularity and interoperability. Additionally, while AI is increasingly recognized as a core component of DTs to automate the data analysis and decision-making process, there has been insufficient focus involved in the existing DT frameworks on ensuring the trustworthiness of AI-driven decisions, particularly in terms of transparency, interpretability, and alignment with user preferences. Therefore, the primary objective of this study is to develop a robust DT framework that enhances road infrastructure management during the O&M phase through employing a multitier and modular architecture, ensuring effective data structuring and integration, and implementing a trustworthy AI-supported decision-making module.

4. Digital twin-based framework for road operation and maintenance

The road DT framework was developed based on a top-down approach in which the objectives of DT are defined first. According to these objectives, the associated use cases (or services) and requisite process steps thereof for implementation were identified, which should be in alignment with the existing practice and regulations. For this, it is recommended to adopt professional process modeling methods, such as BPMN and YAWL [31], to formalize the detailed process map and determine the required data scope for each use case. Since there exists a substantial overlap among different use cases regarding data acquisition, modeling, and analysis, a concept of modularity was implemented to the processes of them, upon which similar process steps are encapsulated into the same units. Consequently, the road DT is structured into a four-layer architecture as shown in Figure 1: data acquisition and pre-processing layer, data structuring and integration layer, data analytics layer, and service layer. Each layer operates as a self-contained unit with clearly defined roles. In this way, it allows for easier upgrades, extensions, and adjustments within individual layers to meet changing needs without compromising the integrity of the DT framework as a whole. It is also important to note that the upper three layers are deployed in a cloud server, which allows flexible remote data access and storage, information sharing, and enhanced collaboration among different stakeholders. In the following subsection, each layer is explained in detail.

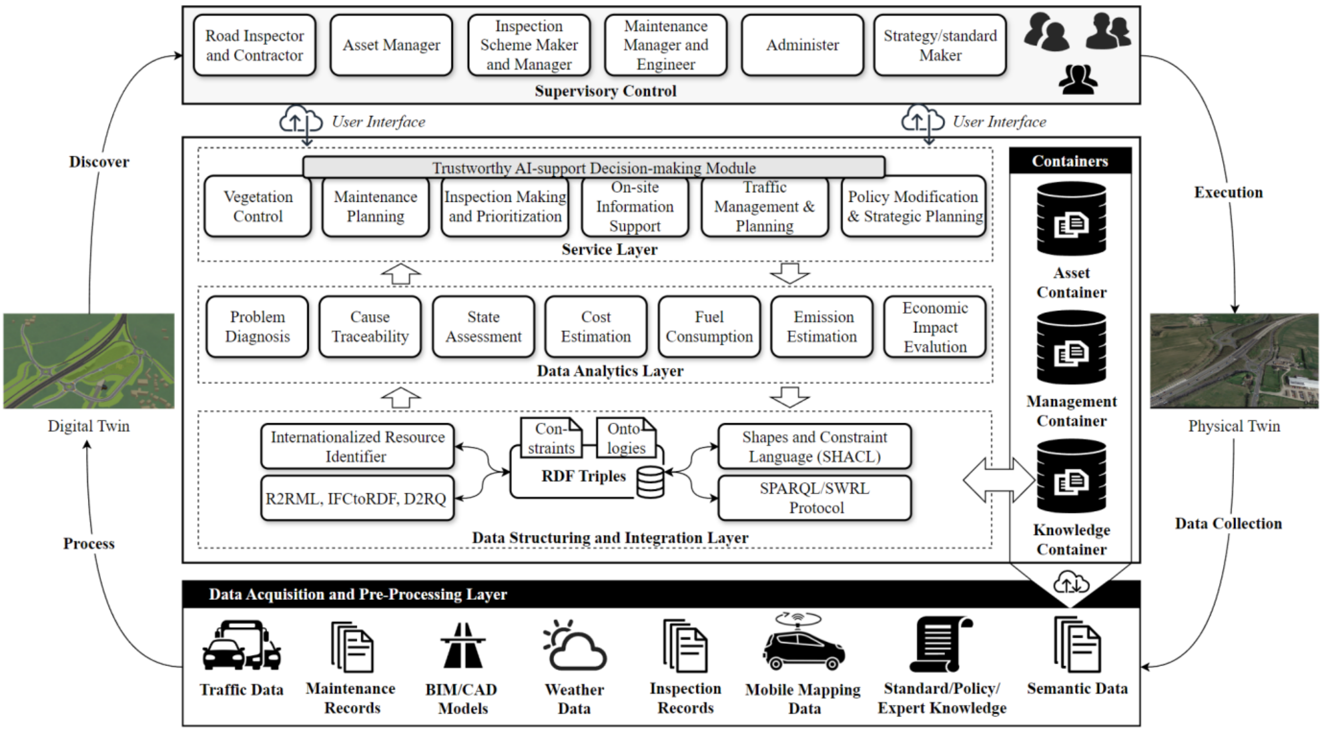

Figure 1. Digital twin-based framework for road operation and maintenance.

4.1. Layer 1: Data acquisition and pre-processing layer

The data acquisition and pre-processing layer is the foundation of the road DTs, which serves as the crucial bridge linking the physical infrastructure to its virtual counterpart. According to the data sources and nature, the road DT data can be broadly structured into three containers (*i.e.*, a collection of any form of files): Asset container, Management container, and Knowledge container, collectively covering the life-cycle information of the road infrastructure as well as relevant operational specifications and maintenance experiences in the O&M phase. Specifically, the Asset container archives the statically detailed characteristic information for individual road assets as well as their sub-components, recording their physical properties, geographical locations, semantic and spatial relationships, and other details, facilitating the identification, monitoring, and management of physical entities within the road system. It includes design files [e.g., Computer-Aided Design (CAD) and Building Information Modelling (BIM)], construction details (e.g., construction date and contractors), operating records (e.g., defect liability period), and so on. The Management container encapsulates all the dynamic data relevant to road asset management activities throughout the O&M phase, contributing to decision-making processes and supporting strategic asset management initiatives. Within its scope, it contains asset condition assessments from manual inspections and mobile mapping surveys, detailed maintenance logs for each asset, and supplementary data that includes climate and traffic statistics. The Knowledge container collects the policies, industry standards, and expert knowledge in the region or country where the road DTs are applied. It provides the rules and constraints for subsequent analysis, modeling, simulation, and optimization of the data involved in the Asset and Management containers. Following collection, a rigorous auditing process is essential to ensure the integrity and reliability of the collected data, which in turn is critical for the effectiveness of the DT systems. This process includes data cleaning, deduplication, and validation to eliminate inconsistencies, remove redundancies, and confirm accuracy. Also, appropriate pre-processing methods are selected to extract essential information from raw data as required, for example, defect detection from images and instance segmentation for the 3D point cloud. Additionally, all data are converted into formats compatible with the DT before being uploaded to the cloud server. These three containers continue to expand and update over time and interact synergistically with each other, constituting a comprehensive data foundation essential for the effective operation of road DTs.

4.2. Layer 2: Data structuring and integration layer

The success of DTs for the road O&M heavily depends on the ability to accurately represent the data and its semantics, as well as the ability to link the heterogeneous data across various containers for efficient and flexible data retrieval. To achieve this, an ontology-based data model based on the Web Ontology Language (OWL) [32] is constructed to specify data definitions across three containers and support the data extraction from heterogeneous sources, thus relating all information. Also, by providing metadata and provenance, a referred ontology can enhance data quality, allowing road stakeholders to make better sense of their data. Importantly, as the data requirements for road infrastructure management vary by region/country, the ontology should be specifically tailored to align with local road asset data requirements and associated governance. Once the ontology is constructed, the reasoning engine, such as Pellet [33], is employed to validate ontology satisfiability and identify any inconsistencies. Based on the ontology model, every collected data is structured and serialized into RDF/Turtle formats to achieve data integration in a unified and semantically consistent environment, which can further enable data sharing and usage among different stakeholders at scale. To streamline this process, various mapping tools, such as R2RML [34], IFCtoRDF [35], and D2RQ [36], can be used to convert data in various formats into RDF instances as required. As for the data types (e.g., point clouds and images) that are impractical to store directly in RDF files, only references to their locations in the containers are maintained. All entities (class, property, and instance) in the RDF graphs are uniquely identified by the Internationalized Resource Identifiers [37] to avoid data conflicting issues. In addition, the Shapes and Constraint Language (SHACL) [38] is utilized to validate the RDF-based data with respect to a set of predefined constraints aligned with the specifications (e.g., data format and precision requirement) in the Knowledge container. For querying and writing back data in the structured format, the SPARQL 1.1 Update protocol, RDF Query Language (SPARQL), and Semantic Web Rule Language (SWRL) are adopted [39], serving as a query/write layer that processes all defined vocabularies and searches and modify data records based on triple pattern matching.

4.3. Layer 3: Data analytics layer

The data analytics layer is the kernel of the road DTs. It contains a series of modularized analysis models (e.g., AI/ML and engineering models) dedicated to data fusion, modeling, simulation, and analysis in support of the condition monitoring, assessment, and prediction of different road assets in real-world scenarios. The corresponding assessment and prediction results would be used to update the as-is conditions of the road assets after validation. Within this layer, a suite of modularized estimation models (*i.e.*, mathematic formulas) is also incorporated to calculate strategic metrics such as cost, fuel consumption, greenhouse gas emissions, and economic impact of maintenance activities made for different goals based on the road asset condition assessment and prediction results. It is worth pointing out that these models are in essence driven by different domain-specific knowledge and are dependent on the standard and policy in a certain region or country. As such, the development and calibration of each model must be in strict accordance with the specifications detailed in the Knowledge container. Moreover, if applicable, the rules and insights derived from the historical analysis results by these models are fed back into and compound the Knowledge container. Through this closed-loop interactive process, the models can realize self-learning and continuously refine their embedded algorithms and parameters over time. Such an adaptive mechanism contributes to increasingly advanced applications in future development. Of note, to ensure the reliability and effectiveness of the entire DT system, particularly in an early development stage, the performance of every model should be systematically and rigorously validated before being implemented in practice.

4.4. Layer 4: Service layer

The service layer is the top and implementation layer of the road DTs, which enables dynamic interaction between DTs and different users while delivering essential services integral to informed decision-making and efficient execution for road O&M tasks. Based on their operational time horizons, the DT services can be divided into three domains: Short-term Service, Medium-term Service, and Long-term Service. The Short-term Service focuses on addressing urgent operational demands within a short-term frame of up to one year. It emphasizes instant monitoring and rapid data analysis to bolster day-to-day operational efficiency and safety. The services in this domain include severe road defect inspection and repair, vegetation control, winter maintenance, and so on. The Medium-term Service deals with a medium-term outlook over 1 to 5 years. It contains services such as road asset condition prediction, scheduling routine maintenance plans, and preventive or corrective maintenance plan design. The Long-term Service gears towards the service within a long-term time horizon of 5 to 50 years. The services in this domain include long-term performance prediction, life-cycle cost-benefit analysis, and strategic planning for asset improvement or replacement to ensure sustained performance and resilience throughout the life cycle of road infrastructures.

