2018

Developing the GIFT Event Report Tool to Support Experimentation for Teams

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Abstract

The Generalized Intelligent Framework for Tutoring (GIFT) is an open source framework for creating Intelligent Tutoring Systems (ITSs). GIFT can provide tailored instruction and remediation that takes into account the current state of the learner, and learner attributes such as individual differences in various domains (Sottilare, Brawner, Goldberg, & Holden, 2012; Sottilare, Brawner, Sinatra, & Johnston, 2017). GIFT is available in both downloadable and in online form (known as GIFT Cloud at https://cloud.gifttutoring.org). GIFT includes authoring tools that can be used to create "GIFT courses," which are a sequence of materials, questions, and instruction that is presented to a learner. While GIFT is primarily a system for authoring ITSs, it can also be leveraged for use in experimentation in both traditional and ITS relevant experiments. For the purposes of experimentation, one of the major advantages of GIFT is its ability to extract participant data from GIFT courses through the use of either the desktop based Event Report Tool (ERT) or the GIFT Cloud Event Report Tool (Cloud ERT). Each time learners participate in a GIFT course, a log file is created that includes all of their entered data, responses to questions, and a record of their actions. Using the Event Report Tools, experimenters can select the specific GIFT data pieces of interest and export those as comma separated value files, which can be easily imported into Microsoft Excel. The Army has expressed a growing need for applying ITS approaches to teams, through Intelligent Team Tutoring Systems (ITTSs). There is also an increase in interest in developing GIFT Cloud to provide a proper mechanism for collecting team-based data. Part of creating a framework for ITTSs is not only providing guidance and authoring tools for the collection of team performance data, but also export tools that provide data in an understandable way. While both the team authoring and export aspects of GIFT are not currently implemented, this chapter's focus provides a starting point on how to make the export tools (ERT) more suitable for team-based data collection. The current chapter will focus on the team elements, while also providing recommendations for overall improvements to the ERT's flow and organization. Although the emphasis is on teams, the suggestions provided can help individual-based data collection as well.

Disciplines

Ergonomics | Human Factors Psychology | Operational Research

Comments

This chapter is published as Boyce, Michael W., Anne M. Sinatra, Stephen B. Gilbert, and Robert A. Sottilare. "Developing the GIFT Event Report Tool to Support Experimentation for Teams." In *Design Recommendations for Intelligent Tutoring Systems: Volume 6 - Team Learning and Taskwork* (A.C. Graesser, X. Hu, A.M. Sinatra, and R.A. Sottilare, eds.). Orlando, FL: U.S. Army Research Laboratory, 2018, pages 227-236.

CHAPTER 22 – DEVELOPING THE GIFT EVENT REPORT TOOL TO SUPPORT EXPERIMENTATION FOR TEAMS

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Introduction

The Generalized Intelligent Framework for Tutoring (GIFT) is an open source framework for creating Intelligent Tutoring Systems (ITSs). GIFT can provide tailored instruction and remediation that takes into account the current state of the learner, and learner attributes such as individual differences in various domains (Sottilare, Brawner, Goldberg, & Holden, 2012; Sottilare, Brawner, Sinatra, & Johnston, 2017). GIFT is available in both downloadable and in online form (known as GIFT Cloud at https://cloud.gifttutoring.org). GIFT includes authoring tools that can be used to create "GIFT courses," which are a sequence of materials, questions, and instruction that is presented to a learner. While GIFT is primarily a system for authoring ITSs, it can also be leveraged for use in experimentation in both traditional and ITS relevant experiments. For the purposes of experimentation, one of the major advantages of GIFT is its ability to extract participant data from GIFT courses through the use of either the desktop based Event Report Tool (ERT) or the GIFT Cloud Event Report Tool (Cloud ERT). Each time learners participate in a GIFT course, a log file is created that includes all of their entered data, responses to questions, and a record of their actions. Using the Event Report Tools, experimenters can select the specific GIFT data pieces of interest and export those as comma separated value files, which can be easily imported into Microsoft Excel. The Army has expressed a growing need for applying ITS approaches to teams, through Intelligent Team Tutoring Systems (ITTSs). There is also an increase in interest in developing GIFT Cloud to provide a proper mechanism for collecting team-based data. Part of creating a framework for ITTSs is not only providing guidance and authoring tools for the collection of team performance data, but also export tools that provide data in an understandable way. While both the team authoring and export aspects of GIFT are not currently implemented, this chapter's focus provides a starting point on how to make the export tools (ERT) more suitable for team-based data collection. The current chapter will focus on the team elements, while also providing recommendations for overall improvements to the ERT's flow and organization. Although the emphasis is on teams, the suggestions provided can help individual-based data collection as well.

