Interactive Visualizations to Support Randomized Clinical Trial Monitoring

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Abstract—Despite current technological advances, interactive tools to facilitate the analysis of data collected during clinical trials are still not widely available. Such a scenario makes researchers rely on time-consuming extractions from databases and subsequent application of analytical methods by statisticians to obtain results from which they can get insights. Moreover, during clinical trials, researchers need to keep track of subjects' progress by monitoring their participation and the quality of the data collected at specific phases of the trial. We have developed a visualization-based interface that assists the epidemiologists of a randomized clinical trial focused on the effects of lifestyle intervention in developing type 2 diabetes for patients with Gestational Diabetes Mellitus (GDM). Coaches are responsible for the intervention, and research assistants collect data from hundreds of questionnaires and clinical exams. We adopted user-centered design principles, which allowed continuous improvements to the visualizations and interactive features during a year-long development process. Besides typical selection and filtering features, the visualizations we have designed allow the research team to monitor each participant's progress and perform analyses that facilitate findings in and between subjects' histories. Two formal evaluations were also performed with experts and non-experts, where the visualization-based interface proved to be intuitive and useful for assisting coaching activities, monitoring the progress of data collection, and performing analyses.

I. INTRODUCTION

Visual interactive technologies have become widely available, allowing applications in several fields of human activity to take advantage of their features for improving human performance and accuracy. One of these fields is clinical research, where the huge volume of complex data is demanding considerable efforts in creating visual interactive, intuitive systems for gathering insights on collected data.

Clinical trials are experimental studies where the researcher intervenes in some aspect of a particular population and follows the outcomes of that intervention [1] over a particular period of time. They often rely on time-consuming extractions from databases and subsequent application of analytical methods. The analyses of these longitudinal data are important to epidemiologists' decision making, which critically depends on visualizing the complete history of subjects in the sample, spotting trends, incidents, and cause-effect relationships between data [2]. Therefore, these studies can benefit from flexible, powerful tools that enable and support exploration [3]. This exploration is vital for assisting researchers in keeping track of patients' progress, enabling dynamic methods for

monitoring participation as well as assessing the quality of the data collected at specific phases of the trials.

The goal of our work is to investigate the benefits of interactive visualization techniques to the workflow of epidemiologists. To support our investigation, we have integrated a number of interactive visualization techniques in an interface to assist epidemiologists of a randomized clinical trial in:

- Tracking the participants' progression for the duration of the trial to assess the effectiveness of the intervention;
- Finding similar participants based on data collected during the trial;
- Tracking the study's status and completion of each phase for each enrolled participant; and
- Discovering incorrect and missing data through the analysis of outliers.

In this paper, after reviewing relevant works related to the context of medical data visualization (Section II), we describe the target domain and the requirements gathered through interviews with the epidemiologists (Section III). In Section IV, we present the interactive visualization-based interface that we have designed and implemented[1]. We then describe the assessments we performed for evaluating the tool (Section V). Finally, in Section VI, we summarize our work, and comment on possible directions for future work.

II. RELATED WORK

Many advances have been made on medical data visualization, but mostly using standardized charts to indicate the need for intervention by medical professionals [4]. In this section, we briefly discuss previous works on the visualization of medical records and epidemiological data based on their primary use. For further reading, we recommend the surveys on interactive visualization systems for electronic health records (EHR) by Rind et al. [5], and West et al. [4], and a recent survey on visual analytics for public health [6].

Plotting time-oriented data. Lifelines [2] was a pioneer work because it used a timeline to depict events in a patient's life employing colors and lines. After that, many tools for analyzing medical data were created where patient information

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[1]Videos demonstrating the tool are available as supplementary material.

was presented as a time series with a common time axis [7]–[9]. For example, MIVA [8], [9] utilizes separate plots sharing the same axis to visualize numerical patient data over time, indicating the normal range of the values on each graph. VisuExplore [7] provides a multiple-view visualization where all graphs also share the same axis to support medical analysis of patients with chronic diseases. Similarly, EPIPOI [10] presents a comparative analytical tool that creates visualizations of epidemiological time-series data.

Dashboards of patient data. Dashboards are also one of the most widespread approaches of data visualization in healthcare [11]. PatientExploreR [12] provides interactive and dynamic patient dashboards to display data from cohorts obtained by user queries. However, it is only possible to visualize data from a single patient, and users must be familiarized with EHR concepts to formulate effective queries. IDMVis [13] is an interactive visualization tool that helps clinicians perform temporal inference tasks on data for a single patient shown in a timeline. The system has limitations on the number of variables that can be shown and the depiction of events that can be hard to discern since an identical token represents them. Bernard et al. [14] present a static dashboard for the visualization of aggregated patient histories represented by a series of symbols. The tool allows creating an overview of a 2,000 patient dataset as well as compare multiple cohorts. The chosen design brings a number of limitations for its static nature and scalability issues when presenting more diverse cohorts.

