Snap4City SUMI Manager: A Digital Twin-Integrated Framework for Sustainable Urban Mobility Indicator Processing and Visualization

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Abstract. Urban mobility is one of the greatest challenges modern cities face today. Traffic congestion, inefficient public transportation, high cost, insufficient road safety, and air pollution are some of the problems related to urban mobility. To evaluate current implementations and promote more sustainable solutions for reducing environmental, social, and economic impacts, and promoting efficient and fast travels, the European Commission developed the Sustainable Urban Mobility Indicators (SUMI) to provide standardized and comparable indexes to assess the actual sustainability of urban mobility in European cities, fostering a continuous improvement of mobility policies. Despite SUMI relevance, currently there is no application that allows public administrations computing SUMI in a simple and automatic way. In this paper, the SUMI Manager is proposed as a tool built on top of the Snap4City Digital Twin platform to manage required data, compute the indicators, compare them among cities and over time, and visualize their temporal evolution in interactive dashboards. The SUMI Manager can be deployed in multiple cities to support municipalities in assessing and improving their mobility policies.

Keywords: SUMI · Urban Mobility · Sustainable Mobility · Indicators · Smart City · Digital Twin

1 Introduction

Mobility plays a fundamental role in the global economy and it is essential for both citizens and businesses. Nevertheless, mobility activities also generate significant costs in terms of air pollution, greenhouse gas (GHG) emissions, noise, road accidents and traffic congestion. For example, a valuable amount of the total GHG emissions derives from mobility activities [1]. Nowadays, a transition toward more sustainable mobility systems is an urgent priority. In particular, increased public and private investments in

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the modernization and environmental sustainability of transport fleets and infrastructure present an opportunity to improve the mobility in the future. To this aim, integrated planning approaches supported by continuous monitoring and evaluation mechanisms are required. More precisely, achieving sustainable mobility solutions is one of the UN Sustainable Development Goals [2]. Then, it is required to provide municipalities and decision makers with tools and solutions to address such problems. Intelligent Transportation Systems [3, 4] combined with Smart City Digital Twins [5] can exploit the ever-increasing amount of data to implement decision support systems helping to design, test, and deploy improved mobility solutions [6].

In particular, mobility systems are characterized by the interaction of multiple actors, infrastructures, and services which determine the performance and sustainability of mobility networks. Urban mobility systems include a wide range of physical and operational components, such as road networks, cycling paths, pedestrian infrastructure, parking facilities, public transport services [7], shared mobility solutions, etc. The effective interconnection of these elements is essential to ensure that mobility services properly respond to travel demand while guaranteeing safety, accessibility, environmental sustainability, and operational efficiency.

In this context, the systematic collection and analysis of mobility data becomes fundamental for supporting data-driven decision-making processes and evaluating the effectiveness of mobility policies and interventions. For these reasons, the European Commission (EC) promoted Sustainable Urban Mobility Plans (SUMPs) [8] as strategic tools for cities to plan cleaner, safer, and more inclusive mobility systems. However, many cities lacked a consistent and comparable way to measure progress toward sustainable mobility. To fill this gap, the EU initiated the Sustainable Urban Mobility Indicators (SUMI) project [9], with support from the World Business Council for Sustainable Development (WBCSD) [10], which had previously developed the Sustainable Mobility Project 2.0 (SMP2.0) framework [11]. The SUMI project adapted and refined these indicators for the European urban context, aligning them with EU policy goals such as the EU Urban Mobility Framework, the European Green Deal, the TEN-T (Trans-European Transport Network) regulation, and the Sustainable and Smart Mobility Strategy. SUMI constitute a standardized framework of 18 distinct metrics (labeled S1 through S18), covering key dimensions such as accessibility, safety, environmental impact, efficiency, and modal balance to support benchmarking across cities for the implementation of sustainable mobility strategies. Therefore, these indicators are used to assess how well a city's mobility or transport system is progressing towards sustainability goals.

Research on sustainable urban mobility has progressively focused on sustainability planning frameworks (SUMPs) and indicator-based monitoring (SUMI and other KPI sets). A study performed in [12] on SUMPs impact assessments has shown that benefits associated to the implementation of specific SUMP measures can achieve about 9% of CO2 reduction and around 11% of external cost reduction, although overall profitability effects have emerged only after about 6 years. However, such results are often constrained by context-specific assumptions (e.g., scenario definitions), and they often omit relevant aspects (e.g., noise level, congestion) which are significant for sustainability evaluation. Moreover, relevant lacks are often reported about public administrations capacity of actuating efficient reporting strategies. Actually, a comparative analysis among European

municipalities performed in [13] shows that the adoption of SUMPs correlates with more frequent deployment of sustainable activities; nevertheless, monitoring and evaluation of such measures are often underestimated in practice.

