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Review

Geospatial Dashboards for Monitoring Smart City Performance

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Abstract: Geospatial dashboards have attracted increasing attention from both user communities and academic researchers since the late 1990s. Dashboards can gather, visualize, analyze and advise on urban performance to support sustainable development of smart cities. We conducted a critical review of the research and development of geospatial dashboards, including the integration of maps, spatial data analytics, and geographic visualization for decision support and real-time monitoring of smart city performance. The research about this kind of system has mainly focused on indicators, information models including statistical models and geospatial models, and other related issues. This paper presents an overview of dashboard history and key technologies and applications in smart cities, and summarizes major research progress and representative developments by analyzing their key technical issues. Based on the review, we discuss the visualization model and validity of models for decision support and real-time monitoring that need to be further researched, and recommend some future research directions.

Keywords: geospatial; dashboard; smart cities; indicator; visualization

1. Introduction

Smart cities focuses on realizing sustainable, efficient, and effective public and private services and infrastructure in urban space [1]. Over the last two or three decades, technology, projects, and initiatives related to smart cities have been rapidly developed, affecting almost all aspects of urban life. However, many challenges and barriers remain in monitoring and evaluating smart city performance, which include linking and analyzing city information with geographic location, handling big geospatial data, and uncovering spatiotemporal patterns in city space.

Geospatial dashboards have been developed to measure the performance of smart cities [1–3], which have attracted considerable interest from academia, industry, and government due to the geospatial nature of city development, function, and management, the need for sustainable urban development, and the interest in new managerialism systems. Massive volumes of geospatial data are generated directly and indirectly on daily basis in cities. Therefore, geospatial dashboards can be used to visualize them and mining spatiotemporal patterns. The geospatial dashboard supports smart city sustainability goals by tracking city performance measurements [1,2,4,5]. Furthermore, the rapidly increasing of available geospatial data has caused a paradigm shift towards data-driven research in cities [6,7], which has promoted a new urban managerialism. The new managerialism involves citizens who generate geospatial data, interact collaboratively with the government [8], and look for evidence-based decision-making [9]. Therefore, these characteristics of new managerialism result in the need for geospatial dashboards to support city management.

A dashboard was originally defined as a key accessory in a vehicle, according to the Oxford dictionary. Meanwhile, a digital dashboard is defined as "a visual display of the most important information needed to achieve one or more objectives" [10,11]. However, no clearly defined terms exist for geospatial dashboards. Other similar terms that have been used include city dashboard, urban dashboard, and spatial dashboard. For consistency, the term "geospatial dashboard" is used in this paper. We extend the definition of geospatial business intelligence from Badard and Dube [12], and define geospatial dashboard as a web-based interactive interface that is supported by a platform combining mapping, spatial analysis, and visualization with proven business intelligence tools. Based on this general definition, a geospatial dashboard can be at scales other than the city level and can be applied to dashboards for different applications such as health and business. However, in the context of this paper, we will focus on the ones related to city management and operations.

Indicator is one of the essential components of geospatial dashboards, which is "a measurement or a set of measures to evaluate a complex social, economic, or physical context" [13]. Considering the spatial context of geospatial dashboards, the indicator is not only the numeric value but also the map-based visualization and analysis to measure or unfold city performance.

Dashboards can be categorized into three types by their roles: operational, analytical, or strategical [11,14,15]. In this paper, we adopt and extend this categorization using geospatial data as follows: (1) Operational dashboards provide descriptive measurements of smart cities using indicators based on original geospatial data and other related data. These indicators provide the evidence of the status of a city. (2) Analytical dashboards are a diagnostic method for smart cities based on data inferred from geospatial data using spatial analytics, such as patterns and the relationships with the data. (3) Strategical dashboards are predictive dashboards used by smart cities to predict the future status of the city based on existing patterns, where data are input into well-defined models to predict future outcomes.

The objectives of this review were to: (1) examine the state-of-art geospatial dashboards and key technologies in architecture, design, indicator, visualization, and applications; (2) review the evolution and research on geospatial dashboards to determine if and how geospatial dashboards can be used to monitor the performance of smart cities; and (3) determine the most common design approach to architecture, dashboard design, indicator modeling, and visualization in geospatial dashboards.

The remainder of this paper is organized as follows. Section 2 outlines our literature review to review the evolution of geospatial dashboard. In Section 3, we examine the key technologies used in developing geospatial dashboards. Applications of geospatial dashboards are discussed in Section 4. Section 5 provides an analysis of the current challenges faced by geospatial dashboards in monitoring the performance of smart cities, and then outlines recommendations for future research work. Section 6 presents a summary and conclusions of this paper.

2. A Brief History of Geospatial Dashboard Development

In this section, we review the evolution of geospatial dashboards, mainly in the context of cities, followed by their technological and research development.

2.1. Evolution of Geospatial Dashboard

Figure 1 illustrates the history of major geospatial dashboard events. Their development can be divided into three main phases: development of digital dashboards, development of geospatial dashboards with mapping components, and modern geospatial dashboards with geospatial analysis functions. Geospatial dashboards stemmed from the digital dashboard that first emerged in early 1990. In this phase, dashboards were mainly used to provide an overview of important information using graphical summaries. At the same time, the development of online analysis processing (OLAP), key performance indicators (KPIs), and other information technology increased the popularity of geospatial dashboards [16]. OLAP is broadly a part of business intelligence and can answer multi-dimensional analytical queries for data warehouses in particular, while KPI measures how efficiently business objectives are achieved. Further development of integrating spatial analysis functions started in about 2010.

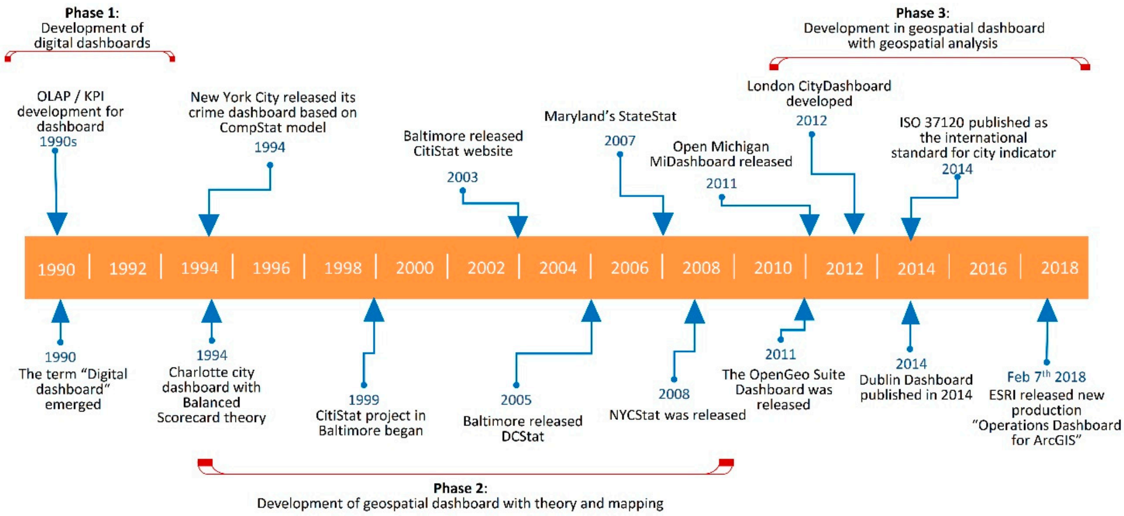

Figure 1. Timeline of some significant geospatial dashboard events.

