# An Urban Dashboard Supporting Situation Awareness for City Branding


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***Abstract*—Urban planners and decision makers increasingly rely on data-driven tools to interpret complex urban dynamics and support strategic planning activities. Nevertheless, many existing urban dashboards mainly provide data visualization features and offer limited support for modeling the overall situation of a city. This paper introduces Janus Urbanis, a situation-aware dashboard designed to integrate heterogeneous urban data and support city branding analysis. The system models the urban situation through a set of dimensions, called Urban Chromas, capturing physical, environmental, and perceptual aspects of the city. These dimensions are combined using Context Space Theory to compute a City Situation Index, which provides a synthetic overview of the urban state and supports exploratory analysis by urban planners.**



***Index Terms*—Urban dashboards, Situation awareness, Context Space Theory, City branding, Decision support systems.**


## I. Introduction

*Smart Cities* are urban areas that utilize digital technologies and data-driven approaches to improve the quality of life of their citizens and tourists. In this context, the concept of *Smart Government* is gaining significant importance, referring to all activities and initiatives that invest in technologies to achieve better government structures and governance infrastructure. Smart Government is closely related to the strategic process of *City Branding*, which involves creating, managing, and promoting a distinctive and appealing image of a city. However, this process requires a deep understanding of the intricate and multidimensional dynamics that shape the reputation of a place, and this complicates the decision-making process of urban analysts and planners.

Existing solutions in the literature have made significant progress in developing situation-aware dashboards, but many current platforms operate as data "silos", lacking deep data integration and a formal framework to represent the overall situation of a city, hindering the effective implementation of Smart Government strategies and limiting the ability of urban decision makers to gain a comprehensive view of a city.

This work introduces *Janus Urbanis*, a modular, situation-aware architecture designed to provide a goal-oriented platform for urban governance, supporting all three levels of Endsley's Situation Awareness model [1] and providing useful insights.

## II. Related Work

Situation-aware urban dashboards focus on integrating diverse data streams—from social media to physical sensors—to support urban planners' decision-making [2]. Systems like Bird's-Eye [3] and SocialGlass [4] emphasize spatio-temporal dynamics and movement patterns, leveraging NoSQL architectures and human-in-the-loop validation for transport analysis. Natural Language Processing methods enable sentiment visualization [5] and detection of small-scale extreme events [6] using data from Twitter (now X.com). Following the *human-as-a-sensor* paradigm, Bayesian models [7] extract public perceptions, while Support Vector Machines [8] categorize urban functions within grid-based spatial windows. These systems illustrate a shift toward multi-dimensional urban analysis capable of aggregating heterogeneous data streams for monitoring and long-term planning.

Supporting Situation Awareness requires computationally efficient techniques for representing situations under uncertainty [9]. Key Computational Intelligence approaches include Granular Computing, Three-Way Decisions, Neural Networks and Deep Learning, Fuzzy Systems, Evolutionary Algorithms, Knowledge Representation and Reasoning, Embodied Approaches, and cognitive-inspired AI [10]–[15]. Fuzzy Logic [16] translates ambiguous qualitative evaluations—such as from spoken language—into structured numeric values [17], while Rough Set Theory [18], combined with Granular Computing, supports Multi-Criteria Decision Analysis and enhances higher levels of Situation Awareness [19]. Context Space Theory (CST) [20] models situations as points in multi-dimensional spaces defined by contextual variables, enabling systematic analysis of situation spaces and their properties. Table I provides a structured overview of state-of-the-art platforms supporting urban monitoring and planning. Platforms are compared in terms of data sources, core analysis methodology, visualization techniques, and focus. This comparison highlights the variety of approaches in the literature, from spatio-temporal analysis to semantic and perception-based evaluation, and shows that each platform addresses specific urban sub-domains. Despite the common reliance on social media data, the diversity of processing techniques underscores the multi-disciplinary nature of situation-aware urban systems.

