

EnsembleDashVis Views and Volunteers: A Retrospective and Early History

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ABSTRACT

This paper offers a retrospective view on the early development stages of EnsembleDashVis, a visualization dashboard specifically crafted to support modelers in interpreting a simulation model utilized to forecast COVID-19 trends. The volunteer effort behind this dashboard was contributed collaboratively with the Scottish COVID-19 Response Consortium (SCRC) with the objective of enabling an enhanced comprehension of the pandemic’s complex dynamics via modeling of a real-world dataset collected by NHS Scotland during the first wave of the outbreak. This retrospective chronicles the design and development journey of the system, guided by feedback from domain experts, all taking place amidst the exceptional circumstances of an unprecedented pandemic. The outcome of this volunteer work is a streamlined relationship discovery process between sets of simulation input parameters and their respective outcomes, that leverages the power of information visualization and visual analytics (VIS). We hope that this retrospective will serve as an insightful resource for future effort in VIS for pandemic and emergency responses, and promote mutually beneficial engagement between scientific communities.

Index Terms: Visual Analytics—Information Visualization—Emergency Response—Visual Design

1 INTRODUCTION AND MOTIVATION

The Scottish COVID-19 Response Consortium (SCRC) [3], in collaboration with the Royal Society’s call to action in March 2020, has taken a proactive approach to address the need for enhanced epidemiological models of COVID-19 transmission. This joint volunteer effort, known as Rapid Assistance in Modelling the Pandemic (RAMP) [2], aims to foster a deeper comprehension of the consequences associated with various exit strategies from lockdown measures. Moreover, this consortium attracted the involvement of distinguished scientists and experts from diverse organizations both within the United Kingdom and abroad, thus augmenting the collective knowledge base and ensuring comprehensive expertise in specialized domains.

RAMPVis [4] is a group of researchers specialized in Data Visualization and Visual Analytics (abbreviated as VIS). This group voluntarily came forward to contribute its specialized skills and knowledge in order to provide valuable support to the SCRC modelers. The term *modelers* used here refers to the SCRC researchers who were actively engaged in the development of epidemiological models at SCRC. This predominantly includes experts in domains such as mathematics, statistics, and epidemiology.

Serving as the volunteer team responsible for providing visualization support to one of the six epidemiological models developed by the SCRC modelers [8], our main objective is to provide VIS researchers and practitioners with valuable insights gained from our research and development (R&D) activities conducted during the

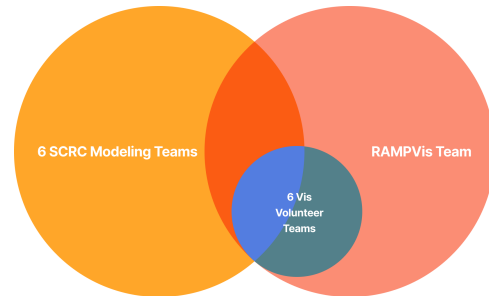


Figure 1: The organization of researchers from the SCRC and RAMPVis. The 6 SCRC modeling team are responsible for developing the epidemiological models leveraging different modeling techniques. The RAMPVis team provides visualization support to the SCRC modeling team, by establishing 6 VIS volunteer teams who work on the actual development under the guidance of the RAMPVis team.

COVID-19 pandemic. In an effort to predict the potential impact of diverse interventions, modelers have actively utilized COVID-19 data, employing a method known as Uncertainty Quantification (UQ). This process seeks to measure uncertainties through the application of mathematical models and simulations. However, modelers are faced with significant challenges, including the aspects of expert elicitation and effective communication. In other words, there is a need for software engineering effort coupled with visualization to provide support for the validation and verification tests, and to create efficient workflows between modelers and researchers from other disciplines [6].

In addressing these hurdles, Data Visualization and Visual Analytics (VIS) emerge as a potent tool, offering the capacity to significantly enhance and streamline their collaborative workflows [25]. While our work may not have showcased the state-of-the-art VIS techniques, it effectively delivered rapid and practical VIS support to the modelers during an exceptional and demanding time. The exemplification of a fully virtual collaboration among researchers from various UK institutions epitomizes the spirit of interdisciplinary cooperation in response to the pandemic.