From an indicator perspective, KPIs such as SUMI have been proven to be beneficial, since they allow to transform sustainability goals into measurable variables. In [14], 21 specific electromobility indicators have been developed through literature analysis and expert consultation, organized across three dimensions (economic, social, environmental) for three transport subsystems. These indicators demonstrated a strong predictive power with regression models, explaining over 90% of variability. However, a limitation is represented by the scarcity or lack of data and the omission of some micromobility elements such as scooters. In order to mitigate data scarcity, other works in literature rely on surveys and interviews to citizens and experts to find the most relevant indicators for sustainable urban mobility. For instance, in [15] 28 experts (including urban planners, transport engineers, environmentalists and policy-makers) have been interviewed, finding as key indicators traffic congestion, affordability of public transport, energy efficiency and multimodal integration. The main limitations of this approach are explicitly addressed by authors: outcomes can be biased by expert selection and their dominant competencies, and the process can be very time consuming, since it requires the experts' availability. Another work presented in [16] evaluates indicators of sustainable urban mobility using questionnaire-based surveys, involving road-user perceptions as a proxy for mobility conditions. The study collects about 2 thousand interviews from citizens, highlighting traffic management, road network management and sidewalk features as key factors to promote modal shift. Nonetheless, this kind of evidence is explicitly perception-driven, since it mostly relies on survey collection.

All these limitations that have been addressed motivate the necessity of more automated solutions for SUMI management, which could resolve or mitigate the issues related to scarcity or lack of data, as well as reduce uncertainty and subjectivity in measurements, while enhancing standardized processing and reporting. In particular, the collection, integration, and analysis of mobility data play a fundamental role in supporting informed planning and operational decisions. The increasing availability of real-time data sources offers the opportunity to enhance the management of urban transport systems and to respond effectively to dynamic mobility patterns.

Nevertheless, the SUMI calculation is typically performed using aggregated and static datasets, which do not fully capture the real-time dynamics of urban systems. More precisely, taking into account only periodic data collection may be a limited approach to promptly detect emerging inefficiencies or to evaluate the immediate impact of policy interventions. This limitation highlights the need for integrated digital platforms capable of continuously collecting and harmonizing mobility data to automatically compute SUMI indicators, ideally integrating such features with Digital Twin (DT) technologies and solutions. Actually, DT frameworks are widely recognized as a promising tool for the design and development of sustainable and resilient urban environments [17], providing advanced simulation and predictive capabilities that can enhance decision-making for operational and strategic planning [18].

In this paper, the SUMI Manager is proposed, as a model and tool developed on top of the Snap4City Digital Twin platform [5], to model and manage required data, compute

the indicators, and visualize their evolution over time in interactive dashboards, and make comparison among cities. The paper is organized as follows: in Sect. 2, the Sustainable Urban Mobility Indicators are illustrated in more detail; Sect. 3 describes the architecture of the proposed SUMI manager; Sect. 4 is dedicated to system validation; finally, Sect. 5 is left to conclusions.

2 Sustainable Urban Mobility Indicators

According to the final version of the SUMI Harmonization Guideline [19], 18 indicators have been defined, divided into core and non-core indicators, ranging in different multidimensional impact areas.

A first key area can be identified considering **social equity and accessibility**. Indicators such as the affordability of public transport (PT) for the poorest group, access to transport services for mobility-impaired users, collectively assess how inclusive the transport system is. Some indicators are related to the **environmental impact** of mobility services. These indicators include greenhouse gas emissions, air pollutant emissions, noise hindrance, as well as energy efficiency that measure the environmental footprint of urban transport systems, ranging from air quality to public impact. A third dimension is **transport system performance and efficiency**. Congestion and delays, commuting travel time, and multimodal integration describe how effectively the system functions in terms of time, reliability, and connectivity. These indicators are crucial for understanding the operational quality of urban mobility and its capacity to meet demand efficiently. Another important area is **safety and health**. Road deaths and traffic safety for active modes directly address the risks associated with mobility. In parallel, the opportunity for active mobility (walking and cycling infrastructure) links safety with public health outcomes, emphasizing the role of urban transport in promoting healthier lifestyles. Finally, a broader **urban quality and spatial impact** perspective is captured through indicators such as quality of public spaces, urban functional diversity, and mobility space usage. These metrics go beyond transport itself and reflect how mobility systems shape urban form, land use, and the overall livability of cities.