TABLE I
COMPARATIVE ANALYSIS OF SITUATION-AWARE URBAN DASHBOARDS AND SYSTEMS.

| System | Data Sources | Core Methodology | Visualization | Focus |
|---|---|---|---|---|
| Bird's-Eye [3] | Twitter, Foursquare | Hierarchical Data Mining | Dashboard Analytics | Transport |
| Weiler et al. [5] | Twitter | Visual Metaphors | Clock-face, Tag Clouds | Events/Emotions |
| Yao & Wang [6] | Geo-tagged Tweets | Online LDA | Interactive GIS | Extreme Events |
| SocialGlass [4] | Social Media, Sensors | Human Computation | Heatmaps, Clusters | Urban Planning |
| Zhou & Zhang [8] | Twitter, Foursquare | SVM & tf-idf | Grid-based Analysis | Urban Functions |
| Doran et al. [7] | Social Media | Bayesian Models | Discrete/Continuous | Perceptions |

## III. PROBLEM FORMULATION AND CONCEPTUAL MODEL

### A. Urban Situation Definition

Although frameworks like Anholt's City Brand Index [21] evaluate a city based on its long-term reputation, they are primarily designed to measure people's perception towards the city rather than its operational state. The overall Situation of a city must provide a more holistic view; therefore, we provide a comprehensive definition of the **Urban Situation**, based on the definition of context-aware computing by Dey [22]: *"The comprehensive set of all structural, social, environmental, and emotional information that characterizes the state of an urban entity (e.g., a square, a neighborhood, or a city) and the multifaceted interactions between people and the built environment."* Therefore, the Urban Situation $S_t$ is defined as the aggregation of the city's Physical and Static state ($P_t$), its Dynamics ($D_t$), and the Emotional and Perceptual ($E_t$) elements of the population: $S_t = \{P_t, D_t, E_t\}$. This ensures that the situation model is at the same time grounded in (i) the physical configuration of the urban environment, (ii) its live dynamics, and (iii) the people's perception about different aspects of the city.

### B. Situation Awareness Framework

To effectively support urban planners, we map our conceptual model to the three-level hierarchy of Endsley's Situation Awareness Model [1], which includes:

- **Level 1 - Perception:** The first stage involves the acquisition of the status and attributes of the elements defining the situation. In our system, this means acquiring data representing the physical infrastructure (e.g., POIs - Points of Interest, buildings, streets), the environmental and operational dynamics (e.g., events, weather conditions, pollution, transports, etc), and the public perception (e.g., social media posts, reviews about POIs).
- **Level 2 - Comprehension:** This level requires synthesizing elements to understand their significance in relation to the surrounding context and to the user's goals. Our framework achieves this through the fusion of raw data streams, allowing planners to understand, for example, how weather conditions (temperature, wind speed, humidity, etc) influence people's perception of thermal stress. Moreover, Context Space Theory enables the computation of a comprehensive and goal-oriented **City Situation Index** based on the values of Urban Chromas.
- **Level 3 - Projection:** The final stage of Situation Awareness (SA) concerns the ability to forecast future states of the system, that is, in this case, the urban situation. This capability is often supported by providing information about how some data varies over time, so that the operator can anticipate future patterns. In addition to this, our framework supports this level of SA leveraging Granular Computing and Rough Set Theory techniques.

### C. Urban Chromas

The application of CST in our system is based on the definition of Urban Chromas ($UC$), each describing a fundamental aspect of the urban environment or the perception of people towards it. Urban Chromas are designed to enhance the comprehension of the operators about *sub-situations* by providing a comprehensive overview of specific information.

The term "*Urban Chroma*" is conceptualized to denote a specific semantic dimension, or *hue*, of the multi-faceted state of the city. Just as chromatic channels combine to define a color scene, the Urban Chromas are aggregated and effectively result in a colored thematic map.

Each Chroma is derived from a particular set of indicators that measure different aspects related to the same dimension of the Urban Situation. For example, the Environmental Chroma ($UC_{ENV}$) used in this study is derived from indicators of human thermal stress perception and air quality.

This enables the construction of the Situation Space based on urban dimensions such as History, Culture, and Environment, effectively integrating the various aspects related to $P_t$, $D_t$, and $E_t$ into a single comprehensive measure

### D. City Branding Perspective

Our framework is based on the well-established City Brand Index (CBI) developed by Simon Anholt [21], which assesses people's perceptions of a city across six dimensions: Presence, Place, Potential, Pulse, People, and Prerequisites. CBI is used as a grounding framework to identify specific, high-impact aspects of the urban situation that effectively shape the reputation of a city.

In this work, we focus on the dimensions "*Place*" and "*Pulse*". The first relates to the physical appeal and the environment of the city, describing *how pleasant or unpleasant* it is to walk around the city. On the other hand, "Pulse" relates to the vibrancy of the city, describing how easy it is to *find interesting things to do*, both as a short-term visitor or long-term resident, including aspects like nightlife and cultural experiences [23].