In the second phase, as with the development of GIS and statistics, visualizing information based on maps and extracting knowledge by statistical models were two essential factors for dashboards. Therefore, geospatial dashboards were introduced. The CompStat model launched in 1994 for the New York city police [17,18] and CitiStat released in 1999 [19] are two examples. The CompStat model could track crime, find statistical patterns, and map them using a GIS. Inspired by CompStat, CitiStat was extended to the city level to monitor city performance including municipal budget, business investment, and publishing public information [19]. Further examples included the CitiStat-inspired DCStat (2005), Maryland's StateStat (2007), and NYCStat (2008) [20,21]. Compared to the first phase, the second phase featured the use of mapping functions and GIS for dashboards, namely geospatial dashboards. However, improvements were still required, particularly in relation to accessibility by the public, analysis, and data mining for geospatial big data.

In the third phase, the more advanced geospatial dashboards with powerful analysis modules were developed, motivated by two changes: the development of information and communications technology (ICT), which can handle greater complexity and real-time data, and the introduction of new data-driven and indicator-driven managerialism. Many cities have developed an urban dashboard, such as Open Michigan MiFuture in Michigan (2011), London CityDashboard (2012), and Dublin Dashboard (2014). In 2014, the International Organization for Standardization (ISO) published the international standard for the indicators, ISO 37120:2014 [22], which provided a crucial reference for geospatial dashboards for monitoring city performance. In the enterprise domain, OpenGeo Suite released the OpenGeo Suite Dashboard in 2011; a product named Operations Dashboard for ArcGIS software were released by Environment System Research Institution Inc. (ESRI) in February 2018. They both provide mature technology for supporting the development of geospatial dashboards.

2.2. Components of Geospatial Dashboard

The two important parts of dashboards are the indicator and the analytical model. The indicator has progressed from providing binary values for alert to the fine-grained and composite indicators for complex geospatial entities or events. Indicators will be further discussed in Section 3.3.

The analytical model for measuring smart cities has also advanced with fine granularity, dynamic visualization, and interactivity. The geospatial dashboards can offer fine-grained measurements by providing both macro and micro views of the details, i.e., providing details and factors driving the metrics [23]. The map-based dynamic and animation visualization support both static information and real-time data dynamic visualization. For example, progressive changes in a histogram to show the indicator change with the time. This transformation from tedious numeric displays to rich context-based representations provides more insights into the patterns behind the data [16,24,25]. Moreover, analytical models have evolved from a descriptive display to interactive models. For example, the interactive dashboard was used for visual analysis with mathematical algorithms to support decision-making [26] and for interactive exploration of spatiotemporal data [27]. Predictive analysis has also been a growing area but faced more difficulties due to the data inconsistencies and accessibility [3,28]

To integrate the analysis model in geospatial dashboards, two integration patterns can be adopted, as shown in Figure 2: *loose coupling* and *tight coupling*. In the former, the dashboard is independent of models. As shown in Figure 2a, the dashboard is normally used to visualize the result of models. For example, the data resulting from the Analytic Hierarchy Processing (AHP) method are visualized in the geospatial dashboard for decision support [24]. However, for the tight coupling as shown in Figure 2b, they are fully integrated into dashboard systems, meaning that the dashboard components and models are dependent on each other. Many analytic models engage the tight coupling pattern.

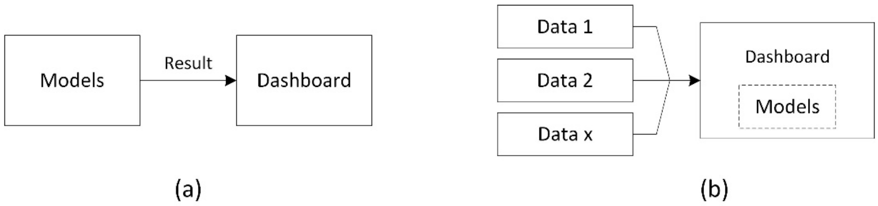

Figure 2. Analytical model coupling pattern. (**a**) Loose coupling; (**b**) Tight coupling.

3. Key Technologies

The development of geospatial dashboards depends on many technologies, which include a system architecture, dashboard design, indicators, and visualization technology. In this section, we will review and evaluate these technologies, and discuss future research interests.

3.1. Architecture

A geospatial dashboard is not only a collection and visualization of geospatial data, but also supports the information mining and decision making [3,29]. Therefore, when considering the multidimensional and heterogeneous nature of geospatial data, scalability, interoperability, and portability are three necessary attributes for structuring a geospatial dashboard.

Scalability refers to the ability to add and remove hardware (including computers and sensor devices), software modules, and graphic user interface (GUI) components for users without affecting the system availability. Widget-based technology is an example of a scalable design that supports the high-level customization of system functionality. In the European Seventh Framework Program (EU FP7 projects), widget-based technology supports the scalability of stream data [30], and environment sensor devices [31] using configurable functions.

Interoperability is a critical feature in the design and building of a dashboard system owing to its multidimensional and spatiotemporal characteristics [32]. London CityDashboard is one example of heterogeneousness with various data, sensors, and users. Semantic interoperability [33,34], geospatial services interoperability [35], heterogeneous sensors, uniform protocol [36], and middleware [37] are the existing solutions to interoperability.

Portability is the provision of access to geospatial datasets and city performance KPI data that can greatly help with understanding city performance [6]. Therefore, one of the challenges in geospatial dashboard design is the accessible portability of geospatial big data to end users for understanding city performance.

As shown in Figure 3, the review indicated that a three-tier architecture has been adopted by many geospatial dashboards, which includes data, analysis, and presentation layers. The data layer manages geospatial data and non-geospatial data using databases. The data models are in charge of data organization and can be mapped to indicator measurements. The models layer includes various analysis models for the indicators, which is the core of geospatial dashboard. The third layer is presentation layer, which is the graphic user interface for the users. The data access and information communication between layers are dependent on the architecture design methodology. Service-oriented architecture (SOA), widgets, model-view-controller (MVC), and event-driven architecture (EDA) are the most popular design technologies.