The multidimensional assessment of urban mobility, from a methodological perspective, implies the integration of heterogeneous types of input data and measurement approaches [20]. Some indicators rely on **quantitative and model-based data** (e.g., emissions, energy consumption, vehicle-kilometers travelled), often derived from transport and environmental models that can be also captured by third party and sensors data (e.g., Floating Car Data, Air Pollutant IoT Sensors). Others require **geographical and spatial data**, typically managed through Geographical Information Systems (GIS), such as infrastructure layouts, accessibility buffers, land use distribution, and population exposure. A further group depends on **administrative or statistical records,** including road fatalities, demographic data, and public transport usage. Several indicators incorporate **qualitative and perception-based data**, collected through surveys, to capture user satisfaction, perceived safety, and quality of public spaces. Others require **mobility** specific spatial and temporal data, such as the General Transit Feed Specification (GTFS) for the time plan and stops for PT or the network topology often modeled as graphs to support traffic flow analysis and network-based computations. The 18 SUMI indicators

with details on impact area and data requirements for their computation are summarized in Table 1.

The computation of SUMI indicators presents challenges related to data sourcing and integration. Three indicators have been chosen to discuss the main challenges related to data heterogeneity integration, spatial analysis and incorporation of expert decision-based information to calculate the indicator.

S3 for example is a challenging indicator to compute not because of the complexity of the formula, but since it requires the integration of heterogeneous data sources. This indicator evaluates the impact of transport-related air pollution on human health within an urban area and the heterogeneity of the data is due to the nature of the pollutant emissions determined by all passenger and freight transport modes, including both exhaust and non-exhaust sources (such as tire and brake wear). The calculation relies on detailed activity data (vehicle-kilometers travelled) disaggregated by mode and vehicle type, which are typically estimated through traffic models, sensor networks, or mobility datasets and are subject to uncertainty and temporal variability. This must be combined with granular vehicle fleet composition data (fuel type and Euro class), which is often incomplete, outdated, or only available at aggregated administrative levels, requiring possible approximations.

Managing spatial based information is critical in mobility analysis. Indicators such as S6 require integrating information about population distribution in different radius from public transportation stops in the urban area of study. This information is mainly acquired by GIS based proximity analysis in combination of cross-reference with the population data. Additional challenges are related to the alignment of temporal data and the management of probably disaggregated heterogeneous transport data sources.

Other complexities may arise when the computation of specific indicators requires a decision performed by transportation experts on the urban road infrastructure, such as in S8. This indicator implies the identification of 10 transport representative corridors in the area of study to base the congestion level estimation. Corridor selection could be performed on urban mobility systems capable of managing the road infrastructure data [21] by transport operators to understand the real bottlenecks of the urban area. Data on travel times and trip volumes is often sourced from multiple systems, including local transport operators, floating car data (FCD), road IoT sensors that require temporal alignment and integration of these heterogeneous data sources.

To address the inherent complexity of calculating SUMI indicators, a dedicated system, i.e. the SUMI Manager, has been developed and integrated within the Snap4City platform [5, 22], an open-source Digital Twin environment designed for Smart City monitoring and planning.

3 SUMI Manager Architecture

The complexity of calculating SUMI indicators relies primarily on the high heterogeneity of the required data. In particular, the system must be capable of integrating information from multiple domains, including socio-economic statistics, public transport operational data, and urban planning datasets. All these heterogeneous data sources require specific data acquisition and representation methods. The system must support both the direct

Table 1. SUMI indicators summary table.