Representing similarities. Characterizing and understanding similarities is instrumental in helping clinicians regarding their treatment decisions [15]. Gravi++ [16] creates an interactive visual clustering method where icons represent patients and questions are positioned around them. The position of each patient is based on the answers to each question, showing patients with similar answers positioned closer than others. The tool is limited to a restricted selection of different questions and patients since the influence of each question is difficult to perceive as the number of variables increase, and person icons tend to overlap. TimeRider [17] is a visualization tool created to help the exploration and analysis of data from a diabetes outpatient clinic. It displays trends in patient cohorts using an animated scatterplot. Even though the tool plots a limited number of variables at a time, users can understand the position of each entry since it is directly related to variable values. The tool also has some limitations, including usability problems and overlapping of data when using the tracing strategy. Lineage [18] is a visual analysis tool for the study of complex diseases by comparing genealogical similarities. Families can be visualized using a tree-like structure, while attributes from each individual or branch of individuals are shown in an attribute table. The tool has a number of performance issues and lacks searching and filtering features.

Comparing cohorts. Besides similarities between patients, another relevant topic in medical research is the comparison of cohorts in order to characterize differences between groups of patients [15]. CAVA [19] provides iterative analysis of user refined cohorts using a number of interchangeable, flexible visualization methods. Its user-friendly exploratory analysis is centered around the definition of cohorts, the visualization of selected patients, and the analytic operations. While the tool allows for a meaningful overview of cohorts, it still shows a limited amount of unstructured patient detail.

In summary, while most of the surveyed tools separate views of single or multiple patients, our work presents a hybrid approach, allowing users to interact with a cohort of participants while viewing specific information from each subject of the study. Most tools are limited to presenting a few data on a single screen, while our work can show an overview of approximately 90 different variables. They also mostly work with data from health clinics to assist doctors in reaching a diagnosis or treatment, while our work is more focused on the progression of patients to perceive the effectiveness of a treatment (i.e., a healthier lifestyle). The interface developed in this work intends to give users larger support compared to other works, especially regarding the interconnection and coordination between representations.

III. Domain Overview and Requirements

This work emerged as a collaboration with researchers from LINDA-Brasil [20], a multi-center randomized controlled clinical trial focused on investigating the effects of a lifestyle intervention program on the prevention of Type 2 Diabetes Mellitus (DM).

Following the nine-stage design study methodology proposed by Sedlmair et al. [21], we conducted a series of meetings with the clinical trial's epidemiology team over one year to assess the needs of researchers and learn about general use cases of an information visualization tool in their context.

A. Clinical Trial Overview

The trial targets specifically women who used insulin during pregnancy or presented intermediate hyperglycemia postpartum. It is based on recruiting women for entering the study between 10 weeks during and two years after pregnancy. These women are to be randomized between conventional care (Control group) and coach-based Intervention group, where habits such as breastfeeding, weight loss, healthy eating, and physical activity are encouraged and followed periodically by coaches through phone calls and visits.

The **primary outcome** of the study is the incidence of Type 2 DM that is verified with laboratory exams for both Control and Intervention groups. This outcome cannot be accessed until the end of the study for all participants since it could interfere with how the intervention is performed.

The trial has 12 different phases with a total of 127 questionnaires, each collecting ten variables, on average. Many of these relate to the same measurements, only collected at different moments of the study. Some of those variables suffer direct intervention from the study and are the focus

of the coach's attention, such as physical activity, weight, body circumference measures, and breastfeeding, considered as **secondary outcomes** of the study.

From this first meeting and subsequent contacts, we identified three high-level tasks: (1) gathering data from a specific participant each time a follow-up call has to be made; (2) tracking participants' progress to assess the effectiveness of the intervention, and (3) accompanying the completion of the trial's phases by the participants.

B. Functional Requirements

Based on the high-level tasks that we identified during the first meetings, we established three main functional requirements for the tool: (1) aggregate data of a single participant so that it can be easily accessed by the coaches when performing the follow-up calls; (2) show temporal variables associated with the secondary outcomes to identify progress, being able to filter participants and compare them according to parameters established by the researcher; and (3) accompany the completion of questionnaires applied in each phase of the trial for each participant enrolled.

These functional requirements led us to define different tasks that were essential for the design of the panels and visualizations proposed for the tool (Fig. 1).
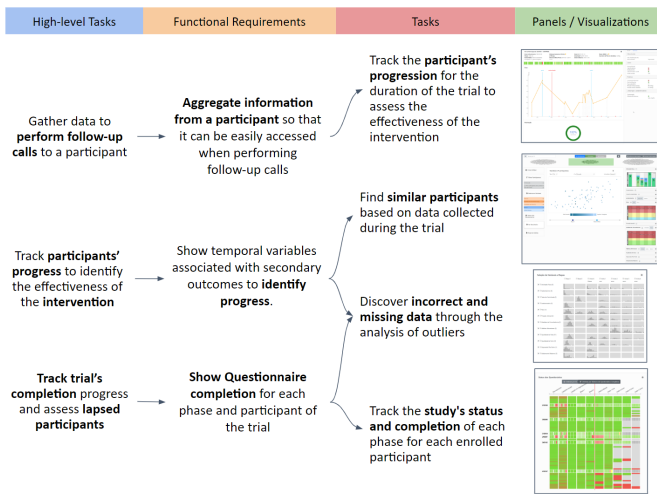

Fig. 1. From high-level tasks to functional requirements and tasks. Different panels and visualizations were integrated into a single interface.