4.5. Trustworthy AI-support decision-making for road DT services

A trustworthy AI-supported module is developed and incorporated with the Service layer to assist users in making the most appropriate (or better, preferred) decisions for various road O&M tasks and subsequently contribute to building trust in the users of the road DT. This module is characterized by human-AI collaborative thinking, namely it leverages human cognitive ability and AI's exceptional computing power to reach the best decision making, rather than completely replacing the human role in the decision-making process. The workflow of this module is detailed in Figure 2. Oftentimes, effective decision-making within each road task requires navigating through multiple, and often conflicting, strategic metrics to formulate an optimal execution plan. These objectives differ not only in terms of the nature of the task at hand but also in other broader concerns, including ethical principles, human preferences, and legal and regulatory requirements. The complexity and specificity of these factors render traditional data-driven and end-to-end AI approaches inapplicable for addressing road-related tasks as such. To address this hurdle, the developed module was designed by taking the decision-making process as the multiple-objective optimization (MOO) problem. It is designed to allow the decision-makers to customize road management objectives and explore the trade-offs among them, upon which the specific solution(s) that align with diverse considerations and preferences of stakeholders can be selected. To this end, the first step in implementing the developed module is to convert the road management tasks and customized objectives into mathematical expressions, which is usually a time-consuming and complex process. To facilitate this, a Description to Model (D2M) converter built upon the large language model ChatGPT-4 was developed, with the latter having been widely recognized as one of the most powerful AI so far [40]. This D2M converter capitalizes on the advanced natural language processing capabilities of ChatGPT-4 to interpret textual descriptions of road tasks and user-defined objectives, transforming them into mathematical expressions that accurately represent objective functions as well as the decision variables and constraints involved. Additionally, explanations for each expression are provided to help users better understand the outputs (see Section 5.4). Users can supervise this transformation process to validate the correctness of the generated expressions, and dynamically adjust their description and provide instructions to guide the D2M to construct the MOO mathematical model as expected. Therefore, the users leveraging the proposed decision-making module are expected to possess domain expertise in both road O&M and MOO to effectively validate and refine the generated models. A vast collection of MOO cases, specifically related to road O&M tasks, was gathered from the literature as the knowledge to train the D2M converter. This enables the D2M converter to understand and transform the provided context better and can help reduce the chances of wrong answers or hallucinations.

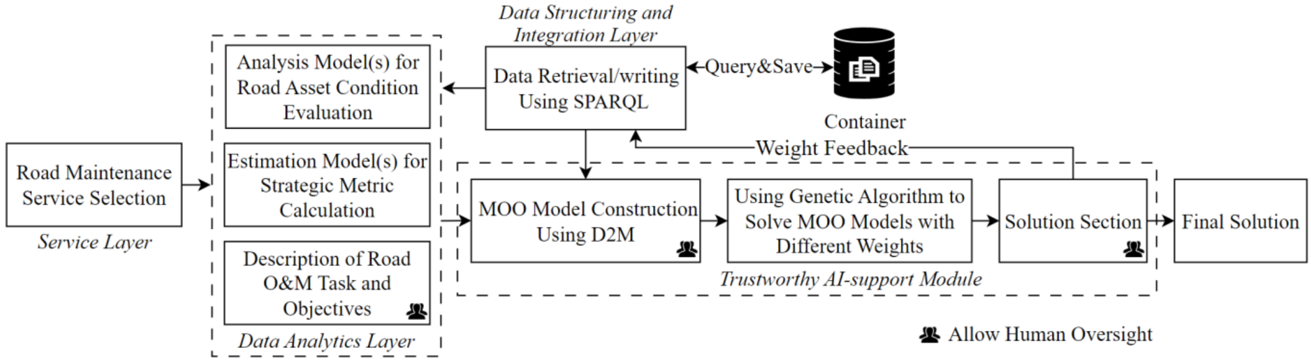

Figure 2. Pipeline of implementing trustworthy AI-support digital twin for road O&M task decision-making.

Once the MOO model is constructed, the genetic algorithm [41] in combination with the weighted sum approach [42] is utilized to solve the MOO problems. This process begins by assigning weights to different objectives, transforming the original MOO problem into a single-objective optimization problem, where the weighted sum of all objective functions is minimized or maximized. Then, the genetic algorithm initializes a population of candidate solutions, where each candidate represents a potential configuration of decision variables. These candidate solutions are iteratively refined through genetic operations such as selection (choosing the fittest solutions), crossover (combining parts of selected solutions), and mutation (introducing small random changes). At each iteration, the algorithm evaluates the fitness of each solution using the provided objective function, progressively guiding the population toward the optimal solution. This process continues until the stopping criterion, such as a predefined number of generations or convergence to an optimal fitness value, is met. The above process is repeated by assigning different sets of weights to the objectives, and the optimal solution set is constructed by aggregating the optimal solution calculated from different sets of weight combinations. This approach ensures a comprehensive exploration of trade-offs, providing a diverse range of solutions rather than being restricted to a single weight configuration, Furthermore, this mechanism inherently includes a sensitivity analysis that enables decision-makers to evaluate the impact of varying weight combinations on optimization results. By understanding these trade-offs, decision-makers can select the most suitable solution(s) based on their preferences, specific requirements, and other practical considerations. Such a weighting and selection mechanism can substantially mitigate the unfairness and bias oftentimes faced by traditional AI models from which only one output can be obtained. Subsequently, the weights corresponding to the selected solution(s) are stored in the Knowledge container that can be used in future practices to provide better decision recommendations for similar road maintenance tasks. It is evident that this developed module and the adopted AI techniques are human-centered, namely the decision-makers can supervise the entire decision-making process and provide interferences, if necessary, which in turn contributes to transparency and comprehension of the rationale behind every action. In addition, the decisions are based on mathematical formulations, thus making them easy to understand, auditable, and open to inspection. These qualities greatly boost user satisfaction and trust in the road DT. In this study, the road service "Vegetation Control" is provided to demonstrate the proposed DT framework and trustworthy AI-support module for road asset O&M decision-making.

4.6. Implementation process and user interface

Based on the developed framework, the implementation of DT for road O&M can be conducted as follows, and the corresponding pipeline is shown in Figure 2. When the users select a wanted service in the Service layer and provide the task descriptions as well as specific objectives, the corresponding data analysis models in the Data Analytics layer are subsequently triggered to perform condition analysis for the targeted road assets. Concurrently, the related estimation models are activated and used as the prior knowledge to instruct the D2M converter in translating the task contexts and user-defined objectives into the MOO mathematical model (see Section 5.4). Once the MOO model is established, users can provide additional prompts to convert the formulated MOO model into the programming language (e.g., Python) compatible with the selected optimization solver (e.g., Gurobi), where different weight combinations are assigned to the objectives. During this process, users are required to supervise the transformation to validate the correctness and reliability of the generated results. Afterward, the generated code can be executed using IDEs such as Jupyter Notebook or similar environments. At this stage, users need to manually instantiate the variables in the code with the parameters derived from the data analysis models (e.g., maintenance location and workloads) and RDF graphs (e.g., hourly wage of each maintenance task and traffic volume of each road section) through query engine (*i.e.*, SPARQL). Following this, the genetic optimization solver is adopted to solve for the optimal solutions for MOO models being assigned different sets of weights. Users are then presented with these solutions, from which they can select the most suitable service option based on their preferences and other concerns. Upon the selection and execution of a service, all relevant data, including inspection records, details of repair methods, and the condition of assets post-repair, are systematically recorded and integrated into the road models (*i.e.*, RDF graphs) and associated containers. As a loop, this procedure is continuously repeated throughout the lifespan of the road infrastructure. To enhance the efficiency and user-friendliness of this process, a web-based user interface (UI) was developed as part of the functionality of the road DT. This interface supports the visualization of data and results, simplifies the documentation process, and fosters improved interaction between the users and the road DT, thereby facilitating a more streamlined and effective adoption of developed DT for road O&M.

5. Case study

5.1. Project background and data collection

A pilot evaluation study of the developed road DT framework for road O&M was conducted on three main truck routes on the Strategic Road Network (SRN) in the United Kingdom, namely the A11, A12, and A14. This research project collaborates closely with the UK National Highways as part of their strategy to explore cutting-edge technologies, such as DTs, to ensure a safe, reliable, and efficient SRN for all road users. Figure 3 provides a detailed map of the studied roads, including the name and length of each section. These road sections are vital for connecting major manufacturing centers, distribution hubs and ports, thereby playing a significant role in regional connectivity and prioritization in inspection and maintenance efforts.

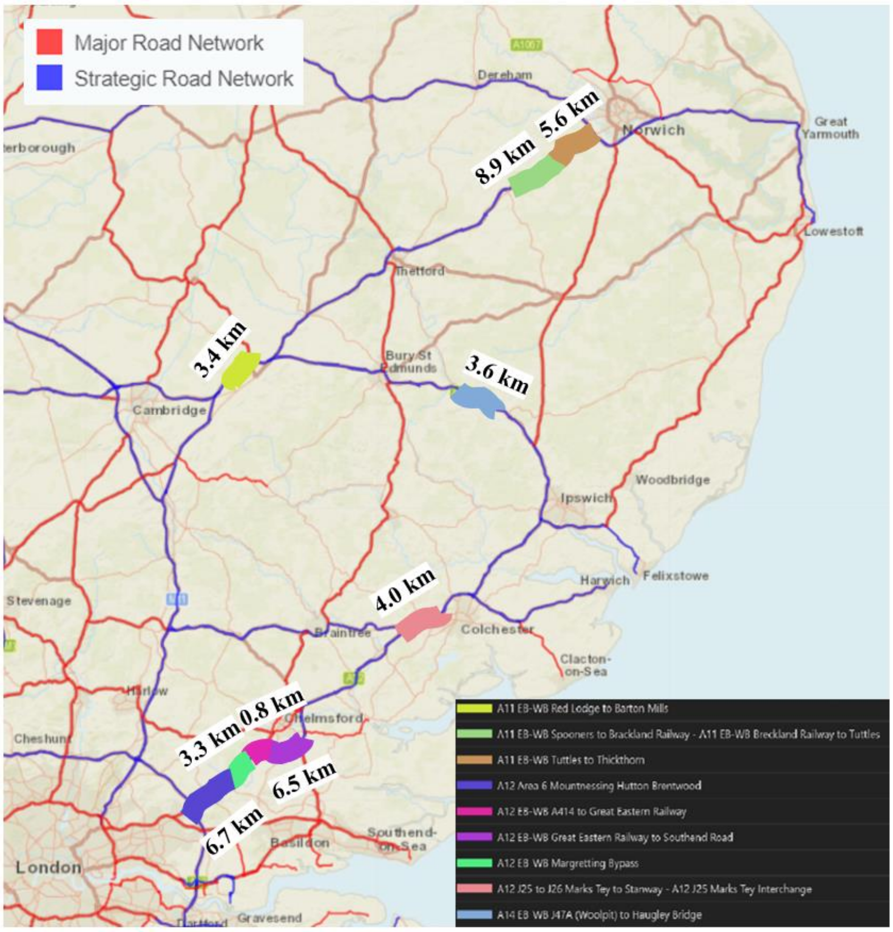

Figure 3. Map of surveyed road sections on A11, A12, and A14 with annotated segment lengths.

