VIZPLAN: A VISUAL ANALYTICS PLATFORM FOR THE ASSESSMENT OF MULTIDIMENSIONAL INDICATORS OVER TIME

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ABSTRACT:

In this paper, we introduce VizPlan, a new platform to support the assessment of multidimensional indicators over time. VizPlan includes a visualisation scheme based on a radial visual structure that allows the direct comparison of indicator values over time, a search tool to support the identification of entities whose indicators are similar to each other, and a clustering tool to group entities according to their indicator scores. VizPlan was designed and implemented to be flexible; it can be easily tailored to the visualization and analysis of any multidimensional temporal data. In this paper, the use of VizPlan is illustrated in the context of three case studies concerning the analysis of sustainability indicators to support urban planning: key performance indicators related to the sustainable development goals, walkability analysis, and bus service availability assessment. All case studies refer to real data related to Norwegian cities, especially Ålesund. VizPlan is available as an open source software at `https://github.com/Rylern/VizPlan` – As of May 2022.

1. INTRODUCTION

Technological advances have fostered the wide adoption of procedures for data acquisition, storage, and communication. A plethora of Smart City applications now relies on the analysis of huge volumes of data (Psyllidis et al., 2015, Costa and Santos, 2017, Mehmood et al., 2019, Zheng et al., 2016). In particular, special interest has been given to the analysis of different "what-if" scenarios based on the use of indicators computed from results obtained from sensors, surveys, and even simulation or data-driven methods. The proper assessment of time-varying indicators is fundamental for decision-making and, therefore, the existence of suitable visual structures to support the understanding of patterns across space and time (including changes) plays a relevant role (Zheng et al., 2016). Our study aims to understand how to support the analysis of multidimensional numerical indicators with temporal variability.

In this paper, we introduce VizPlan, a visual analytics platform for the assessment of multidimensional indicators over time. VizPlan includes a radial visual structure that allows the direct comparison of indicator scores for different categories, for example, in the analysis of smart city key performance indicators (KPI) based on sustainable development goals. The developed platform supports map-based navigation, selection of indicators, and their comparison across different years. In a typical usage scenario, cities that have available KPI data can be displayed on an interactive map. Users can then select one of the cities by clicking on a map location to visualize its respective KPI chart. Other features included in the interactive chart refer to filtering on performance values, zooming, panning, label toggling, and the ability to compare segments against other cities. The platform also supports clustering and similarity searches, which allow the identification of entities (e.g., regions, cities) that are similar to each other according to a pre-defined set of indicators.

The platform was designed and implemented to make it flexible. That platform can be easily tailored to different applications and problems. We have demonstrated its use in the context of three appealing applications related to decision-making based on the analysis of indicator changes over time: assessment of KPI indicators related to Sustainable Dvelopment Goals (SDG), evaluation of walkability properties in different regions of a city, and the analysis of bus service availability in several neighborhoods. The considered applications are linked to SDG 11 (target 11.2), which refers to providing "safe, affordable, accessible, and sustainable transport systems."[1]

This paper is organized as follows: Section 2 briefly covers relevant related work; Section 3 introduces VizPlan, highlighting its main components and features; Section 4 illustrates the use of VizPlan in three case studies; finally, Section 5 outlines our conclusions and presents directions for future studies.

2. RELATED WORK

The literature is vast with regard to studies related to the visualization of multidimensional data (Ltifi et al., 2020, Liu et al., 2017). Popular strategies rely on the use of scatter plots (Friendly and Denis, 2005), radar charts (Albo et al., 2016), and parallel coordinates (Inselberg, 1985). Another successful strategy relies on the use of radial structures (Draper et al., 2009, Albo et al., 2016). Encoding and representing changes of multidimensional data over time has also been investigated in several applications, especially for urban data (Zheng et al., 2016). For more details regarding successful approaches for time-oriented

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[1] `https://unstats.un.org/sdgs/metadata/?Text=&Goal=&Target=11.2` (As of July 2022).

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data visualization, the readers may refer to (Aigner et al., 2008, Aigner et al., 2011).

Mariano et al. (Mariano et al., 2018, Mariano et al., 2019), for example, integrated visual rhythms with radial structures to support the analysis of phenological data encoded in stack of relational tables (Mariano et al., 2018) or images (Mariano et al., 2019). The main goal was to support the analysis of temporal changes of phenological variables. In the current version of VizPlan, we utilize a similar strategy for the visualization of indicators associated with different geographical objects.