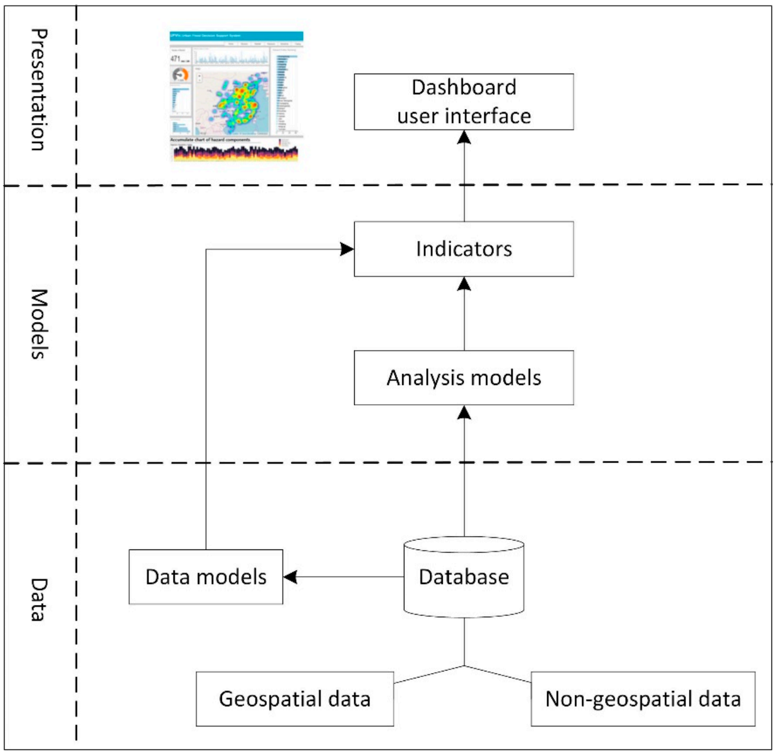

Figure 3. A conceptual architecture for geospatial dashboards.

In the My City Dashboard platform [38], the SOA architecture was implemented, where web services were designed for locations management and noise retrieving and aggregating, which could be used in the data or analysis layers. A widget-based geospatial dashboard was developed for streaming data in the EU FP7 FOCUS project [30] and environment data in the EU FP7 SMART project [31]. Two representative examples of MVC-based geospatial dashboards were the Dublin dashboard [29] and Skopjeinfo dashboard [39]. In both dashboards, the three main components, model, view, and control lie in the data layer, presentation layer, and model layer, respectively, and are independent of each other. Pestana provided an event-driven architecture for surveillance of business activities [40]. The event streams were generated using multiple localization technologies, stored in a spatial data warehouse, and triggered the change in the GUI representation layer.

In short, geospatial dashboards follow the digital dashboard architecture with mainstream principles. However, there still are challenges for design geospatial dashboards. With the exception of the spatial and temporal specific design, the big geospatial data fusion and semantic interoperability for heterogeneous geospatial data both need more attention.

3.2. Geospatial Dashboard Design

The design of geospatial dashboards addresses how information is modeled and arranged on a screen. The experiences and methods learned from digital dashboards can be extended to geospatial dashboard design. This section examines the design principles and summarizes several design patterns for geospatial dashboards based on the review of both digital and geospatial dashboards.

3.2.1. Design Considerations

Dashboard design has partially been considered as communication tools between data and knowledge [10]. Many practices in other domains can contribute to the geospatial dashboard design. In particular, technologies such as user-orientation, visualization perception, and graphic media played an important role in geospatial dashboard design. Generally, dashboard design should consider a number of aspects.

First, dashboard design must be in line with user requirements and the type of dashboard [14]. Emphasizing gauge and metric data is more suitable for operational dashboards during the design phase. However, in analytical and strategical dashboards, a drill-down functional module or complex design is needed to validate the data and mine the knowledge. One example is the adaptable geospatial dashboard for geospatial query and analysis requirements, which supports the adaptive change of user graphic interface according to the spatial functions [41,42].

Second, a better designed visual perception method plays an important role in effectively displaying data [11,43]. The Gestalt psychology method [10,42] and coordinated multiple views (CMV) [42,44] are the main simple and interactive methods used in information visualization design. Rahman summarized six Gestalt principles for geospatial data and applied them to adaptable geospatial dashboard design [42]. However, designing coordinated geo-visualization environments in the context of geospatial big data and integration with non-spatial data are still challenges [44].

Finally, the selection and organization of display media, such as line graphs, bar charts, and bullet bars, are other key issues in dashboard design. A balance between the complexity and media design is needed [10,11]. Some studies conducted by Few have highlighted the pitfalls of dashboard design [11]. Rahman summarized these pitfalls as 13 mistakes and provided examples [42]. Santiago and Shanks adopted these pitfalls when designing a dashboard to support the management of business activities [45]. Understanding these pitfalls contributes to best practices for dashboard design.

3.2.2. Geospatial Dashboard GUI Design Pattern

GUI style, layout of indicators, and integration with map context, are the main issues for geospatial dashboard GUI design pattern.

There are two main dashboard GUI styles, for example, one-page style and drilldown style. Many studies advocate the single one-page dashboard design [10,11,42], in which all indicators are laid out, allowing users to see them all at once. This style is more suitable for displaying indicators in operational dashboards. A dashboard named London CityDashboard is an example of this style. The drilldown style is designed for more deeply observing information. The Dublin, Skopje, and Alaska dashboards are examples of this type of dashboard. The common feature of these drilldown geospatial dashboards is having many indicators that cannot be display in one screen, in which indicators are often designed as menus. The boundary is blurry between the one-page and drill down styles in some cases.

By reviewing the literature and government websites, we selected some representative dashboards from university laboratories or operating dashboards in some cities. We investigated styles from existing geospatial dashboards, as summarized in Table 1. The screenshots of some classical dashboards are shown in Figure 4.

Table 1. Adoption of the two different dashboard styles.

Name	Dashboard Style	Layout Pattern	Design Feature
London CityDashboard	One-page	Row-column	Supporting graphic user interface (GUI)configuration; no drilldown but other linkers for indicators
Dublin Dashboard	drilldown	Row-column and menu	Multiple dashboard supporting drilldown; some dashboard support map context
Bandung dashboard [46]	One-page	Row-column and filter	With map context
Edmonton citizen dashboard	One-page	Row-column	With the KPI and goal state, no map context
Boston performance management	One-page	Row-column	Sorted by title, supporting drilldown to detailed information page
Skopje dashboard, Macedonia	Drilldown	Menu and row-column for sub-indicators	With map context; supporting configurable for sub-indicators
Sydney CityDashboard, Australia	One-page	Row-column	Supporting switch between grid view and map view
Iowa dashboard, USA	One-page	Row-column, filter	Supporting filter view; chart and graph are the main media
Alaska HMIS dashboard, USA	drilldown	Menu and filter	No map, graph and table, filter for detail
OSU Columbus dashboard	One-page	Row-column, menu	With menu on homepage; map context

The layout pattern of media components and indicators represents visualization salience and attention cues, which include row-column array, menu style, and filter style, as shown in Figure 5. In the row-column array pattern, indicators are arranged as row and columns, which are used for multiple indicators (Figure 5a). A representative example is the London CityDashboard [47] (Figure 4a). The screen is divided into a small grid for indicator display. The menu pattern is based on themes, in which each menu indicates one independent theme. As shown in Figure 5b, the menu area lies in the left, meanwhile, the right is the indicator workspace. This style has potential application in analytic dashboards and strategical dashboards for deep analysis on specific themes. The Dublin dashboard is an example of the menu pattern (Figure 4b). The filter style is designed based on some rules for the required data and information, which are powerful for synthetic analyses such as spatiotemporal visualization. The layout is shown in Figure 5c. The left side has the various filters, and the right side has the indicators. The Iowa dashboard implemented filter functions for efficient data access (Figures 4c and 5c).