SUMI	Description	Impact Area	Input	Output
1 (core) Affordability of public transport for the poorest population	Share of the household budget of the poorest quartile (25%) of the population required to purchase public transport passes (unlimited monthly travel or equivalent) in the urban area of residence.	Social equity and accessibility	Administrative: Monthly PT pass prices from authorities and average household size from municipal records; Quantitative: Average monthly income from the poorest 25%; Geographical: Spatial alignment of socio-economic data with urban boundaries	Affordability score (% household budget towards PT services)
2 (core) Accessibility of public transport for mobility-impaired groups	Determines the accessibility of public transport services for persons with reduced mobility (PRM) by evaluating the proportion of facilitated services across vehicles, stops, and ticket offices	Social equity and accessibility	Administrative: Records from local transport operators on accessible moving assets, stations, and ticket machines; Mobility: Annual ridership numbers per transport mode used to calculate modal weights; Quantitative: Percentage of accessible features across all modes	Overall accessibility score (% of services facilitated)
3 (core) Air Pollutant Emissions	Measures total emissions of Nitrogen Oxides NOx and Particulate Matter PM2.5 from all passenger and freight transport modes, including exhaust and non-exhaust sources	Environmental impact	Quantitative: Activity volume (million vkm/year), exhaust emission factors, and non-exhaust emission factors (g/km); Administrative: Vehicle stock composition (shares of fuel types and emission classes) from statistical records; Geographical: Total inhabitants (capita) and spatial alignment with urban area boundaries	Emission Harm equivalent Index (EHI in kg PM2.5 eq./cap per year)
4 (core) Noise hindrance	Measures the percentage of the population hindered by noise generated by urban transport (road, rail, air) based on exposure bands L_{den}	Environmental impact	Geographical: Population exposure per noise band (from EEA noise maps or GIS data); Quantitative: High Annoyance weight factors and hindrance factors	Hindrance Index (NI as % of hindered population)
5 (core) Road deths	Evaluates traffic safety by measuring the number of fatalities (within 30 days of an accident) per 100,000 inhabitants.	Safety and Health	Administrative: Yearly statistical records of persons killed per transport mode; Geographical: Total urban population (capita).	Fatality Rate (FR per 100,000 inhabitants)

(*continued*)

Table 1. (*continued*)

SUMI	Description	Impact Area	Input	Output
6 (core) Access to mobility services	Share of the population with appropriate access to public transport, considering both proximity to stops and service frequency.	Social equity and accessibility	Geographical: Population distribution within GIS-calculated buffers (417 m and 833 m); Mobility/Administrative: PT stop locations and average hourly departures (frequency) from timetables.	Appropriate Access Index (AccI as % of population)
7 (core) Greenhouse gas emission	Total well-to-wheels CO2 equivalent emissions produced by all passenger and freight transport modes.	Environmental impact	Mobility: Activity volume (million vkm/year) per mode; Administrative/Quantitative: Vehicle stock composition (fuel/Euro class share), energy intensity, and emission factors; Geographical: Total urban population (capita).	Tons of CO_2 eq. per capita per year
8 (core) Congestion and delayes	Measures peak-hour delays for private and public transport on representative corridors compared to off-peak or optimal times.	Transport system performance and efficiency	Mobility: Peak and off-peak travel times on 10 road and 10 PT corridors (often from Floating Car Data); Administrative: Modal shares; Mobility: trip volume per corridor	Congestion and Delay Index (% delay during peak-hour traffic)
9 (core) Energy Efficiency	Measures the total energy use by all urban transport modes per unit of transport volume, calculated as an annual average across passenger-kilometers and tonne-kilometers	Environmental impact	Quantitative: Activity volume and transport volumes, fuel consumption factors; Administrative: Vehicle stock composition (shares of fuel types) and fuel energy content constants; Mobility: Modal split data used to derive transport volumes; Geographical: Spatial alignment of transport activity with urban boundaries	Energy consumption rate (MJ/km)
10 (core) Opportunity for active mobility	Evaluates the infrastructure for walking and cycling by measuring the length of roads with pavements, bike lanes, 30 km/h zones, and pedestrian zones relative to the total urban road network	Safety and health	Administrative: Official records of 30 km/h zones and pedestrianized streets; Quantitative: Lengths of pavements (min. 0.6 m width) and bike lanes (min. 0.75 m width); Geographical: Total city road network length (excluding motorways)	Share of road length adapted for active mobility

(*continued*)

Table 1. (*continued*)

SUMI	Description	Impact Area	Input	Output
11 (core) Multimodal integration	Evaluates the average level of connectivity at urban interchange points by measuring the variety of transport modes available at each hub	Transport system performance and efficiency	Administrative: Network characteristics from PT operators and facility data from local administrations; Geographical: Identification of interchange locations and assessment of physical barriers (e.g., rivers, heavy traffic); Quantitative: Binary (YES/NO) availability of 10+ specific modes per hub.	Multimodality Index (average share of available modes across all interchanges)
12 (core) Satisfaction with public transport	Measures the perceived satisfaction of residents regarding PT affordability, safety, ease of access, frequency, and reliability	Social equity and accessibility	Qualitative: Perception survey responses from approximately 500 telephone interviews (e.g., "satisfied" to "not at all satisfied"); Administrative: Data from the EC's Urban Audit or existing operator surveys	Average reported satisfaction (%)
13 (core) Traffic safety active modes	Assesses the risk for pedestrians and cyclists by relating the number of fatalities to their actual exposure in terms of total trips	Safety and health	Administrative: Yearly fatality records for pedestrians and cyclists (3-year average); Mobility: Exposure data representing the annual number of trips in millions per mode; Quantitative: Calculated risk factor per billion trips	Risk Factor (fatalities per billion trips)
14 Quality of public spaces	Measures resident satisfaction with green spaces (parks/gardens) and non-green public spaces (markets, squares, pedestrian areas)	Urban quality and spatial impact	Qualitative: Perception survey data (Urban Audit or local surveys) regarding satisfaction with specific public space dimensions	Average reported satisfaction with green and non-green areas (%)
15 Urban functional diversity	Measures the mix of spatial functions (e.g., schools, shops, parks) within 1 km x 1 km grids to evaluate the proximity of daily activities to residential areas.	Urban quality and spatial impact	Geographical: Division of city territory into 1 sqkm grids; Administrative: Population distribution per grid zone; Quantitative: Binary presence (0 or 1) of 10 specific daily functions per grid.	Functional Diversity Score (FDS %)