In the context of urban data analysis, information visualization approaches have been employed to several applications, such as the assessment of mobility data (Feng et al., 2021), water source management (Xu et al., 2022), urban pollution (Bello et al., 2019), and land use evolution (Santos et al., 2021). In broader formulations, data integration infrastructures that include visualization components have been proposed (Psyllidis et al., 2015, Costa and Santos, 2017, Mehmood et al., 2019, Ferreira et al., 2015). Ferreira et al. (Ferreira et al., 2015), for example, explored parallel coordinates to support the analysis and comparison of attributes related to multiple entities (neighborhoods or buildings). In the platform proposed by (Psyllidis et al., 2015), map-based data visualizations based on dynamic point clusters, choropleth maps, activity paths, and data graphs are available. No radial layout is employed. The visualization strategy proposed by (Costa and Santos, 2017) relies on several dashboards that integrate map and multiple charts. Similar to our platform, their platform supports entity (buildings) clustering based on their properties (e.g., energy consumption). No similarity search is supported, though. The data visualization component in the infrastructure proposed by (Mehmood et al., 2019) relies on dynamic dashboards that include bar and pie charts, facet-based grouping, and time series graphs. Search is not supported.

The visualization of sustainability-related indicators associated with different locations have been explored before. Major et al. (Major et al., 2021) integrated a radial structure to present SDG performance indicators in a city digital twin (3D scene). Leplat et al. (Leplat et al., 2022), in turn, investigated the use of a map-based infrastructure to support indicator analysis. None of those formulations integrate similarity-based analysis.

3. VIZPLAN

This section presents VizPlan and its components. We first provide an overview of formal aspects related to its design (Section 3.1). Next, we describe architectural, functional, and implementation aspects in sections 3.2, 3.3, and 3.4, respectively.

3.1 Formalization

Let $\mathcal{O} = \{o_1, o_2, \ldots, o_n\}$ be a set of geographical entities (e.g., cities). In a vectorial representation, an object $o \in \mathcal{O}$ may refer, for example, to a point, a line, or a polygon. In a raster formulation, o may refer to a pixel in a raster image. Let $\mathcal{A} = \{a_1, a_2, \ldots, a_m\}$ be set of indicators. Each indicator a can be seen as a numerical variable (*attribute*), i.e., $a \in \mathbb{R}$. For the sake of simplicity, we assume that each object $o \in \mathcal{O}$ has the same set of indicators $\mathcal{A}$. In this case, the notation o_{ij} stands for the j-th attribute of the i-th object in $\mathcal{O}$.

For the sake of simplicity, in our formulation, we assume that all indicators associated with an object evolve over time, i.e., $o \in \mathcal{O}$ can be seen as a multidimensional temporal variable. In this case, the sequence $o_{ij}^1, o_{ij}^2, \ldots, o_{ij}^T$ refers to the values associated with indicator j of object i from timestamps 1 to timestamp T.

The goal of VizPlan is to support the comparative analysis of the temporal evolution of indicators associated with multiple geographical entities (e.g., countries, states, cities, city neighborhoods). The direct comparison among entities based on their associated indicator scores is of paramount importance in the decision-making process. It could, for example, be used to identify appropriate procedures of an entity that could be explored by another. For example, if one can identify that a city is performing well regarding a specific indicator (e.g., CO2 pollution), procedures adopted by that city could be explored by others.

VizPlan not only supports the direct comparison of indicators, but also allows for the similarity-based assessment of entities, fostering the quick identification of suitable operations towards improving indicators based on performance of other geographical objects. Similarity-based assessment is supported by *ranking* and *clustering* tasks, detailed next.

Ranking: This feature refers to the task of ranking objects in a collection (dataset) according to its distance to an input object (query object). A common strategy for ranking refers to the use of a distance function $\rho : \mathbb{R}^p \times \mathbb{R}^p \rightarrow \mathbb{R}^+$ that determines how close two objects are (i.e., their similarity) given their vector representations defined by means of indicators. If we use ρ for all objects in the collection, it will be possible to rank them according to their distance to the input object. In the produced ranked list, top-ranked objects are closer to the input object.