Integrating the map and other indicators has two mainstream patterns, as shown inFigure 6: the map as part of the GUI, and the map as the background of the GUI. The former is often used in the CMV method, in which the map is only one of the view media, as shown in Figure 6a. The Skopje dashboard (Figure 4c) is one example. The heat map of the population is displayed as one of the media elements, which is coordinated with other graphical charts. Another integration method is using the map as the background of many indicators, as shown in Figure 6b. This pattern can be used to compare multiple indicators, infer their relationships, and discover knowledge based on the map's context. The Dublin real-time traffic and travel dashboard (Figure 4b) is one example.

In general, design principles, special considerations, patterns and interface design have been studied in the past with respect to the design of a workable geospatial dashboard. However, the existing designs are often used for representing information or knowledge rather than for extracting knowledge. Furthermore, these studies on dashboard design had little consideration of adaptive design that is used by multiple stakeholders. Therefore, designing smarter modules for handling big data and dynamic sensor data to extract knowledge and meet the requirements of various stakeholders is part of important future work.

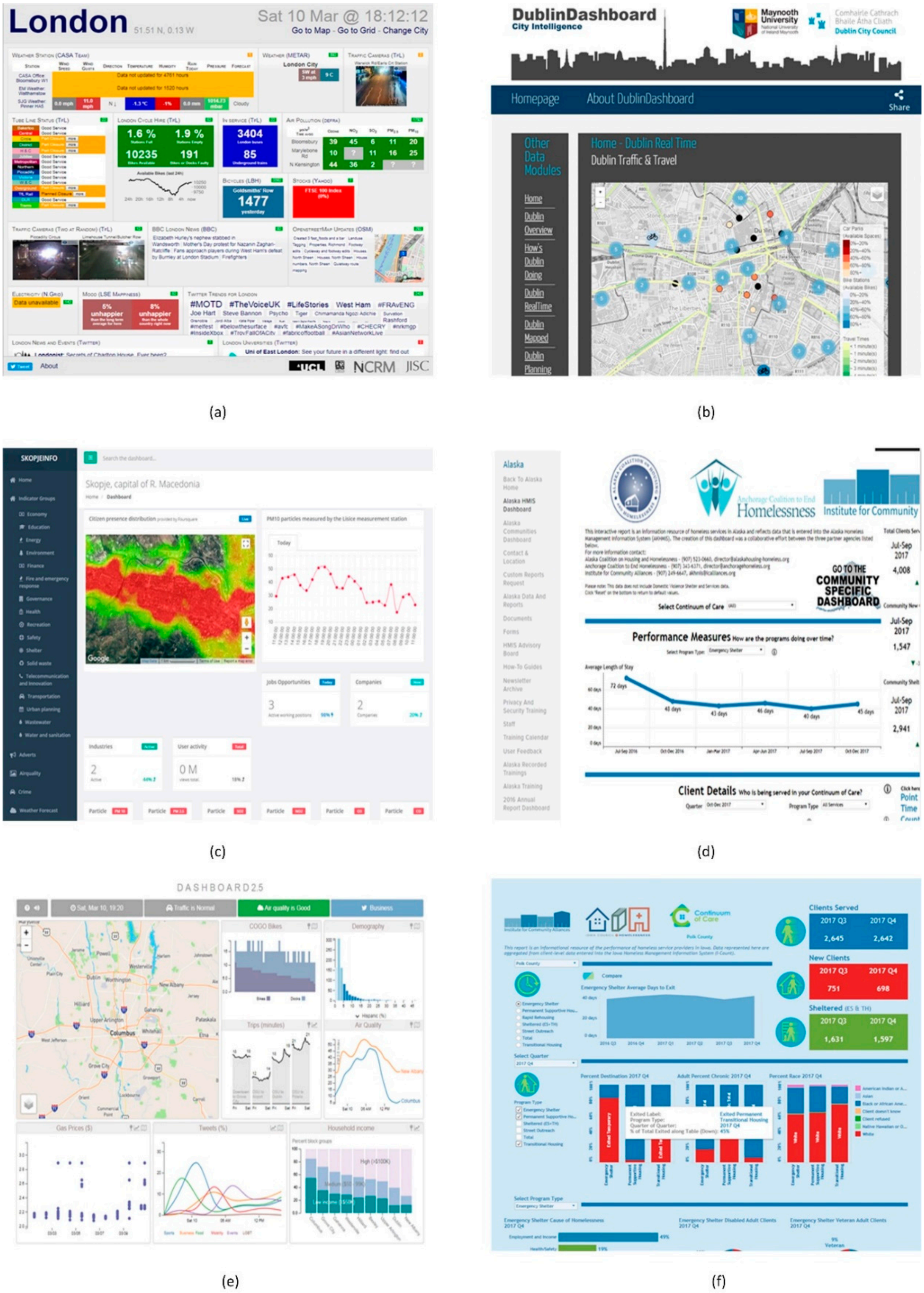

Figure 4. Screenshots of some example dashboards. (**a**) CityDashboard London, one page with row-col, (**b**) Dublin Dashboard, drilldown with menu, (**c**) Skopje dashboard, drilldown with menu, (**d**) Alaska dashboard, drilldown with menu, (**e**) Columbus OSU dashboard, one page with row-column, and (**f**) Iowa Dashboard, one page with filter.

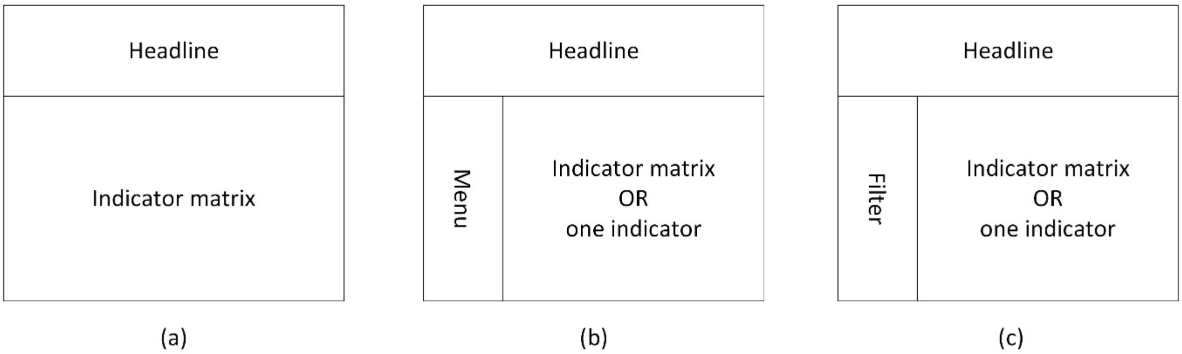

Figure 5. Layout patterns of dashboard: (**a**) row-column array, (**b**) menu style, and (**c**) filter style.