(*continued*)

Table 1. (*continued*)

SUMI	Description	Impact Area	Input	Output
16 Commuting travel time	Measures the average daily duration of travel to and from work or educational establishments for all transport modes.	Transport system performance and efficiency	Qualitative: Mobility survey data regarding trip durations; Mobility: Modal breakdown (car, PT, bike, walking) and average travel times to/from destinations; Administrative: Survey metadata.	Average commuting travel time (minutes/day)
17 Mobility space usage	Assesses the proportion of land used for all urban transport applications, including both direct (roads, rails) and indirect (parking, stations) uses.	Urban quality and spatial impact	Geographical: Total number of city inhabitants (capita); Administrative: Land use records for transport categories; Quantitative: Hectares (ha) of roads, railways, ports, parking, and logistics centers.	Mobility space usage per capita m^2/cap
18 Security	Evaluates the perceived risk of crime and passenger security within the city transport system across various modes and times of day.	Safety and health	Qualitative: Perception survey data regarding feelings of safety (Very safe to Very unsafe); Administrative: Survey demographics ensuring adequate representation of mode users and gender; Mobility: Alignment of survey participants with local modal split.	Perceived Security Score (SEC)

input of pre-calculated indicators and the computation of indicators from raw data, requiring a flexible interface capable of handling different formats, measurement units, and levels of data processing. In addition, data management involves careful temporal and spatial synchronization: all inputs must be aligned with specific validity periods and clearly defined geographic contexts, such as cities like Florence, Pisa, or Siena, to ensure consistency and comparability of results. From a management perspective, the acquisition process also involves complex data flows, both internal and external, which must be authenticated, secured, and compliant with privacy requirements (e.g., GDPR). Furthermore, to transform raw data into actionable insights, the system incorporates visual analytics and interactive business intelligence tools, enabling users to engage directly with maps and charts within a dashboard environment.

The Snap4City SUMI Manager has been developed exploiting the architecture and functionality offered by the platform. Snap4City provides efficient data ingestion pipeline during which data are semantically indexed in the knowledge base and shadow stored in a NoSQL database [23]. On the other hand, ingested data are made available to processes [24] and dashboards [25] with dedicated API capable to retrieve information with relational, temporal and geographic queries, exploiting both Client-Side

[26] and Server-Side [27] Business Logic (CSBL and SSBL). To facilitate the ingestion and retrieval of entities belonging to the same category and force their adherence to a well-defined format, data model can be created and exploited to instantiate new entities.

The SUMI Manager exploits different data models. At first, each of the 18 SUMI has been represented with a dedicated model defined according to the variables required to carry out the specific SUMI computation. For example, for SUMI S1 (Affordability Of Public Transport for the Poorest Group) the data model includes the variables *avgIncome*, *avgHouseholdSize*, and *ptPrice*, respectively representing the average monthly income of the 25% poorest inhabitants, the average household size, and the monthly price for public transport services. In addition to the variables required for the computation, each data model includes a *dateObserved* variable to set the date-time. In this way it is possible to obtain temporal sequences of the data, useful to be stored and observe their evolution during time. Then, a general SUMI model is defined including a *dateObserved* variable and 18 additional variables, each one dedicated to store the computed values for each one of the 18 SUMI.

Data required to compute the indicators are information related to the urban context, like, for example, public transport stops, positions of bike sharing parking, locations of services, population income, etc. This information is modelled with additional data models and can be exploited to facilitate the computation of specific SUMI variables. Part of these data is already available into the Snap4City platform; when missing it must be ingested in order to enable the automatic computation of the SUMI.

