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A Knowledge-Based AI Framework for Mobility as a Service

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Abstract: Mobility as a Service (MaaS) combines various modes of transportation to present mobility services to travellers based on their transport needs. This paper proposes a knowledge-based framework based on Artificial Intelligence (AI) to integrate various mobility data types and provide travellers with customized services. The proposed framework includes a knowledge acquisition process to extract and structure data from multiple sources of information (such as mobility experts and weather data). It also adds new information to a knowledge base and improves the quality of previously acquired knowledge. We discuss how AI can help discover knowledge from various data sources and recommend sustainable and personalized mobility services with explanations. The proposed knowledge-based AI framework is implemented using a synthetic dataset as a proof of concept. Combining different information sources to generate valuable knowledge is identified as one of the challenges in this study. Finally, explanations of the proposed decisions provide a criterion for evaluating and understanding the proposed knowledge-based AI framework.

Keywords: mobility as a service; knowledge-based; explainability

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1. Introduction

With an increasing number of transport services offered in cities and technological advancements [1], an innovative Mobility as a Service (MaaS) is needed to seamlessly and intelligently combine various transportation modes and deliver efficient mobility services to travellers based on their needs. A smart MaaS can offer more sustainable solutions than other forms of transportation, such as walking or bicycling [2] and make commuting convenient for travellers by offering flexible, price-worthy, reliable, and sustainable mobility services for goods shipping and delivery. Integrating electronic ticketing, booking, route planning, and payment services in MaaS across different modes of transportation is an example of the Smart Cities transformation services [3]. Leveraging Artificial Intelligence (AI) in MaaS can help develop advanced mobility services [4] with the help of spatial (location-based) and temporal detail recorded frequently by devices such as smartphones, micro-mobility vehicles, on-board vehicle computers, or app-based navigation systems. AI can assist in improving traffic flow or transportation logistics, predicting the best routes for the transportation of goods, optimizing fuel consumption, and preventing accidents [5].

One of the prerequisites of using AI models in a multi-stakeholder domain such as transportation is to provide explainability and the possibility of tracing back the decisions made to their sources. This is crucial for building trust and adopting AI systems in settings where transparency is required due to high-stakes scenarios [6]. Explainable AI (XAI) aims to provide human-centred explanations related to the reasoning process; in transportation, this amounts to justifications similar to how a domain expert makes decisions based on mobility knowledge. Including explicit knowledge is one of the key tools allowing for human-understandable explanations and enabling decision-making in practice [7]. A knowledge-based system helps to make decisions based on various information items we have. It is essentially a monitoring system to recommend tailored solutions to travellers.

With data such as traveller preferences, traffic, vehicle information, weather data, etc, we can support users in making effective decisions. Another highly significant factor in MaaS is personalizing mobility services to travellers. Personalization can be seen here as delivering relevant services or information to specific travellers in the format and layout specified at appointed time intervals. It can increase the efficiency of mobility services and user engagement as it offers relevant and customized recommendations.

On the other hand, interpreting the huge amount of data collected from several sources cannot be achieved without an effective knowledge-based system in mobility. A knowledge acquisition process may consist of collecting facts, designing rules, concepts, procedures, heuristics formulas, relationships, ontologies, statistics, or other helpful information. Acquiring specific knowledge about travellers allows MaaS to recommend a ranked list of MaaS plans/routes to select the ones that better fit the user's preferences by inferring the similarity of available plans to the user's profile. Although obtaining this knowledge by extracting and structuring data or information from various sources, including human experts, and storing the data in a knowledge base is challenging, it enables the possibility of providing the right information to the right user with understandable explanations. It also allows travellers to exclude plans or routes they are not interested in.

In this study, we investigate how to combine different information sources with an understanding of the traveller's context to present personalized services to travellers based on their preferences. In particular, we propose a knowledge-based AI framework covering procedures for data collection, extraction, inference, recommendations and explanations and using a knowledge base and rule-based system to deliver smart mobility services to service providers, drivers, travellers, and other mobility users. This paper is an extension of our previous short study [8], by implementing the framework leveraging synthetic data with a presented scenario. This framework covers procedures for data collection, knowledge extraction, inference, recommendations and explanations and presents a complete literature review.

The structure of this paper is as follows. In Section 2 we discuss AI developments in MaaS. We present the proposed framework in Section 3. The implementation of the proposed framework, based on synthetic data, is shown in Section 4. The results, along with challenges and opportunities, are described in Section 5, followed by a conclusion in Section 6.

2. AI in Mobility as a Service

The key uniqueness of MaaS, which is proving to be challenging from an AI perspective, is the necessity of involving many different systems, actors and stakeholders. Transportation is a prototypical example of a "system of systems" where a multitude of already complex and independent entities such as road authorities, public transport systems, taxi services, insurance agents, and many more interact in ways that are only somewhat regulated [9]. The emerging complexity of the complete ecosystem thus created is, typically, surprising, sub-optimal, and often hard to comprehend even for specialists. This is due to a lack of sufficient data since each actor only has an overview of their responsibility, and the "big picture" is virtually impossible to obtain. Another complication in mobility is the competing need for predictability and flexibility. In particular, the important promise of MaaS is increasing efficiency by combining different modes of travel; each part of the journey should be carried out using the best available means. This promise inherently requires long-term planning and predictability to guarantee smooth interactions at the connection points. On the other hand, unpredictability is an inherent feature of our mobility; delays and cancellations are an everyday aspect of the complexity of the transportation system. Travellers would need a possibly unreasonable amount of flexibility to adapt to the specifics of any novel multi-modal system. The unpredictability increases greatly as soon as multiple actors and modes are involved. Therefore, an AI system supporting the MaaS solution needs to be able to handle these competing objectives.