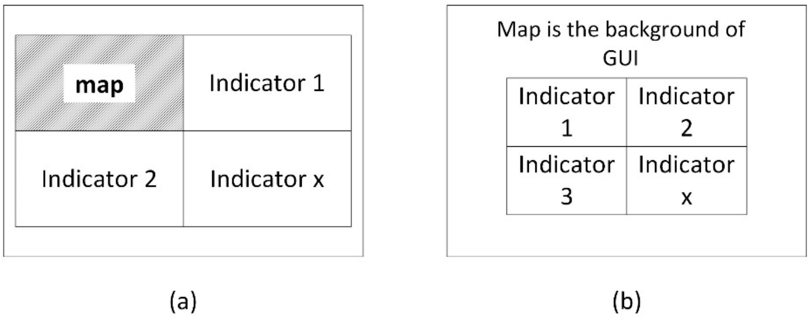

Figure 6. Patterns of map and indicator integration design. (**a**) Map as part, and (**b**) Map as background.

3.3. Geospatial Dashboard Indicator

3.3.1. Indicator Development

The indicator acts as a gauge to measure how well or poorly some aspect performs. Integrating these indicators, some models or frameworks were developed to monitor the performance of cities. For an example, the smart city reference model, composed of seven interconnecting city layers with indicators, was developed to evaluate a city's success in reaching sustainable goals [48]. The indicators of cities should be tailored to quantitatively measure the progress toward achieving the unique goals set by each city. For example, the Edmonton Citizen Dashboard is structured over six key topics and their subtopics: transportation, livability, environment, urban form, economy, and finance, while the Birmingham, Bristol, and Manchester in the United Kingdom are obliged to measure a large number of city KPIs against their city strategies and actions [49].

Development of city indicators were driven by two main forces [28]. The first is the urban sustainability agenda that proposed the international standard urban indicators named ISO 37120 [28,50,51]. It is categorized into 17 themes related to economic, social, and environmental performance, which are used to measure the performance of city services and quality of life [22]. In addition to the ISO standard, many other urban indicators have been analyzed and compared in the literature, such as Global City Indicator Facility and European common indicators [1,39,52,53]. Compared with ISO 37120, these indicators provide real-time temporal, spatial, and personalized performance monitoring [39]. Second, the new urban managerialism has promoted the development of urban indicators [28,54,55], with the target of improving the efficiency, effectiveness, and transparency of city services for public section management, to encourage citizen's participation in urban planning and management [28].

Numerous classifications of indicators exist. Alibegović et al. summarized indicator classification as policy-based, a thematic approach, or a system approach, which are widely used by international agencies [56]. Kitchin et al. classified them as single indicators and composite indicators with respect to indicator rationale [2]. The former means only one indicator is used to measure one aspect; the latter is the combination of several indicators for complex measurements, such as using household income, employment information, and health status to provide a single overall score. Kitchin et al. provided another indicator classification system with the following categories: descriptive or contextual indicators, diagnostic indicators, and predictive indicators [28]. Descriptive indicators provide evidence for the city performance, diagnostic indicators can be used to probe the cause of the phenomenon, and predictive indicators can be used to predict and simulate future situations and performance. Analyzing these indicators, we conclude that they are heterogeneous in their measuring methods and covered topics [1]. Building a set of unified indicators for all applications is a difficult task. Selecting appropriate indicators for each city is always a good practice.

3.3.2. Application of Indicators in Geospatial Dashboards

Based on our review, a workflow for integrating indicators in dashboard applications is proposed in Figure 7, which includes four stages: business requirement, indicator selection and aggregation, modeling, and indicator implementation. Since the business requirement analysis and indicator implementation involve specific businesses and technology, they are not discussed here. We put more emphasis on the indicator selection, aggregation and modeling. The spatiotemporal characteristics of urban areas increase the difficulty of integrating indicators with a geospatial dashboard compared with the numerical indicators based on statistics. Therefore, selection and modeling of indicators in geospatial dashboards are more challenging than in traditional digital dashboards.

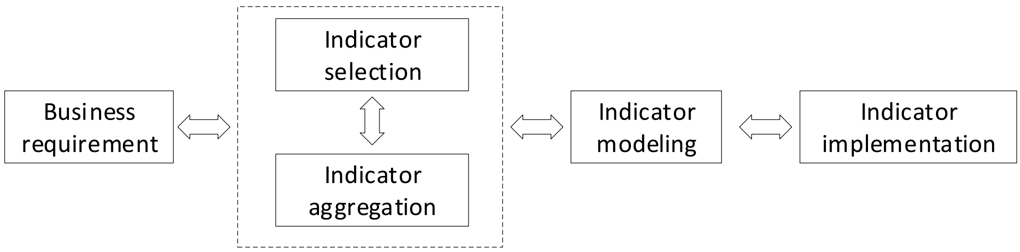

Figure 7. A workflow of integrating indicators in dashboard applications.

Fernandes extended the general selection principles of the International Telecommunication Union into a smart city, which include comprehensiveness, comparability, availability, independence, simplicity, and timeliness [52]. Kitchin et al. argued that the selection of indicators should be politically-, data-, or economically-driven [28]. Veleva et al. developed an iterative conceptual model with five steps for selection of indicators (see Figure 8) [57]. In Figure 8, indicator selection will include identifying potential indicators and selecting suitable ones, and monitoring the progress of the implemented indicators against the set targets. Based on this theory, Mathijsen used this model for defining and selecting indicators and used it in Vught, the Netherlands [58]. For indicator aggregation, weight determination, spatial distribution, and aggregation methods are the key issues. For weight evaluation, multiple-criteria decision analysis (MCDA) [59] and the analytic hierarchical process (AHP) [60] have been widely used. Different aggregation methods are adopted according to the purposes of projects. For example, multiple aggregation methods for flood vulnerability assessment indicators in flood management were compared [61]. ATKearney Global Cities Index blended five dimensions of simple indicators with weights [28,62].

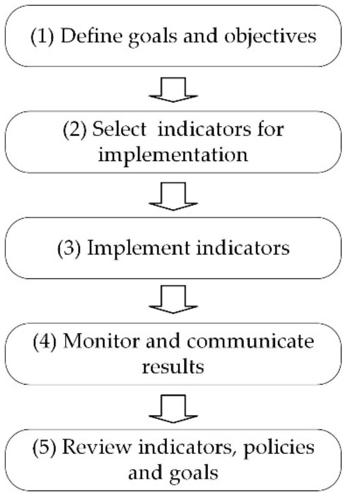

Figure 8. Model for the selection and measurement of indicators (modified from Veleva et al.).