The structure of this chapter begins with a discussion on the related literature to date on data reporting for teams. It then looks at challenges that are faced by researchers trying to run experimentation with teams on GIFT and the needs they have. This follows with some high level recommendations to fit those needs, and concludes with an initial mockup of potential future ERT functionality.

Related Literature

History of Intelligent Tutoring Systems to Support Teams

There is a vast literature expressing the characteristics of team training, team tutoring, and team performance metrics that is well beyond the scope of this chapter, but a high-level discussion can assist in providing context for the rest of the chapter. There have been a couple of attempts at developing team tutoring systems. The Advanced Embedded Training System was developed by the Navy to support team training on ships (Zachary et al., 1998). The system acted as a support tool to reduce workload. It performed less than optimally because the amount of feedback in a real-time team scenario turned out to exceed the capabilities of the instructor to provide remediation, thereby reducing performance. More recently, researchers using the Team Multiple Errands Task (TMET) were able to quantify and assess team performance without demonstrating ceiling or floor effects (Bonner et al., 2016; Walton, Gilbert, Winer, Dorneich, & Bonner, 2015). This computer-based task, which involved coordinating with a team and purchasing items from a list, had strong team characteristics and necessitated interdependence from the team members.

Sottilare and colleagues (Sottilare, Burke, et al., 2017) performed a large scale meta-analysis on connecting teamwork behaviors (communication, coordination, cognition, etc.) to the appropriate team outcomes (learning, performance, satisfaction, and viability). Their research focused on team measurements being represented by attitudes, behaviors, and cognition (Sottilare, Burke, et al., 2017). Understanding the states and traits of an individual and how those relate to the progression of goals can provide guidance on specific actions during a tutor event. The research resulted in identifying six sets of behavioral markers: trust, collective efficacy, cohesion, communication, and conflict / conflict management (Sottilare, Burke, et al., 2017), which can assist in measuring team behaviors. While this research focused on a large scale meta-analysis of the team literature, the majority of the articles available were in non-computer based and non-ITS related areas. Additionally, the behavioral markers identified must still be operationalized in order to be implemented in an ITTS. This research demonstrates the need for further investigation on learning with teams and the complexities that come with ITTSs.

Teams and Learning through Data

Teams of two or more are the building blocks for all military collective performance. It is important to be able to quantify how teams are performing relative to their stated goals, the solutions being generated to solve team problems, and how the complex challenges from the military are being met (Sottilare, Burke, et al., 2017). Past research identified some of the big challenges in developing ITTSs. This includes: measuring team performance, improving team performance, and studying team formation and development (Dorsey et al., 2009; Sottilare, Burke, et al., 2017). A defining characteristic of an ITTS is that it needs to account for individual interactions as well as team interactions with the tutor, and take into consideration the external factors associated with the environment of interest (Bonner et al., 2016; Gilbert et al., 2017). Since team skills contain social components like communication and coordination, it becomes harder to represent them quantitatively (Gilbert et al., 2017). In the military, communication and coordination can be manifested through collaborative learning or cooperative learning.

Irrespective of the type of learning, these additional components increase the amount of data available exponentially as each additional learner is considered (Bonner et al., 2016). Team data can come from a variety of sources such as real time learner data, learner states determined from classification, and long term attributes established from previous data (Sottilare, Burke, et al., 2017). Data can be used both as a source for experimentation or as a basis to shape the learner experience. A challenge for ITTSs is being able to transform data based on empirical hypotheses into a format that can be readily interpreted and understood (MacAllister et al., 2017).