The overview of the architecture of the SUMI Manager is provided in Fig. 1. SUMI Manager is composed by a frontend implemented using the dashboard system of Snap4City and including CSBL for managing both interface interactivity and data ingestion and retrieval. In addition, SSBL is used to implement processing logic for computing the SUMI and for elaborating possible preliminary data. All the created entities with their variable are saved in the Snap4City storages (including indexing in the knowledge base, built according to the KM4City ontology, and shadow storing in NoSQL databases).

First, the user must create an entity representing the city for which computing the SUMI, thus defining the spatial context. This is achieved exploiting the *Create new city* functionality in the dashboard. API calls, implemented in CSBL in the *Add new city* process, allow to retrieve the SUMI Model and all the 18 models of the single SUMI and then proceed to create the entities for the specific city into the Snap4City knowledge base. At this moment, all these entities are empty, without any data in their variables.

To insert data and enable the computation of the SUMI, the user must select a date-time (corresponding to the validity period of the SUMI to be ingested) and use the *Insert SUMI Data* functionality. SUMI Manager provides three different ways to ingest SUMI data. In the first solution, the user directly provides the value of the SUMI. In this case the SUMI Manager acts as a simple storing interface. A second solution allows the user to provide the information that is required for the computation of the SUMI, as for example the average household size for SUMI S1. With dedicated API in CSBL these data are ingested in the respective SUMI_X devices (with X indicating a SUMI from 1 to 18). The third solution offers a fully automatic computation: using the *Load Preliminary Data* functionality, SUMI Manger searches for available data in the Snap4City storages (considering also the selected date-time and the spatial context to retrieve data in the

correct time span), and whether all the required information is found, it automatically fills the interface fields with the retrieved values. Then the user continues as in the second ingestion solution submitting the data to the SUMI_X devices. Differently, if not all the required data are found, an error message is returned to the user.

In all the three cases, when a new data ingestion is carried out, a message is sent to the *SUMI MailBox* entity. Sending a message to the mailbox activates a listener placed in the SSBL *Proc. Logic: Compute SUMI* and starts the execution of a processing flow devoted to the computation of the indicator and their ingestion in the general SUMI entity of the city.

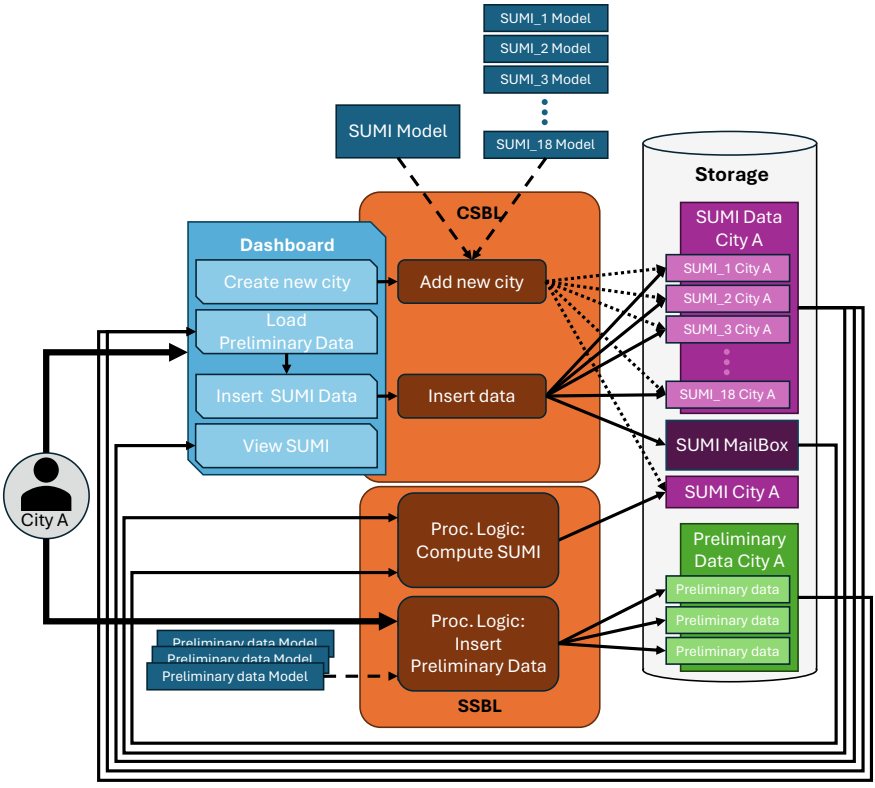

Fig. 1. SUMI Manager architecture.