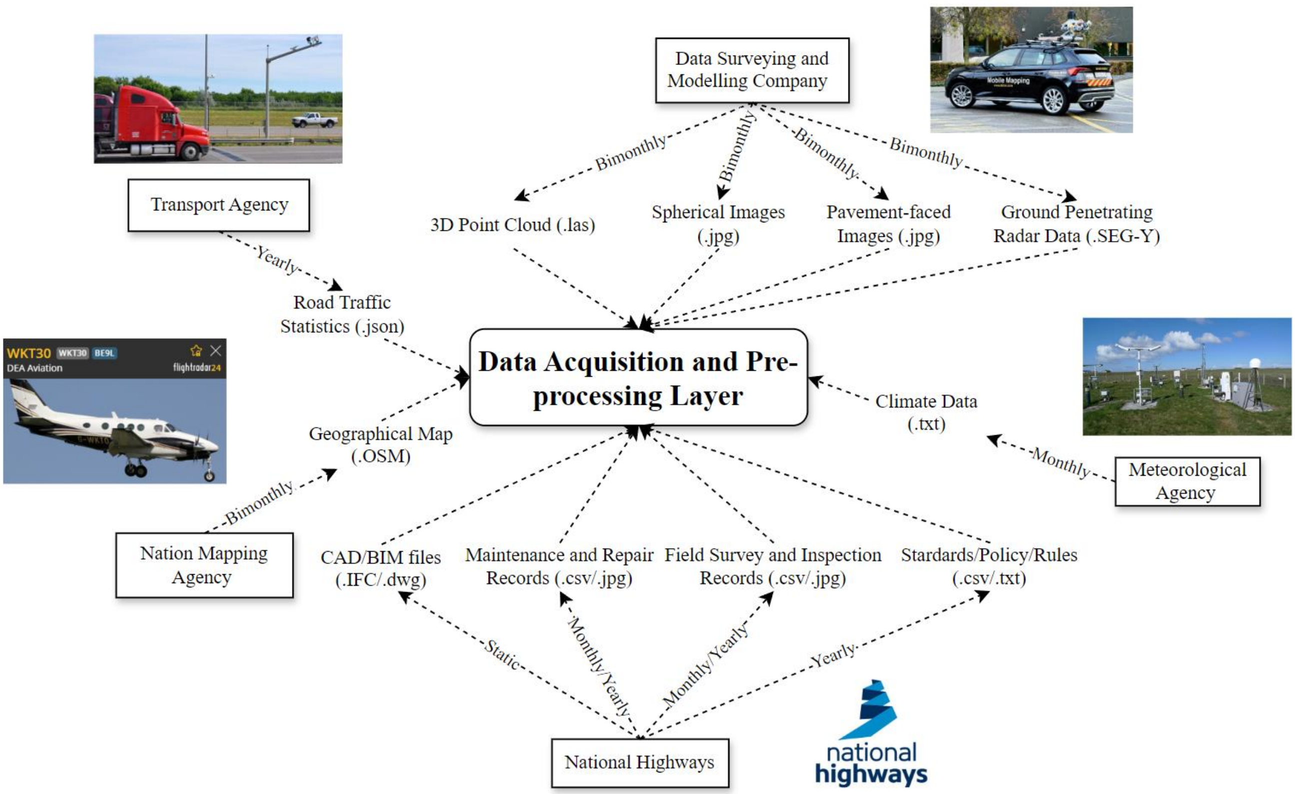

Figure 4. Data contributors in road digital twin development.

There are five critical data contributors engaged in this study for constructing the road DT, as illustrated in Figure 4. Specifically, National Highways serves as the primary data contributor, providing detailed road CAD/BIM models that include geospatial information, asset characteristics, and 3D representations of road segments. In addition, they also contribute comprehensive records of inspection and maintenance activities pertinent to road O&M, which encompasses task schedules, condition assessments, performance metrics, associated costs, and so on. Furthermore, National Highways offers information on standards, policies, and rules governing the road O&M. The data surveying and modeling company, KOREC, contributes mobile mapping data for each road section collected from a Trimble MX9. This dataset includes 3D point clouds, panoramic and pavement-faced images, and ground penetrating radar data. Ordnance Survey, the national mapping agency, provides a detailed geographic map scanned by a business aircraft, which covers the whole of the research area and serves as the basemap layer for data visualization and supporting the top-layer services provided by the road DT. While the transport agency and meteorological agency did not directly participate in the study, historical road traffic statistics and climate change data were downloaded from their respective websites for digitization purposes. It is worth pointing out that each set of data has been meticulously timestamped and georeferenced according to the British National Grid (EPSG:27700). This ensures that data collected from different locations and at different times can be easily synchronized.

Among the collected data, the mobile mapping data entails a data pre-processing step to extract the necessary information that is required in the upper layers of the road DT. The specific pre-processing techniques utilized, along with the types of information extracted, are summarized in Table 1. Furthermore, Figure 5 presents a glimpse into the intermediate outcomes of this data pre-processing process. The processed data is then formatted for compatibility with RDF instance files. To allow for more targeted and efficient management of the road infrastructure, the extensive road sections under investigation were properly divided based on the detailed divisions provided in the BIM/CAD files, in which the road sections are relatively homogenous. As a result, the original nine road sections spanning a total length of 42.8 km were redivided into 215 segments with each being allocated as a unique "Global ID". Accordingly, both the intermediate and well-processed data were grouped into these indexed homogenous road segments and subsequently uploaded to the suitable containers in the cloud server through the Internet.

Table 1. Data processing techniques and corresponding outputs for mobile mapping data.

	Methods/Software	**Outputs**
3D Point Clouds	TopoDOT, Agisoft Metashape	• Road Marking, Curb, Road Furniture Geometric Data (.csv) • Segmented 3D Point Clouds (.las) • Non-pavement Road Asset Condition Data (.csv)
Spherical Images	Manual Labeling, Agisoft Metashape	• Non-pavement Road Asset Condition Data (.csv)
Pavement-faced Images	MATLAB, GDAL, Mask R-CNN	• Pavement Orthmosaic Images (.GeoTIFF) • Georeferenced Defect Shape (.shp) • Pavement Defect Categories and Statistics (.csv)
Ground Penetrating Radar (GPR) Data	GDAL, Manual Labeling	• GPR images (.GeoTIFF) • Georeferenced Underlayer Defect Shape (.shp) • Underlayer Defect Categories and Statistics (.csv)

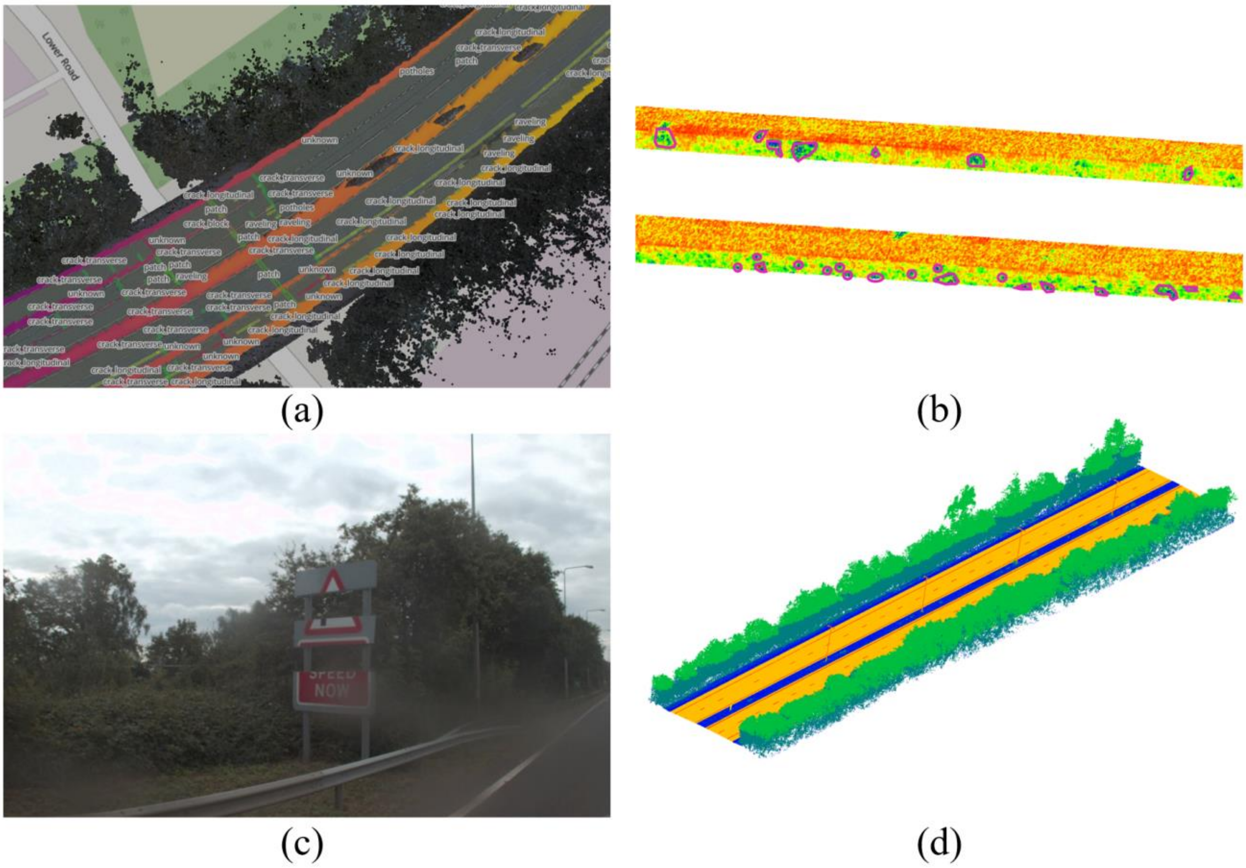

Figure 5. Pre-processing results of mobile mapping data: **(a)** defect detection in pavement-faced images, **(b)** void detection in GPR data, **(c)** damaged road asset identification in spherical images, and **(d)** instance segmentation for point cloud.