IV. Interface Design

Three main interactive visualization tools were designed, each one providing a view of the dataset:

- The Participant's Dashboard (Section IV-A) focuses on displaying data of a single participant, showing the dossier information necessary for performing follow-up calls and plots from important variables of the study.
- The Participants' Information Analysis view (Section IV-B) provides a set of tools to filter out subjects and select variables to analyze the progression of patients and their similarities.
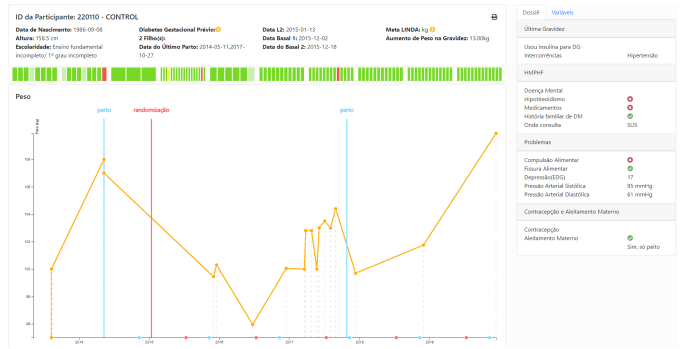

Fig. 2. Participant's Dashboard interface, showing dossier data. Its main components are a plot of the progression of participant's weight over time, with important dates of the study marked in the axis, and a simplified view of the questionnaire status of the participant shown above the plot.

- The Questionnaire Status visualization (Subsection IV-B5) was created to show an overview of the trial's progress and was incorporated as a plug-in to the Participants' Information Analysis view.

A. Participant's Dashboard

Phone sessions are the primary method for delivering the clinical trial's intervention, and to perform these calls, specialists need access to all relevant information about the participant at hand, especially its weight progression and other important milestones of the study. Such information is held as a dossier. The Participant's Dashboard (Fig. 2) shows all information needed for performing the call to a single participant as well as additional graphs and data. The most important information that needs to be visualized by researchers is the progression of weight changes, the weight goal defined for the participant, and certain events' dates. The dashboard also contains all information available in the dossier, and a tab in the same panel provides additional visualizations of temporal data (not shown in Fig. 2), which are described in Section IV-C. Furthermore, the status of the questionnaires of this single participant is displayed above the line graph (refer to Subsection IV-B5 for details).

B. Participants' Information Analysis View

In the Participant Information Analysis view (Fig. 3), we provide ways for comparing cohorts of participants by representing their similarities while still providing a detailed view of important variables for a single or a group of participants.

The comparison between patient histories is supported by the display of a scatterplot built using a dimensionality reduction (DR) technique on user-selected variables for a group of participants. The scatterplot is displayed at the center of the view, while commands for specifying filters and selecting the variables for the DR techniques are shown at the left. On the right, several plots show important variables for selected participants. Comparing participants' history regarding their progression allows coaches to perform better in subsequent phone sessions. Observing similar participants can help to

Fig. 3. Participants' Information Analysis interface, showing PCA results for a group of 91 participants. The upper portion shows an overview of all study's participants: the group of currently selected individuals is in the center of the screen (green rectangle) and the filtered or manually excluded ones are at each side (grey dots). On the left side of the view a menu is available for informing the filter, selecting the variables to be considered for building the scatterplot, viewing results and more. The right side of the view allows visualizing graphs of temporal variables on demand.

identify those that are about to abandon the study. We chose PCA [22] and t-SNE [23] due to users' previous experience.

Visualizations provided in this view are coordinated based on user interaction. Highlights made in one visualization are made visible in others, allowing a better contextualization of the participant. Participants represented in the views can be highlighted in two different ways: a mouse-over provides all visual representations of the participant to be highlighted, including where she stands within the histograms of temporal variables (Fig. 4, Subsection IV-B3), and a click marks the participant in all views and adds her data to the compact visualizations displayed on the right part of the view. Several participants can be selected simultaneously, allowing a comparison between them.

In the following, we give details of all components in the Participants' Information Analysis view.

1) Overview Visualization: All selected participants are displayed as small circles inside a green area at the center of the view. As the participants are filtered out, their circles are moved outside of the green area to the left of the screen if they were randomized to the intervention group and to the right if they belong to the control group. The changes are animated so users can track whether specific participants are being excluded. The visualization of temporal variables for both filtered out and non-filtered participants are updated accordingly.