Modeling indicators faces challenges with robustly organizing and representing indicators [63]. Ontology and the knowledge graph were proposed. Fox introduced ontologies as the semantic description of the ISO indicators for the city indicators in the Polis Gnosis Project [64]. Santos et al. used a knowledge graph to discover and describe urban indicators [63].

Lessens can be learned from past development of geospatial dashboards on designing a good set of indicators to work seamlessly within dashboard environment following the process shown in Figure 7. It is also clear from the review that the trade-off between indicator standardization and specific dashboard requirements matters. The indicators with spatial and temporal dimensions require special effort in their selection, modeling and implementation. Semantic representation of indicators is another challenge. The existing studies put more emphasis on its organization rather than its quality such as uncertainty quantitation. Therefore, novel semantic representation algorithms considering data uncertainty or model uncertainty need to be further studied.

3.4. Data Visualization

3.4.1. Data Model

Along with the availability of new sensors and new methods of collecting all kinds of data (such as the volunteer geographic information data collection method) in smart cities, completely new data sources and types related to city performance across economic, social, and environmental aspects are available. This has inspired data model development for data access and organization in geospatial dashboards. Extending the traditional models and proposing new models are the focus of research.

Extending the traditional file-, database-, and services-based methods can be used for data access and handling. Venek et al. [30] proposed pull- or push-base dissemination methods based on open geospatial consortium (OGC) web feature service (WFS) to integrate streaming data into dashboards. Two geospatial dashboards, CityEye and My City Dashboard, used the RESTful application programming interface (API) to integrate real-time data in dashboards [38,65], which included data from sensors, cameras, social feeds, and real-time location tracking data.

Star schema, the big data model, and the semantic model are new technologies [66]. The star model structures one-dimensional data into a star schema, which can link to other schema using common tables. This simplifies multidimensional data query and analysis, which supports various drill down, roll up, and slice and dice data operations. This data model has been applied in public infrastructure planning [67] and utility network analysis and visualization [68]. Big data models, such as the hive model, support massive amounts and multi-dimension data. This model has been used to fuse massive complex and unstructured data for decision support [69,70], big environment data management [71], and the smart city dashboard in Stockholm [69]. The semantic models represent and model knowledge from geospatial data. Sheth et al. proposed the continuous semantic data model to bridge the gap between domain concepts to indicators, which improved the effectiveness of information transfer [72]. Santos et al. used the knowledge-graph-based data model to compute indicators for bicycle-sharing performance in a city in Brazil, which generated high-level composite indicators for decision-making [63].

To sum up, these data models can provide matured data organization schema for geospatial dashboards. However, the data model with spatial and temporal dimensions for big geospatial data should be developed urgently. It can result in the efficient extracting knowledge by supporting big data analysis. Another issue is that these existing models do not consider the metadata organization schema. Particularly, for the real time sensor data, the metadata is lacking. If one model can infer metadata and enable the user to be aware of it, then the indicator needs to be more precise to measure performance.

3.4.2. Data Visualization and Visual Analysis

Visualization technologies and interactive visualization have received considerable attention. Geospatial information visualization is crucial for information summary and abstraction, especially for quantitative data and operational dashboards [14,42]. A well-designed dashboard with better visualization methods can simplify data and help with knowledge mining.

Many methodologies are used for geospatial data visualization, such as heat maps or cluster maps, which are used to describe spatial patterns, outliers, or clusters. In addition to location information, visualizing the attributes of geospatial data helps with mining knowledge. However, most of these data are semi-structured or unstructured data. Word cloud and network diagrams are the most popular techniques used for these types of data [73]. Given the multiple dimensional nature of geospatial information, some particular visualization methods have been developed, such as the space-time cube method and multiple-linked view. The space-time cube is a tool used to aggregate spatiotemporal data for visual analysis to find feature events. For example, Newton et al. used the space-time cube to detect vehicle-stopping behaviors [74]. The multiple-linked view is another visualization technology that allows the user to work with various visualizations among multiple views [6,75], which is more effective than using views separately [76]. Sjobergh and Tanaka developed a geospatial dashboard based on multiple-linked views for real-time data visualization, and applied in snow removal in Japan [77]. Rahman included this visualization method in spatiotemporal origin—destination airline data exploration [42]. These existing visualization methods can unfold the patterns behind data, but they may be incapable of meeting user on-demand visualization. With the assistance of the user's background knowledge, interactive visual analysis can partly resolve these concerns. Interactive visual analysis provides new opportunities to reduce computation bias. The computational algorithm is a black box with only input parameters and output results, in which users are not aware of the processing. Interactive visual analysis helps users to retrieve to specific information when necessary. Al-Hajj et al. designed an interactive dashboard to integrate visual analytics into the decision-making process [26]. An interactive visual analytics approach helps to extract and explore spatial knowledge to detect characteristic spatiotemporal patterns [78]. An interactive dashboard for visualizing big spatial-temporal data in an urban area was designed and implemented by Xiao et al. [27]. Map context analysis provides interactive map operations or geospatial algorithms that can reduce complexity and summarize complex spatial data sets [44]. For example, spatial clustering algorithms have been adopted for large and complex datasets with interactive visual analysis [78].

Experiences from these reviewed visualization methods are helpful for the knowledge extracting. However, these methods do not consider the uncertainty of data and model, which can affect the accuracy of analysis, and users may not be aware of its uncertainty. Furthermore, it is clear that the interactive visual analysis can meet user's on-demand requirements, but it cannot support all stakeholders with one method. Therefore, more efficient knowledge extraction methods with appropriate information should be developed in the future research.

4. Dashboards for Monitoring Smart City Performance

4.1. Urban Indicators Used for City Performance

Geospatial dashboards have been used in various areas of smart cities, such as urban planning and governing [65], and social analysis [79]. These studies proved the concept that dashboards are "more than just a communication tool or scorecard for city performance, dashboards can be built with business-intelligence and models for analysis and predictive decision support" [3]. As mentioned previously, indicators are used to monitor and identify the level or stages of the city for ranking and positioning in the dashboard. The importance of indicators was proved by making proper decisions and clear communicating city performance to citizens, administrative, potential investors, and so on.

The city development index (CDI), developed to readjust the human development index, is one of the best-known indicators [80], which was issued by United Nations Development Programme (UNDP) Human Development Report Office. Dameri investigated many studies and summarized seven city indicators [1]: urban audit (UA), European common indicators (ECI), global city indicators facility (GCIF), quality of life (QoL) reporting system, cities data book (CDB), global urban indicators, and global sustainable urban development (GSUD). Analysis of these indicators highlights their heterogeneous nature in terms of spatial coverage, dimension of indicators, and their goals. The spatial coverage indicators support multiple spatial scales from global and regional to city levels. The UA is scalable for multiple city levels, from the administrative boundaries, functional urban areas or commutes, and greater city areas. UA has been used for comparison of European cities. QoL is a regional indicator for Canada. The global city indicators issued by the United Nations (UN)-Habitat is global. In terms of the goals of indicators, the ECI is designed for environmental monitoring, whereas GSUD covers the social, environmental, and economic dimensions to provide a comprehensive view of a city. The mission of UN-Habitat's global city indicators is to promote quality of life.