One important tendency in recent times that promises to improve the situation is the move toward understanding contextual data. As more resources become available to a broader range of actors, it becomes easier for any given MaaS service to access and understand the proper context of the activities. In general, mobility does not happen in a vacuum, and every travel or action has underlying reasons; they are chosen by the travellers among viable alternatives due to certain circumstances and under certain preferences. Understanding this context will increase the efficiency and sustainability of the transportation system since fulfilling user needs is the crucial requirement for adoption [10].

AI-based models have been used in different studies in the MaaS domain to, e.g., classify driving styles or vehicle path prediction using trajectory data. The classification algorithms can customize driver assistance systems and assess mobility, crash risk, fuel consumption, or emissions. For example, Mohammadnazar et al. [11] extracted volatility measures based on speed, lateral longitudinal acceleration, and temporal driving volatility (using a 3-s time-frame window) from a set of data and used them for cluster drivers (in aggressive, normal, and calm) using K-means and K-medoids methods. In another study, Carpatorea et al. [12] proposed a machine learning methodology for quantifying and qualifying driver performance, concerning fuel consumption, based on naturalistic driving data. In a recent study [13], two ensemble learning algorithms (random forests and AdaBoost) were used to predict the traffic intensity before vehicles reach the intersection. The vehicle trajectory data were collected from GPS sensors, longitudinal, lateral, and yaw motion, heading and speed of automobile movements. The vehicles with similar conditions were clustered to provide a route planner to users. In terms of traffic flow prediction, Li and Xu [14] developed a short-term traffic flow prediction model based on Support Vector Regression (SVR) to improve the accuracy of traffic flow prediction systems on the California Highway Performance Evaluation System (PeMS) videos. Abdellaoui et al. [15] proposed an automatic management system in bike sharing, which can predict the number of bikes shared per hour, day or month by taking several dynamic parameters using a Random Forest regressor. Another interesting perspective of the MaaS system is proposed in [16], which is a study conducted based on the Santa Clara transit system. The report evaluates the financial feasibility of integrating public and private transportation systems and further extends to developing a method to infer missing data. Citing [17], the study provides insight into using a crowd-sensing model for optimizing urban transportation problems. They developed a prototype and demonstrated use cases to include accessible transportation models. In regard to the recommendation system in MaaS, a plan recommendation system using constraint programming and similarity metrics was presented in [18] to support the MaaS end-users. The recommender was used to identify the mobility plans that fit the transportation needs and rank filtered mobility plans. Despite the numerous studies applying AI-based methods [19–21], a few of them considered knowledge-based systems to provide personalized mobility services. Notably, Arnaoutaki et al. [22], proposed a hybrid knowledge-based system that uses constraint programming mechanisms to provide mobility plans to travellers based on their preferences and exclude the routes that do not match those preferences. Similar to this study and in conjunction with the other AI-based models, we propose a knowledge-based AI mobility framework that utilizes context information and knowledge of mobility (acquired from travellers and vehicles) to provide personalized mobility services while being interpretable and explainable for both travellers and domain experts. Our proposed framework covers the profile preferences of travellers and other stakeholders and explains why such recommendations and personalized services are provided to them.

3. Proposed Framework for Mobility as a Service

With the proliferation of different kinds of mobility data captured from various sources, such as wearable GPS-enabled devices and geolocated social media, many big data applications have appeared to analyze such data in traffic management and urban development. We propose a knowledge-based framework (Figure 1) for an expert system that includes both explainability and personalization for mobility. We considered various sources of mobility data sources such as contextual data (weather, traffic, and disruptions), operational (routes, schedules, business rules, and deliveries), personal (passengers, travellers, and drivers) and transactional (booking, tickets, and payments). Our proposed framework integrates different mobility data types processes, analyzes them, and recommends a real-time personalized service with customized explanations based on mobility users' needs. We will discuss the main modules of this framework below.