2) Filtering of Participants: Removing certain participants depending on their data is a common strategy when analyzing clinical information and creating a cohort of patients. Three main characteristics were suggested by the epidemiologists to be used as filters.

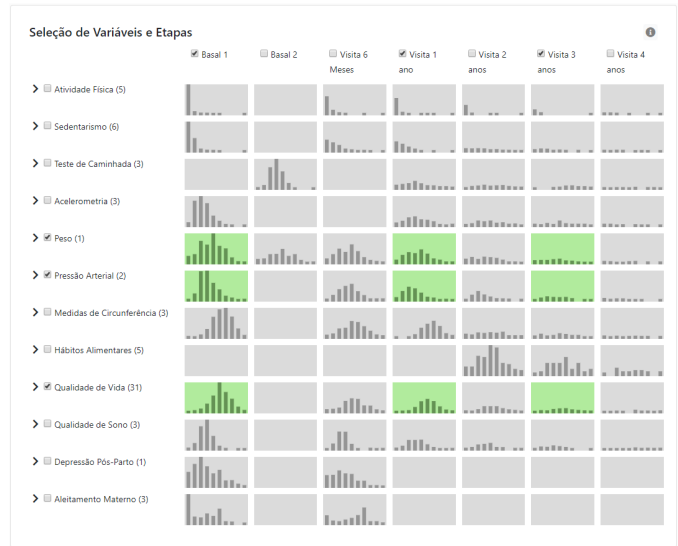- **Field center in which the participant is enrolled:**

Fig. 4. Matrix of variables per phase, where histograms depicts the distribution of values for each phase. Combo-boxes are used to select variables and phases, the resulting selection of cells being painted green. Sub-variables can be observed by clicking on the arrow to the left of each variable's name, showing their histograms with slightly lighter color tones.

each field center is plotted depending on its geographical location on a map, and its marker size is defined by its number of participants compared to other centers. Each one can be clicked to be filtered out or selected.

- **Randomization group of the participant:** the number of participants in the control and intervention groups is shown in a donut chart, where each partition can be clicked to select or filter out the participants in the group.

- **Time since the last activity the participants had on the trial:** an area chart shows the number of participants that were last contacted for each number of days. An area of the graph representing the number of days can be selected to filter out participants outside it. It is also possible to filter out the participants that are active in the study to allow identifying those that lost contact to be called and returned to the trial.

3) Variable Selection: To create the scatterplot of a cohort of participants, users must select variables and trial phases as a multidimensional descriptor of each participant. In each phase, a set of questionnaires is applied to participants. So, researchers are required to have a comprehensive understanding of the minutia of each phase as well as the overall trial protocol to know which variables are available to be used as a descriptor of each participant.

With this in mind, we envisioned a visualization (Fig. 4) to help researchers understand the distribution of each variable and to clarify which part of the dataset is being selected. To achieve this goal, we created a matrix of histograms, where each column corresponds to a phase, and each line contains histograms for a variable. In order to show the difference between the amount of participants' data for each phase, the same scale is used for all histograms created for the same variable. When the user marks variables and phases, the histograms of the chosen (variable, phase) pairs are colored green to show what data is currently selected. The selection of variables and phases triggers the creation of the matrix used for PCA or t-SNE techniques. Participants with not enough information on the selection made are immediately filtered out, allowing the user to analyze the resulting group and change the selection accordingly.

Each variable holds a varying number of sub-variables, which can also be viewed individually in their histograms and deselected from their groups. Sub-variables can be seen by clicking on the arrow to the left of each variable's name, showing their histogram with slightly lighter color tones. The histogram of a variable is created by calculating the average of all selected sub-variables' values.

Some other small interactions with the view were implemented to coordinate the histograms with the overview visualization. Histogram bars can be clicked, causing all participants with values within that range to be selected. This is useful for analyzing participants within that range and removing outliers from the visualization. Furthermore, when participants are highlighted in other views, the bars representing the range of their variables are also highlighted. This coordination feature allows for rapid visual analysis of subsets of participants.

4) Cohort scatterplot: The exploration of cohorts using multiple variables is often benefited from dimension reduction techniques (DR) [3]. This comparison can be useful for discovering patterns between similar patients, allowing specialists to more easily discriminate which factors influenced more positive and negative results in a participant's health.

Variables and phases selected on the Variable Selection view are used to generate the chosen DR scatterplot, ignoring patients filtered or removed by the user. Each selected phase generates a different scatterplot. If more than one phase is chosen, the DR scatterplot of a phase includes data from the previous phase. The reason behind this approach is to avoid temporal incoherence, an impairment in the visualization of temporal trends due to the independent application of a DR technique for each time step.

Each phase scatterplot to be displayed can be chosen from a timeline below the visualization. When transitioning between phases, an animation is played to show how participants' positions change from one to another. There are some customization options available, including selecting a variable to be assigned to the color of each participant marker, as well as modifying the colors used for the scale, changing the speed of the animation between subsequent phases, and altering the type of DR (PCA or t-SNE) being used and its parameters.