5.2. Ontology construction for data integration and management

To align with the data management requirement in the UK, one road ontology was developed in this study based on Asset Data Management Manual (ADMM), serving as a data schema for integrating the heterogeneous data in three containers and facilitating data management and retrieval. The ADMM, released by National Highways [43], sets out the requirements and process of collecting and validating data during all stages of a road's lifecycle. It is structured into four main spreadsheets with each dedicated to a unique facet of asset data specification: *Asset Information and Attributes*, *Management Information and Attributes*, *Asset Rules*, and *Domain List*. Figure 6 visualizes the detailed configuration and interconnections of these spreadsheets. For more details, interested readers can refer to National Highways [43]. The interconnected entries within these spreadsheets facilitate the semantic expression of RDF, allowing for the serialization of collected data into an ontology for semantic extension. To achieve this, a semantic mapping process was conducted to transform these four spreadsheets into a road ontology framework. Specifically, the *Asset Information and Attributes* and *Domain List* sheets were mapped to Asset ontology for the Asset container; the *Management Information and Attributes* and *Domain List* sheets were mapped to Management ontology for the Management container; and the *Asset Rules* sheet was mapped to Knowledge ontology for Knowledge container. The semantic mapping of each sheet to the ontology is illustrated in Figure 6, in which different mapping operations are color-coded.

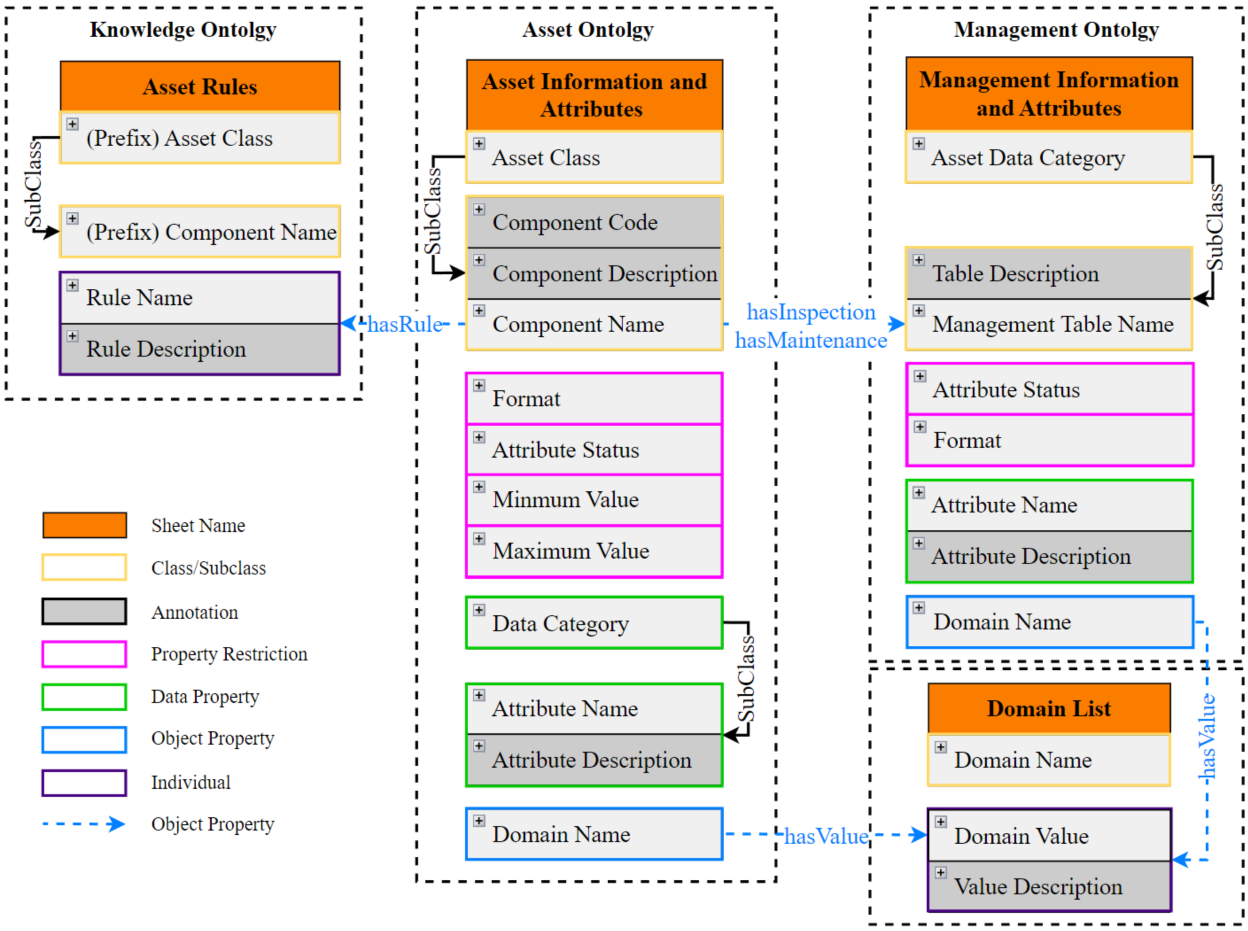

Figure 6. Configuration of spreadsheets in ADMM and their semantic mapping to road ontology.

The *Domain List* sheet is predefined and contains domain values and the meaning of these values referenced by the *Domain Name* column in the *Asset Information and Attributes* sheet. Its mapping relationship with the Asset ontology is specified as follows: (1) the Domain List sheet is mapped to the *DomainList* class of the Asset ontology; (2) the entries in the *Domain Name* column are mapped to the subclasses of the *DomainList* class; and (3) the values in the *Domain Value* column are mapped to individuals of the corresponding subclasses. For instance, the *PV_CON_PAVEMENT_CLASS* column within the *Domain List* sheet contains 13 enumerations, which were mapped as individuals of the *PV_CON_PAVEMENT_CLASS* subclass, as shown in Figure 7. The *Asset Information and Attributes* sheet defines the hierarchical structure (asset/sub-asset/component) for each asset class and defines the required data records and associated attributes. Its mapping to the Asset ontology follows five basic steps as shown in Figure 8: (1) the entries in the *Asset Class* column are mapped to the classes of the Asset ontology; (2) the entries in the *Component Name* column are mapped to the subclasses of the corresponding classes [see Figure 8(a)]; (3) the entries in the *Data Category* and *Attribute Name* columns are hierarchically mapped to data properties of the corresponding subclasses [see Figure 8(b)]; (4) the values in the *Attribute Status*, *Format*, *Domain Name*, *Minimum Value*, and *Maximum Value* columns are mapped to the property restriction of the corresponding subclasses [see Figure 8(c)]; and lastly, (5) the entries in the *Domain Name* column are mapped to object property of the corresponding subclasses, constraining the subclasses' scope to the individuals within the *DomainList* class [see Figure 8(d)].

Domain Name	Domain Value	Value Description
PV_CON_PAVEMENT_CLASS	CORE	Coring
	EXPANDEF	Extracted from PANDEF
	GPRC	GPR (Calibrated)
	GPRU	GPR (Uncalibrated)
	INLAY	Inlay
	INVENTORY	Generated from Inventory
	NA	Not Specified
	NEW	Newly Constructed
	OVERLAY	Overlay
	PROV	Provisional
	RECON	Re-construction
	RESET	Re-setting Condition Factors
	RESURFACE	Re-surfacing

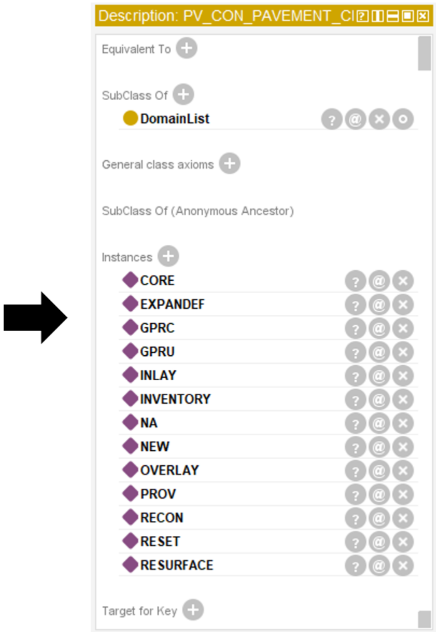

Figure 7. Example of mapping entries in *Domain List* sheet into Asset ontology.

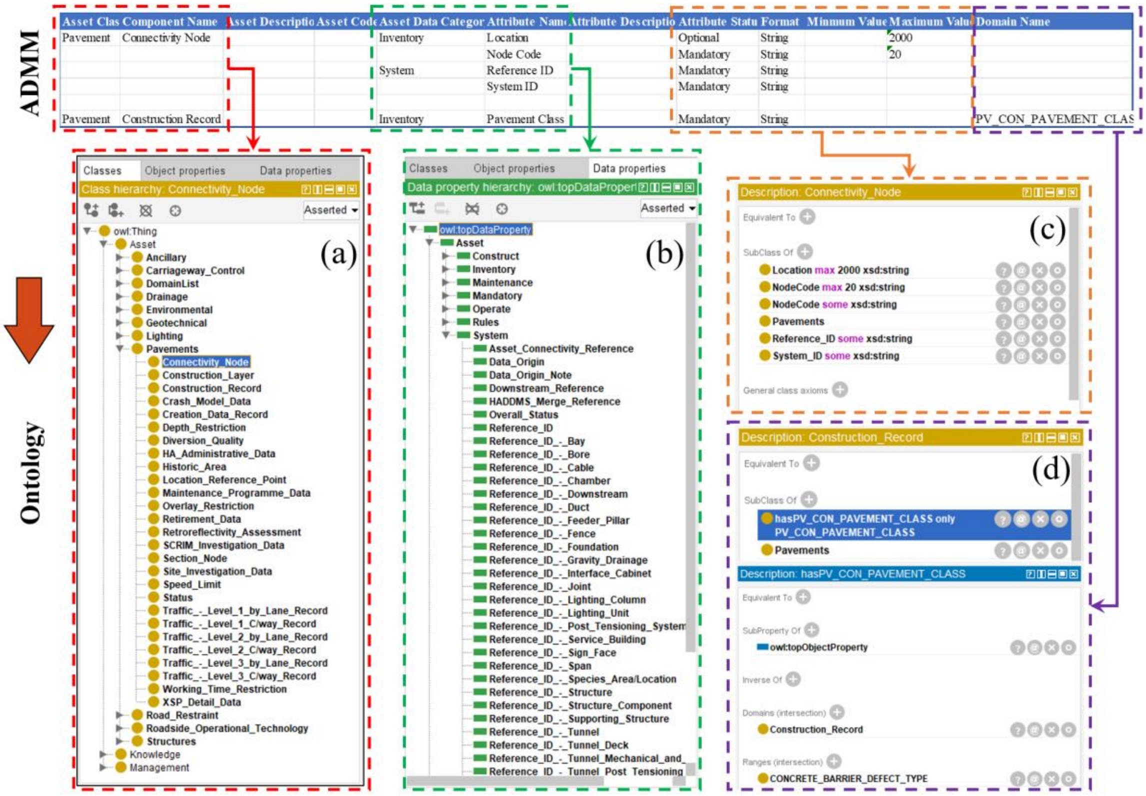

Figure 8. Semantic mapping between *Asset Information* and *Attributes* sheet and Asset ontology: **(a)** Asset class hierarchy, **(b)** data properties of Asset classes, **(c)** property restrictions, and **(d)** object properties.