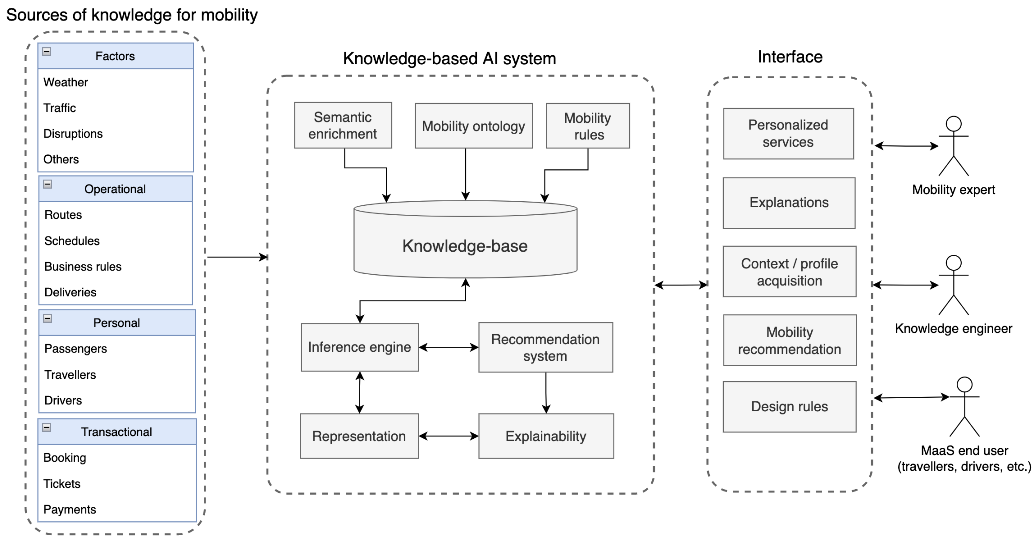

Figure 1. Knowledge-based AI Framework for Mobility as a Service.

3.1. Semantic Enrichment

A semantic enrichment module assists data integration based on several selected linked data sources, as it can match different concepts in a system with the most appropriate semantic entities available from various sources. The semantic enrichment process has been used in different studies [23–25] to enrich mobility data in transportation systems. In particular, ref. [25] takes a raw trajectory and several Linked Data sources as input and builds a semantic trajectory repository using ontologies. This study applied a semantic enrichment module, including ontologies, vocabularies, and API services, to fetch and match concepts from different resources, leading to an enriched set of entities injected into a knowledge base.

3.2. Mobility Ontology

Ontologies represent concepts with their properties and relationships in a domain. We can define mobility entities as terminologies and vocabularies and develop ontologies to acquire knowledge and allow knowledge reasoning. The semantic heterogeneity in mobility systems can be addressed by defining ontologies in knowledge bases and enriching services' descriptions. This makes transportation systems more semantics machine-interpretable and provides efficient search results. The role of domain experts in defining those concepts, terminologies, and relationships between entities is significant, as it ensures the accuracy and precision of definitions [26].

3.3. Rule Engine

We can represent information about the context and procedural knowledge by logic rules in the form of the condition–action pairs (e.g., IF condition holds, THEN perform action) [27,28]. These rules contain patterns and variables that may be linked to facts. A logic rule may have variables linked to values using pattern matching [29] and conditions. For example, consider a rule stating that a traveller would not use an e-bike in rainy weather;

the variables ?t (traveller), ?e (e-bike), and ?u (uses) are matched to all the available data that satisfy the condition.

3.4. Recommendation System

The main goal of transportation recommendation systems is to understand mobility users' preferences, needs, context, and environment to assist them with a personalized experience and service. Recommendation systems have been used in transportation in various studies [30–32]. For example, ref. [31] presented a new recommendation system in collaborative mobility that combines carpooling, car sharing, and shared parking using graphs and time series in multi-dimensional data models. The authors proposed an inference engine in the recommendation system to provide a customized mobility service based on inductive reasoning. Similarly, our proposed framework leverages a reference engine connected to the explainability and representation modules to provide personalized explanations to the MaaS users. The representation module is responsible for preparing the outputs of the recommendation and explainability modules to be presented visually to users understandably and convincingly. Since different explanations and visualizations might be provided for different system users, this module assigns proper explanations and recommendations and delivers them to the interface layer to be visualized.

3.5. Explainability

Explainability refers to techniques that help a user of AI models understand the behaviour of models and how they perform [33]. Explainability makes an AI system more understandable, transparent, and responsible. Explainability embedded in a knowledge base can assist end users with their decision-making process, which is somewhat different and more challenging than the most commonly used concept of explainability—for understanding machine learning systems for verification and trust building. This module is responsible for justifying the personalized recommendation made by the recommendation system—towards both travellers and domain experts. For example, the module explains why a specific service (e.g., a taxi with an electric car) is recommended for a traveller or, in an extreme case, why no recommendations are available for a particular user. One approach towards explainability is using features suggested by experts as means of bridging the gap between knowledge-driven and data-driven approaches [34].

Furthermore, including explainability in this system is an excellent way to avoid any bias in the system and ensure transparency. It helps to understand why the system makes certain decisions. We can also track back the steps when there are any errors. Moreover, having a user-centric personalized solution is another way to ensure the system is unbiased. This ensures that we consider the human factor while providing the solution. At the same time, as with any AI solution, there is a risk for bias in the system itself. Therefore, the usual ways to avoid biases in AI systems are employed throughout the lifetime, such as collecting and using diverse and representative data sets, helping to ensure that the model is not overfitting to a specific group or demographic; continuous monitoring and testing of the model for bias during development and deployment, with detection tools and key metrics; using fairness constraints or debiasing methods to mitigate any bias that is found; incorporating human oversight to ensure that the decisions taken are fair and justifiable.