In VizPlan, the (vector) representations of objects are defined in terms of their indicator values. In the platform, users may select which indicators should be used in the ranking procedure. Let $\mathcal{I}' = \{a'_1, a'_2, \ldots, a'_p\}$ ($\mathcal{I}' \subset \mathcal{I}$) be the set of p indicators defined by a user. The current version of the platform supports ranking objects according to Minkowski-based distance functions:

$$\rho_{Minkowski_q}(o_x, o_y) = (\sum_{j}^{p}(o_{xj} - o_{yj})^q)^{\frac{1}{q}} \tag{1}$$

where o_x and o_y are two objects in $\mathcal{O}$.

When $q = 1$ or $q = 2$, Equation 1 leads to the Manhattan and to the Euclidean distances – Equations 2 and 3, respectively.

$$\rho_{Manhattan}(o_x, o_y) = \sum_{j}^{p} |o_{xj} - o_{yj}| \tag{2}$$

$$\rho_{Euclidean}(o_x, o_y) = \sqrt{\sum_{j}^{p}(o_{xj} - o_{yj})^2} \tag{3}$$

Clustering: This task concerns grouping objects based on their distance. In our case, two geographical entities would belong to the same cluster if they are close enough. In VizPlan, geographical entities can be grouped together according to their indicator scores. In our implementation, users may again define

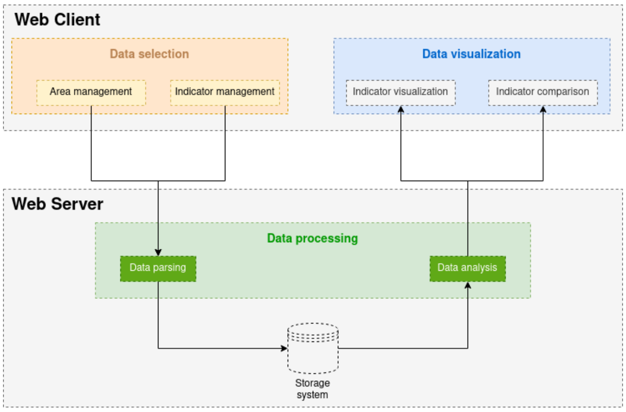


Figure 1. Architectural view of the VizPlan platform.

the set of indicators $\mathcal{I}'$ that should be used in the clustering algorithm and also the distance function that should be used (e.g., the ones defined in Equations 1, 2, and 3). More formally, clustering will produce a set of K partitions clu_k of $\mathcal{O}$ such that $\cup_k clu_k = \mathcal{O}$. In the current version of VizPlan, the k-means clustering algorithm (Hartigan and Wong, 1979) is available.

3.2 Architectural view

The architecture of VizPlan (Figure 1) is divided into two entities: a web client and a web server. The web client represents what the user can see and interact with. The data visualization part handles features related to the visualization of indicators, for example by showing graphs and diagrams, and features related to the comparison of indicators between different areas. The customization of the platform is represented by the data selection part which handles features related to indicators and management areas.

The web client needs data to work with. Therefore, a web server will store the datasets into a storage system, which is here a file system. The interaction between the client and the server is made possible with the data processing component. This component is responsible for processing input data before sending it to the visualization component, and parsing data before storing it into the storage system.

3.3 Functional View

A functional view of VizPlan is presented in Figure 2. VizPlan is organized according to three main components to support indicator analysis: data selection, similarity-based assessment, and indicator visualization. Data selection refers to the definition of indicators and the geographical entities (area management in the figure). The similarity-based assessment component supports the evaluation of entities according to their similarity by means of ranking and clustering. Finally, the visualization component includes map-based browsing, indicator evolution charts, and a radial layout for indicator comparison.

Interface Overview: The first screen of the platform represents a map of the world that displays the areas present in the handled collection. Each area is clickable, which leads to the indicator visualization screen for that particular area. Here, the user gets an overview of the indicator values with a sunburst diagram: if a value is high, the associated indicator will be colored green, and if a value is low, the associated indicator will be colored red. Some of the interface components are illustrated in Figure 3.