The *Management Information* and *Attributes* sheet outlines the necessary data records and associated attributes pertinent to inspection and maintenance activities for each asset or component. Its mapping to the Management ontology can be performed in a similar manner as that of the *Asset*

Information and Attributes sheet. To save space, the detailed mapping process is presented no more. Additionally, the Management ontology was enriched by incorporating the *DomainList* class to supply the values referenced within the management data schema, and by creating additional data properties to link road assets with mobile mapping, traffic, and temperature data not covered in the ADMM document. The Asset Rules sheet compiles a set of rules corresponding to different assets and components, giving guidance on their data requirement and recording. Its mapping relationship with the Knowledge ontology follows: (1) the entries in the *Asset Class* and *Component Name* columns are mapped to the Knowledge ontology with the prefix "*Rule*" to avoid naming conflicts with the Asset ontology and arranged in a taxonomic hierarchy; (2) the entries in the *Attribute Name* column are mapped to the individuals under the corresponding subclasses. In addition, policies, industry standards, and expert knowledge from other sources were further supplemented in the Knowledge ontology.

Once the Asset, Management, and Knowledge ontologies were constructed, they are interconnected by establishing additional constraints and object properties, as shown in Figure 6. Specifically, the *hasInspection* and *hasMaintenance* object properties establish associations between the *Component Name* class in the Asset ontology and the *Management Table Name* class in the Management ontology, while the *hasRule* object property associates the *Component Name* class in the Asset ontology with the *Rule Name* in the Knowledge ontology. Subsequently, these interconnected ontologies collectively form the road ontology framework, which serves as the basis for instantiating and aggregating collected road asset data into an RDF graph. In conjunction with this process, a set of SHACL constraints was defined based on the rules in the knowledge dataset to ensure the quality of the resulting RDF graph and identify invalid data. Figure 9 presents some SHACL constraints applied to the RDF graph, to which each instance in the RDF graph must conform. In this way, it ensures stringent validation of the RDF graph, providing a comprehensive framework for maintaining high-quality road asset data.

Example 1: the Start Chainage data for Bridleway asset is Mandatory; it needs to be recorded in the decimal format with 3 digits before the decimal point and 1 digit after.

```
ex:Bridleway_DataShape
    a sh:NodeShape ;
    sh:targetClass ex:Bridleway ;      # Applies to all Bridleways
    sh:property [                      # _:b0
        sh:path ex:Start_Chainage ;    # Constrains the values of ex:Start_Chainage
        sh:minCount 1 ;                # Start_Chainage is mandatory
        sh:maxCount 1 ;                # Only one value allowed
        sh:severity sh:Violation ;     # Violation if not present exactly once
    ] ;
    sh:property [                      # _:b1
        sh:path ex:Start_Chainage ;    # Constrains the values of ex:Start_Chainage
        sh:datatype xsd:decimal ;      # Must be of datatype decimal
        sh:pattern "^\\d{1,3}\\.\\d{1}$" ;  # Pattern for the specific decimal format
        sh:severity sh:Warning ;       # Warning if pattern does not match
    ] ;
```

Example 2: the Width data for Combined Cycle Track and Footway is Mandatory; it needs to be recorded as a decimal and must be between 1 and 10 meters.

```
ex:Combined_Cycle_Track_and_Footway
    a sh:NodeShape ;
    sh:targetClass ex:Combined_Cycle_Track_and_Footway ;     # Applies to all Combined_Cycle_Track_and_Footway
    sh:property [                        # _:b0
        sh:path ex:Width ;   # Constrains the values of ex:Width
        sh:minCount 1 ;                  # Width is mandatory
        sh:maxCount 1 ;                  # Only one value allowed
        sh:severity sh:Violation ;       # Violation if not present exactly once
    ] ;
    sh:property [                        # _:b1
        sh:path ex:Width ;   # Constrains the values of ex:Width
        sh:datatype xsd:decimal ;        # Must be of datatype decimal
        sh:severity sh:Warning ;         # Warning if datatype is not decimal
    ] ;
    sh:property [                        # _:b2
        sh:path ex:Width ;   # Constrains the values of ex:Width
        sh:minInclusive 1 ;              # Minimum value of 1 meter
        sh:maxInclusive 10 ;             # Maximum value of 10 meters
        sh:message "Value must be between 1 and 10 meters" ;  # Message if value is out of range
    ] ;
```

Figure 9. Examples of using SHACL for road asset RDF graph data validation.

5.3. Web-based user interface development

A web-based UI based on Potree [44] was developed to establish the connection between users and the road DT hosted on the cloud server, offering enhanced service support and exploitative interaction. The main inference of the developed UI is shown in Figure 10(a), through which authorized road users can access and explore the road DT within an accessible web environment. Within the UI viewer, various types of data for each road section can be individually or simultaneously visualized by toggling on/off the objects (e.g., point clouds, panoramic images, and GPR data) listed in the "Scene" section sidebar. Since the collected/processed data were fully georeferenced, they can be easily converted to GIS data (e.g., shapefiles) and accurately displayed on the geographical map if needed. Users can zoom out to view data over a large region in the UI viewer, making it easier to capture valuable insights and make informed decisions in a macroscopic fashion. Also, the UI supports effortless navigation to specific road sections using view toggles for detailed inspection and analysis [see Figure10(b)], in which the local records thereof are included into annotations and pinpointed on the geographical locations where they were originally collected. Upon clicking on them, the UI shows a pop-up window with the detailed description and images (if any) attached to the annotation of interest [see Figure 10(c)]. The data visualization is essentially realized by activating the SPARQL functions to query the corresponding data from the RDF instance file and containers, followed by displaying them through the WebGL-based rendering engine [44]. The "Tool" section provides a diverse set of toolkits that enable accurate distance, angle, volume measurement, and cross-sectional views within the point clouds. Additionally, users can switch to the street view by clicking on the white spheres over the road surface [see Figure 10(d)], which represent the locations of the mobile mapping system (*i.e.*, Trimble MX9) at the capture time. With the help of these tools, users are able to verify the correctness of the collected data across different resources in a semi-immersive virtual reality manner.

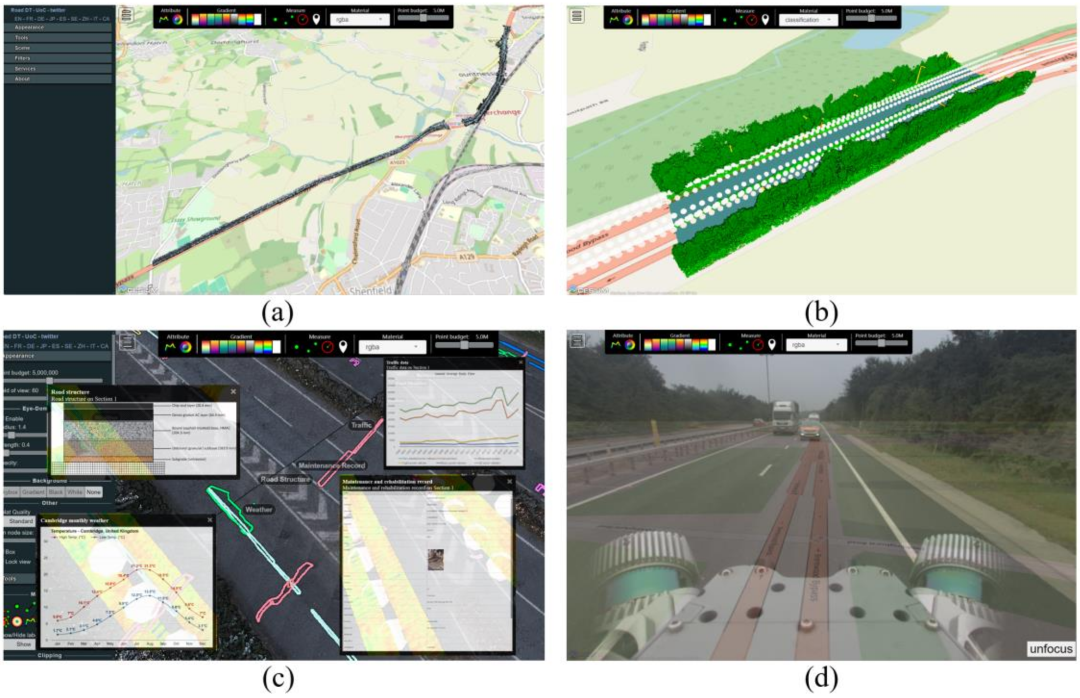

Figure 10. Developed user interface for road DT: **(a)** overview interface viewer, **(b)** detailed road section visualization, **(c)** local data collection display, and **(d)** street-level view.

Another noteworthy feature of this developed UI is the ability to allow the users, particularly the inspectors and maintenance engineers, to directly upload field activity records into the road DT. This is achieved by manually annotating the geographical map at the locations where these records are generated. Users can then detail these annotations with relevant descriptions and supplementary images under the “Properties” column in the sidebar, as illustrated in Figure 11. Upon verification and approval by managers, these records are automatically formatted and stored in the appropriate containers within the road DT. This feature can not only streamline the data updating and integration but also facilitate right-time updates on the condition of road assets, consequently contributing to more informed decision-making and supporting proactive maintenance activities. Moreover, the “Services” section of the sidebar provides various control tabs, each associated with a specific road service activated by user clicks. Triggering a service launches service engines including D2M and genetic algorithm engines in new windows, where users can provide detailed task descriptions and specify their objectives. The genetic algorithm engines then receive the MOO model from the D2M and propose a set of optimal solutions from which users can select the most appropriate. Subsequently, the chosen solution is fed back to the UI and visualized in the viewer, providing guidance for users to execute.

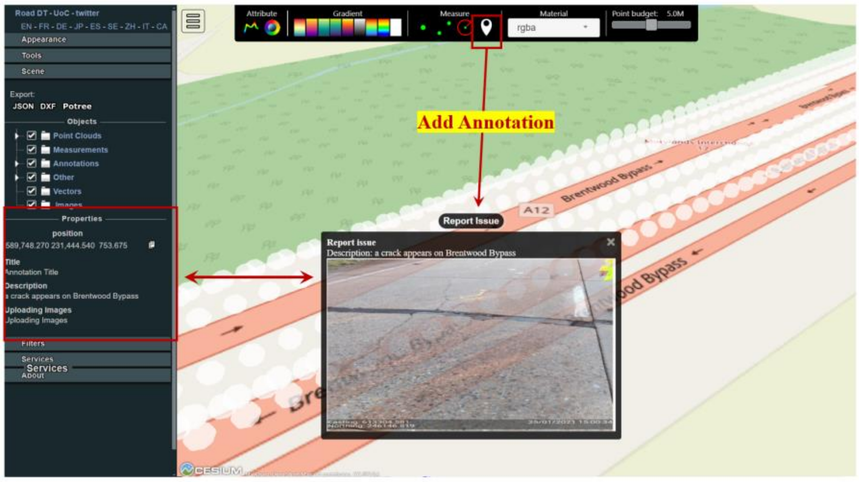

Figure 11. Uploading of field activity records using developed user inference.

