Preparedness for visualization in the next pandemic

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Abstract—This article discusses considerations on how visualization can be best positioned to help response to future pandemics. We examine visualization, along with the corresponding and necessary enabling technologies and platforms, as a tool to facilitate a rapid and effective response to a forthcoming pandemic. We consider challenges in terms of an infrastructure supporting world-wide response, corresponding training and stakeholder engagement, integration of future technologies, and appraisal of such systems, Finally, we discuss how addressing these challenges also helps emergency response beyond infectious diseases.

Data visualization became an important element of our response to the COVID-19 pandemic. It was used to inform decision making from governments and organizations, to frequently inform the public through different media, to assess the impact of implemented policies, and to facilitate epidemiological analysis. Such usage examples highlight the versatility of visualization to be applied in a plethora of applications, as well as indicate its multifaceted importance in responding to future pandemics.

In this article, we discuss how visualization can continue to play such an important role in future pandemics response, both in terms of how it can be applied in our preparation for them, as well as considering how we can utilize it better during such events. We elaborate on six key challenges (see Figure 1) relating to the use of visualization during the COVID-19 pandemic, as identified from published works (e.g., [3], [5]) and discussed during the Dagstuhl Seminar 24091. We map these challenges to corresponding actions (see Figure 3) that we propose to prepare for future pandemics and beyond.

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In our analysis we consider important visualization enablers, identified during the COVID-19 pandemic, such as: a) the technologies needed to support it, b) its importance for modeling and epidemiological analysis, c) insights and awareness from stakeholders that can drive it, and d) how to evaluate its effectiveness. We point to synergies with other domains such as Artificial Intelligence (AI), human-computer interaction and edge and distributed computing. We discuss infrastructure along with any necessary, novel and existing, technologies, methods, expertise and attitudes needed for making visualization a 'first class citizen' in our future response to pandemics. Finally, we consider how visualization and infrastructure can be used to support other emergency responses and even research in general beyond pandemics.

C1: Infrastructure for data, modeling & visualization

As evidenced by the pandemic, addressing global issues necessitates collaboration on a global scale. Interdisciplinary teams must work together to implement data, visualization, and modeling technologies. More than ever, reliable digital infrastructures support-

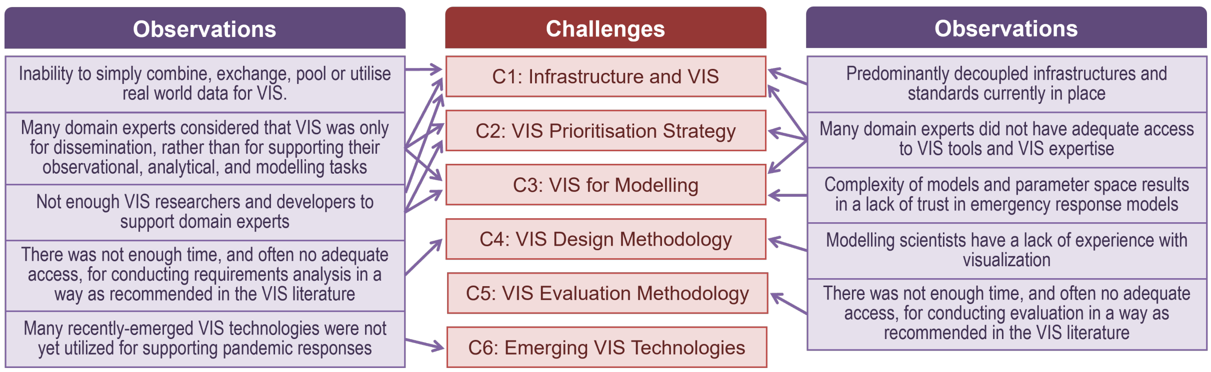

FIGURE 1. Overview of the observed problems and associated challenges.