Although many classification are discussed in Section 3.3.1, the following two categories are generally used for the smart city performance: core indicators and advanced indicators [81]. The former can be universally used in all cities and provide a basic measurement of city performance. The latter provide a holistic and in-depth view of city performance. Indicators are components of the framework for evaluating city performance, which includes economic, environmental, and social dimensions.

4.2. Dashboards for City Performance in Practice

Geospatial dashboards for monitoring smart city performance have been used in one of the two application patterns: a control or command center, and citizen engagement tools that allow users to be informed about a city's performance [28,29]. Examples of the former are city-level dashboard platforms such as the London CityDashboard and Dublin dashboard. This type of dashboard is designed for monitoring the performance of the whole city. Conversely, particular applications may focus on certain aspects or themes of city performance such as flood monitoring, which are the representative examples of the latter form.

Geospatial dashboards for smart cities provide synthetic analysis and visualization of urban data. London CityDashboard and Dublin Dashboard are representative examples of geospatial dashboard platforms, which have been extended to other cities such as Amsterdam and Manchester. These dashboards can quickly transfer up-to-date overview information to city managers and citizens [28]. Some in-practice city-level dashboards are summarized in Table 2. The data and extensions were examined in this table.

Table 2. City-level dashboards in practice.

Name	Data	Some Extensions
Dublin Dashboard	Static information, real-time information, time-series indicator data, and interactive map	Dublin housing, Dublin planning, Dublin report
London CityDashboard	Sensed data, social media information, and official reports in CSV or HTML format	Eight cities in the U.K., a number of bespoke projects such as Amsterdam
Skopje dashboard	Four groups: statistical and municipal information systems data, municipal Internet of Things (IoT) data, social data, and personal sensor data	Disaster risk reduction and crowdsourcing information from citizens
CityEye	Three categories: environment sensors data, KPI data generated from external services providers, and data generated from citizens	Two modules: website for overview indicators and mobile app for local view.
Search-the-city	Support sensor data, video data, indicator gauge data, and real-time data	Can be extended as an urban sensing or urban monitoring platform

We thoroughly reviewed the thematic applications of dashboards (see Table 3). These applications cover the social, environmental, and economic dimensions, which form a holistic view of city performance. In some popular fields such as traffic and urban planning or management, there are more related praxis of these dashboards. From the technology aspect, all three types of dashboards are involved in discussion, but the analytical type is the most common (16 out of 24 applications). Only 2 of the 24 applications are strategical dashboards due to the lack of sufficiently consistent data and predictive models [3]. The operational dashboard is often used to depict the performance of some measures, especially in environmental and economic areas. The analytical dashboard is suitable for socially-related fields, such as urban floods and traffic, due to its ability to provide tools for insight into performance and to unfold the patterns and reasons for the patterns. For the policy-related applications, such as urban governing and urban management, the strategic dashboard is capable of supporting decision making and predication, being applied in both urban governing and management.

Table 3. Applications of dashboards.

Area	Type	Key Application Features
Energy	Analytical	Decision-making based on defined knowledge rules in a smart grid [82].
Environment	Analytical	Environmental building performance analysis and visualization [83]; event dashboard to visualize data, detect events, and monitor the environment [84].
	Operational	A zoomed dashboard with a five-level location scale for architecture engineering and construction [85].
Social	Analytical	A big data dashboard for urban mobility for city operational and planning purposes and as a learning system [86]; a widget-based dashboard to support scholars' awareness of their research networks [79]; a real-time dashboard system with multimodal social intelligence [87].

Table 3. *Cont.*

Area	Type	Key Application Features
Traffic	Analytical	A real-time dashboard for online visualization of streaming data including from the social media data and traffic data [30]; an event-driven architecture for spatiotemporal surveillance of business activities [88]; a dashboard for real-time traffic data inferred from social media data such as tweets using state-of-the-art machine learning algorithms [89].
	Operational	An adaptive dashboard that provides users with tools that change the GUI according to the required context of user [15,41]; a spatial dashboard for presenting the safety performance of vehicles in airport, one part of the AIRNET project [90].
Urban development	Operational	Dashboard of sustainability (DS) to support the decision-making process in sustainability evaluations [91].
Urban flood	Analytical	An analytics dashboard visualization for flood decision support system [92]; a dashboard built on open-source frameworks, made use of geoservices based OGC, and established a wireless sensor network [93].
Urban governing	Analytical	A dashboard to monitor local policy and its objectives concerning the decentralizations in the social sector [58]; an analytics geospatial dashboard for a water management system [94].
	Strategical	A dashboard for city management using big data from people and traffic flows [95].
	Operational	A dashboard for urban governance and an urban safety measuring indicator model [80].
Urban management	Analytical	CityEye, a platform that integrates operations, sensor, and citizen feedback data through a web-based dashboard and a service-based mobile application [65].
	Strategical	A knowledge graph for supporting automatic generation of dashboards, used in the bicycle-sharing system in Fortaleza, Brazil [63].
	Operational	A dashboard with which all visualized results can be interacted, and selections or groupings using one visualization result [77].
Urban planning	Analytical	A dashboard as a decision making tool for higher education planning [96]; an interactive dashboard for visualizing big spatial-temporal data in an urban area [27].

4.3. Best Practices for Measuring Smart City Performance

Geospatial dashboards have been applied in many aspects of smart cities. However, the performance of the dashboard in monitoring smart city performance must be evaluated. This section outlines the best practices for geospatial dashboards according to three dashboard types.

The operational dashboard is the most popular geospatial dashboard, which engages the indicator to focus on the monitoring and visualization performance of smart city. The main usages of indicators include indicator visualization, indicator mapping, and analytic result validation.

- The indicators for monitoring performance answer the "what is it?" kind of question. Therefore, they are also called operational or descriptive indicators [28]. For example, indicators inferred from social media data were used for traffic conditions performance [89]. Adaptive indicators were used for various visualization requirements in operational dashboards [41,42].
- Indicators are mapped to uncover patterns. Due to the cognitive advantage of maps, indicators can be mapped to unfold their distributions or spatial relationships. For example, the citizen presence distribution is mapped as a heat map for the human mobility indicator in the Skopje dashboard. For location tracking applications, location streaming data are dynamically mapped online [30].
- Indicators are used for validating results. In some applications, the geospatial dashboard provides a better validation solution for the results of a third-party analysis model, for example, the candidate location resulting from AHP based on geospatial data [24] or traffic information based on multiple data source fusion analytic model [88].

For the analytical dashboard, the analysis model is its core that is used to explore the reasons behind patterns and results [2,97], which includes visual analysis [92,94], spatiotemporal analysis [27], and decision support [90,93]. To integrate models into dashboards, data exchange and application program interface (API) callback are the most popular methods. For example, dashboards integrates some business analysis models to access and interpret city data [28]. Another example is that spatiotemporal analysis is used to extract knowledge from a large repository of voluminous and varied data using the geospatial API.