What we present here is an early history of our volunteer response from a software and visualization perspective. We present the earliest stages of visualization dashboard, EnsembleDashVis, developed from 2020, aiming to assist the modelers in interpreting an Approximate Bayesian Computation Sequential Monte Carlo (ABC-SMC) inference model that they have developed using COVID-19 data collected during the first wave of the outbreak in Scotland [1]. Much of this effort and the reasoning behind this volunteer was never documented.

2 BACKGROUND AND RELATED WORK

VIS has been widely utilized in critical applications such as emergency responses and healthcare, assisting public officials and decision-makers in understanding intricate datasets and extracting useful, actionable insights from them [10]. VIS has also played a prominent role in disseminating COVID-19 information through various media channels. It has contributed significantly to facilitat-

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ing more efficient and clearer public communication, facilitating a broader understanding of the crisis [17].

In our work, our primary objective was to extend support through VIS to two distinct user groups. Firstly, the statisticians, who could significantly benefit from VIS in comprehending their models more effectively and fine-tuning them. Secondly, to the epidemiologists, whom VIS could assist in interpreting the outcomes of these computational models. Our outcomes are later included in multiple publications [8, 11, 18, 19, 24]. The early stages functioned as the preliminary VIS prototype, shaping a portion of their respective studies. See Ensemble in Figure 7 by Rydow et al. [24].

VIS for Emergency Response

Previously, we have described related work that focuses on the use of VIS in emergency response. We refer the readers to the related work section in Chen et al. [8]. The aforementioned literature review laid the foundation and was conducted prior to the development of our study in 2020.

Maciejewski et al. [21] develop a VIS toolkit to analyze the effect of decision measures enforced during a simulated pandemic, the tool was later utilized by the Indiana State Department of Health during an outbreak of H1N1 (swine flu). Ribicic et al. [23] leverage VIS with the intention of delivering real-time feedback derived from flood simulations to non-expert users, while Konev et al. [20] use VIS to support decision-making in flooding scenarios.

Jeitler et al. [16] use VIS to analyze social media data to aid rescue teams, specifically in terms of optimal allocation of resources during emergency response situations. Similarly, Nguyen and Dang [22] harness social media data, paired with VIS, to facilitate and improve post-earthquake resource allocation and rescue effort.

In contrast to the majority of previous studies mentioned here that generally focus on preparing for future emergencies, our work was undertaken during the COVID-19 pandemic as a rapid response to a current and ongoing emergency.

VIS for COVID-19 Data Modeling

In the rest of the section, we focus on the use of VIS to analyze the computational modeling of COVID-19 data. These studies were not published or available to us during the development of the work we present here (from July 2020 to April 2021). In fact, the use of VIS in epidemiological modeling was rare, the modelers might have been unaware that they had such a potent instrument readily available [8].

He et al. [14] developed an SEIR (Susceptible, Exposed, Infected, and Recovered) model for spread prediction by leveraging COVID-19 data obtained from the Hubei province in China. They employed a variety of 2D plots to estimate the parameters of the model and interpret the results that the model yielded. Godio et al. [13] took the same approach in developing an SEIR model for the Lombardy region in Italy.

The IHME COVID-19 Forecasting Team [15] take the application of data visualization (VIS) a step further in their development of the SEIR model for accessing social distance mandates, they extend the use of VIS to include choropleth and violin plots, and small multiples for 2D plots.

Chinazzi et al. [9] develop a model to simulate the effectiveness of international travel restrictions in containing the spread of COVID-19. In addition to the use of 2D plots to refine their models, they also utilize a range of geospatial approaches. This enabled them to more effectively interpret the results generated by their models. The use of geospatial visualizations is also adopted by Alvarez Castro and Ford [7] in their development of a model for analyzing transmission in a university campus in the UK.

In contrast to these studies that highlight the efficacy of VIS in supporting the computational modeling of COVID-19 data with a primary focus on model development, as they are formulated by

Table 1: 16 input parameters for the ABC-SMC inference model. The constant K here is ignored in our visual designs.