5.4. Vegetation control application

Vegetation that overhands the roadway should be crown-lifted to at least 5.2 m to allow safe passage of high-sided vehicles as well as being cut back sufficiently at least 1.2 m from the boundary lines of the carriageway to allow clearance for wing mirrors [45]. Thus, regular maintenance of roadside vegetation is essential to ensure a safe and comfortable roadway environment. Once the “Vegetation Control” service is triggered by the users, the “Overgrowth Vegetation Detection” model in the Data Analytics layer is immediately activated to identify the parts of vegetation that violate the clearance regulation, which is essentially based on the analysis of the spatial relationship between the vegetation and the road boundary lines. To support this, the SPARQL query engine is utilized to extract the 3D vegetation point cloud (derived from 3D instance segmentation) and the boundary line geometry models (polygon lines) of each road segment from the ontology and containers [see Figure 12(a)]. For each road segment, the 3D vegetation points up to 5.2 m in height are projected onto the ground plane. The latter is defined by the shifted boundary lines that are 1.2 m away from their original counterparts relative to the road center.

By doing so, the overgrowth vegetation parts can be subsequently identified based on whether their projected points fall within the ground plane [see Figure 12(b)]. Following this, the k-means clustering algorithm [46] is utilized to cluster the 3D points of overgrowth vegetation, with the volume of each cluster being calculated by determining the minimum-volume bounding box thereof [see Figure 12(c)]. To simplify the modeling and programming process, the adjacent road segments are grouped into the same maintenance sites, within which the volumes of overgrowth vegetation are aggregated. The statistics of overgrowth vegetation volume in each maintenance site are summarized in Table 2.

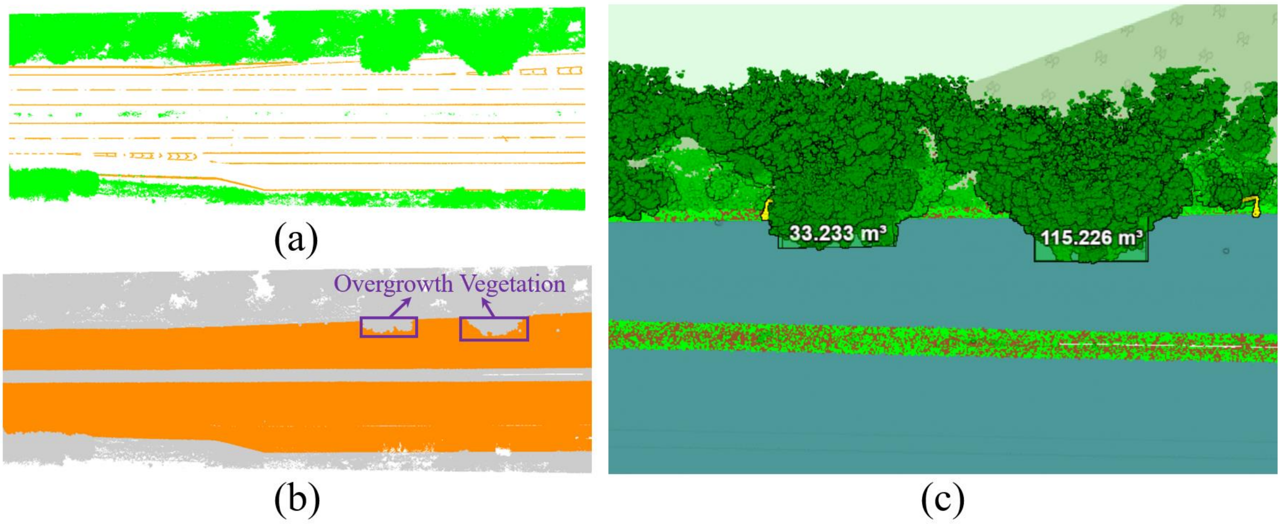

Figure 12. Overgrowth vegetation detection and volume estimation: **(a)** 3D point cloud and boundary line, **(b)** overgrowth vegetation detection, and **(c)** overgrowth vegetation volume estimation.

Table 2. Volume and required work hours of overgrowth vegetation on different maintenance sites.

	Site 2	**Site 4**	**Site 7**	**Site 8**	**Site 11**
Volume (m3)	202.7	893.6	246.1	273.9	948.4
Required Work Hours (h)	2.5	8.5	3.0	3.5	11.5

In general, the vegetation control task can be formally defined on a geographical graph $\mathbf{G}=\{\mathbf{N},\mathbf{E}\}$, as illustrated in Figure 13, where the elements represent the nodes and edges, respectively. The nodes $\mathrm{N}=\{0,1,\cdots,11\}$ in this project comprise two distinct types of locations, that is, the vegetation maintenance sites $\mathrm{K}=\{2,4,7,8,11\}$ (in blue color) and the road junctions $\mathrm{J}=\{0,1,3,5,6,9,10\}$ (in white color). Each edge $e_{(i,j)}\in\mathbf{E}$ in the graph is characterized by distance $dist_{(i,j)}$ (in mile) for $i,j\in\mathbf{N}$ and $i\neq j$. Additionally, each maintenance site $i\in\mathbf{V}$ is associated with a total overgrowth vegetation pruning volume and equivalent work hours W_i, as detailed in Table 1. The vegetation service company is located at node 0, from which a fleet of five identical vegetation pruning machines are available. The pruning machines start from and return to depot 0 after completing their daily mission. Each pruning machine is allowed to head out to serve one or multiple maintenance sites during its operational day, but within its maximum working hours including both travel time to and from the sites and the on-site working time for vegetation maintenance.

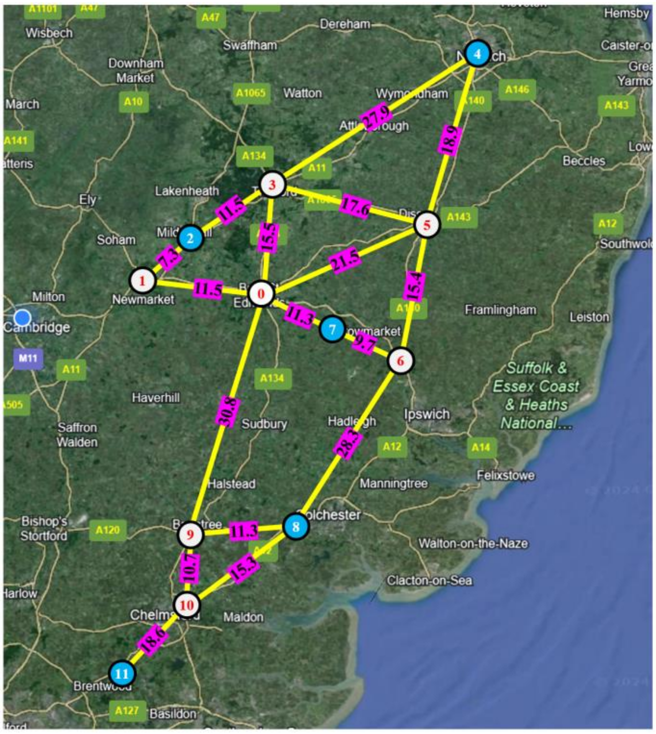

Figure 13. Geographical graph of studied road network.

The road maintenance managers from National Highways have specified two primary objectives for this vegetation maintenance task: (1) minimizing the total maintenance cost, and (2) minimizing the overall traffic impact (namely, prioritizing road sections with the highest volumes); both of which are constrained by a given maintenance timeframe of two days. In response, the estimation models "Vegetation Maintenance Cost Model" and "Traffic Impact Model" predefined in the Data Analytics layer were activated and fed into the D2M converter as the prior knowledge. Upon this, the D2M converter is implemented to convert the user-defined description of vegetation control task and objectives into the MOO model including objective functions, decision variables, and parameters, as shown in Figure 14. Meanwhile, the D2M also autonomously defines the relevant constraints for the MOO model based on its built-in inferential capabilities. However, it was found that one constraint aimed at preventing subtours was missing, which is essential within the context of a routing or network flow optimization problem. Thus, human interference was performed to instruct the D2M converter to incorporate this essential constraint, ensuring the MOO model was accurately and completely formulated as intended. Once the MOO model is established and validated, additional prompts were provided in the D2M to convert the formulated MOO model into Python code compatible with the Gurobi solver [47], where different weight combinations are assigned to the objectives. Similarly, the correctness of the generated code was validated manually. Then, the parameters involved in the MOO model were instantiated based on the geographical graph, required working hours in each maintenance site, and the information retrieved from the Knowledge container through the SPARQL query engine. The retrieved information is summarized in Table 3. Figure 15 illustrates a part of the Python code generated by the D2M for the established MOO model. Subsequently, the genetic algorithm engine Gurobi was applied to solve the MOO models being assigned different sets of weights and seek out optimal solutions thereof. Finally, detailed vegetation maintenance schedules corresponding to each optimal solution were constructed for decision-makers to choose from based on their priorities assigned to the objectives. Figure 16 showcases two maintenance schedules for this investigated vegetation control task, one prioritizing cost efficiency and the other traffic benefits. Note that the correctness of the intermediate results generated by the D2M converter, as well as the effectiveness of the maintenance schedules, had been validated by experts from road agencies and the MOO research field. However, more user feedback is needed to thoroughly evaluate the performance of the proposed decision-making module, which will be carried out in future work.