When conducting research with an ITTS, there are four forms of data to collect and analyze. The first type is the low-level data such as users' interface clicks, movements of entities in a system, and timing between events. These data are typically passed along to the tutor to trigger real-time feedback. This process is what VanLehn (2006) called the "inner loop" of an ITS. To analyze team data, one might conduct a "team loop" process, in which the behaviors of the team as a whole (a second type of data) are sent to the tutor to generate team feedback. The third type of data is present in VanLehn' s "outer loop" process, in which data about users' accumulated skill profile or learner model (not their real-time clickstream) are used to choose the best next training scenario for them based on the skills that need bolstering. The fourth type of data are those that are averaged across multiple teams and used for statistical analysis by researchers to evaluate learning effectiveness or the usability of the system (sometimes called educational data mining or educational data analytics). Each of these four types represents four different forms of data-based decision making that need to be made by either the tutor or the researcher (Gilbert, Dorneich, Walton, & Winer, in press).

Past research using GIFT with teams made strides on increasing understanding and working with data through visualization. Data Visualization is the presentation of data in a graphical format so that it is easier to understand (Chen, Härdle, & Unwin, 2007). Data visualization can assist in organizing and grouping information to make it align with the mental model or schema of decision-makers with many different styles and techniques available (Bertini, Tatu, & Keim, 2011). Data visualization can be static (i.e. a snapshot of user / team performance) or it can be dynamic (e.g. a dashboard with consistently updating information). A data visualization can be passive, such as a view that can't be changed or it can be interactive where individuals can modify the data as needed and the data is rendered to represent those changes. Data visualization can also be expanded to encompass related information that is not directly represented within the data (Chen et al., 2007). As datasets become larger, individuals are forced to comprehend this data quickly and accurately.

Research conducted at Iowa State University used multiple techniques to manipulate and represent data for two-person teams. The researchers created customized post-processing solutions to be able to represent team variables (Gilbert et al., 2017; MacAllister et al., 2017). They also created a timeline chart, which provided information on the specific activities participants were doing during critical points in the experiment (MacAllister et al., 2017). While the output created was highly task-dependent, the approaches that they used (i.e. time series analyses), and data they extracted are relevant in determining the types and groupings of data that are relevant to extract from an ITTS (MacAllister et al., 2017).

Outside of the military environment, Dashi (2016, 2017) used Excel to generate macros to analyze student data. The data could be analyzed in a post processing format or during a class as they were interacting with an online learning platform, as well as creating pivot table solutions to better visualize the data. Specifically, student engagement was quantified through metrics such as mouse clicks, page views, and quiz scores. Data representations like these can provide insight on both the underlying empirical data and the complex relationships which often accompany team-based research studies.

Information and Data Visualization Foundations to Support Understanding

In developing concepts for improvements to the ERT, seminal research by two of the key contributors to the area of information and data visualization were examined: Ben Shneiderman and Edward Tufte.

Shneiderman, a leader in the field of human-computer interaction, developed a list of "Eight Golden Rules for Interface Design" such as consistency, informative feedback, and reducing short term memory load (B. Shneiderman & Plaisant, 2005). He also developed a task by data type taxonomy to support data visualizations where he created his mantra for visual information seeking: "Overview-first, zoom and filter, then details on demand." He breaks this down further into seven tasks when working with data visualizations:

- Overview – Provide an overview of the entire interface
- Zoom – Zoom in on areas of interest
- Filter – Remove non-relevant items
- Details on Demand – Provide ability to select specific items for more information
- Relate – Show relationships among items
- History – Maintain a history to support undo
- Extract – Allow for collections of subsets of the data (Ben Shneiderman, 1996)

These tasks are similar to the tasks that an individual might complete when using the ERT.

Edward Tufte is one of the key figures in maximizing the understanding of data representations. Tufte had four primary themes that echoed through his writings: graphical excellence, visual integrity, maximizing the data to ink ratio, and aesthetic elegance.