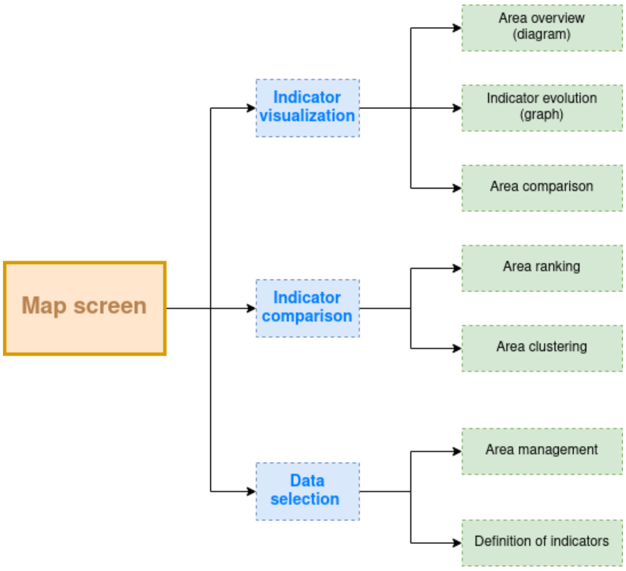


Figure 2. Functional view of VizPlan.

Two graphs are also present on that screen. They display the monthly evolution of the selected indicator and the values of the selected indicator for all other areas. Finally, a panel on the left of the screen allows the user to compare two different areas with the sunburst diagram.

A menu is present on the top-right corner of the map screen, which allows the user to perform a comparison between the different areas (geographical object). Two methods are provided by the platform. The first one supports searches, based on which, areas are ranked according to their similarity. The user chooses a reference area, some indicators, and the platform is able compute the distance between the reference and all other areas based on the selected indicators. The type of distance (Manhattan, Euclidean, or Minkowski) is chosen by the user. The areas will then be ranked based on the computed distance, as defined in Section 3.1.

3.4 Implementation Aspects

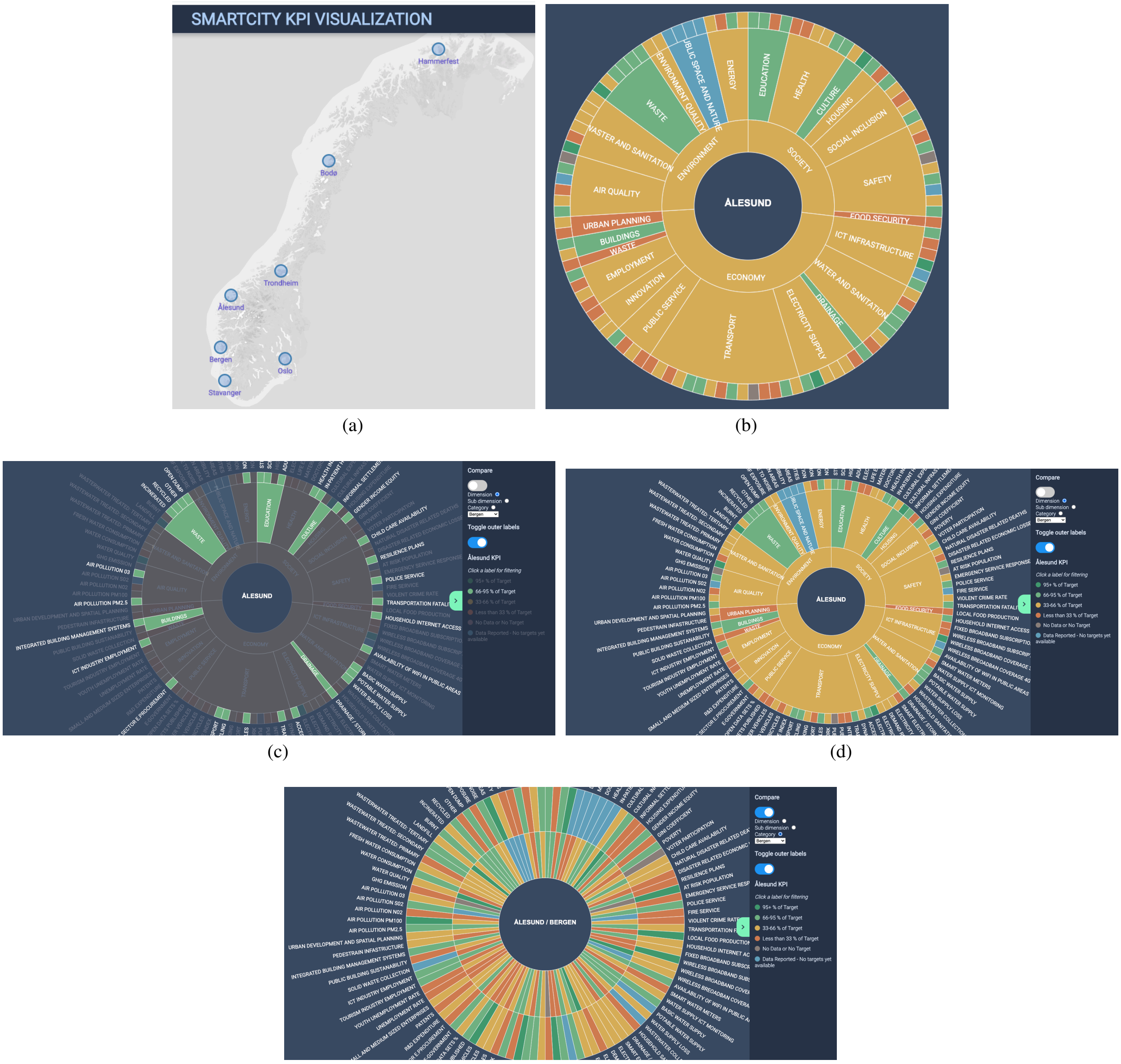
VizPlan is a web-based application developed using the HTML, CSS and JavaScript programming languages. The Node.js[2] JavaScript runtime environment was used to develop both the client and the server side. All data are stored into JSON files.