## IV. The Janus Urbanis Dashboard

### A. System Overview

In this work, we propose Janus Urbanis: a service-oriented, scalable, and adaptable software designed to support urban planning activities. The underlying architecture, illustrated in Figure 1, consists of an ETL (Extract, Transform, Load) pipeline responsible for collecting data from external sources (such as weather APIs and OpenStreetMap) and for transforming and processing this information; a data storage layer that supports polyglot storage using both SQL and NoSQL technologies; and a presentation layer that assists urban planners by delivering high-level insights while allowing them to drill down into individual widgets to examine raw data values.

Each different service is deployed as an independent Docker container and can be scaled according to different computational needs. For example, collectors may be replicated at runtime to parallelize the data collection process, and the "Data Access API" service might be replicated to allow for more requests to be processed concurrently. At the same time, database services can have replicas to improve data availability.

### B. Data Integration and Indicators Computation Strategy

The Collector services are responsible for extracting data from a variety of heterogeneous external sources:

- Points Of Interest (POIs): Data is gathered from OpenStreetMap (OSM) and Foursquare. This work focuses on those collected from Foursquare, which have a strict, platform-fixed taxonomy. In contrast, OSM data are based on community-driven tags, resulting in a more fluid folksonomy.
- Weather Conditions: Environmental metrics (e.g., temperature, humidity, precipitation, etc.) are ingested via the OpenMeteo API.
- Air Quality Index (AQI): Atmospheric pollution levels and air quality data are retrieved from OpenWeather API.
- User Reviews: Text feedback and numerical ratings about POIs in the "Food and Drink" area are collected from Google Maps and processed using Large Language Models.

Indicators are computed favoring proximity to the data collection phase whenever possible. Indicators such as the *Thermal Stress Indicator* are computed during the ingestion phase: being derived on a per-record basis, they are calculated and permanently stored in the database. Conversely, other indicators, like the *Relative Frequency Indicator*, are context-dependent, relying on user-defined parameters, such as a time range filter for the analysis. In this case, when possible, computing operations are offloaded to the database level, leveraging its native optimization for large-scale aggregation. When neither of the aforementioned strategies is applicable, the computation is delegated to the "Data Access API".

### C. Situation Evaluation

*1) Indicator-to-Chroma Mapping:* The overall City Situation Index (CSI) is calculated using Context Space Theory, where the context space is defined across a set of dimensions referred to as Urban Chromas. Each Chroma represents a sub-situation capturing specific facets of the city's state: $P_t, D_t$, or $E_t$. This work focuses on the following Chromas:

- Historical Chroma $UC_{HST,P}$: Reflects the Physical ($P_t$) state of the city in terms of "Historical" POIs.
- Cultural Chroma $UC_{CLT,P}$: Represents the Physical ($P_t$) state of the city in terms of "Cultural" POIs.
- Food And Drink Chroma $UC_{FD,P}$: Evaluates the Physical ($P_t$) state of the city in terms of "Food And Drink" POIs.
- Food And Drink Sentiment Chroma $UC_{FD,E}$: Captures the Emotional ($E_t$) state of the population towards "Food And Drink" POIs in the city.
- Environmental Chroma $UC_{ENV,D}$: Measures the Dynamic ($D_t$) condition of the environment, such as Air Pollution and Thermal Comfort.

Each Chroma is defined based on a set of indicators. While certain indicators are unique to a single Chroma, others serve as cross-functional metrics. In the latter case, the same indicator type may be used to compute different Chromas by filtering the underlying POI data according to its urban function (e.g. historical vs cultural classification).

Table II summarizes the mapping between Urban Chromas and their underlying indicators. As shown, the Relative Frequency, Dispersion and Specialization indicators are multi-purpose: they are computed using the same formulas but over different POIs data. In contrast, indicators like Thermal Comfort or Air Quality are domain-specific.

*2) Chroma Aggregation and Global Situation:* The Situation evaluation follows a hierarchical approach based on Context Space Theory. First, CST is applied to aggregate indicators into their respective Urban Chromas. Subsequently, CST is applied recursively to obtain the City Situation Index (CSI) at time $t$ as a weighted synthesis of all Chromas, representing the final projection of the situation in the context space: $CSI_t = \sum_{k=1}^{|UC|} UC_k \cdot w_k$, where $UC = \{UC_{HST,P}, UC_{CLT,P}, \dots\}$ is the set of all the Chromas, and $w_k$ is the weight assigned to the $k$-th Chroma, with $\sum_{k \in UC} w_k = 1$.