Once computed and ingested, the indicators can be retrieved and visualized with the *View SUMI* functionality populating different plots including a temporal evolution of the indicators, so as to allow the user to observe the trends and identify the most critical problems. Details on the user interface with example of the SUMI Manager dashboard are provided in **Sect. 4**.

As described above, to enable the automatic SUMI computation, preliminary data must be available into the Snap4City platform. In the case such data are missing, the user has the possibility to provide by itself the required information. In this case, a dedicated

Proc. Logic flow must be developed to create and ingest new entities according to a set of predefined models. These data models must be used to ensure that the data are ingested with a format compatible with the SUMI Manager logics. Note that this responsibility is left in the hand of the user, since most of the missing data are usually provided in specific format and not always freely accessible, therefore it would be impossible to preload all these data without specific user knowledge and access rights.

Finally, it is worth noting that Snap4City is a multi-user and multi-tenant platform and enforces entity and resource ownership in compliance with privacy regulations. For this reason, SUMI Manager has been developed considering two main roles: a managing role *sumi_admin* and a user role *sumi_user*. Only one *sumi_admin* is admitted, and it is the owner of all the data models, the dashboard, the *Compute SUMI* processing logic and of the entity *SUMI MailBox*. Differently, multiple *sumi_user* are possible (ideally any municipality should have its *sumi_user*). *sumi_user* is the owner of the SUMI devices (the global one and all the 18 for the indicator data) as well as all the entity with preliminary data created and ingested by itself. To allow the SUMI Manager to work, respecting the ownership rights, the delegation mechanism of the Snap4City platform has been exploited. The dashboard and the data models have been made public, so as to be accessible by any user. Note that a user can load and visualize in the dashboard only its owned data. The *SUMI MailBox* has been delegated only with write permission to any *sumi_user* to allow them to send messages into it and prevent them to read messages from other users. On the other hand, all the SUMI entities have been delegated to the *sumi_admin* to allow the *Proc. Logic Compute SUMI* to retrieve the necessary data and ingest the computed indicator.

Figure 2 shows the sequence diagram of the SUMI Manager. A user interacts with the SUMI Dashboard, CSBL initializes the widgets and retrieves the list of available cities. When a new city is added, the system creates the corresponding city SUMI entity with the 18 SUMI_X entities used to store the indicator input data. The user can enter the data required for the indicators either directly or by calculating it from the input variables, optionally retrieving information from the Snap4City knowledge base. After submission, a message is sent to the SUMI MailBox, which triggers the Compute SUMI *Proc. Logic* (SSBL). The *Proc. Logic* retrieves the input data, computes the SUMI indicators, and saves the final values in the 18 SUMI_X entities. Finally, the dashboard retrieves the indicators and updates the visualization widgets, allowing the user to observe the last values and their temporal trends.

4 SUMI Dashboard and System Validation

An interactive dashboard (as shown in Fig. 3) is provided by the SUMI Manager built on top of the Snap4City platform [25]. Within the dashboard, data management operations such as adding a new city are supported; SUMI values can be computed by defining the validity period, selecting the computation mode or directly inserting the indicator value; besides, both the indicator values and their trends over time can be visualized across different cities.

In the SUMI Manager dashboard, a new city can be added (Fig. 3-d) and multiple cities can be managed (Fig. 3-a), enabling comparative analysis between different urban

contexts. When a new city is added, the entities required to store the values of all SUMI indicators and the related input data are automatically generated, as described in **Sect. 3**.