On the client side, the Webpack.js[3] module was used to bundle the source code into a single JavaScript file. Several other modules were used, such as Leaflet[4] to display the world map, d3.js[5] to create diagrams, and Highcharts[6] for the graphs. On the server side, the module Express.js[7] was used to create a simple web server.

4. CASE STUDIES

This section demonstrates the flexibility of the developed platform in the context of thee case studies: SDG KPI (Section 4.1), bus service availability (Section 4.2), and walkabiliy assessment (Section 4.3).

[2] `https://nodejs.org/en/` (As of May 2022).
[3] `https://webpack.js.org/` (As of May 2022).
[4] `https://leafletjs.com/` (As of May 2022).
[5] `https://d3js.org/` (As of May 2022).
[6] `https://www.highcharts.com/` (As of May 2022).
[7] `https://expressjs.com/` (As of May 2022).



(a) (b) (c) (d) (e)

Figure 3. Overview of features of the developed tool. (a) Map-based municipality selection. (b) Example of a KPI chart. (c) Visualization of SGD labels. (d) Selection of SGDs based on performance. (e) Comparison of KPIs of two municipalities.

4.1 On the Assessment of SDG KPI

The first case study is about the visualization of the Sustainable Development Goals (SDGs) of different cities across Norway. A set of SDG-based indicators has been defined by the United 4 Smart Sustainable Cities (U4SSC) initiative as a way to measure and monitor progress towards the SDGs and targets. Information about these indicators may be found in their methodology report (U4SSC, 2017).

Dataset: In this case study, 108 indicators regrouped in 24 parent indicators, themselves regrouped in three main categories, have been applied to 10 cities in Norway. The considered cities are shown on Figure 4. Figure 5 displays the list of indicators.

Visualization of Indicator Scores: The platform provides an efficient way to obtain an overview of the indicator of a particular area. Figure 5 shows the indicator diagram for the city of Ålesund, Norway. Four colors are present: red, yellow, and green. Those colors respectively indicate a low, medium, and high value of an indicator. Gray means that the value is unknown. For example, we can see that the ICT infrastructure is well-developed in Ålesund, as opposed to the culture indicator. We have no information about food security.

Each indicator on the diagram is clickable and will change the graphs presented in Figures 6 and 8. Figure 6 presents the monthly evolution of an indicator. In this example, it is the environmental waste for Ålesund in 2020.

Comparison of Indicator Scores: The platform provides ways to compare areas based on their indicator scores. The goal is to support the identification of the strengths and weaknesses of each of them. For example, the radial diagram can be used to compare two cities. Figure 7 shows a comparison between Ålesund and Trondheim. We can observe, for example, that

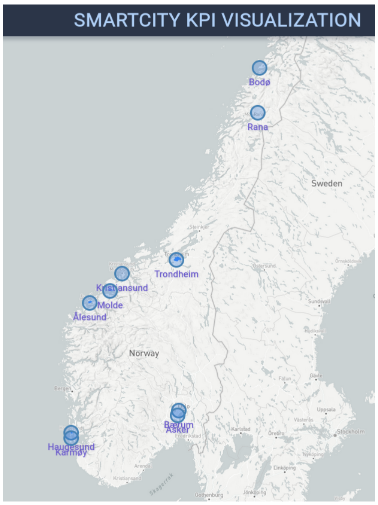


Figure 4. Map-based browsing tool to support the assessment of indicators related to the Sustainable Development Goals of different cities across Norway.