5) Questionnaire Status View: With the Questionnaire Status view, researchers can have an overview of the questionnaire completion for all participants, being able to check how far in the study each one has come, and if questionnaires were neglected in previous phases.

In the Questionnaire Status view (Fig. 5), each row represents a different subject, while each column shows a phase of the clinical trial. Rows are ordered from patients that completed the most questionnaires to patients with the lowest amount of data collected. Users can also choose to order them by their ID number. A rectangle is created for each item in the table, and its color is defined by the number of questionnaires completed for the phase, ranging from red (low) to green (high). Although we have questioned these colors, users' have been used to them due to a calendar tool they employ in a longitudinal study that their group is developing.

Questionnaires and Phases that are still not expected to be completed by participants are painted grey. This information is not available on the database and is calculated using the expected return date as described by the trial's specialists. These calculations take into consideration the patient's enrollment, labor, and randomization dates (for example, "6-Months Visit" phase should happen six months after the randomization date of the participant).

A participant's line can be clicked to expand the phases, creating a rectangle for each questionnaire where its current status of completion defines its color. This also causes the participant to be selected in other visualizations, i.e., temporal variables plots and the cohort scatterplot. The expanded line enables new interaction options, such as a tool-tip in each questionnaire to check its name and shows the ID of the selected participant, which can be clicked to trigger the display of her dashboard, described in Section IV-A.

C. Temporal Variables

Many variables collected over time help indicate changes in lifestyle and quality of life of participants, which is part of the intervention proposed by the clinical trial. We designed a series of compact visualizations to allow quick analysis of the progress of a single or several participants concerning
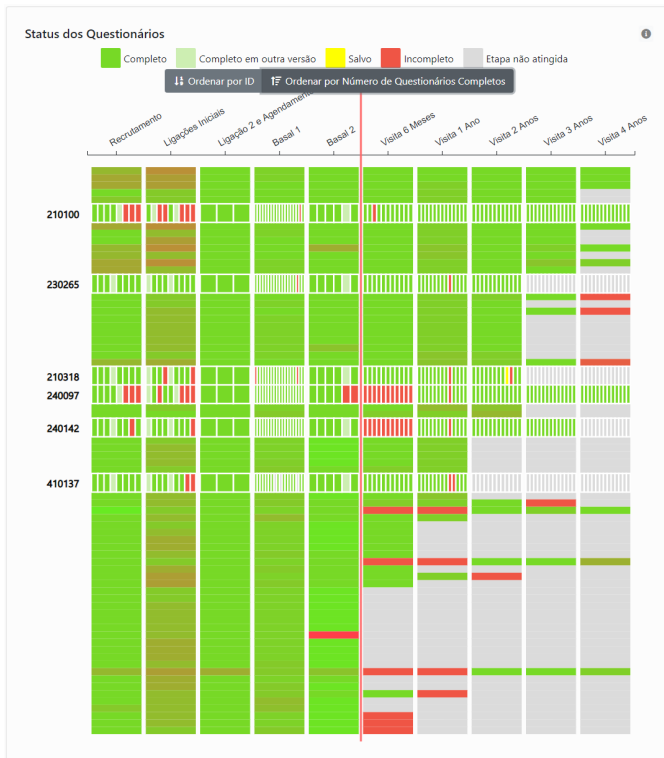
Fig. 5. Questionnaire Status view, showing detailed information about 6 participants. Each column represents a phase and each line a participant, that can be clicked to present the status of all her questionnaires.

important temporal variables. These visualizations, which are shown on the right in the Participants' Information Analysis view (Fig. 3), can be accessed by clicking on participants on this view (refer to Section IV-B), or on each participant's dashboard (Section IV-A). They can all be maximized for better visualization, and some of them provide alternative versions that can be toggled by buttons on their cards.

A table provided in the supplementary material shows an overview of each variable and its corresponding visualization, each one specifically designed to show positive or negative results in the intervention progress quickly.

D. Implementation Aspects

The front-end of the system was developed using JavaScript with Angular, Bootstrap, and D3 [24] for creating the visualizations. Some auxiliary libraries were also used to generate the dimensionality reduction-based visualizations (numeric and tsnejs), and some other minor features such as color pickers (Pickr), tutorials (Intro.js), and interface icons (Font Awesome). Icons embedded in the visualizations were individually created in Inkscape.

V. USER EXPERIENCE TESTING

The first formal evaluation was performed by one of the trial researchers so that we could collect feedback regarding features and usability issues. We also developed usage scenarios to compare with the needs we gathered in our meetings.

Then, the final version of the interface underwent two formal evaluations, one with clinical trial researchers and another with people who had no epidemiology background. Herein, we describe these two last evaluations.