ing the timely and accurate dissemination of data, information, and models in appropriate formats to the right users are essential. However, the predominantly decoupled infrastructures, standards and visualizations are significant challenges. There are separate and non-integrated solutions available for various fields, e.g., the collection and storage of medical and healthcare-related real-world data, the modeling of epidemiological scenarios, simulation efforts, or the diverse tasks performed by government organizations. Shared, interoperable and accessible infrastructures for supporting cross-institutional visualization, simulation, prediction and modeling teams are missing, thus, hindering global collaboration in pandemics [10]. Initially, modeling scientists struggled with a lack of data. Even when available, the vast and diverse array of data sources in the digital healthcare landscape must be effectively managed [9]. The inability to simply combine, exchange, pool or utilize real world data is a significant issue. Real-world data remains difficult to integrate due to heterogeneity, non-standardization, and fragmented systems. Without a common semantic standard, even similar data cannot be easily shared. Additionally, up-to-date information is crucial for visualization and modeling, making outdated data less useful. A significant challenge for decision-makers is dealing with data that is frequently potentially out of date, and the absence of data reflecting recent changes.

To address these challenges, overcoming decoupled infrastructures and standards becomes the critical action point. A readiness data platform optimized for pandemic visualizations with integrated visualization capabilities can help. It should be standards-based yet flexible, ensuring interoperability across systems, services, and teams while consolidating diverse data sources efficiently. Given that models generate a considerable amount of data that may not necessarily require persistent storage, it is also necessary to consider flexible approaches for intermediate storage and archiving. The platform must ensure data accuracy and quality, hinged on mutually agreed-upon metadata descriptions. This necessitates agreement on worldwide standards for the representation of the most relevant data valuable for pandemic visualizations. Semantically rich data models require meticulous requirements engineering. To reach valuable data models, versatile questions must be answered, such as which data sources are relevant at which time, which data formats occur, which visualizations require which data, and which access rules should be followed. For visualization and analysis, another promising avenue lies in an agent-based flexible transformation approach, wherein simple agents dynamically translate data into a unified format. This concept, although in need of further validation, offers potential solutions to the multifaceted challenges of data integration [3].

The infrastructure, hardware and software of the platform should have readily deployable visualization capabilities, scaling visualizations expediently and, optimally, incorporating real-time processing features. Embedding of standard visualizations is an integral part. Rapidly created, customizable visualization dashboards are necessary to create effective workflows for different stakeholders [6]. In addition, a stringent data protection regime needs to be integrated, alongside data access controls to provide domain experts with appropriate access to data and visualization tools. The construction of this platform would necessitate intensive interdisciplinary collaboration and human resources. Ongoing research into automated visualization techniques, e.g., ontology, agents also remains pivotal [7].

C2: Making visualization a first class citizen

In a pandemic response, there are many factors to consider with respect to visualization, related to the amount of data, associated sources and users (and their tasks), as well as the modes and types of visualization. Data can be collected from sources (testing centers, hospitals, etc.), for different regions, at different levels (often aggregated), and with data results featuring future predictions and uncertainty. The data itself is voluminous, dynamic, high-dimensional, and may arrive in numerous streams. The set of users is also large and diverse, for example, healthcare professionals (doctors, nurses, administrators, etc.), epidemiological modeling scientists, Machine Learning (ML) modeling scientists, governmental decision makers, and the general public, with many sub-groups and sub-roles. There are different modes of visualization, with a wide range of response times, such as routine data monitoring (real-time or in a few minutes), supporting decision making (in tens or hundreds of minutes), in-depth data analysis and data mining (in days), supporting model-development workflows (in weeks or months). Visualizing data for public communication and engagement can also be considered a separate mode. Finally, related to the modes are the different types, from simple dashboard visualizations to interactive visualization tools for data analysis and model development. Public engagement may require other types such as storytelling visualizations. These modes and types need to be considered as early as possible in the process to mitigate their impact on any rapid response.

Among the large diverse set of users, many perceive that visualization is only for dissemination, overlooking the benefits of visualization supporting their observational, analytical, and modeling tasks (see also C4). This is also exacerbated by the lack of direct support of visualization scientists and practitioners in the many workflows for pandemic responses.

The complexity of the aforementioned factors can be addressed considerably by having visualization capabilities available at an infrastructural level. At the beginning of the COVID-19 pandemic, to the best of our knowledge, most countries (if not all) encountered challenges in providing visualization facilities due to the lack of adequate infrastructural support, e.g., regional dashboards only became available after many months, epidemiological modeling workflows did not include adequate support for visualization. Attempts to develop visualization related infrastructure during the pandemic often encountered many obstacles, e.g., limited availability of experienced developers or readily-deployable software solutions [7]. Embedding visualization in the infrastructure is challenging (see also C1).

