Toward Human-Machine Interaction: An Interactivity Analysis of the Existing COVID-19 Dashboards

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Keywords: map interactivity, human machine interaction, gis, dashboard, solap, information interfaces and presentation

Introduction

The tremendous health, societal and economic impacts of COVID-19 have motivated the scientific community to explore the pandemic worldwide (Dowdy & D'SOUZA, 2020). Geographic Information Systems (GIS) as an interdisciplinary research field through various spatial tools and methodologies can provide new insights into the pandemic (Shao et al., 2020; Wang, 2010; Rey & Anselin, 2010). The John Hopkins COVID-19 Dashboard exemplifies a cross-collaborated project involving GIS tools and technologies under the hood (Johns Hopkins, 2020). Up until the time of crafting this research, there have been a total of 71 dashboards developed worldwide to present COVID-19 information. Some of the present dashboards have partially employed GIS in their frameworks. However, spatial computation, exploratory data analysis, and spatial data exploration tools have yet to become fully integrated within the academic and professional frameworks. Therefore, many existing COVID-19 dashboards only provide basic information (i.e., last week's total cases) and do not allow users to interact with or customize the data visualization.

Evaluating the interactivity level of dashboards is important regarding the goal of human-machine interactions and online knowledge discovery mentioned in MacEachren's cartography cube (MacEachren et al., 2004). According to MacEachren's cartography cube that categorizes maps by three dimensions. The first dimension conceptualizes maps as either private thinking or public communication. The second dimension groups maps based on their presentation versus creation of knowledge. The third dimension categorized maps based on their interaction levels. Maps with high levels of interaction enable users to manipulate and combine data compared to low interaction level maps, which just present predefined information/data.

In this research project we explored 71 COVID-19 dashboards, representing 51 states, 5 Universities, 5 broadcast companies, and 10 internationally recognized sources. We developed an evaluation scheme to measure the interactivity level of the existing dashboards with a focus on GIS.

Methods

We classified the existing COVID-19 dashboards based on their interactivity levels, separated them into three groups of interactivity components (Figure 1). Levels of interactivity were defined by the controls used. Basic interactive components included mouse events such as panning, zooming in and out. Data interactive components enabled the user to customize the cartographic attributes of the map, like map color scheme and base map selection. They also allow visualizing different data sets on the same map, exporting information, and displaying statistical charts and diagrams. Exploratory components consist of more advanced features like time-series animation, spatial and/or temporal scalability, data reclassification, and visualization of pre-processed data (e.g., clustering information).

Map Controls (Basic)	Data Interaction (Intermediate)	Exploratory Tools (Advanced)
Pan	Color Scheme Selection	Animation
Zoom in/out	Change Base Map	Change Geographic Scale
Hover	Charts or Diagrams	Change Temporal Scale
Click	Choose Data Layer	Data Reclassification
Scroll	Export Map	Pre-Processed Information

Figure 1. Interactivity levels and associated map features

We also considered three criteria to expand our evaluation. These criteria consist of temporal resolution and scalability, processed data visualization, and spatial versus non-spatial data visualization. The binary factor of spatial visualization checks whether the dashboards provide any spatial maps to represent a piece of georeferenced COVID-19-related information or not. Likewise, the non-spatial visualization criterion categorizes the dashboards based on their ability to present the disease statistics in the form of charts and figures. Temporal resolution and scalability is a factor that first identifies the temporal resolution of the maps then checks whether changing the time scale is enabled or not.We also explored the websites by the type of their information layers to see what portion of them provide pre-processed information. In this criterion, we considered any combination of at-risk population and disease counts as incidence, and any type of averaging was categorized into one single group.

Results

The result of our dashboard survey analysis showed that most of the existing frameworks have implemented only the basic and intermediate levels of interactivity. According to figure 2, there were only three dashboards that had at least one exploratory tool implemented.

	Static	Basic	Intermediate	Advanced
Map Controls		✓	✓	✓
Data Interaction			✓	✓
Exploratory Tools				✓
	7	36	25	3

Figure 2. Interactivity levels and associated map features

Based on our observation, 91% of the dashboards provide spatial information (i.e., maps) and about 92% present non-spatial information like charts and tables. About 76% of the dashboards provide only cumulative counts of the disease cases and mortalities, 4% show only today updates, 7% represent the data daily and enable date selection, 1% provides the information weekly, and roughly 11% of them provide only two temporal resolutions to the user. According to our observations, 57% of the dashboards provide only the raw counts of the disease cases and deaths, 37% represent incidence layers, 4% perform some type of averaging on the raw data, and only 1% provide weekly clusters as a spatially processed data (see Table 1).

Table 1. The result of evaluation for each criterion.

Temporal Resolution and Scalability	Cumulative Cases	Today Only	Daily Cases	Weekly	Multiple Time Scales
Dashboard Counts	53	3	5	1	9

Processed Data	Raw Counts	Weekly Hotspots	Average	Incidence
Dashboard Counts	40	1	3	27

	No	Yes
Non-spatial Visualization	5	66
Spatial Visualization	6	65

Conclusion

Our results show that most of the existing COVID-19 dashboards are lacking an analytical module to allow users to produce knowledge rather than visualize the pre-defined information. This study highlights the necessity of the development of a Spatial Online Analytical Platform (SOLAP) that integrates spatial analysis tools that enable users to explore and learn more about spatial patterns of COVID-19. We suggest that an ideal COVID-19 SOLAP should be composed of three elements: 1) spatial data, 2) geovisualization 3) spatial analysis methods such as spatial clustering.

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