4. Implementation

We implemented a scenario (depicted in Figure 2) using a simulated dataset and contextual data. In this scenario, two travellers, Alex and Mary, typically use e-bikes on Wednesdays. However, the system notices that next Wednesday will be rainy, based on weather forecast data. The AI system uses a rule engine and concludes that travellers cannot ride e-bikes in rainy weather and recommends an alternative, a personalized transportation solution, to each traveller. According to the knowledge base, Mary is interested in sustainable transportation and prefers using electric cars, while Alex likes gas automobiles. Then, the AI system searches the taxi drivers in Mary's area and arranges a taxi service with an electric car for her. It also suggests a gas car to Alex according to his location. Both travellers are connected to the corresponding taxi drivers. While providing recommendations to them, the AI justifies each suggestion, using the explainability module to build trust. If no taxi drivers are available for these travellers, the AI system might not provide any recommendations to them and notifies the domain expert or knowledge engineer that a new rule should be added to the system to expand its functionality. When the mobility expert receives a notification regarding the inability to provide suitable recommendations, they may define a new rule in the system to recommend other modes of transportation (for example, public transportation) to the travellers in case of a lack of taxi services in the area. Figure 2 illustrates this scenario.

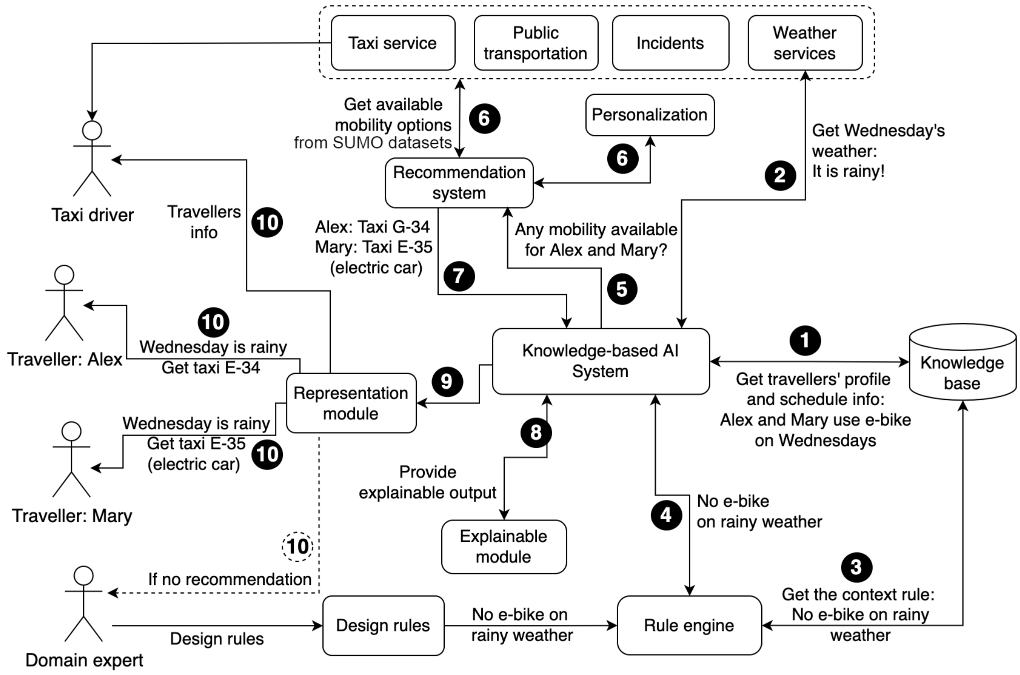

Figure 2. A scenario based on the proposed Knowledge-based AI framework.

To implement this scenario, we use weather forecast data to recommend customized MaaS for travellers when inclement weather is expected. This experimentation uses the proposed framework and considers the preference of travellers to choose pre-defined fuel-efficient vehicles among the ones available. The system helps commuters make smart decisions and will also impact the environment. We created a MaaS dashboard (https://my-weather-dash.herokuapp.com/, accessed on 30 January 2023) for a traveller to access weekly weather information, view any notifications arising due to inclement weather, choose vehicle recommendations, and pre-book a vehicle for the day based on its profile information. Vehicles are recommended for days of inclement weather based on passenger preferences.

In the experimentation, we consider personalized profiles for two travellers with different fuel preferences (electric or gas). Vehicle profiles are also generated, and simulated drivers' details with their contact information are added for each vehicle. We identify the vehicles in the traveller cluster and filter them based on their preferences, in this case, taxis or Ubers.

The weather-based mobility solution is built using Python and its libraries (https://www.python.org/, accessed on 30 January 2023) The traffic data used in this study is the outcome of running a 24-h traffic simulation of Monaco City developed by [35]. This simulated dataset was created based on a research project to develop a solution for Cooperative Intelligent Transportation Systems (C-ITS) using a traffic simulator. SUMO (Simulation of Urban Mobility) (https://sumo.dlr.de/docs/SUMO_at_a_Glance.html, accessed on 30

January 2023) is a multimodal and microscopic traffic simulation program designed to handle massive networks. Numerous datasets can be generated using SUMO comprising information on city roadways, taken primarily from OpenStreetMap, as well as other pertinent synthetic data pertaining to various traffic flows, including passenger vehicles, pedestrians, Mopeds, bicycles, buses, and trains. In our experiments, the "road network data set" extracted from SUMO is among the used datasets listed in Table 1. To combine the road data with the floating car data, we identify the vehicle's lanes and obtain the road coordinates from the road network dataset by using laneID.