Strategical dashboards can be used to predict and simulate future situations and performance, such as predicting human mobility [95] and inferring city performance [63]. Due to the complexity and inconsistency of data, developing such predictive models has been challenging [3]. However, it is presently a growing field [28].

Overall, from an application point of view, geospatial dashboards should focus more attention on the map-context visualization or knowledge extraction due to powerful and clear perception gained from maps. However, existing applications focus on the various data fusion to provide city performance measurements, rather than developing a big geospatial data analysis model for knowledge extraction. Although many geospatial dashboards have developed, less attention has been paid towards the prediction and strategical analysis for the decision making. Another concern is that these dashboards put more emphasis on the data and did not pay much attention on the uncertainty and veracity of data or model. Thus, the quantitative and visualizing methods for data uncertainty or model uncertainty should be developed for efficient and appropriate decision-making, which will surely support the development of predication and strategical dashboards.

5. Challenges and Future Directions

The development of geospatial dashboards is interdisciplinary and relies on technological advances, which has attracted the attention of researchers from computer science, geographic information science, and urban planning. Combining geospatial dashboard with big data would advance the geospatial dashboard research on visualization and decision support.

5.1. Visualization and Analysis Challenge from City Big Data

The increase in geospatial big data has created a challenge for data visualization and analysis in smart cities. Geospatial dashboards do not just simply describe the performance of smart cities, but also actively help create new visions of cities that reshape policy formulation and decision-making [2,3]. However, both the volume and complexity of geospatial data increase the challenge for geospatial dashboard development.

Despite the significant progress of ICT and other related technology, challenges remain in developing novel visual algorithms and analytic models for geospatial dashboards in smart cities. Particularly, the space and time characteristics have created some additional challenges in geospatial dashboards: (1) determining how to extract appropriate knowledge integrating geospatial information and numeric information. Although visual summary models for numeric information have been developed, these approaches are challenged with efficiently and appropriately using big geospatial data. Therefore, developing a specific geo-based knowledge extracting model is one of challenges for geospatial dashboards. (2) Designing an adaptive geospatial dashboard including functional modules and user interface layout to satisfy various stakeholders in smart cities is another challenge. Multiple stakeholders in smart cities mean various requirements for geospatial dashboards must be met. Although some research work, such as map cartography quality metrics, can provide different experiences, the new challenge is developing new methods for geospatial dashboards. (3) The third challenge is how to prompt the efficiency of decision making for smart cities based on the geospatial knowledge and technologies. Geospatial dashboards support the synthetic visualization of information, which supports decision making. However, new algorithms or models need to be developed to improve the decision making efficiency.

Considering these additional challenges faced by geospatial dashboard, further research interests may include:

(1) Big data fusion on map to aid the extraction of knowledge. Numeric information is more abstract than a map; therefore, a fused-information-based map would help visualize the indicator distribution and patterns, and reduce the complexity of extracting information.
(2) Developing map-based visualization and analysis algorithms for geospatial dashboards. Map-based or geography-based algorithms support interactive visualization analysis and big data. They may satisfy multiple stakeholders through interactive analysis.
(3) Extending dynamic visual analysis for synthetic indicators. The short period for data updating and real-time sensor data need dynamic analysis functions that support synthetic indicators for knowledge generation and transformation. This research should cover the weight determination of multiple factors, highly efficient computation, and other interests.

5.2. Veracity of Data and Model for Decision Support

Studies have argued that the veracity of geospatial data is a substantial challenge [98], which affects geospatial dashboards due to using similar data sources. The two main challenges for geospatial dashboards are data veracity and the uncertainty of analysis models, which affects knowledge extraction and decision making.

The veracity of data arises from the multiple data sources, and different paradigms such as accuracy, scalability, and timely available of the data [99,100]. The problems with data veracity are the insufficiency and lack of metadata that describe the data properties [2,6,101], which limits the data fusion and analysis in geospatial dashboards. Therefore, the first challenge is how to precisely and efficiently extract knowledge without metadata, which is more difficult for real-time data such as stream data due to the lack of explicit metadata about content and accuracy [100].

The second challenge is measuring the uncertainty of data and the model in geospatial dashboards, and inform users. The accuracy of analysis models is affected by the accuracy of the input data and parameter uncertainty. As stated by Kitchin et al. [2], "garbage in, garbage out", meaning less valid or inaccurate data may mislead decision-making, which is the same for model parameters. Therefore, quantitative research on uncertainty and informing users are both crucial to understanding decisions resulting from geospatial dashboards. The representative example is the modifiable areal unit problem (MAUP) in geospatial data, wherein the opposite results may be obtained when using different spatial scales or parameters.

In these regards, further research work may include:

(1) Inferring algorithms for metadata based on heterogeneous data. Metadata are crucial to understanding urban performance; therefore, more efforts are needed for inferring metadata. These algorithms should pay more attention to scalable and timely data and the spatial dimension of data, particularly for VGI and stream data.
(2) Quantitative measurement and visualization of uncertainty. Although smart cities and big data have been well studied, the quantitative and visualization of uncertain big data and analysis models still remain major challenges [6,102]. This research should measure uncertainty and ensure users are aware of any uncertainty, which would help with the interactive selection of analysis models.
(3) Quality assessment-based analysis algorithm. The traditional algorithms in geospatial dashboards produce certain results. However, when considering the data validity, the result may be uncertain or unstable. Novel algorithms depending on probability and based on quality assessments should be developed for geospatial dashboards.

(4) Ontology interoperation between heterogeneous data. Although space-time is the main feature of geospatial data, semantic heterogeneity among heterogeneous data increases the complexity of analysis models. Ontology-based technology can provide solutions for semantic interoperability [63]. Extending space and time dimensions with a semantic dimension would help with extracting knowledge in geospatial dashboards.

6. Conclusions

We conducted a critical review on the development of geospatial dashboards, from its evolution to key technologies, applications, and challenges, in which theory and technology for architecture, design, indicators, and visualization were examined. The results suggest that some evidence exists that geospatial dashboards can help monitor smart city performance. Geospatial dashboards support urban sustainability goals and new managerialism, and are considered to be a powerful knowledge communication tool for smart cities. The several geospatial dashboards used for smart cities provide evidence of feasible solutions for monitoring city performance. We further identified common designs for geospatial dashboards, including three-tier architecture framework, model coupling patterns, dashboard GUI design styles, and conceptual models of indicators. Based on the review, future research challenges were discussed.

Ethical issues [9] and big data technology are equally important and key aspects especially in the geospatial field. They are necessary for geospatial data handling and management, but were not included in this paper because this paper focuses on the measurement of smart city performance. Furthermore, the advantages and disadvantages of key geospatial dashboard technologies will be investigated in future work.

Geospatial dashboards have both challenges and opportunities. As ICT and smart cities develop and once the challenges addressed in this paper are solved, the opportunities highlighted by geospatial dashboards could be extended to all aspects of smart cities.

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