- Graphical excellence refers to expressing the greatest number of ideas in the simplest form as possible, using minimum amounts of space, and the fewest words.
- Visual integrity refers to having numerical scales that are proportionate to the values they represent. They should be tied directly to the data, rather than any sort of artistic interpretation.
- Maximizing the data-ink ratio refers to comparing the amount of ink needed to describe the data as opposed to the total ink used for illustrative purposes. The visualization should be less distracting and more useful for the user.
- Aesthetic elegance, in Tuft's view, is being able to clearly and simply display the complexity of data that is being represented via figures and tables (Tufte, 1983).

As organizing team data and output is a complicated and information-intensive task, it is important to consider visualization heuristics that will make the process easier to understand for users. It is through learning from previous research on teams, learning with ITTSs, and information visualization that we use to frame our concepts and mockups for improving the ERT for teams. However before going into improvements, there is a need to understanding the difficulties of running a team experiment in GIFT.

Challenges and Functional Needs for Team Experiments

When researchers retrieve data from an experiment, they face challenges to overcome and functional needs that must be fulfilled in order to support team based research.

Challenges

Tool Selection: Desktop vs. Cloud ERT

After collecting data, researchers can select the types of data that they want to extract from logs using GIFT's ERT. The ERT includes data categories such as survey responses, learner state, and more. However, researchers must decide whether to use the Desktop ERT or the Cloud ERT.

Both the Desktop and Cloud ERT architectures are currently configured to focus on individual learners. As mentioned earlier in the chapter, the shift from desktop to the Cloud is resulting in different requirements for the ERT and ultimately a redesign to improve usability. The Desktop ERT has can produce greater granularity and the ability to handle sensor based data, which the Cloud ERT cannot. The Cloud ERT focuses more on usability, but has limitations in regard to the types of data that can be extracted and the organization of the data.

For instance, the data from the Desktop version is pulled from an output folder in the GIFT installation folders, and allows experimenters to individually select the log files that they wish to include in the analysis. In the case of the Cloud ERT, all data from the specific instance of the course is housed online, and the output includes all logs relevant to the experiment. This may result in issues if there are participants with missing data or who had technical difficulty during the data collection. Experimenters need to realize that all participants were included and edit their output file appropriately to remove the data that should not be included. A current work-around for this issue is to download the log files from the cloud and import them into the Desktop version for analysis. However, this is not the ideal long-term solution. Below we discuss an improved approach for the Cloud ERT system.

Data Representation: Working with and Merging Data

Next, researchers need to decide the format for their data output. Currently, when experimenters want to collect data from an experiment run on GIFT Cloud, they have two options: download all of the raw data logs in order to export them using the desktop based ERT, or build a report by selecting the specific information of interest. If experimenters decide to build a report, they must first choose from frequently reported event types, training application event types, and other event types. Depending on the type of data that is included in the report, experimenters can select an option to combine all data for a single user onto a horizontal line. This option is useful in regards to survey output, and it facilitates the import of the output file into Excel or SPSS for further analysis.

It is important to note that in the Desktop ERT, experimenters have the option of merging data by certain characteristics like Use rid or Username, whereas in the Cloud version, the merging occurs based on the specific log and user session. While in most cases this would not be a problem, it may be helpful to include survey questions within a course which asks for a Use rid so that it is clear which user the data came from when the data file is output. Currently, one of the solutions for identifying how to group team data would be to include questions within the course that requires the team number and participant number to be entered. The data could then be sorted by the experimenter after it is output.

Participant number management is particularly important in the online ERT, as currently the only way to extract data from Cloud GIFT is through using the Publish Courses function and distributing links to participants that do not require logins. Due to this lack of a login requirement, the data logs that are being parsed are not associated with any particular participant number. It is important for the experimenter to realize this and include a question in their data set that asks for this information.

Functional Needs of the ERT

High-Level Needs

The high-level needs consist of those that could be applied across all experiments, which includes team-based experiments. They are discussed here to show both the potential of larger scale changes, and to delineate general changes from those that are especially relevant to teams.

Ontological Mapping of Across Levels of Data
To facilitate effective analysis, data needs to be encapsulated into a hierarchical model. At the lowest level is the raw data that is streamed from the system, it could be combined with data collected by human experimenters. Above that level are tools and methods to organize and present data for analysis. At the top level of the hierarchy is the collection of analyses compared against criteria for successful completion (Gilbert et al., 2017). Implementing this into the ERT will require a visual way for researchers to select and organize the log files that are being analyzed for the output.