Table 1. The dataset attributes.

Dataset	Attributes	Details
Road network data set	'laneID', 'lat', 'lon'	The road network of Monaco was imported into SUMO from OpenStreetMap. Each edge has one or more lanes that correspond to actual road lanes, in accordance with the roads
FCD (floating car data) contains GPS location and speed in addition to other data for every vehicle in the network at every timestamp. The output resembles a high-precision, high-frequency GPS device for each vehicle.	vehicle_id	Each vehicle on the road is assigned a unique ID
	timestamp	Time of the day when the information is recorded or logged. Mostly every second.
	vehicle_type	The name of the vehicle type, such as passenger, bus, or train, etc.This column is also used in identifying pedestrians (Type = 0 is pedestrians)
	x, y	Longitude, latitude coordinates of a vehicle position on the map logged at a specific timestamp.
	person_edge	The edge ID where the person was located at a certain timestamp. Edge corresponds to the road in the city.
	person_id	Each pedestrian is assigned a unique identifier
	person_x, person_y	Person's GPS location at a certain timestamp.
Weather data set	'weekday', 'date', 'temp', 'weather'	The dataset contains the weather information by hour.

4.1. Experimental Setup

As the dataset is relatively large, we narrowed down the area of interest. The available locations were clustered into various sections, and one cluster was chosen for development purposes. We performed clustering based on the geolocation and randomly selected one of the clusters as an area of interest. Then, we selected two passengers from the selected cluster. Then, we created a subset of the dataset, pre-processed and cleaned it for more analysis. We proceeded to develop personalized profile information for two sample travellers (e.g., Alex and Mary) and selected e-bike as their preferred travel mode. We also considered their alternative fuel preference (gas and electric cars). Vehicle profiles were generated via code and drivers' details with their contact information for each vehicle in the cluster.

To identify the chance of rain, we looked at the weather data and observed if there was a chance of inclement weather the following day. Our goal was to recommend an alternate transport mode for travellers in inclement weather.

4.2. Method

This section describes the recommendation method we designed based on the individual traveller's locations, vehicle information, and weather data. To implement the scenario, we should artificially create a situation where passengers cannot travel based on their ideal (or typical) travel mode. For example, if their mode of travel is an e-bike, the recommendation system activates whenever rainy weather is expected. Based on the weather forecast for the following day, it will recommend another mode of travel to each affected person. Figure 3 shows the architecture of this implementation.

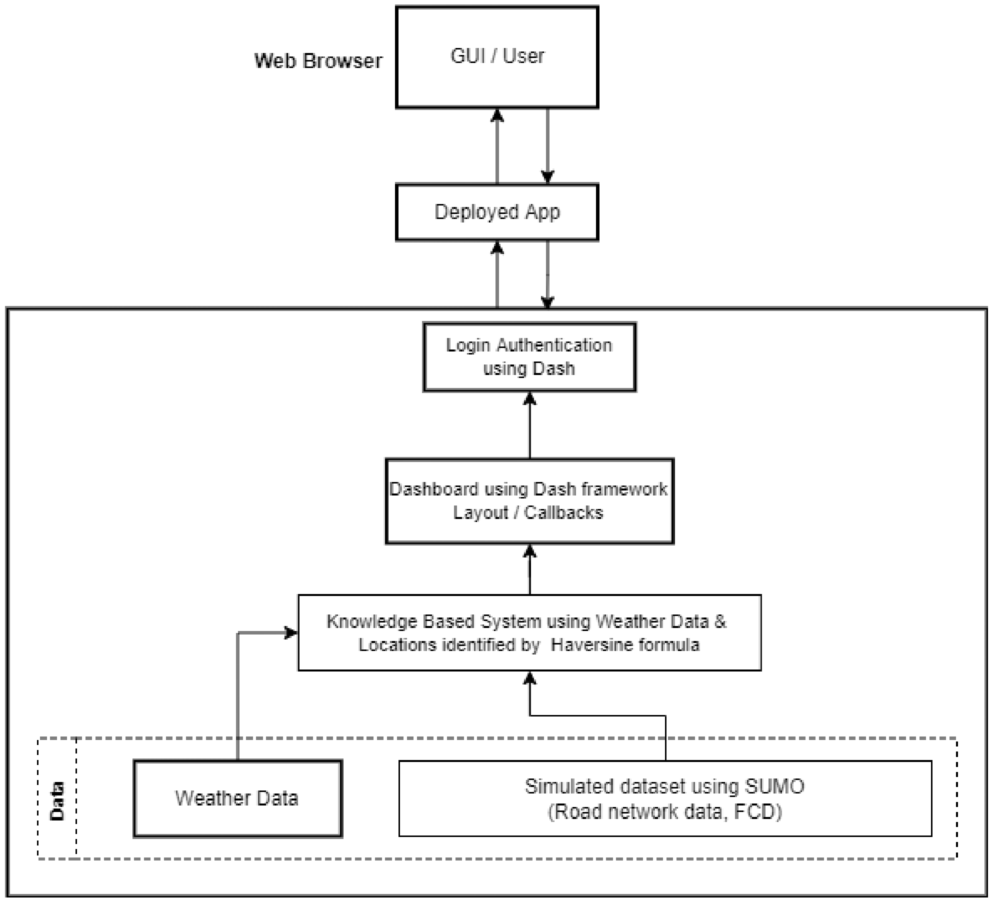

Figure 3. Architecture.