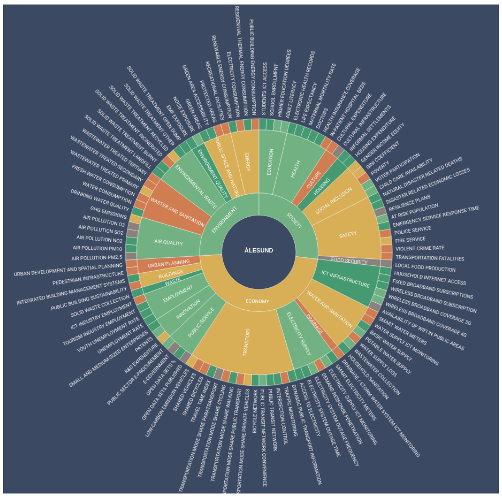


Figure 5. SDG indicators forÅlesund, Norway.

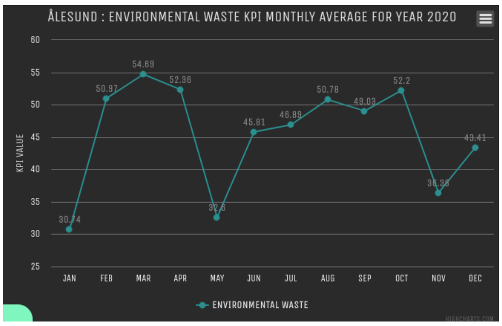


Figure 6. Monthly evolution of environmental waste inÅlesund, 2020.

Ålesund is better than Trondheim in terms of environment quality. The opposite relation is observed for the indicator related to public services.

A graph was also developed to compare with all the cities at the same time. Figure 8 presents the values of one indicator for all cities. In this example, the analysis focuses on the environmental waste indicator. We can observe that Ålesund is among the worst cities in this category.

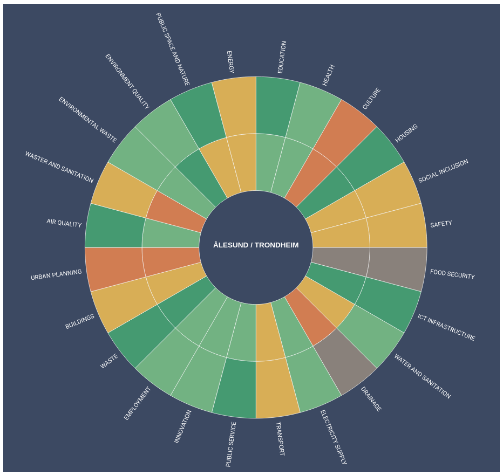


Figure 7. Comparison betweenÅlesund and Trondheim.

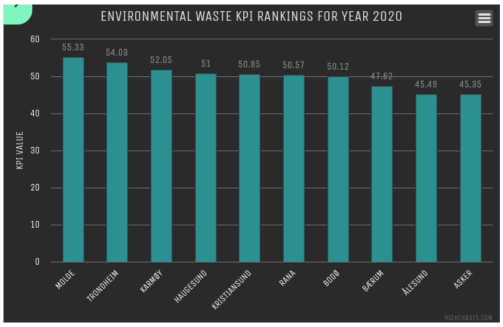


Figure 8. Environmental waste for all cities in 2020.

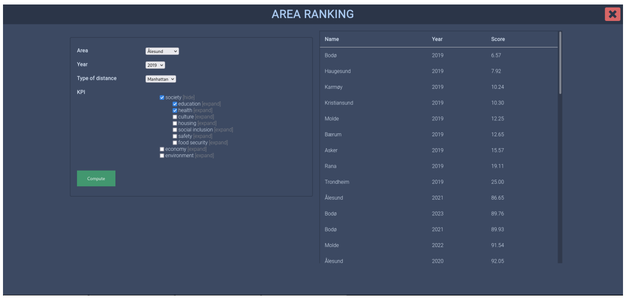


Figure 9. Screenshot with ranking results.

Search for Cities with Similar SDG indicators: VizPlan also includes a ranking feature that can be used to search for similar cities by taking into account their indicators. An example is illustrated in Figure 9. On the provided example, the user is interested in finding the cities similar t oÅlesund with regard to the society, education, and health indicators. The result on the right shows that Bodø has the minimal Manhattan distance to Ålesund for these indicators, and Haugesund is the second city in the ranked list.