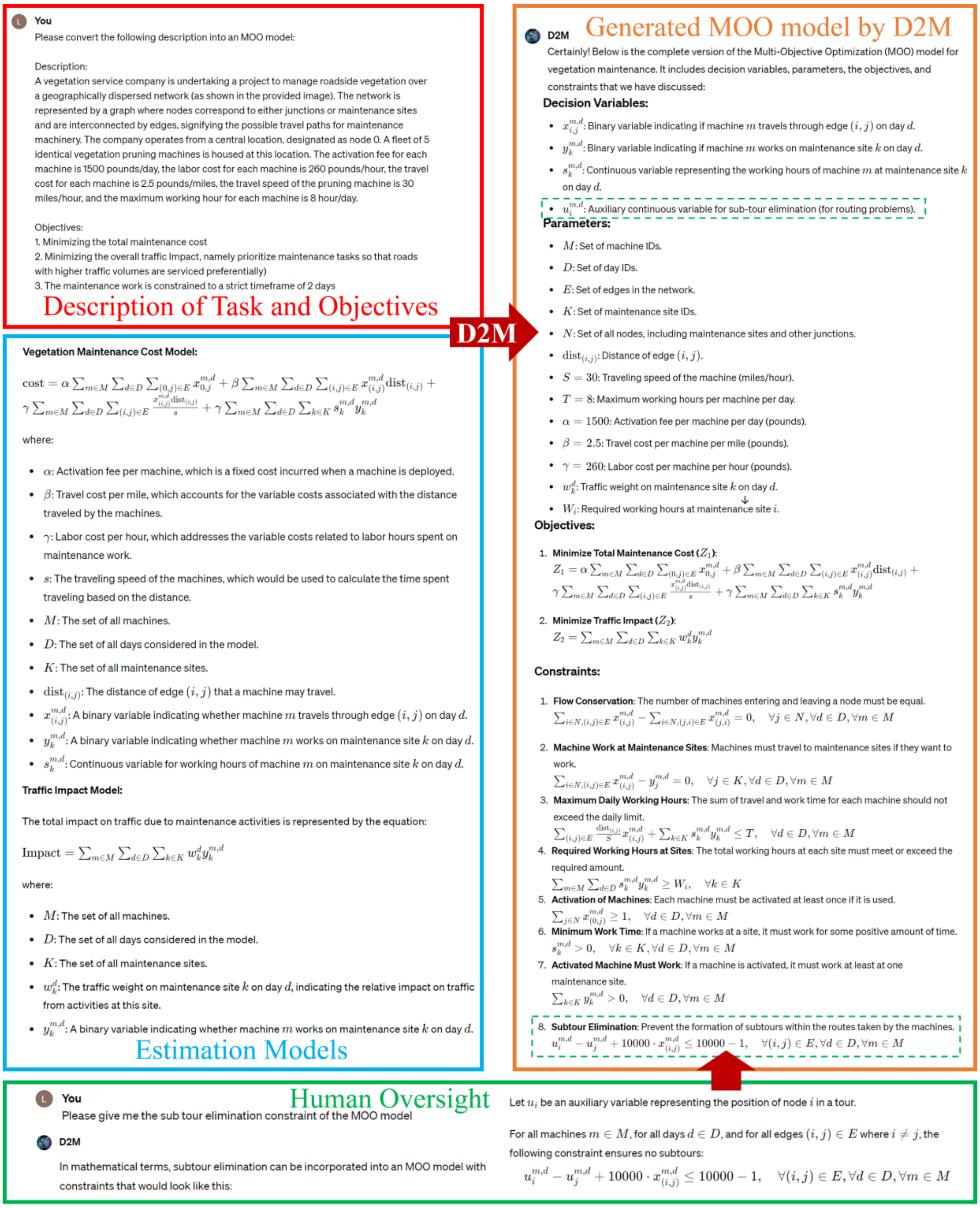

Figure 14. Multiple objective optimization model construction using D2M converter.

Table 3. Retrieved information from Knowledge container for vegetation maintenance task.

	Site 2	Site 4	Site 7	Site 8	Site 11
Traffic Volume	42540	49139	41966	86014	68182
Traffic Weight (Day 1)	1	0.86	1	0.49	0.62
Traffic Weight (Day2)	1	1	1	1	1

Activation Fee: £ 1,500/day, Labor Cost: £260/hour, Travel Cost: £2.5/mile, Travel Speed: 30 mile/hour, Maximum Work Hour: 8 hour

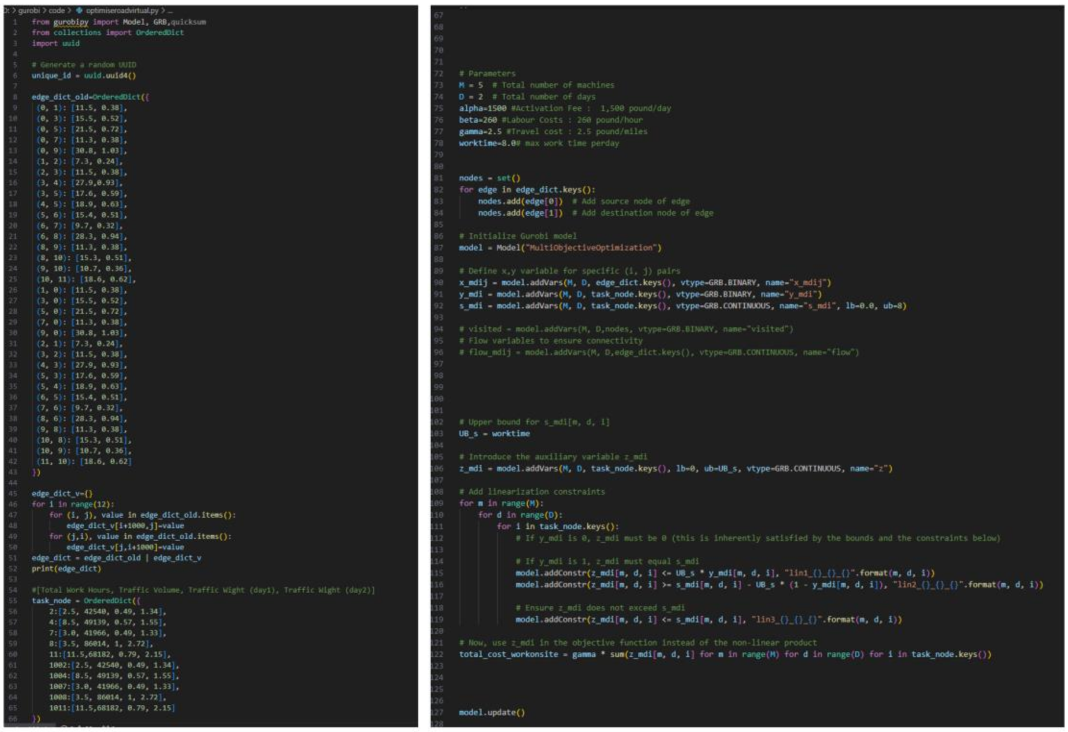

Figure 15. Part of the Python code generated by the D2M for established MOO model.

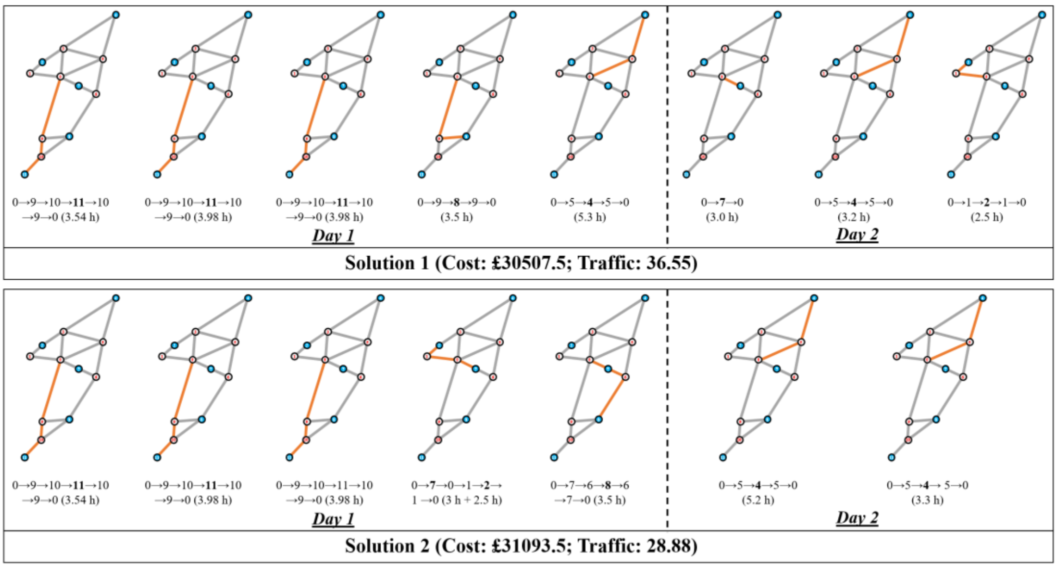

Figure 16. Vegetation maintenance schedules with prioritizing different objectives.

6. Discussions and future works

The key attributes of the developed road DT can be identified as flexibility, modularity, interoperability, and trustworthiness. First, the road DT's flexibility is exemplified by its cloud-based deployment and the creation of a web-based UI, enabling stakeholders with internet access to interact with the DT using any web browser, from any location. Second, the architecture of the DT is built on the principle of modularity during both the design and implementation phases, simplifying the system complexity and enhancing the reusability of various functions. This modularity supports the development of diverse O&M services, facilitating easier updates, expansions, and modifications thereof to adapt to changing requirements. Third, the application of ontology for data management within the developed road DT framework enhances the semantic organization, which facilitates the integration and interoperability of data across different systems. This data structuring approach enables the road DT to seamlessly communicate and integrate with other DTs in various sectors, such as urban planning or utility management, creating a cohesive and interconnected digital ecosystem. Last, the developed road DT significantly enhances its trustworthiness through the integration of a trustworthy AI-supported module specifically designed to ensure ethical decision-making. This module employs advanced natural language processing technology and MOO techniques that not only improve the transparency of the decision-making process but also ensure that all outputs are consistent with stakeholder expectations and other considerations. By embedding these trust mechanisms, the road DT provides stakeholders with confidence in its operational integrity and the validity of its recommendations, fostering broader acceptance and utilization in critical decision-making for various road O&M tasks.

On top of the current study, there are still some tasks that should be carried out in the future. First, the current approach of randomly assigning weights to different objectives in the decision support module may occasionally result in an excess of redundant recommendations, potentially diminishing user satisfaction on road DTs. To address this hurdle, it is essential to survey to collect insights from stakeholders involved in roadway system management. This would include gathering preferences, priorities, and requirements from various stakeholders, from frontline operators to high-level policymakers, specifically in the regions or cities where the road DT is deployed. Such insights would enable the assignment of a more tailored range of weights to the MOO models, ensuring they align more closely with the actual needs and expectations of the road management sector. Second, there is a need to design and integrate more service modules that cater to various aspects of road O&M. These modules should be capable of addressing a broader spectrum of management needs, thereby enhancing the utility and comprehensiveness of the road DT. Subsequently, the performance of these new modules should be rigorously evaluated in real-world applications to assess and enhance the effectiveness of the underlying analysis and estimation models. Third, while the current study demonstrated the feasibility of integrating the AI-supported module into the road DT framework, the module's trustworthiness requires further evaluation. Future efforts should include the development of specific metrics to assess dimensions such as accuracy, transparency, interpretability, and fairness. For example, accuracy could be evaluated by comparing the module's outputs with expert decisions or historical benchmarks, while transparency and interpretability could be assessed through user feedback. Additionally, fairness could be validated by examining whether the module's outputs are unbiased across different conditions or scenarios. Extensive real-world testing and validation of the module under diverse scenarios will also be critical to strengthening its practical applicability and trustworthiness. Fourth, ensuring data quality is crucial for the effectiveness and trustworthiness of AI- and DT-based systems. Future research should focus on developing automated mechanisms for data validation, anomaly detection, and error correction. Integrating these into the data acquisition layer will enhance the reliability and scalability of the road DT framework across diverse scenarios.