Interface Enhancements to Work with Complex Experiments
One of the successes of the latest redesign of GIFT has been the incorporation of easier to use interfaces. This includes features like being able to drag and drop course objects in course authoring. In the same vein, an experimenter needs to be able to drag and drop experiment objects to represent their experiment design, much like what is possible in current leading experimental design software applications such as E-Prime (Schneider, Eschman, & Zuccolotto, 2002) and Open Sesame (Mathôt, Schreij, & Theeuwes, 2012). Rather than reinventing the wheel, integration with these software tools might provide the necessary infrastructure to better support experimenters using GIFT.

Matching Capabilities Between ERT Tools

As mentioned in the previous section, experimenters must choose between the Desktop ERT and the Cloud ERT. This presents a problem for most experimenters using GIFT because they are not going to have a clear understanding of the capability differences between the ERT tools unless they try to perform a function that exists only in one tool or the other. Since the ERT is a post processing tool, it does not have the runtime restrictions that experiments visualizing live data might require.

Scaffolding for First Time Users

The first time someone attempts to use the ERT, there needs to be scaffolding which demonstrates how the ERT works. This could be in the form of an instructional overlay with coach marks, where GIFT highlights a series of user interface features to show them how the ERT works. Although this is currently done using documentation and videos, a short action-based (non-voice) tutorial could help. It could be done by keeping track of every time a GIFT user enters a new part of GIFT that is unfamiliar. Then, after they see the tutorial once, they do not have to see it again. However, it could be retrievable again from a help menu or button on the screen if users feel that they need a refresher.

Linking to Data Sources

Linking to the sources of data can ensure that an experimental measure is being used as it is intended to be used. This could be done by providing references to previous data repositories, published research papers, or user's guides. It may also be of benefit to provide recommendations of related measures or data sets that might be of interest to the experimenter.

Team-Specific Needs

It is important to note that team experiments have different needs than individual learning experiments. The ERT can be improved and redesigned to allow researchers to include options to better frame team experiments, and provide easier to deal with data output. A few needs that we have identified include the following.

Team Variables

There needs to be a way to set team-specific variables that are dependent on multiple users before the data is requested from the ERT. This type of change can also have relevance to improving the log file analysis problems that exist in the current Cloud ERT. If specific user data logs could be selected in the ERT, and potentially grouped by the experimenter, it would assist in solving these problems. For instance, if the experimenter included questions such as "User ID" and "Team Number" in their questions, then perhaps these could be displayed to experimenters for selection as they begin analysis.

Pre-Processing of Experimental Data

Ideally, the ERT would begin the analysis process by populating the available logs on the screen for the experimenter, and instead of listing a title in the form of a string that does not have meaning to the experimenter. The title could pull specific values from the surveys in the file such as Use rid or Participant Number. This could be achieved in two ways: 1) creating standard questions that should be asked of all participants if it is indicated that an experiment is being created (e.g., "Use rid", "Participant Number") or 2) providing experimenters with a way to select specific survey answers that they want displayed as log titles for ease of use. Regardless, selectivity of specific logs and visibility of the participant identification are essential features as the Cloud ERT moves forward.

Considerations and Mockup for a TEAM ERT

While the overall ERT would benefit from a thorough redesign that is focused on usability and functionality, it would be helpful to start from a design that is both helpful for individual and team data. While researchers often take individual data and compile it in a single line of a large spreadsheet that has data from all participants, the design of the output file or features may look differently in a team setup. It might be helpful to have a way to easily determine which individuals were part of the same team, and to group their data close to each other in the output spreadsheet, or to even provide outputs that are specific to individual teams. The design of the ERT interface and functions needs to support multiple types of teams, multiple types of tasks, and different size teams, among other considerations. Therefore, it needs to be highly configurable and include highly generalizable functionality. Then a potential second level could be to represent those measures of team performance that may not necessarily be an aggregate of individual data.