A. Expert Evaluation

We conducted an assessment to evaluate the usability of the tool and know what tasks would be hard to perform without assistance. This evaluation was performed by experts on the field of epidemiology, preferably by specialists with connections with the trial.

1) Method: We allowed researchers to use the tool freely and collected answers using standardized usability questionnaires [25], [26] and other more specific questions about each presented visualization.

They were invited by e-mail to interact with the system and fill the questionnaires. Participants from outside of the study were presented to the interface in person since it was their first time accessing the system.

2) Demographics: This evaluation was conducted with two members of the clinical trial, one holding an MSc degree and the other a Ph.D. degree, and a third external researcher also with a Ph.D. degree, with experience in software for the management of clinical trials. They were all females, ranging from 32 to 34 years old.

3) Results: Since we had only three specialists, the results will be presented and discussed qualitatively. Nevertheless, results from the User Experience Questionnaire (UEQ) [26] and System Usability Scale (SUS) [25] (average score of 78.3) were positively increased compared to the preliminary evaluation performed during the design process.

Regarding the Participants' Information Analysis, all specialists agreed or strongly agreed that they understood how to use each interface feature (such as filtering, selections of variables, and results).

Two of them agreed that the tool helped them discover information that would be hard to achieve otherwise. As for the Participants Overview visualization, one participant was neutral, and the others agreed that the visualization helped them understand how their actions affected the selection of participants. The neutral user (a specialist from the research team) commented that she found the visualization and selection possibilities interesting even though the selection (especially including variables) was not intuitive and required more familiarization.

In the variable selection interface, both trial members agreed that the histograms helped them understand what was being selected, while the external specialist stated that the histograms were not easy to understand.

As for the DR scatterplots, only one specialist agreed that she understood the meaning of the points' position. She also agreed that the scatterplot helped her to gather insights into the trial's progress. The second trial member and the external specialist both stated that they were not familiar with PCA or t-SNE and did not understand very well the logic behind it.

All specialists agreed or strongly agreed that they understood the meaning of each row and column of the questionnaire status visualization and understood how selections and filters influenced the view. They also agreed that it was useful as an overview of the trial's progress regarding questionnaire completion.

Regarding the graphs generated for the temporal variables of the trial, two specialists agreed that the visualizations are useful for the comparison of participants, while the other was neutral. The external researcher commented she wished some basic statistics was presented for the variables.

B. Non-Expert Users Evaluation

We designed a second formal experiment where we could gather feedback from more users and check if people new to the system could perform essential tasks. We also aimed at discovering general usability problems of the tool.

1) Method: The evaluation was performed in person, one at a time, and the user was observed while interacting with the system. We first presented a text briefly describing the trial and the goals of our work. Then, we guide the user through the interface showing its most relevant features and how they could be used by specialists working on the trial. After feeling confident about the tool, the user was presented with tasks based on a possible usage scenario of the tool.

2) Demographics: Sixteen non-expert users participated in this experiment, ranging from 21 to 59 years old, 75% male and 25% female. Only 18% had some previous knowledge about the clinical trial. 81.2% graduated in Computer Science and are MSc or Ph.D. students of varying topics inside the field, while 18.7% of participants were graduated in other areas, such as Design and Social Sciences.

3) Results: During the exploration phase of the evaluation, most users asked questions and seemed interested in using the interface. Table I shows the tasks presented to users, their success in completing them, their perceived difficulty based on the Single Ease Question, and the average duration of each. The description of the task is a simplified version of the text.

After the tasks were performed, users filled UEQ and SUS questionnaires. Benchmark results from UEQ showed excellent results in all categories and a good score for Perspicuity, which indicates how easy it is to get familiar with the tool.

SUS results achieved an average score of 86.2, which can be considered excellent and above average when compared to mean scores from SUS results for web applications (68.05).

As users finished the test, many pointed out that the system was intuitive and easy to learn. Some also added suggestions in the final comments section of the evaluation form, all related to minor changes to some aspects of the tool. Moreover, all non-expert users who left suggestions also said the tool seems to be very useful to the field of study, and it is easy to use, attractive, and well-integrated.

C. Discussion

There are several challenges in performing formal evaluations with expert users. The completion rate becomes a

TABLE I
RESULTS FROM THE FORMAL EVALUATION TASKS PERFORMED BY 16 NON-EXPERT USERS. THE COLUMNS SHOW AVG. SUCCESS RATE (AS), AVG. DIFFICULTY (AD) AND AVG. TIME (AT). DIFFICULTY WAS SELF-REPORTED BY USERS AND MEASURED BY THE SINGLE EASE QUESTION (SEQ), RANGING FROM 1 (VERY HARD) TO 7 (VERY EASY).