The two potential approaches are embedding visualization software in data infrastructures and close-coupling visualization infrastructure with data infrastructure. Regardless of which approach is taken, providing adequate and sustainable human resources in the development as well as deployment of visualization-enabled infrastructures is an important point that requires action. The more domain experts can access visualization capabilities from infrastructures and visualization software and the more they can receive direct support from visualization experts embedded in their teams or in collaboration with, the more users will appreciate the uses of observational, analytical, and model-developmental visualization, in addition to disseminative visualization. In this way, visualization will become a “first class citizen” in data science. Meanwhile, it is necessary to make visualization experts as part of the human infrastructure in preparation for future pandemics, e.g., by attaching visualization practitioners to infrastructures and allowing them to become familiar with rapid methods for requirements analysis and evaluation, while providing support to a wide range of users.

C3: Visualization for modeling & analysis

The COVID-19 pandemic gave rise to an unprecedented level of complex epidemiological modeling activities around the world, while highlighting issues in epidemiological modeling workflows, where visualization can and should play a significant role in supporting modeling scientists (see Figure 2). In addition to huge data volume and complexity (see C1 and C2), there are the challenges of large parameter spaces and gaining trust in the model prediction. The huge heterogeneous dynamic data streams mean that it is time-consuming for scientists to gain useful information from a variety of data to improve a model. Automated or semi-automated visualization can enable scientists to observe data from different data sources, notice unexpected patterns, compare model prediction with newly arrived ground truth data, and compare the performance of different models (including parameter variations). The process for parameter optimization often features a significant amount of unplanned trial-and-error exploration of a parameter space, while the total number of parameter sets that can be tested is very limited in comparison with the size of the parameter space. Ultimately, it is important that analysts trust

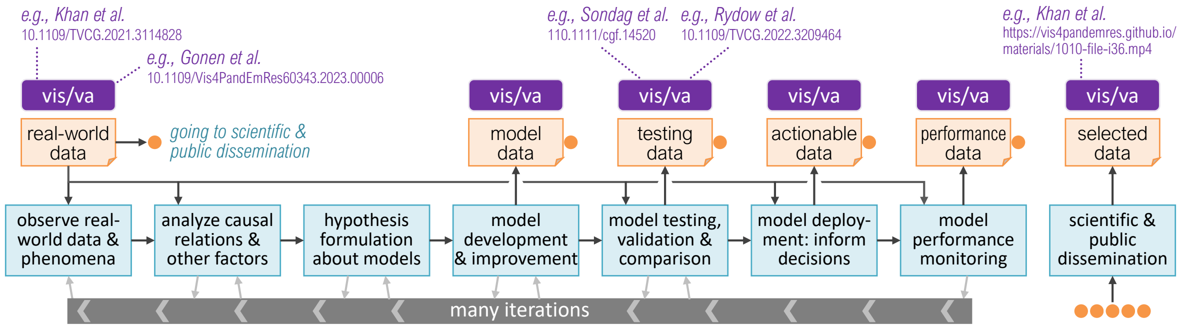

FIGURE 2. A detailed breakdown of the complexity of modeling processes and the associated opportunities for visualization.

the results, especially given the impact of bad outputs informing pandemic response.

Fundamentally, the model space, which includes all possible models due to variation of their structures and parameters, is huge. For a pandemic response, as with most applications, it is intractable to explore all models in the space in order to find the optimal model. Many approaches have been used to reduce the amount of brute-force exploration, e.g., uncertainty analysis for determining if further exploration is beneficial, sensitivity analysis for focusing the exploration on a subset of parameters, ensemble modeling for making use of a group of less-optimized models, and so on. Some (ML) approaches are often referred to as a black-box, as the model internals are not clear. Being able to explain how A leads to B and trusting each step on the way is even more important when an ML model is used. Engendering trust in the model, and understanding why the model makes the predictions the way it does, are important action points to be taken, especially in cases when the modeling approach is based on AI. Some efforts were made to develop models using ML during the COVID-19 pandemic, and there will no doubt more such models being developed in the future. Many visualization techniques have been developed to support ML and can be used to further engender explainability and trust in these models, ensuring that they are accepted by their different stakeholders [2]. Visualization can be used to explore model sensitivity to small input changes, and also to optimize parameters [12]. There is also much to be offered in terms of helping users to understand the uncertainty of models. Related to this are ensemble visualization approaches, which convey information about model outputs over a range of parameters or runs.