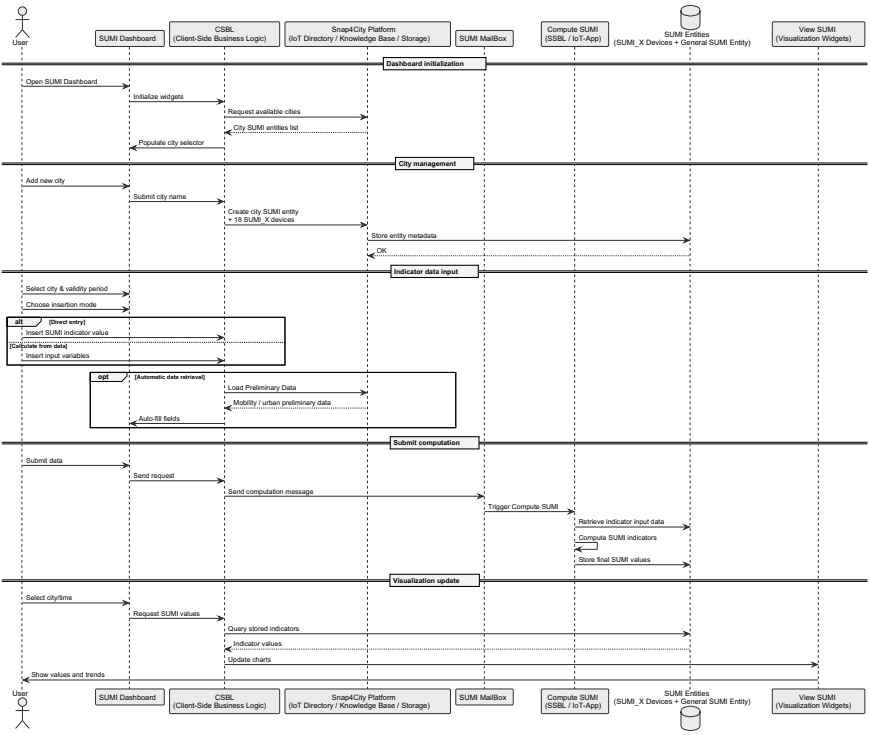

Fig. 2. SUMI Manager sequence diagram.

In addition, users can manually enter indicator values or provide the input parameters necessary for automatic indicator calculation. In Fig. 3-e, the indicator, the validity period (start and end date), the computation mode and the city can be selected. The SUMI Manager supports three data ingestion modes: (i) indicators can be directly inserted manually; (ii) they can be computed from user data: in this case, for each selected indicator the system requests the specific input variables required for its computation, corresponding to the parameters listed in Table 1 (column Input); (iii) finally, if the required data are available within the Snap4City platform, the system can automatically retrieve them from the knowledge base, enabling the automatic pre-filling of the fields required for indicator computation**.** Figure 3-f shows an example of input variables for indicator S12.

Finally, the dashboard provides data visualization tools (Fig. 3), allowing users to analyze indicator values over time and across different cities, both in terms of the latest available value (Fig. 3-b) and their time trend (Fig. 3-c). The visualization area includes time-series, bars, and radar charts, supporting the identification of SUMI indicators.

The proposed SUMI Manager has been validated through functional testing by creating multiple city instances (Florence and Pisa), using partially simulated data for different



Fig. 3. SUMI Manager dashboard.

SUMI indicators, and entering values in both direct mode and indicator calculation mode. It is worth noting that the process of retrieving all the required involves a considerable complexity, and this is typically entrusted and carried out by public administration officers. The validation focused on verifying the correct integration of the various system components, including data acquisition, indicator calculation and visualization (comparing values of indicator over time and among cities), as well as the correct management of data ownership and delegation permissions. A broader validation on fully real-world datasets, including a comparison with traditional manual SUMI computation workflows, is left to future work. The scalability of the system is ensured by the Snap4City platform, which currently manages a large number of users, entities and services. In particular, it

includes 25 organizations, 3,127 users and developers, over 122,000 entities, 885 processing logic instances, and 2,316 dashboards/views, with approximately 2.6 million data entities ingested per day [26, 28].

5 Conclusions

In this paper, an innovative framework for computing, managing, and monitoring the Sustainable Urban Mobility Indicators (SUMI) has been presented. This work addresses a practical and widely recognized gap in the adoption of SUMI: despite their relevance as a standard framework for assessing urban mobility sustainability, public administrations still lack solutions that enable their computation and monitoring in a simple, systematic, and scalable way. To bridge this gap, the SUMI Manager has been proposed, implemented on top of the Snap4City Digital Twin platform, with the goal of supporting municipalities in managing the heterogeneous data required by the indicators, computing SUMI values, and visualizing their temporal evolution through interactive dashboards and the comparison of the SUMI indicators among different cities. The SUMI Manager provides a unified operational framework that supports multiple ingestion modes (i.e., manual insertion of indicator values, computation from user-provided input variables, and automatic pre-filling and computation when preliminary data are available within the platform), thus enabling gradual adoption under different data availability conditions. In addition, the integration with the Snap4City knowledge base and data models supports reproducibility and standardization, by allowing structured representations and facilitating the computation of SUMI variables. The validation of the proposed system included functional testing on multiple city instances, verifying the correct integration of the various components, for instance: data acquisition, indicator computation and visualization. The results highlight the feasibility of deploying the SUMI Manager as a reusable service across different municipalities, leveraging the multi-tenant and scalable nature of the Snap4City ecosystem, while respecting ownership and privacy constraints through its delegation mechanisms.

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