Clustering of Municipalities according to SDG indicators: Finally, it is often useful to gather cities into groups by similarities. The clustering screen on Figure 10 shows an example of this feature in the context of SDG indicator assessment. In this example, the user is interested in computing three clusters with the same indicators as before. The result on the right shows, for example, that all cities that were similar in 2019.

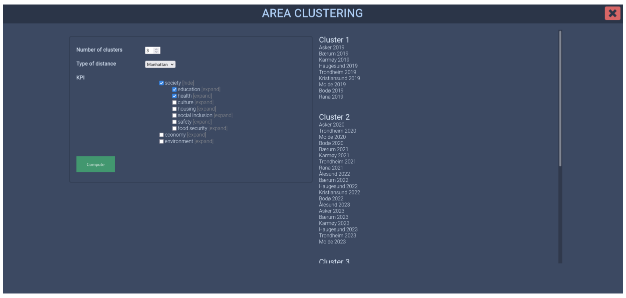


Figure 10. Screenshot with clustering results.

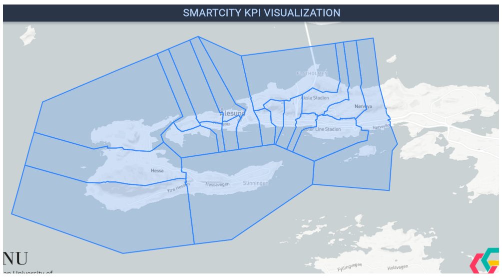


Figure 11. Districs ofÅlesund.

4.2 On the Assessment of Bus Service Availability

The second case study concerns bus service availability in the city of Ålesund, Norway. The Public Transport Access Level (PTAL) (Wu and Hine, 2003) was computed for different districts of Ålesund and at different intervals of time.

Dataset: To divide Ålesund into districts, we used maps from Statistics Norway.[8] This platform provides this information in the GeoJSON format. Therefore, it could be directly processed in VizPlan. Data related to buses (bus stops, frequency) was collected from Entur, [9] which operates the national registry for all public transport in Norway.

To determine the PTAL for one district, we computed the PTAL for all buildings inside that district and then made an average of the result. The building data was provided by Mapbox.[10] The PTAL is computed following the algorithm described in (Wu and Hine, 2003). For each location, the walk times to the nearby service access points and the scheduled waiting time for each of these access point are calculated. These two values are then combined into an index ranging from 0 (worst) to 40 (best).

Visualization of Indicator Scores: Figure 11 shows the division of Ålesund into districts on the map screen. The previous use case was using points to show cities on the map, while here, we use polygons to represent districts. This demonstrates the flexibility of the tool.

Figure 12 shows the diagram associated with the district of Apotekertorget. At the edge of the diagram, we can see the PTAL for different intervals of time. Here, as expected, buses are more available between 12:00 and 16:00 and virtually not available between 00:00 and 06:00. Between the center and the edge of the diagram, the yellow color indicates the average PTAL for the entire day. Comparing the situation across different neighborhoods may provide insights regarding the available mobility options using the public transport system. This is addressed next.

[8] https://kart.ssb.no (As of May 2022).
[9] https://developer.entur.org/stops-and-timetable-data (As of May 2022).
[10] https://www.mapbox.com (As of May 2022).

Figure 12. Diagram of Apotekertorget,Ålesund, Norway.

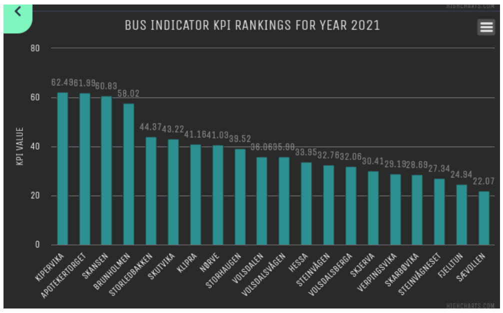


Figure 13. Comparison between all the districts.

Comparison of Indicator Scores: Figure 13 provides a comparison among all the districts. Here, the average value on one day is used. We can see that the district of Kipervika has the highest bus availability, while the district of Sævollen has the lowest. This kind of information may be explored by planners to change transportation service availability across different districts in the city.