That is, CST facilitates the semantic abstraction from raw data towards the comprehension of the situation. By mapping indicators to a multidimensional space (Table II), each Urban Chroma becomes a structured representation of a city's sub-situation.

It is important to highlight that indicators are calculated per-area, and the considered area might be the whole city area, as well as a portion of it. This is particularly useful because the area of the city could be split in different neighborhoods or standard-sized hexagons for a fine-grained analysis using the visual map provided by the Janus Urbanis Dashboard.

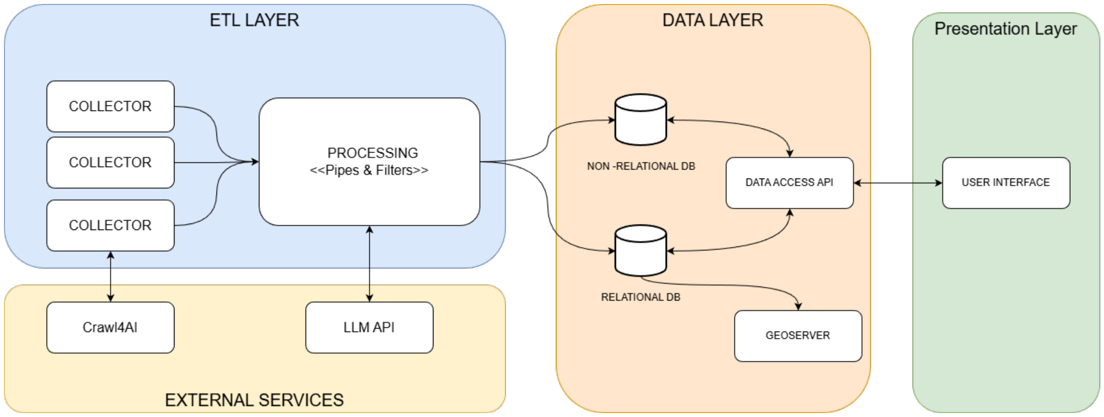


Fig. 1. Janus Urbanis Architecture - Module View

TABLE II
MAPPING BETWEEN URBAN CHROMAS AND INDICATORS.

| **Urban Chroma** | **Dim.** | **Indicators** |
|---|---|---|
| Historical ($UC_{HST,P}$) | $P_t$ | Rel. Frequency, Dispersion, Specialization |
| Cultural ($UC_{CLT,P}$) | $P_t$ | Rel. Frequency, Dispersion, Specialization |
| Food & Drink ($UC_{FD,P}$) | $P_t$ | Rel. Frequency, Dispersion, Specialization |
| Food & Drink Sentiment ($UC_{FD,E}$) | $E_t$ | Review Ranking, Rel. Pos. Opinion Frequency |
| Environmental ($UC_{ENV,D}$) | $D_t$ | Air Quality Indicator, Thermal Comfort Indicator |

*3) Uncertainty Management:* To account for the inherent imprecision in urban data and human perception, Fuzzy Logic (FL) [16] is employed with a dual purpose: (i) to smooth the crisp boundaries between different classes of values of the indicators and (ii) to map the values of the indicators in the unit interval $[0, 1]$.

Fuzzy Inference Systems (FIS) are specifically applied to Dispersion, Specialization, and Thermal Comfort indicators. In the case of Thermal Comfort, for example, LF allows for a better representation of human sensation that captures the transition from one stress class to another.

The final, precise output for each of these indicators is obtained using a Takagi-Sugeno FIS [24], which avoids the computational overhead associated with Mamdani [25] defuzzification, enabling a scalable and adaptable system.

### D. Projection for Situation Discovery

Janus Urbanis supports the Projection phase of the Situation Awareness model by employing Granular Computing (GrC) approaches and Rough Set Theory (RST) [18], as in the work by D'Aniello et al. [19]. Specifically, the equivalence (or indiscernibility) relation is leveraged to model the situation as a lattice of partitions, where a partition represents a set of objects which are equivalent based on the considered attributes. Defined in this way, lattices allow to reason about the different groups of objects, with the possibility to calculate similarity and dissimilarity metrics between different lattices.