7. Conclusions

The development and implementation of the road DT framework in this study represents a significant advancement in the field of road infrastructure management, particularly within the O&M phase. Through the development of a multi-tiered, modular architecture that employs cutting-edge technologies and trustworthy AI, this research has demonstrated the potential to enhance the efficiency and sustainability of road management practices. The road DT framework developed not only supports the dynamic integration of heterogeneous data but also ensures the transparency and reliability of decision-making processes, thereby increasing stakeholder confidence and encouraging wider adoption. However, the road proposed DT framework is still in its early stages of development. Future work will focus on refining the decision support module to reduce redundancy, expanding the range of road O&M services, and enhancing data security to address the vulnerabilities inherent in cloud-based systems. By continuing to evolve and adapt to the road DT framework, this research will contribute to the sustainable management of road infrastructure and pave the way for future innovations in the field.

Acknowledgments

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 101034337. The authors are grateful for the support. Any opinions, findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of European Horizon.

Conflicts of interests

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.

Authors' contribution

Data curation: L.L.; Formal analysis: L.L. and M.Y.; Investigation: L.L.; Methodology: L.L., M.Y., M.W. and Y.X.; Software: L.L. and Y.P.; Validation: L.L., M.Y. and Y.P.; Visualization: L.L. and Y.P.; Writing – original draft: L.L., M.W. and Y.P.; Proofread: M.Y. and Y.X.; Conceptualization: L.L., I.B., Y.X. and Y.P.; Funding acquisition: I.B.; Project administration: I.B.; Resources: I.B.; Supervision: I.B. All authors have read and agreed to the published version of the manuscript.

References

[1] American Society of Civil Engineers. A comprehensive assessment of America's infrastructure. 2021, pp. 1–21. Available: https://infrastructurereportcard.org/wp-content/uploads/2017/01/Roads-2021.pdf (accessed on 3 March 2021).

[2] Department for Transport. Road investment strategy 2: 2020–2025. 2020, pp. 1-131. Available: https://assets.publishing.service.gov.uk/media/5ffb39808fa8f56405c5f5bf/road-investment-strategy-2-2020-2025.pdf (accessed on 11 March 2020).

[3] Ministry of Transport of China. Statistical development report on traffic and transport in China. 2023. Available: https://xxgk.mot.gov.cn/2020/jigou/zhghs/202306/t20230615_3847023.html (accessed on 29 February 2024).

[4] Federal Highway Administration. 2024 FHWA Forecasts of Vehicle Miles Traveled (VMT). 2024. Available: https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.cfm (accessed in June 2024).

[5] Department for Transport. National road traffic projections 2022. 2022, pp. 1–88. Available: https://assets.publishing.service.gov.uk/media/63975bcfd3bf7f3f7d1cf440/national-road-traffic-projections-2022.pdf (accessed on 12 December 2022).

[6] Federal Highway Administration. Budget estimates fiscal year 2024. 2024, pp. 1–217. Available: https://www.transportation.gov/sites/dot.gov/files/2023-03/FHWA_FY_2024_President_Budget_508.pdf (accessed on 13 March 2023).

[7] Jiang F, Ma L, Broyd T, Chen K. Digital twin and its implementations in the civil engineering sector. *Autom. Constr.* 2021, 130:103838.

[8] Jiang F, Ma L, Broyd T, Chen W, Luo H. Building digital twins of existing highways using map data based on engineering expertise. *Autom. Constr.* 2022, 134:104081.

[9] Machl T, Donaubauer A, Kolbe TH. Planning agricultural core road networks based on a digital twin of the cultivated landscape. *J. Digit. Landsc. Archit.* 2019, 4:316-327.

[10] Jiang F, Ma L, Broyd T, Chen W, Luo H. Digital twin enabled sustainable urban road planning. *Sustain. Cities Soc.* 2022, 78:103645.

[11] Jiang F, Ma L, Broyd T, Chen K, Luo H. Underpass clearance checking in highway widening projects using digital twins. *Autom. Constr.* 2022, 141:104406.

[12] Han C, Tang F, Ma T, Gu L, Tong Z. Construction quality evaluation of asphalt pavement based on BIM and GIS. *Autom. Constr.* 2022, 141:104398.

[13] Han C, Han T, Ma T, Tong Z, Wang S. A BIM-based framework for road construction quality control and quality assurance. *Int. J. Pavement Eng.* 2023, 24(1):2209903.

[14] Deria A, Ghannad P, Lee YC. Integrating AI in an audio-based digital twin for autonomous management of roadway construction. In *Construction Research Congress 2022*, Arlington, Virginia, March 9–12, 2022, pp. 530–540.

[15] Lu L, Dai F, Zaniewski JP. Automatic roller path tracking and mapping for pavement compaction using infrared thermography. *Copmut. Aided Civil Infrastruct. Eng.* 2021, 36(11):1416–1434.

[16] Kušić K, Schumann R, Ivanjko E. A digital twin in transportation: Real-time synergy of traffic data streams and simulation for virtualizing motorway dynamics. *Adv. Eng. Inform.* 2023, 55:101858.

[17] Lu L, Dai F. Digitalization of traffic scenes in support of intelligent transportation applications. *J. Comput. Civ. Eng.* 2023, 37(5):04023019.

[18] El Marai O, Taleb T, Song J. Roads infrastructure digital twin: A step toward smarter cities realization. *IEEE Netw.* 2020, 35(2):136–143.

[19] Consilvio A, Hernández JS, Chen W, Brilakis I, Bartoccini L, *et al*. Towards a digital twin-based intelligent decision support for road maintenance. *Transp. Res. Procedia* 2023, 69:791–798.

[20] Steyn WJ, Broekman A. Development of a digital twin of a local road network: A case study. *J. Test. Eval*. 2022, 50(6):2901–2915.

[21] Yu G, Zhang S, Hu M, Wang YK. Prediction of highway tunnel pavement performance based on digital twin and multiple time series stacking. *Adv. Civ. Eng.* 2020, 2020:1–21.

[22] Emaminejad N, Akhavian R. Trustworthy AI and robotics: Implications for the AEC industry. *Autom. Constr.* 2022, 139:104298.

[23] Czarnowski J, Dąbrowski A, Maciaś M, Główka J, Wrona J. Technology gaps in human-machine interfaces for autonomous construction robots. *Autom. Constr.* 2018, 94:179–190.

[24] Liang CJ, Le TH, Ham Y, Mantha BR, Cheng MH, *et al*. Ethics of artificial intelligence and robotics in the architecture, engineering, and construction industry. *Autom. Constr.* 2024, 162:105369.

[25] Wang T, Reiffsteck P, Chevalier C, Chen CW, Schmidt F. An interpretable model for bridge scour risk assessment using explainable artificial intelligence and engineers' expertise. *Struct. Infrastruct. Eng.* 2023:1–13.

[26] Jiang X, Harun SN, Liu L. Explainable artificial intelligence for ancient architecture and lacquer art. *Buildings*, 2023, 13(5):1213.

[27] Chi NW, Wang JP, Liao JH, Cheng WC, Chen CS. Machine learning-based seismic capability evaluation for school buildings. *Autom. Constr.* 2020, 118:103274.

[28] Meijer D, Scholten L, Clemens F, Knobbe A. A defect classification methodology for sewer image sets with convolutional neural networks. *Autom. Constr.* 2019, 104:281–298.

[29] Emaminejad N, Maria North A, Akhavian R. Trust in AI and implications for AEC research: A literature analysis. In *ASCE International Conference on Computing in Civil Engineering 2021*, Florida, United States, September 12–14, 2021, pp. 295–303.

[30] European Commission High-Level Expert Group on AI, Ethics guidelines for trustworthy AI. 2019, Available: https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai (accessed on 08 April 2019).

[31] Aguilar-Savén RS. Business process modelling: Review and framework. *Int. J. Prod. Econ.* 2004, 90(2):129–149.

[32] World Wide Web Consortium, OWL 2 web ontology language document overview. 2012. Available: https://www.w3.org/TR/owl2-overview/ (accessed on 11 December 2012).

[33] Sirin E, Parsia B, Grau BC, Kalyanpur A, Katz Y. Pellet: A practical OWL-dl reasoner. *J Web. Semant.* 2007, 5(2):51–53.

[34] Rodriguez-Muro M, Rezk M. Efficient SPARQL-to-SQL with R2RML mappings. *J Web. Semant.* 2015, 33:141–169.

[35] Bonduel M, Oraskari J, Pauwels P, Vergauwen M, Klein R. The IFC to linked building data converter: Current status. In *6th Linked Data in Architecture and Construction Workshop*, London, UK, June 19-21, 2018, pp. 34–43.

[36] Bizer C, Seaborne A. D2RQ-treating non-RDF databases as virtual RDF graphs. In *3rd international semantic web conference (ISWC2004)*, Hiroshima, Japan, November 7–11, 2004.
[37] Dürst M, Suignard M. Internationalized resource identifiers (IRIs). 2005. Available: https://www.ietf.org/rfc/rfc3987.txt (accessed in January 2005)
[38] Kontokostas D, Westphal P, Auer S, Hellmann S, Lehmann J, *et al*. Test-driven evaluation of linked data quality. In *Proceedings of 23rd international conference on World Wide Web*, Seoul, Korea, April 7–11, 2014, pp. 747–758.
[39] World Wide Web Consortium, SPARQL 1.1 update. 2013, Available: https://www.w3.org/TR/sparql11-update/ (accessed on 21 March 2013)
[40] Achiam J, Adler S, Agarwal S, Ahmad L, Akkaya I, *et al*. GPT-4 technical report. *arXiv* 2023, arXiv:2303.08774.
[41] Kramer O. *Genetic Algorithms Essentials*, Cham: Springer Cham, 2017, 11–19.
[42] Marler RT, Arora JS. The weighted sum method for multi-objective optimization: new insights. *Struct. Multidiscip. Optim.* 2010, 41:853–862.
[43] National Highways, Asset Data Management Manual (ADMM). 2021. Available: https://nationalhighways.co.uk/suppliers/design-standards-and-specifications/admm-and-other-management-and-maintenance-guides/ (accessed in October 2021)
[44] Schütz M, Ohrhallinger S, Wimmer M. Fast out-of-core octree generation for massive point clouds. *Comput. Graph. Forum* 2020, 39:155–167.
[45] Cambridgeshire County Council, Highway Operational Standards 2023–2033. 2024, pp. 1–181. Available: https://www.cambridgeshire.gov.uk/asset-library/highway-operational-standards-25-jan-2024.pdf (accessed on 25 January 2024).
[46] Ikotun AM, Ezugwu AE, Abualigah L, Abuhaija B, Heming J. K-means clustering algorithms: a comprehensive review, variants analysis, and advances in the era of big data. *Inf. Sci.* 2023, 622:178–210.
[47] Gurobi Optimization. Gurobi Optimizer. Available: https://www.gurobi.com/solutions/gurobi-optimizer/ (accessed in 2008).