Algorithm 1 also describes the function for identifying the days with rain. The weather data are passed to the function. Then the week's weather data are displayed on the dashboard. The average weekday weather is calculated along with identifying days with weather type as rainy. The rainy days, weekdays, dates, and temperature for the corresponding days are returned as the output of the function.

By comparing the geolocation of Mary and the suitable vehicles she could use, we could identify the closest taxi using the Haversine formula [36].

$$hav(c) = hav(a - b) + sin(a)sin(b)hav(C).$$

This method is used to calculate distances between points on a sphere by applying geo-coordinates. It can be used to identify the closest vehicles to the travellers and recommend their preferred alternate travelling type. For example, in the case of Mary, it recommends the top closest electric vehicles in a nearby location. The same steps can be replicated for other travellers. The pseudo-code for the above-mentioned method (using the Haversine formula [36]) is given in Algorithm 2.

Algorithm 1: Function to identify rainy days

Input : Weather Data set
Output: The days of the week with days, temperature recorded for the days, days that are expected to rain

```
day_delta = 1                    // Interval between days;
start_date = Today                    // Week starts date;
end_date = start_date + 7 * day_delta ;
                        //  7th day from today ;
tomorrow = start_date + day_delta ;
                      //  Next date to start date;
weekly_weather = (Weather dataset) filter by start_date to end_date;
                      /* Average weekly weather */;
grpWkday = Mean(weekly_weather) groupedby Date;
   //  For the weekday, store the day, date, temperature, weather;
for each row in grpWkday do
   wkday.append(Weekday in row) ;
   wkdate.append(Date in row) ;
   temptre.append(Temp in row) ;
   raindy.append(rain in row) ;
   //  If the date is the start date or the next day, check if there
   is a chance of rain and store the weekday.;
   if wkdate_in_today or tomorrow then
      if value_in_column_rain > 0 then
         rainy_days.append(Weekday in row)
      end if
   end if
end for
return rainy_days,wkday,temptre,wkdate
```

Algorithm 2: Function to identify closest points based on latitude and longitude

Input : vehicle locations(lat, lon), traveller location(lat, lon)
Output: closest location(lat, lon)

```
;// Calculate the haversine distance  and find the minimum;
p = Math.PI / 180 = 0.017453292519943295 hav = 0.5 -
 cos((lat2-lat1)*p)/2 + cos(lat1*p)*cos(lat2*p) *
 (1-cos((lon2-lon1)*p)) / 2;
6371 * 2 * asin(sqrt(hav));

min (haversine dist of vehicle and traveller location)
return minimum distance location
```

Algorithm 3 describes the function to identify the vehicles recommended for the passengers based on their preferences. First, we check whether there is any chance of rain in 24 h. If there is, we get each traveller's start location, which is considered the first recorded location of the traveller. We use it along with the vehicle distances to identify the closest vehicles, filtered by their respective fuel preference. This output is then used to build the dashboard.

Algorithm 3: Recommendation algorithm to recommend vehicles to travellers

```
Input   : Traveller data sub-set,vehicle data sub-set,weather data
Output  : Closest electric vehicles for Mary, Closest gas vehicles for Alex, passenger names, passenger
          locations
p_points = []                                    // Passenger location;
p_name = []                                      // Passenger name;
electric_veh = []                                // Electric vehicle;
gas_veh = []                                     // Gas vehicle;
    // If there is rain, then for each traveller in the dataset, get their name and
location ;
if rainy_days > 0 then
    for each row in traveller_ dataset do
        if traveller_name = Mary then
            p_points.append(lat ,long) ;
            p_name.append(traveller_name) ;
            // From the vehicle dataset, get the nearest vehicles to the passenger by
            applying the haversine formula ;
            for each row in vehicle_ dataset do
                points.append(lat ,long) ;
                closest_row ⟵ closest(points, p_points);;
                second_nearest_row ⟵ second_nearest(points, p_points);
                third_nearest_row ⟵ third_nearest(points, p_points);  // Calculate distance on
                the map;
                electric_veh_dist ⟵
                circle_rad(third_nearest_row, traveller
                coordinates);          // Get the vehicles and its attributes ;
                electric_veh ← veh_dataset
                  filtered by closest ,second_nearest ,
                  third_nearest_row fuel_type electric
            end for
        end if
        if traveller_name = Alex then
            p_points.append(lat ,long) ;
            p_name.append(traveller_name) ;
            points = [];
            // From the vehicle dataset, get the nearest vehicles to the passenger by
            applying the haversine formula ;
            for each row in vehicle_ dataset do
                points.append(lat ,long) ;
                closest_row ⟵ closest(points, p_points);;
                second_nearest_row ⟵ second_nearest(points, p_points);
                third_nearest_row ⟵ third_nearest(points, p_points); gas_veh_dist ⟵
                circle_rad(third_nearest_row, traveller
                coordinates);          // Get the vehicles and its attributes ;
                gas_veh ← veh_dataset
                  filtered by closest ,second_nearest ,
                  third_nearest_row and fuel_type
                  gas
            end for
        end if
    end for
end if
return electric_veh, gas_veh, p_points, p_name,
  gas_veh_dist, electric_veh_dist
```