C4: Visualization awareness & stakeholder design

Traditional methods of visualization development require close engagement with stakeholders and take time. Public health emergency responses are characterized, among other challenges, by time pressure and uncertainty while policies are implemented in parallel at a population level, with a quickly evolving and changing evidence-base.

It is challenging but necessary to define and agree on short-, medium- and long-term perspective milestones and outcomes for the approaches chosen. These can be user and/or purpose led approaches, such as data analysis, dashboards for dissemination of data with different levels of complexity/aggregation/stratification. The focus of the approach may be epidemiological characterized by time, place, person. As mentioned in other challenges, the turnaround time, amount and dynamism of data- and evidence-generation during a pandemic differs considerably. Additionally, in relation to these aspects, challenges around data validity, confidentially, relevance and limitations exist and require epidemiological assessment and classification, from the expert users.

Flexibility, agility and continuous adaptation of surveillance, data generating and monitoring systems are essential. To leverage the full potential of visualization for epidemiological data validation, exploration, analysis, reporting and dissemination, stakeholder engagement, and dedicated time for knowledge exchange to foster reciprocal understanding are a prerequisite but difficult to achieve in emergency situations. While visualization can provide a range of support to epidemiological modeling workflows, often modeling scientists are not accustomed to such support, perceiving visualization as only for dissemination of modeling results [3] (see also C2). During the COVID-

19 pandemic, some visualization teams found it difficult to follow recommended practice, such as having frequent meetings with domain experts and conducting field observation. Many design decisions had to be made quickly as part of emergency responses. This challenge can be addressed by building awareness of the capabilities of visualization among domain experts and vice versa (by developing understanding of epidemiological measures and modeling). It is necessary to develop mutual understanding and build trust based on best practice examples in the inter-pandemic phase and engage in collaborative projects which make the case for visualization and have an impact on the initially agreed and well-defined purpose. This can be done, for example, by providing better documentation of past experience, e.g., through notebooks [5]. An important role is played by collaborative projects where domain and visualization experts co-develop approaches, models and agile solutions to support epidemiological data analysis and dissemination during inter-pandemic phases. These are an opportunity to build the base for a more effective uptake and integration of visualization tools during the pandemic response where iterative processes are dominating. Ensuring a suitable composition of teams for this should be a consideration for any project proposal, and possibly even a prerequisite for project calls issued by funding agencies.

Additionally, well-categorized and analyzed technical solutions in the visualization literature, can be quickly adopted and adapted. For example, dashboards can be further enhanced for fast deployment [6] and easy customization, which must be clearly communicated for each use case (see C1 and C2).

Within the visualization community this challenge can also be addressed by advancing theoretical understanding and developing requirements analysis methodologies that enable visualization researchers to identify requirements rapidly, e.g., the use of four-level visualization tasks in organizing visualization teams [3], [5]. To encourage such progress, the visualization community should encourage research into alternative methods, while avoiding an assumption that the current status-quo for requirements analysis is the only acceptable approach.

C5: Evaluation

In terms of building systems as we prepare for the next pandemic, current and emerging work on evaluating visualizations is, and will remain, immensely useful. However, the goal here is to develop visualization and demonstrate effectiveness for the user´s task, rather than a rigorous evaluation to advance visualization research. It is necessary to develop new evaluation strategies that facilitate and do not hinder rapid responses during a pandemic. For example, during the COVID-19 pandemic, a key difficulty in evaluating visualizations was receiving unbiased feedback that reflects on the quality of visualization approaches and not other issues with the overall infrastructure that supports said visualizations. The close proximity of the visualization experts to end users may result in personal dynamic clouding an appraisal of approaches, even if the visualization is in some way successful. Additionally, the domain experts may not be aware of alternative techniques [5], and they may accept flaws without being aware of visualization best practices.