Name	Description
T_lat	Mean latent period (days)
juvp_s	Probability of juvenile developing symptoms
T_inf	Mean asymptomatic period (days)
T_rec	Mean time to recovery if symptomatic (days)
T_sym	Mean symptomatic period prior to hospitalization (days)
T_hos	Mean hospitalization stay (days)
inf_asym	Reduction factor of infectiousness for asymptomatic infectious individuals
p_inf	Probability of Infection
p_hcw	Probability of Infection (Healthcare Worker)
c_hcw	Mean number of Healthcare Worker contacts per day
d	Proportion of population observing social distancing
q	Proportion of normal contact made by people self-isolating
p_s	Age-dependent probability of developing symptoms
rrd	Risk of death if not hospitalized
lambda	Background transmission rate
K	Hospital bed capacity

Table 2: 13 output parameters from the simulation performed by the ABC-SMC inference model.

Name	Description
iter	The simulation number.
day	The day number.
age_group	The age group of the population.
S	Number of susceptible individuals (not infected).
E	Number of infected individuals but not yet infectious (exposed).
E.t	Number of exposed individuals and tested positive.
I.p	Number of infected and infectious symptomatic individuals but at pre-clinical stage (show yet no symptoms).
I.t	Number of tested positive individuals that are infectious.
I	Number of infected and infectious asymptomatic individuals.
I.s	Number of infected and infectious symptomatic individuals.
H	Number of infected individuals that are hospitalized.
R	Number of infected individuals that have recovered from the infection.
D	Number of deceased individuals due to the disease.

the modelers, our study takes a different approach. We focus our attention on exploring VIS as a potent tool that can significantly improve the computational modeling of COVID-19 data, all viewed through the unique lens of a VIS practitioner.

3 DATA DESCRIPTION

The data used in our work includes simulation parameters and outcomes from an ABC-SMC inference model [26] developed by a group of modelers from Durham University, the University of Edinburgh, the University of Exeter, the University of Glasgow, and the London School of Hygiene & Tropical Medicine. The pandemic data used for the simulation was collected by NHS Scotland during the first wave of the outbreak in Scotland spanning a period of 59 days [1]. The model was built to analyze the data and infer the parameters of the model that best fit the data. The model has 16 input parameters (see Table 1) and 13 output parameters (see Table 2), and it performed 1,000 simulations with 160 sets of input parameters that were inferred via random seeding. The resulting output file is a CSV file that is over 6GB in size.

It is worth mentioning that after plotting the output data using a line chart, an error was immediately spotted, see Figure 3, where an unusual spike can be observed on day 20. The modelers were notified and the bug was fixed. However, the rectified output file was never made available to us.

4 ENSEMBLEDASHVIS

This section presents the history and development behind our fully virtual collaboration between volunteer researchers from multiple UK institutions. Being one of the six VIS volunteer teams, we received guidance from the RAMPVis team via regular virtual meetings. The RAMPVis team communicated with the SCRC modeling team regularly and provided us with the important information and data. We chronicle the development of different views of the data,

the order in which they were introduced and the reasons and motivations at the time. In 2020 we were all in an unprecedented and unfamiliar situation, thus, some of our decisions were ad-hoc.

Meeting #1 - July 2020

On 27 July 2020, amid the UK's first national lockdown and stricter measures imposed by local authorities, we convened the initial virtual meeting with VIS researchers from King's College London, Loughborough University, Swansea University, University of Nottingham, University of Warwick, and University of Oxford.

During the meeting, we received an overview of the SCRC and the responsibilities of the visualization volunteer team. Our assigned task was to create visual interfaces for the model, for the purpose of enabling the modelers to analyze the outcomes of the model.

Following the initial meeting, we engaged in email correspondence with the modelers to delve into the visualization requirements. The modelers shared a comprehensive list of parameters and model outcomes, along with the corresponding outcome data [1].

Commit #1 - Sep 2020

We proceeded to create an initial prototype of the visualization, which was subsequently reviewed by the modelers. Incorporating their input, we refined the prototype during our weekly internal discussions. On 14 Sep 2020, England introduced the 'rule of six', which banned any gatherings above six. On the same day, we made our first commit to a GitHub repository, signifying the commencement of our development. At the same time, we began preprocessing the data. A week after the initial commit, the UK witnessed the implementation of additional restrictions, such as mandatory work from home and a 10PM curfew.