	Task	AS	AD	AT
1.1	Select participants 230424, 260109, 220513, 260107, 220469	100%	6.3	47.2s
1.2	Save group of participants	100%	6.9	2.5s
2.1	Filter all field centers except Porto Alegre	75%	6.6	11s
2.2	Filter randomization group Control	100%	6.5	8.25s
2.3	Filter participants with more than 300 days since they lost contact with the study	87.5%	6.1	28s
2.4	Check the total number of participants filtered	93.7%		
3.1	Remove participants 240327, 240287, 260086	93.7%	6.3	41s
3.2	Load group of participants	81.2%	6.6	5.3s
4	Check number of incomplete questionnaires from 230424	87.5%	6.3	25.2s
5.1	Hover participant to check its histogram bins	100%		18s
5.2	Select variables Physical Activity, Weight, Accelerometry, and phases Basal 1, 1 Year Visit	100%	6.5	12.6s
6.1	Change color variable on PCA to Lost Contact	100%	6.8	8.3s
6.2	Find similar participant(s) to one of the selected subjects on PCA	100%	5.5	56.6s

more significant problem than in evaluations with non-experts since the process needs to be fitted into the tight schedule of few individuals. In our case, we proposed to perform the evaluation remotely, but that seemed to have worsened the problem because there was no commitment to a scheduled date for the test, and they tended to forget about the evaluation. Nevertheless, the comments provided were very useful in pointing out problems with the tool and improvements that were not brought up during informal meetings.

When comparing results from specialists and non-expert users, we can see that the SUS average score was considerably higher for non-experts (86.2 compared to 78.3 for experts). Also, although such comparison can be biased by the small number of responses from experts, UEQ results for non-experts showed overall better scores, so they seemed to understand how the tools work better. On the other hand, specialists had slightly higher scores for stimulation and novelty parameters, possibly for not being exposed to innovative systems so often, as was common for the majority of non-experts who performed the experiment.

VI. FINAL COMMENTS

This work presented a visualization-based interface designed for monitoring the development of a randomized clinical trial [20] focused on the effects of lifestyle intervention in the development of Type 2 Diabetes for patients with Gestational Diabetes Mellitus (GDM). We analyzed a list of requirements gathered from epidemiologists directly working within the trial and designed an intuitive interface for a more straightforward assessment of the information stored while allowing for a deeper analysis of similarities between subjects.

Visualization techniques were created to allow following a participant's progress and compare it to others. The resulting tool integrates several features inspired in previous works in a single interface, creating a hybrid approach for discovering similarities and trends between groups of participants and detailed visualizations of individuals.

Many interesting future works can be developed to improve the tool and the techniques adopted herein. Adding the possibility of comparing multiple cohorts of patients would improve the analysis of the effects of the intervention in different subjects. As suggested by one of the experts, we could add the possibility of calculating some basic statistics for subsets of participants. Also, it would be interesting to provide adaptive visualizations, i.e., those that the user can modify to better fit with the intended analysis.

Finally, although we developed the tool for a specific clinical trial, which is a limitation of the current implementation, its concepts, and many visualizations can be easily converted to other clinical trials, with some extra-coding for importing data in a standardized way.

Acknowledgments

References

[1] M. S. Thiese, "Observational and interventional study design types; an overview," *Biochemia Medica*, vol. 24, no. 2, pp. 199–210, 2014.

[2] C. Plaisant, B. Milash, A. Rose, S. Widoff, and Shnei-derman, "Lifelines: Visualizing personal histories," *SIGCHI Conference on Human Factors in Computing Systems Proceedings*, vol. 1, pp. 221–227, 1996.

[3] B. Preim, P. Klemm, H. Hauser, K. Hegenscheid, S. Oeltze, K. Toennies, and H. Völzke, "Visual analytics of image-centric cohort studies in epidemiology," *Mathematics and Visualization*, no. January, pp. 221–248, 2016.

[4] V. L. West, D. Borland, and W. E. Hammond, "Innovative information visualization of electronic health record data: a systematic review," *Journal of the American Medical Informatics Association*, pp. 330–339, 2015.

[5] A. Rind, "Interactive information visualization to explore and query electronic health records," *Foundations and Trends® in Human-Computer Interaction*, vol. 5, pp. 207–298, 01 2013.

[6] B. Preim and K. Lawonn, "A survey of visual analytics for public health," *Computer Graphics Forum*, vol. 39, no. 1, pp. 543–580, 2020.

[7] A. Rind, W. Aigner, S. Miksch, S. Wiltner, M. Pohl, T. Turic, and F. Drexler, "Visual exploration of time-oriented patient data for chronic diseases: Design study and evaluation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7058 LNCS, pp. 301–320, 2011.

[8] A. Faiola, C. Boston-Clay, J. Jones, M. Downey, and C. M. Newlon, "Managing patient health across diverse spaces: Using activity theory to model pervasive decision support," *Proceedings of the CHI2012 Workshop "Bridging Clinical and Non-Clinical Health Practice: Opportunities and Challenges"*, 2012.