This work focuses on the set of attributes composed of Thermal Stress, Specialization, and Dispersion. The operators of the system can create lattices based on the selection of the attributes and the order of the selection, and they can project future situations by modifying the attributes of the different areas, e.g. by changing the "Specialization" value from "Cultural" to "Historical". This approach offers a high degree of flexibility and also ensures, at the same time, an improvement of perception and comprehension. It also enhances projection, allowing operators to visualize the impact of structural changes.

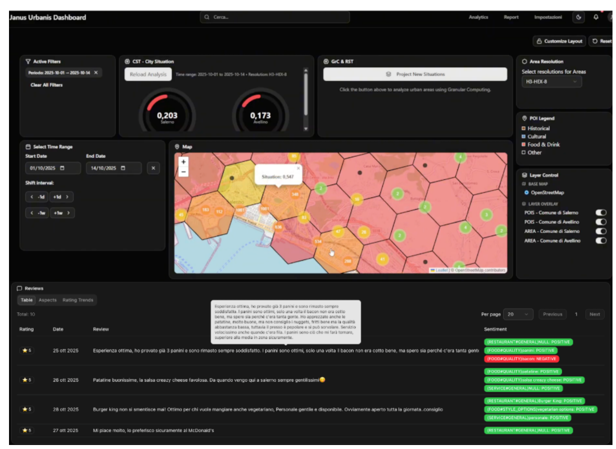


Fig. 2. Janus Urbanis User Interface design

## V. DASHBOARD DESIGN AND INTERACTION

The User Interface of the system, shown in Figure 2, has been designed according to the Situation Awareness UI Design Principles [26]. To provide an immediate and intuitive

TABLE III
CHROMA VALUES FOR SALERNO AND AVELLINO

| City | Environment | Cultural | Historical |
|---|---|---|---|
| Salerno | 0.892 | 0.072 | 0.033 |
| Avellino | 0.863 | 0.043 | 0.008 |

overview of the urban state, the global results are visible in the upper section of the dashboard. The City Situation Index is presented both through its numerical value and a dynamic visual indicator that maps the CSI value onto a color spectrum. The gauge progresses from red, through orange and yellow, and finally reaches green.

To facilitate a better understanding of the CSI value, operators can make a drill-down analysis into the value of each chroma, and further into specific widgets, positioned in the lower section of the dashboard, that show raw data, supporting Levels 1 and 2 of SA. In addition, line graphs showing data trends over time also support Level 3 of SA.

Furthermore, operators have the ability to resize and reposition each widget independently. This feature enables them to configure the user interface to their needs, effectively supporting the concurrency of multiple goals.

## VI. ILLUSTRATIVE URBAN SCENARIO

To illustrate the capabilities of the proposed dashboard, we consider a scenario in which urban operators analyze the *cultural* and *historical* situation of two medium-sized Italian cities: Salerno and Avellino. The objective is to compare the two cities with respect to the distribution and relevance of cultural and historical Points of Interest (POIs) during the time interval from October 17 to October 31, 2025.

The analysis begins by configuring the spatial and temporal parameters of the dashboard. The selected geographic granularity is *H3-HEX-8* [27], which partitions the urban area into hexagonal cells with an average size of approximately $0.73\,km^2$. This spatial discretization enables a fine-grained exploration of the urban environment and supports localized situation assessment.

Once the spatial grid is generated, the City Situation Index (CSI) map is initialized using the default configuration. To align the analysis with the operators' objective, the weighting scheme of the Urban Chromas is then adjusted. In particular, the *Historical* and *Cultural* Chromas are prioritized by assigning them a weight of $0.4$ each, while the *Environmental Chroma* is retained with a lower weight $(0.2)$ in order to preserve a minimal influence of environmental conditions on the final evaluation. All the remaining Chromas are temporarily excluded from the computation by setting their weights to zero.

Following this configuration update, the system automatically recalculates the City Situation Index for both cities. The resulting CSI values are visualized through the CST widget and summarized in Table III.

The results show that both cities exhibit relatively low scores for the Cultural and Historical dimensions. However, Salerno consistently achieves higher values than Avellino across the considered Chromas, indicating a comparatively stronger presence of culturally and historically relevant urban features.