Meeting #2, View #1 - Nov 2020

On 5 Nov 2020, the first day of the second national lockdown in the UK, we completed the first view of the simulated input parameters, a parallel coordinates plot, see Figure 2. We chose to use a parallel coordinates plot as it is a common technique for visualizing multivariate data, and is particularly useful to explore relationships and patterns across multiple input parameters. The parallel coordinates plot supports brushing and linking, which enables the modelers to select a subset of the input parameters to focus on outliers and interesting configurations. This followed by the second meeting with the RAMPVis team from other institutions, where we received feedback on the first view, on 6 Nov 2020.

Meeting #3, View #2 - Nov 2020

On 11 Nov 2020, the group convened for the third meeting, where we received further feedback from the RAMPVis team on the parallel coordinates. As per the modelers' requests conveyed via email, we incorporated a line chart to depict the model outcomes, see Figure 3. Line chart and other classic visual designs are widely used by the modelers, they are familiar with these designs and can easily interpret the results. The line chart is coordinated with the parallel coordinates plot, enabling the modelers to select a subset of the input parameters and quickly identify the corresponding model outcomes. A focus+context technique is used to highlight the selected subset of the input parameters in the parallel coordinates plot.

Meeting #4, View #3 - Nov 2020

On 25 Nov 2020, the group convened for the fourth meeting, held just a day after the announcement of the gathering rules for Christmas in the UK. During the meeting, we received feedback from the RAMPVis team on the new view of the input parameters, a table with glyphs, see Figure 4. We incorporated this table view featuring glyphs to depict all 160 input parameter configurations, following discussions with the modelers. The table views enables the modelers to sort configurations by individual input parameters.

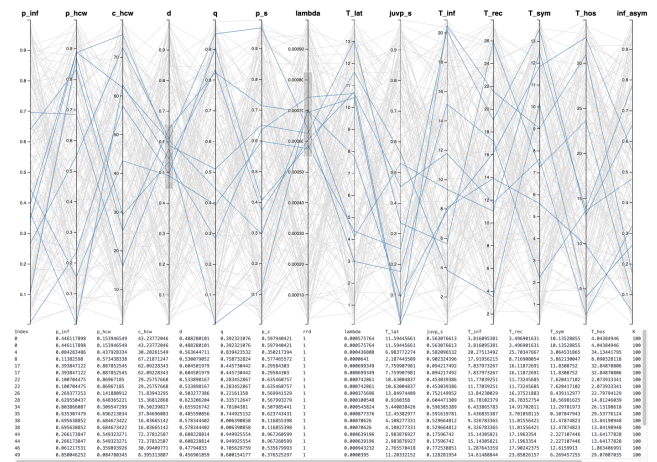


Figure 2: The first visual design, a parallel coordinates plot depicting all 160 input configurations of the model, was completed on 5 Nov 2020. The table below shows the configuration details. Each axis represents an input parameter, and the y-axis represents the value of the parameter.

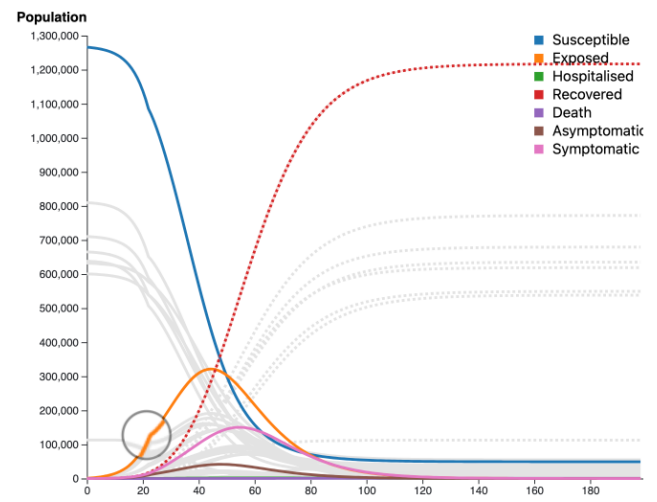


Figure 3: A line chart depicting the model outcomes. The x-axis of the chart corresponds to the number of days since the first date in the Scottish dataset, while the y-axis represents the population. To differentiate between different population categories, a color map was incorporated: **susceptible**, **exposed**, **hospitalized**, **recovered**, **death**, **asymptomatic**, and **symptomatic**. The focus+context technique is used here to highlight the outcome of the current configuration, while the grey lines represent other outcomes. On day 20, there is an unusual spike which was later identified as caused by an error in the model.