[9] A. Faiola and C. Newlon, "Advancing critical care in the icu: A human-centered biomedical data visualization systems," *Ergonomics and Health Aspects, Proceedings of the International Conference on Human-Computer Interaction (HCII 2011), (M. M. Robertson, ed.)*, vol. 6779, pp. 119–128, 2011.

[10] Alonso and McCormick, "Epipoi: A user-friendly analytical tool for the extraction and visualization of temporal parameters from epidemiological time series," *BMC Public Health*, vol. 12, no. 982, 2012.

[11] D. T. Wu, A. T. Chen, J. D. Manning, G. Levy-Fix, U. Backonja, D. Borland, J. J. Caban, D. W. Dowding, H. Hochheiser, V. Kagan, S. Kandaswamy, M. Kumar, A. Nunez, E. Pan, and D. Gotz, "Evaluating visual analytics for health informatics applications: A systematic review from the american medical informatics association visual analytics working group task force on evaluation," *Journal of the American Medical Informatics Association*, vol. 26, no. 4, pp. 314–323, 2019.

[12] B. S. Glicksberg, B. Oskotsky, P. M. Thangaraj, N. Giangreco, M. A. Badgeley, K. W. Johnson, D. Datta, V. A. Rudrapatna, N. Rappoport, M. M. Shervey, R. Miotto, T. C. Goldstein, E. Rutenberg, R. Frazier, N. Lee, S. Israni, R. Larsen, B. Percha, L. Li, J. T. Dudley, N. P. Tatonetti, and A. J. Butte, "Patientexplorer: an extensible application for dynamic visualization of patient clinical history from electronic health records in the omop common data model," *Bioinformatics*, vol. 35, no. 21, pp. 4515–4518, 2019.

[13] Y. Zhang, K. Chanana, and C. Dunne, "IDMVis: Temporal Event Sequence Visualization for Type 1 Diabetes Treatment Decision Support," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 512–522, 2019.

[14] J. Bernard, D. Sessler, J. Kohlhammer, and R. A. Ruddle, "Using dashboard networks to visualize multiple patient histories: A design study on post-operative prostate cancer," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 3, pp. 1615–1628, 2019.

[15] B. Shneiderman, C. Plaisant, and B. W. Hesse, "Improving healthcare with interactive visualization," *Computer*, vol. 46, no. 5, pp. 58–66, May 2013.

[16] K. Hinum, S. Miksch, W. Aigner, S. Ohmann, C. Popow, M. Pohl, and M. Rester, "Gravi++: Interactive information visualization to explore highly structured temporal data," *Journal of Universal Computer Science*, vol. 11, no. 11, pp. 1792–1805, 2005.

[17] A. Rind, W. Aigner, S. Miksch, S. Wiltner, M. Pohl, F. Drexler, B. Neubauer, and N. Suchy, "Visually exploring multivariate trends in patient cohorts using animated scatter plots," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 6779 LNCS, pp. 139–148, 2011.

[18] C. Nobre, N. Gehlenborg, H. Coon, and A. Lex, "Lineage: Visualizing multivariate clinical data in genealogy graphs," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 3, pp. 1543–1558, 2019.

[19] Z. Zhang, D. Gotz, and A. Perer, "Iterative cohort analysis and exploration," *Information Visualization*, vol. 14, no. 4, pp. 289–307, 2015.

[20] M. I. Schmidt, B. B. Duncan, C. Castilhos, E. M. Wendland, P. C. Hallal, B. D. Schaan, A. Drehmer, M. Costa e Forti, C. Façanha, and M. A. Nunes, "Lifestyle intervention for diabetes prevention after pregnancy (linda-brasil): Study protocol for a multicenter randomized controlled trial," *BMC Pregnancy and Childbirth*, vol. 16, no. 1, pp. 1–12, 2016.

[21] M. Sedlmair, M. Meyer, and T. Munzner, "Design Study Methodology: Reflections from the Trenches and the Stacks," *IEEE Trans. Visualization and Computer Graphics (Proc. InfoVis)*, vol. 18, no. 12, pp. 2431–2440, 2012.

[22] G. H. Golub and C. Reinsch, "Singular value decomposition and least squares solutions," *Numerische Mathematik*, vol. 14, no. 5, p. 403–420, 1970.

[23] L. van der Maaten and G. Hinton, "Visualizing high-dimensional data using t-sne," *Journal of Machine Learning Research*, vol. 9, pp. 2579–2605, 2008.

[24] M. Bostock, V. Ogievetsky, and J. Heer, "D3 data-driven documents," *IEEE transactions on visualization and computer graphics*, vol. 17, no. 12, pp. 2301–2309, 2011.

[25] J. Brooke, "SUS: A quick and dirty usability scale," *Usability evaluation in industry*, vol. 189, no. 194, pp. 4–7, 1996.

[26] B. Laugwitz, T. Held, and M. Schrepp, "Construction and evaluation of a user experience questionnaire," in *Construction and Evaluation of a User Experience Questionnaire*, vol. 5298, 11 2008, pp. 63–76.