Furthermore, in terms of rapid response, traditional comparative evaluation of visualization using a null hypothesis approach is too time consuming and low level. Crowds-sourced evaluations may be considered to yield fast results, yet the domain experts insight must also be taken into account. This may be remedied by having a combination of evaluation strategies for experts and non-experts. Nevertheless, the complexity, specificity and intricacies of visualization may still require a level of visualization expertise from the evaluation participants. Pandemic response visualization deployment may be considered to have a lot in common with the a design study approach to visualization (such as that described by [13]), albeit with a very limited precondition phase. Reflection time is very limited, and writing time even more so. Waiting until there is time to do serious reflection, as well as collection and analysis of evaluation data, unfortunately means that poor performance may have been part of an emergency response tool for quite some time.

Indeed, the agile improvement process during a pandemic would benefit from rapid feedback and reflection. Therefore, the development of new (and adaption of existing) evaluation methods is an action point. For example, with an instance-based evaluation method, as soon as an issue is identified in a rapid evaluation process, instead of waiting for statistically-significant evaluation data, visualization experts can analyze the issue (symptom), determine the likely causes, identify possible remedies, and consider adverse side-effects [4] before selecting a solution. This would rely on visualization experts' broad knowledge about problem-solution space, and their ability to address an issue without introducing new problems by anticipating potential side-effects and applying best practices. Likewise, standardized questionnaires and quick feedback mechanisms, potentially integrated with the infrastructure itself would be suitable for time constrained scenarios and may help rapid evaluation.

Therefore, to prepare for the next pandemic, it is desirable for the visualization community to improve, collectively, its theoretical understanding, technical knowledge, and practical design skills in evaluation in a rapid response mode. This includes exploring and researching alternative methods for evaluation. Researchers in the next pandemic should be able to leverage existing theory and reduce time spent obtaining and responding to feedback.

C6: Emerging technologies

An important consideration in any future infrastructure is the integration of emerging and novel technologies, as these become available and pervasive. For example, the use of AI in modeling the Covid-19 pandemic (see C3). Similarly, wastewater monitoring had been used to monitor viral load. To facilitate continuous monitoring and rapid information dissemination, other tools were deployed via smartphone application, for reporting symptoms, or tracking and indicating exposure to known infection nodes. In this regard, any infrastructure that will be put in place for preparation and response to future pandemics should be able to accommodate the integration of emerging and future technologies into visualization solutions. For example, technologies from the domains of edge computing and distributed computing can enable such an infrastructure to combine high resolution, frequently updated localized information with coarser large-scale information as an epidemic or pandemic evolves. This can provide new opportunities for targeted fast interventions capitalizing on localized infrastructure and issues. Developments in ubiquitous visualization systems [8] indicate a future where visual analysis and data sense-making will take place away from our desktops in different locations, settings and scales, e.g., in regional healthcare, hospitals, urban and rural areas, as well as in our personal environments. Coupled with more capable data collection through smartphones, edge and distributed commuting nodes, ubiquitous computing infrastructures and AI-enabled data processing, we will be able to provide faster public information and interventions. The quarantine restrictions of a pandemic also motivate the development of distributed command and control centers, where users each have their own remote set of displays, but integrated as part of a unified system.

In addition, emerging tech has been used in new ways, such as for training and emergency response, Existing approaches for first response training in Augmented Reality, such as visualizing of radiation threats in an environment [11], may be adapted for a pandemic response training use case, to help understand risk of airborne transmission. Moreover, as such beyond-the-desktop visualization systems become easier to integrate with the current mainly Web-driven data and visualization infrastructure, the opportunity for tighter integration with the infrastructures described in this work becomes significantly more viable. Automatic visualization has been a topic of interest for some time, and in 2005 Brodlie et al. outlined the need for a visualization infrastructure with many autonomous facilities [1]. However, currently the technical advancement in automatic visualization has not been fast enough to meet the aforementioned visualization needs at the scale encountered in the COVID-19 pandemic. However, the synergies between ML and visualization mean visualization should go hand in hand with any emerging AI or ML based approaches as part of any pandemic response. Visualization for explainable and trustworthy machine learning, is an important contemporary research topic [2] in the field of information visualization (see also C3). We anticipate the synergies between visualization and AI will be instrumental in the development of future infrastructures. In visualization research leveraging emerging technologies, pandemic response should be considered a use case, to allow flexibility in the choice of technologies used to address the next pandemic.