Each parameter value is symbolized by a bar glyph, the color and length correspond to its deviation from the group's average value.

The table view provides the functionality to sort the parameters according to their values and can be dynamically updated by brushing the parallel coordinates plot for the input parameters in Figure 2. The line chart in Figure 3 can be quickly updated to display the corresponding model outcomes by clicking on the configuration index in the table view.

Meeting #5 - Dec 2020

On 9 Dec 2020, a week after the end of the second national lockdown,



Figure 4: The table view depicting all 160 input parameter configurations. The view enables the modelers to sort parameter values and identify interesting configurations. Upon clicking on the index of a configuration, the line chart in Figure 3 is updated to display the corresponding model outcomes.

down in the UK, with England facing a stricter three-tier restriction policy, the group convened for the fifth meeting. At this point, we still had not met with the modelers, all communications and discussions took place via emails. The RAMPVis team decided to organize a meeting with the modelers, to present our prototype for feedback.

Meeting #6, View #4 & 5, Feedback #1 - Dec 2020

On 10 Dec 2020, a week after the second UK national lockdown, we finally met with modelers from Durham University, the University of Edinburgh, the University of Exeter, the University of Glasgow, the London School of Hygiene & Tropical Medicine, for the first time. In contrast to sharing screenshots via email and deploying a website with a live view of our development (which they might not have been proficient in using), we delivered a live presentation, fielding numerous questions. The modelers were pleased with the visualization, and a list of ad-hoc requirements was provided. Furthermore, we collected insightful feedback that we elaborate on in detail in Section 5.

1. The modelers found the parallel coordinates plot is useful in identifying outliers, and requested the incorporation of another one for the model outcomes. Given that the outcome data mirrors the input in a multivariate format, employing a parallel coordinates plot could potentially be useful. We implemented this as shown in Figure 5.
2. The modelers requested all the simulation results be displayed in the line chart, with the current one highlighted. This resembles their usual workflow of analyzing multiple simulation outcomes. We implemented this as shown in Figure 3.
3. The modelers requested the incorporation of a scatterplot to visualize the model outcomes, specifically a Principal Component Analysis (PCA) result obtained from another VIS volunteer team. The motivation behind is to reduce the dimensionality and identify key parameters. We implemented this as shown in Figure 6.

Furthermore, we received the exciting news that initial funding had been successfully secured [12], which led to the transition of our volunteer work to a team of paid developers, who would continue with further implementation of the project.

Meeting #7, Feedback #2 - Mar 2021

On 25 Mar 2021, the UK was in the process of cautiously lifting its third national lockdown, the 'rule of two' was still in place. The group convened for the seventh meeting, where we received further feedback from the modeling team on our implementation. We detail the feedback in Section 5.

Last Commit - Apr 2021

By 28 Apr 2021, more restrictive measures were abolished, although the prohibition on mixing between households was still in

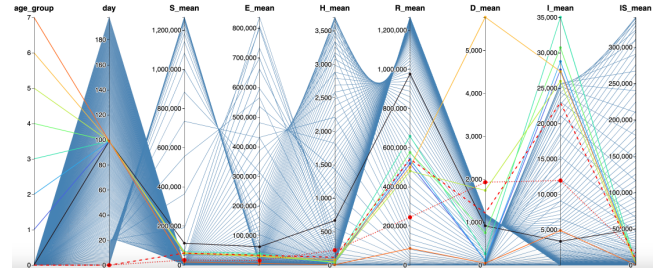


Figure 5: A parallel coordinates plot depicting the model outcomes by age group. As requested by the modelers, the mean value of 1,000 simulations generated by each input configuration, as well as for each age group, was computed and rendered here. Each axis represents one variable from the outcome and its value. Each age group is mapped to a color, the dashed red line --- represents the average value, and the dotted red line represents the standard deviation.