Once the vehicles are identified, a personalized dashboard (see Figure 4) is built for each user (i.e., Mary and Alex) to observe the weather condition and help choose the closest vehicles to her/his location on a map (depicted in Figure 5). A geographical visualization is shown in the dashboard to explain why those vehicles are recommended to users. We also created a notifications page to allow travellers to see the weather alert and a list of available vehicles to book. Users can book a ride from any of the available cars. For this particular case study we considered the closest vehicles to the passenger considering their preferences. In addition, we can also consider other parameters such as shortest travel path or fastest mode of transport, or accommodate route preferences.

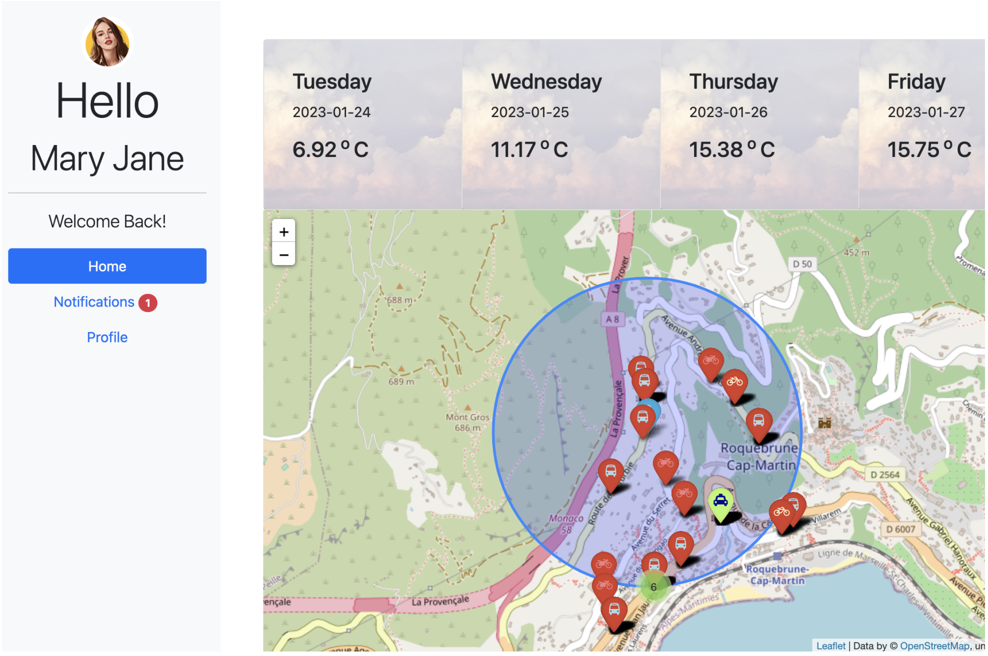

Figure 4. A personalized dashboard for the mobility traveller.

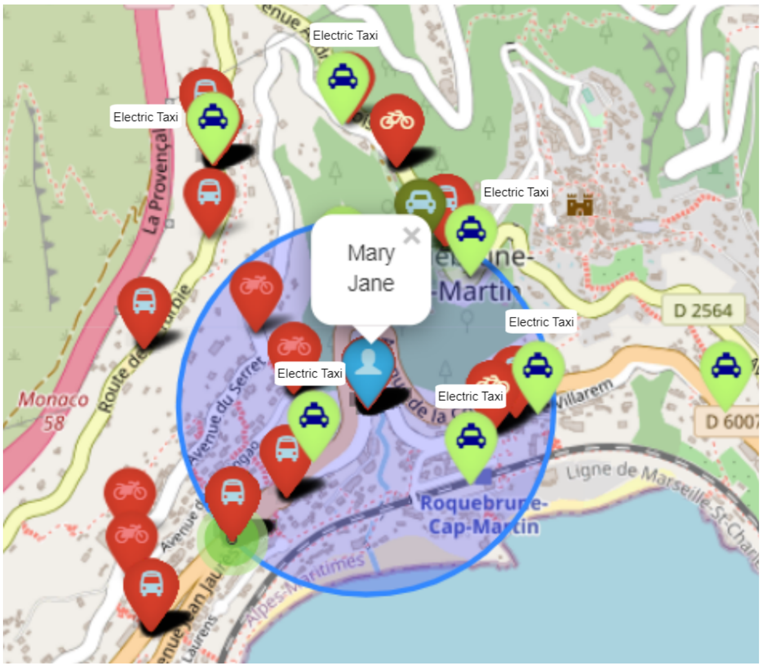

Figure 5. Visualization of Mary Jane and vehicles in proximity. Electric taxis are marked as light-green markers. Vehicles that are in the proximity but not aligned with Mary's preference are red markers.