Finally, integrating emerging technologies in infrastructures, such as the ones described in C1, requires the development of standards that facilitate interoperability. In some themes, such as for ubiquitous visualization aforementioned, this is already a key motivational driver for new systems [8]. The same approach should be adopted for further emerging technology innovations.

CONCLUSION

Addressing each of the challenges described will enable data visualization to be at its most effective in the next pandemic. We summarize action points for each challenge in Figure 3. These are not simple problems and are often major challenges outside the context of the pandemic. The lessons learned from the COVID-19 pandemic can prepare us for other emergencies, beyond those related to infectious diseases, as they often exhibit characteristics similar to pandemics, including suddenness and unpredictability, social disruption, and increasing demand for medical care. Some ways in addressing the challenges helps with general emergency response are:

1) Risk management and response planning: Visualization for modeling and analysis to support

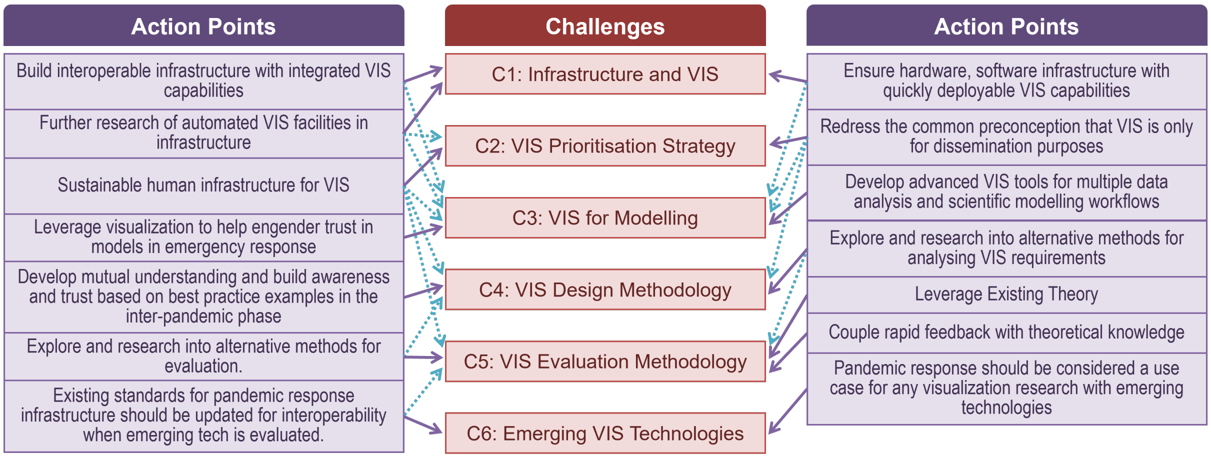

FIGURE 3. Action points and associated primary (solid arrows) and related (dotted arrows) challenges.

(C3), and highly reliable digital infrastructure, for data and visualization (C1, C2).

2) Improve information sharing and communication: Establish an infrastructure framework to improve interoperability and accessibility (C1), and take time to promote mutual understanding among stakeholders (C4).
3) Strengthen medical and public health systems: Establish reliable digital infrastructure (C1), develop integration / linkage between visualization and digital infrastructure (C2), and continue to ensure close coordination among stakeholders (C4), which can be done only in the inter-pandemic phase.

Rapid and highly specific, but extremely innovative, approaches can be transformed into sustainable solutions, which can be used beyond the context of pandemics. In Germany, the COVID-19 Data Exchange Platform (CODEX)(https://num-codex.de/home) was initially established as a secure, expandable and interoperable data platform for the provision of research data on COVID-19 that connects university hospitals nationwide. Although originally designed for the management of data related to the novel coronavirus, the associated frameworks, processes and infrastructures are not restricted to this domain. It was recognized that the structures can also be operated and expanded beyond the use case in the sense of a generic Research Data Platform for the Network University Medicine (NUM RDP https://www.highmed.org/en/num-rdp) or the German Portal for Medical Research Data (FDPG https://forschen-fuer-gesundheit.de/). This is an example of how technologies can be kept alive, generating added value out of the emergency situation also for other domains and increasing the state of preparedness.

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