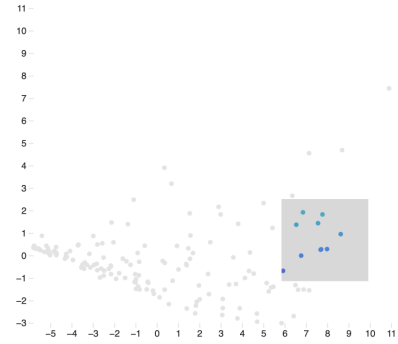


Figure 6: A scatterplot depicting the PCA outcome from another VIS volunteer group, was added upon request by the modelers. Upon brushing, the selected configurations are highlighted in the table view in Figure 4.

effect. On this day, we made our last commit to the GitHub repository, this act signified the completion of our volunteer work, as we had smoothly transitioned all tasks to a team of paid developers.

During the entire development process, our meetings were exclusively conducted virtually, and our communication relied heavily on email correspondence. Despite the lack of in-person interactions, we successfully met the modelers' initial requirements and delivered a VIS solution that received very positive feedback from the SCRC modeling team.

Meeting #8, Feedback #3 - May 2021

On 19 May 2021, the UK was viewing the light at the end of the Covid tunnel, weddings and funerals were still restricted to 30 people, and indoor gathering over two households was still banned. The group convened for the eighth and final meeting. During this final meeting, a modeler joined and gave us some in-depth feedback on the influence our work had on their modeling process, as well as suggesting potential improvements. We detail the feedback in Section 5.

5 DOMAIN EXPERT FEEDBACK

In this section, we share the invaluable feedback collected from the modelers. Meeting #6 and #7 were held prior to the conclusion of our development, serving as an iterative process of refinement aimed at validating and improving our visual designs while ensuring their relevance and utility to domain experts. Meeting #8 was held after the conclusion of our development, functioning as a means to gather

feedback on our work and to identify potential future work. Here, we present some of the original quotes collected from the domain experts during these meetings.

Domain Expert #1 - Professor in Statistics, Durham University

During our live demonstration, the domain expert appreciated the interactions provided by the visual designs in depicting the relative importance of different input parameters on the model's predictions. *"The visualizations are able to show how important a particular input is for a particular output."*

In addition, the ability to present the link between the input and output parameters visually. *"The real interesting game here is the connection techniques to understand the relations between the input and output."*

The linked visual designs also potentially enable the domain expert to identify ineffective parameter combinations. *"The different configurations is the sort of history of calibration and by looking at those visualizations you can start saying certain combinations may not be useful."*

Furthermore, the domain expert also expressed interest in the potential of our visual designs to aid in the identification of model discrepancy, when the observational data becomes available. *"The visualization would be helpful for us to identify model discrepancy when we eventually plot the observational data."*

Domain Expert #2 - Professor in Statistics, the University of Exeter

The domain expert was pleased by the visual designs' ability to provide the potential to filter redundant input parameter configurations, enabling users to concentrate on the most influential configurations. *"For particular input configurations after filtering, the visualization shows some of the input parameters can be ignored, which reduces the dimensionality of the problem, and we can focus on the important parameters."*

Domain Expert #3 - Assistant Professor in Statistics, the University of Glasgow

The domain expert praised the visual designs' ability to provide a clear overview of the input parameters and their distributions. This enables them to quickly identify possibility adjustments they can make to their input parameters, as well as to identify the most influential parameters. *"The table view is really useful in showing how close those input parameters are to the threshold, which is very useful for us to understand the affordability."*

The domain expert also noted that some overlapping distributions can be ruled out quickly via the interactivity provided by our visual designs, this enables them to eliminate unnecessary complexities and increase the overall efficiency of their model. *"It's fairly obvious that some of the parameters can be ruled out quite quickly, including some overlapping distributions."*

An avenue for future work, as unanimously identified by all three domain experts, involves integrating new visual designs to effectively render and compare observational data against model predictions.

6 LIMITATIONS

Due to the impact of the pandemic, the project was conducted in a fully virtual manner, with all meetings and discussions taking place online, between a large group of researchers from different disciplines and different institutions. In total, 33 VIS researchers and 7 modelers were involved in this volunteer work. The development was ad-hoc in some ways due to the unprecedented nature of the pandemic. This resulted in a number of limitations, which we will discuss in this section.