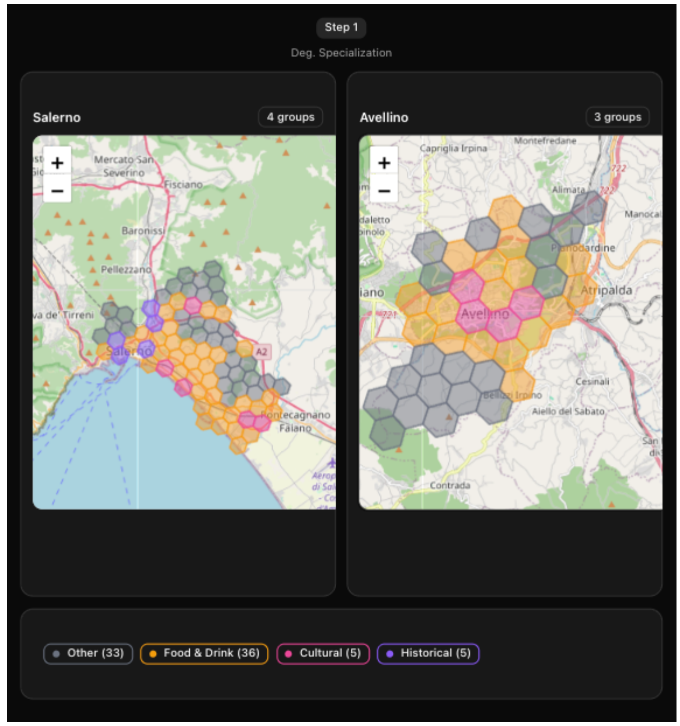


Fig. 3. Area aggregation by Specialization

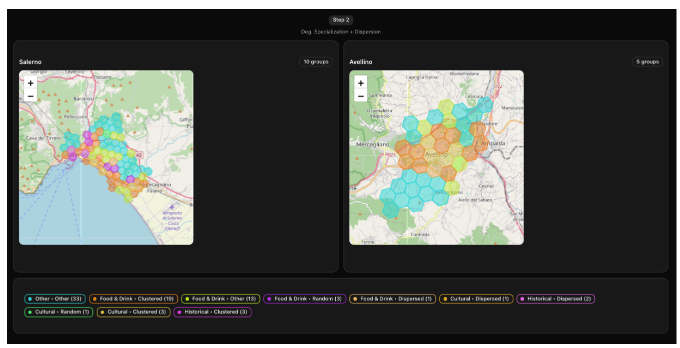


Fig. 4. Area aggregation by Specialization and by Dispersion

To better understand the origin of this difference, operators can perform a deeper spatial inspection of the POI distribution. Figure 3 presents the hexagonal grid where each cell is colored according to its dominant functional specialization. For instance, hexagons colored in purple correspond to areas characterized by a high concentration of historical POIs. This analysis reveals that Avellino lacks clearly identifiable historical areas, while Salerno exhibits several zones where historical specialization emerges.

A further level of analysis is shown in Figure 4, where hexagons are classified according to the dispersion pattern of the dominant specialization. This visualization highlights that the cultural areas identified in Avellino tend to display a clustered spatial distribution, suggesting a localized concentration of cultural activities rather than a widespread urban presence.

Overall, this scenario demonstrates how the Janus Urbanis dashboard supports multi-level urban analysis. By combining adjustable chroma weighting, spatial aggregation, and visual exploration, the system enables decision makers to quickly identify structural differences between cities and investigate the spatial factors influencing their cultural and historical profiles.

## VII. Conclusion and Future Work

This work presents a novel approach to integrating heterogeneous urban data sources for building Situation Awareness–oriented dashboards for city branding activities. Janus Urbanis manages the entire pipeline, from raw data acquisition—which supports Level 1 of the Endsley SA model—to the processing, enrichment, and visualization of information, supporting Levels 2 and 3. Its architecture ensures scalability, flexibility, and maintainability of the system, allowing it to easily adapt to increases in data volume and complexity.

Additionally, a framework for the quick global assessment of the city's situation has been proposed based on Context Space Theory, allowing the calculation of high-level indicators from raw data and to easily drill-down. On the other hand, a tool for the visualization of the current and the projected Situations based on Granular Computing and Rough Set Theory has been developed and presented.

The presented approach suffers from some limitations: the City Situation Index is calculated based on a small number of Chromas, which mainly cover "static" aspects of the city (e.g., presence, dispersion), and, at the same time, the tool for projecting future situations only supports modifications over a small set of attributes, only for the areas.

Future work will focus on the extension of the capabilities of the platform, with the definition of new Urban Chromas and Indicators, so to capture new nuances of the Brand of a city. Finally, the situation projection tool will be further developed to support more refined modifications, also with the possibility to add or remove POIs from the map and understand how the CSI would change.

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