Considering travellers' preferences or travel routes makes it possible to recommend solutions to passengers. When we connect this with information such as weather data, we can efficiently suggest transportation means to passengers, which they can book in advance in anticipation of inclement weather. We can notify the system admin to expand the scope if no recommendations are available to fulfil the constraints. The implementation is available at https://my-weather-dash.herokuapp.com/, accessed on 30 January 2023.

5. Results and Discussion

This paper suggests a knowledge-based AI framework for MaaS. The framework is intended to meet requirements when combining typical MaaS data types and processes (contextual, operational, personal, and transactional). Based on the proposed framework and the implemented scenario as a proof of concept in previous sections, the results and the potential challenges in developing our proposed framework are discussed in this section.

First, users with travel preferences may find it difficult to obtain vehicles of their preference, especially on a rainy day. This could be due to more people opting to travel via taxis due to inclement weather, which could cause a surge in demand. There might also be increased wait times for them due to this. With the MaaS implementation, travellers could see the weather for the week and choose to book vehicles of their choice, which would be efficient and save them time.

Considering the above scenario, the MaaS system has the potential to provide highly productive explainable solutions to the issues associated with mobility and travel planning. Even though we only consider one scenario as a proof-of-concept in this study, we can infer that the knowledge base system gives a robust platform on which we can build a multi-modal travel platform. It supports an informed decision-making process, and results can be traced back to personal preferences and the data used. It can also be extended to be used along with other AI models to solve complex transportation problems, such as MaaS route planning for both MaaS travellers and drivers.

Knowledge systems can make valuable contributions to generate flexible and intelligent solutions. However, there are several challenges using knowledge-based systems for MaaS due to the complexity of services, as MaaS combines various modes of transportation and therefore requires a diversity of data to present intuitive, personalized services to travellers with explanations based on their transport needs. Needs are changing and situated, and access to data depends on many factors. Collecting the preferences and requirements of MaaS users and products starts with data acquisition and is challenging due to their limited availability. Beyond that, accessing real-time data from several sources, such as travellers' profiles and civic and contextual information, is another challenge. Updating the knowledge base, as the source of knowledge in MaaS, requires real-time services to respond to the travellers' up-to-date requirements and needs. For example, the most recent weather or traffic data should be fused into the knowledge base to respond to MaaS users on time. With more data available, the AI system will recommend more mobility services with more explanations. Although connecting different types of data (contextual and non-contextual) with various structures and identifying their semantic relationships provide richer explainable services, it adds another challenge. A semantic enrichment module proposed in our framework is intended to address the interoperability issue in MaaS; however, a semi-automatic approach should be followed to enrich different types of data coming into the system. In particular, a mobility expert with extensive knowledge of mobility data should construct an ontology or adjust existing ontologies (similar to [37]) in the system and define logic rules in the system. To answer questions such as "what should happen if someone uses e-bikes in rainy weather?" the mobility expert should inject a rule into the knowledge base. The system should provide tools and interfaces to update and optimize the system's rules efficiently.

In such a framework, explainability enables the communication between MaaS users and the AI framework by describing proposed actions or decisions without the need to understand all the aspects of how a system works. However, mobility experts, knowledge engineers, and Maas end-users require different explanations for each recommendation coming from the knowledge-based system, and one explanation cannot be sufficient for all users. We presented both text and visualization explanations in the implemented scenario; however, the explainability approaches that have recently emerged have not been adapted to address the requirements of mobility stakeholders and end-users, despite a few preliminary approaches [33]. Recommendations augmented with reasoning and explanations can increase awareness of the framework's performance, which can be gradually improved in a long-term perspective.

6. Conclusions

Knowledge-based systems provide pieces of the puzzle to solve transportation requirements in mobility. We proposed an AI-based framework considering all the necessary modules to address the mobility users' needs and provide seamless services in MaaS. As proof of concept, we leverage synthetic data and simulation to illustrate how such a framework works based on a defined scenario. We applied three important modules (knowledge base, recommendation system, and explainability) in the proposed framework to provide personalized and explainable services using recommendation systems to MaaS users. For further research, the knowledge base can be extended to include more features by integrating with other systems. For example, live traffic data can be added to the knowledge base, and journeys could be planned to take efficient routes and suggest the fastest modes of transportation. We can also consider other parameters while making recommendations, such as delays on pre-set routes due to collision or construction, faster mode of transport other than the preferred mode, or include more options to personalize the choices. The system can also be extended to capture the driver's preferences. Depending on the demand, the hour of the day, or even the driver's personal choice to pick a route, the system can be built to capture the driver's interests and can be used to suggest rides for them. This can also benefit companies or platforms offering mobility services to keep track of customers and drivers (considering their privacy) to improve their services and may even re-assign fleets on demand. Depending on the data we have and the choices of the customers, we can also suggest car sharing for people travelling to the same destination. We are also on the path to using social analytics to draw parallels with the MaaS system and improve the urban transport network.

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