6.1 Lack of Novel and Advanced Visual Designs

Operating under a time constraint, the primary objective of our project centered on offering immediate visual analysis assistance to the modelers. Thus, we were unable to explore the inclusion of innovative and advanced visual design approaches. Instead, we integrated a series of classic views, such as line charts and scatter-plots. These are visual designs commonly leveraged by modelers in their day-to-day research. Interestingly, the modelers welcomed the introduction of a less conventional (to them) visualization technique: parallel coordinates. They had never before employed this, and its introduction proved beneficial to their research. Consequently, they expressed a desire for the incorporation of an additional parallel coordinates to assist in the visualization of model outcomes.

We believe that this is a testament to the effectiveness of advanced visual designs in enhancing the modelers' understanding of their models, this signals the possibility for future inclusion of more sophisticated visual designs.

6.2 Lack of Proper Requirement Gathering

We were unable to meet with the modelers until a particularly late stage. Instead, we had to rely on email correspondence, which was arguably not as effective as face-to-face or even virtual meetings. In a traditional software engineering project, requirements are gathered through a series of meetings and discussions with end users. This did not occur in our case.

This resulted in a lack of proper requirement gathering, which in turn led to a number of challenges during the development process. For example, the modelers made ad-hoc requests to incorporate different views at different stages of the project, resulting in unexpected changes on the development side. This could have been avoided if we had a better understanding of their requirements from the beginning.

6.3 Dynamic Group Membership

The group membership was dynamic, with researchers joining and leaving the group at different stages of the project. This introduced some lack of continuity, as newcomers had to spend time to familiarize themselves with the project. Furthermore, members came from different disciplines, with different levels of expertise in visualization. This has resulted in a lack of consistency in the development process, as different members have different ideas on how to implement the views. The responsibility of each member, apart from the only developer in the group, was not clearly defined.

6.4 Unclarified Project Direction

The exact direction of the project was not clearly defined from the beginning. Many details remained unknown to us during the development process, such as the exact purpose of the visualization, the target audience, and the end product. Consequently, the final product suffered from a non-ideal utilization of screen-space, as more views were requested to be added, the implementation of a multi-screen display design or collapsible views became time-constrained and unachievable.

7 CONCLUSIONS

In this paper, we present the stories behind the development of EnsembleDashVis, an interactive dashboard designed to visualize the input parameters and outcomes of an ABC-SMC inference model used to analyze COVID-19 data collected during the first wave of the outbreak in Scotland.

Given the multitude of uncertainties and challenges during this exceptional period, a considerable amount of information was unavailable to us during the development process. It was only through the Scottish COVID-19 Response Consortium Stakeholder Report [5], published in late 2021, and various publications [8, 11, 18, 19, 24] that

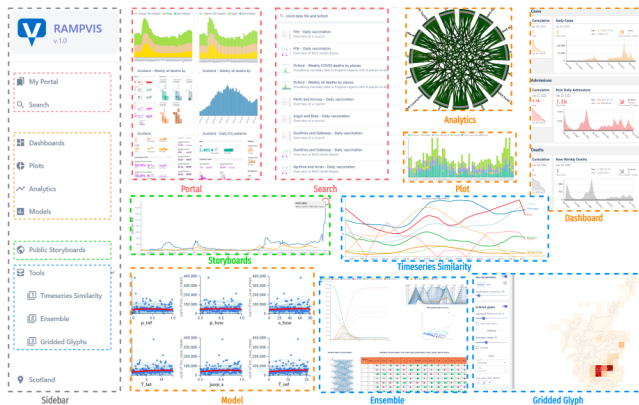


Figure 7: EnsembleDashVis has undergone extensive development by multiple UK institutions and is currently maintained by the Oxford e-Research Centre at the University of Oxford, serving as a vital element of the RAMPVIS infrastructure. It is well-prepared to offer rapid and invaluable visualization support for future emergency responses. Image courtesy of Rydow et al. [24].

unveiled the remarkable endeavors undertaken by other volunteer teams, that we gained additional insight and details.

We hope that our experience serves as a valuable source of insight on how VIS research and techniques can play a crucial role in emergency response initiatives and aid in effectively preparing for future emergencies.

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