4.3 On the Assessment of Walkability

The third case study concerns the assessment of Walkability in the city of Ålesund, Norway. Walkability refers to what extent a particular region is walking friendly (Beiler and Phillips, 2016). Several indicators can be used to compute various aspects of walkability, such as attractiveness and safety.

In this use case, we used the following indicators:

- Population density: a higher density means a more walkable area.
- Park areas: the indicator is higher when a park is nearby.
- Street connectivity: the more street intersections, the better for walkability.
- Elevation: the highest score is at the lowest altitude.
- Speed limit: it is safer when the speed limit is low.
- Pedestrian crossings: the indicator is higher when a pedestrian crossing is nearby.

Figure 14. Diagram of Storhaugen, Ålesund, Norway.

Dataset: As for the use case on bus service availability, we divided Ålesund into districts with maps from Statistics Norway.[11] For each district, we then computed one value of each indicator. Walkability is the weighted combination of all indicators. In this case study, all weights were set to one.

To compute the population density indicator, we use a dataset[12] that was released in 2020 and consists of hexagons with population counts at 400m resolution. The park areas, street connectivity, speed limit, and pedestrian crossings datasets were obtained from OpenStreetMap[13]. OpenStreetMap is a free, editable map of the whole world that is being built by volunteers. The elevation data was obtained from Open Topo Data[14]. It is a free elevation API that can give access to several datasets. We chose to use the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) dataset that offers a 1 arc second resolution, corresponding to a resolution of about 30m at the Equator.

Visualization of Indicator Scores: The same division of Ålesund presented on Figure 11 was used in this case study. Figure 14 shows the diagram associated with the district of Storhaugen. At the edge of the diagram, we can see the values of the different indicators. We can see that Storhaugen is very walkable if we consider elevation, distance to crossings, or proximity of parks, but it has low indicator values for the average speed limit and the number of intersections. Between the center and the edge of the diagram, the yellow color indicates the overall walkability value for this district.

Comparison of Indicator Scores: Figure 15 provides a comparison of the walkability values between all the districts. We can see that Kipervika has the best walkability score, while Larsgård is the less walkable district. This analysis may foster better-informed decision-making towards improving the walkability of particular neighborhoods in the city.

5. CONCLUSIONS

In this paper, we introduce VizPlan, a new platform to support the assessment of multidimensional indicators over time.

[11] `https://kart.ssb.no` (As of May 2022).
[12] `https://data.humdata.org/dataset/kontur-population-dataset` (As of May 2022).
[13] `https://www.openstreetmap.org/` (As of May 2022).
[14] `https://www.opentopodata.org/` (As of May 2022).

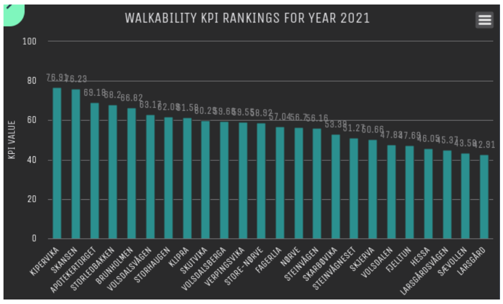


Figure 15. Comparison between all the districts.

VizPlan is a generic and flexible visualization dashboard which includes features for direct comparison of indicator scores associated with different geographical entities, for the analysis of the evolution of indicator evolution over time, and for the search and clustering of regions of interest according to their indicator similarity. The flexibility of the platform was demonstrated through three cases studies related to the assessment of sustainability aspects of cities: SDG key performance indicators, bus service availability and walkability of neighborhoods in Ålesund, Norway. The considered case studies are linked to SDG 11 (target 11.2), which refers to the access to safe, affordable, accessible, and sustainable transport systems.

The platform is freely available as an open source software (`https://github.com/Rylern/VizPlan` – As of May 2022). By providing data according a pre-defined CSV file format, the tool can be easily tailored to other cities.

Future work concerns the inclusion of new services in the platform, such as indicator time series search, and recommendation of entities based on their indicator performance. Other visualization approaches (e.g., radar chart (Albo et al., 2016) and map-based indicator visualization (Leplat et al., 2022)) are also potential avenues to explore in the context of the proposed platform. We also plan to investigate the scalability of the tool, when handling large datasets. We plan to integrate indexing schemes to support large-scale similarity-based searches and clustering tasks (Muñoz et al., 2019, Muñoz et al., 2022).

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