It is important for the interface to elicit the following information from the researcher:

- How are team groupings identified in the data? (e.g., are they an entry in a specific survey field?)
- How are team roles represented in the data? Are team roles unique or duplicated?
- What are the team performance variables and what are the individual performance variables?
- Should data output be separated at the team level or the individual level?

Current Cloud ERT Design

Figure 1 represents the current interface screen of the Cloud ERT. . In the figure it can be seen that each event type requires a check box next to it to be included in the output report. Additionally, there's a single check box for merging each participant's events into a single row. However, all participants are included in the outputs and there's no way from the assigned log file numbers to tell which participant is which. Therefore, it would be helpful to have an earlier screen which allows for definition of the type of study (team or individual), and asks the user to define the above questions that will be used to help parse the data if it is a team study.

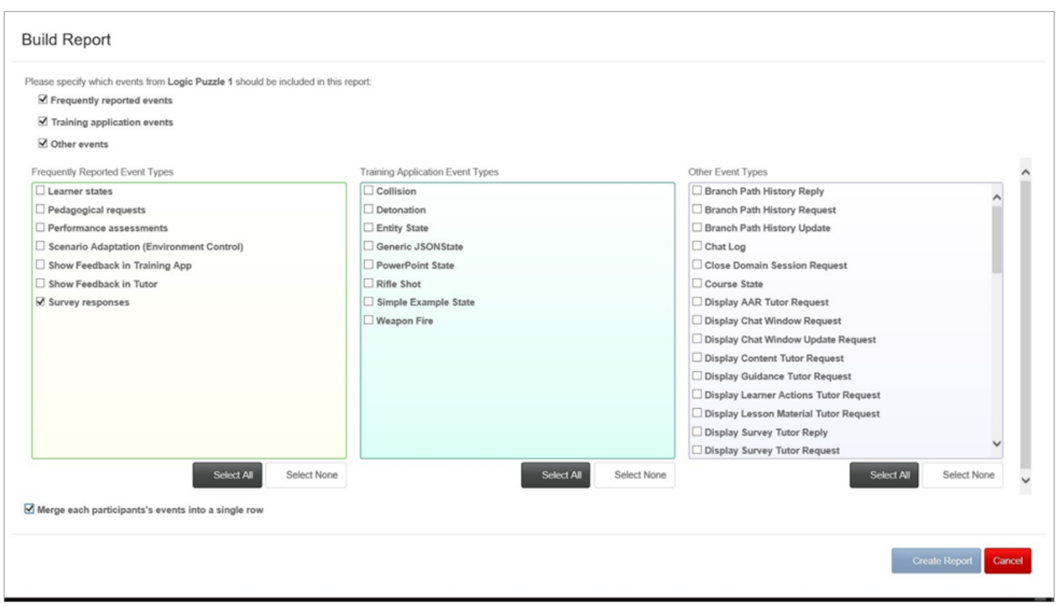

Figure 1. A screenshot example of the current Cloud Based Event Report Tool selection screen.

Mockup for ERT for Teams

A mockup for the ERT for teams can be seen in Figure 2. Attention was paid in the mockup to the design of the initial experimental set up screens to support the experimenter. The mockup is meant to provide an overview on the potential options that are available (per Shneiderman), and the screens are meant to be as simple and clear as possible (per Tuft's graphical excellence). As mentioned above, it would be to the benefit of the experimenter to tell the ERT the relationship among the participants and their relationship to the data. "Import your data" allows the researcher to use data files from various statistical or data management formats. "Define experimental conditions" allows the experimenter to set up relationships. "Create new variables" provides a way to build team-specific variables from existing data. For the purposes of this discussion, we will focus on the process for defining experimental groups.

Figure 2. Mockup of ERT for Teams Selection Screen

The screen for defining experimental groups is shown in Figure 3. An experimenter would be able to set the relationship for each participant in terms of team and experimental condition. Participants could be assigned to more than one team, and they could also be assigned to more than one condition (in the event that the participant is going through the experiment more than once). As the experimenter would set the different groupings, GIFT would begin building a visual map of the structure. The assignment of groups and conditions could be modified to fit the researchers need (such as randomization). Once experimenters are finished making the selections, they would then move ahead and review their assignments.

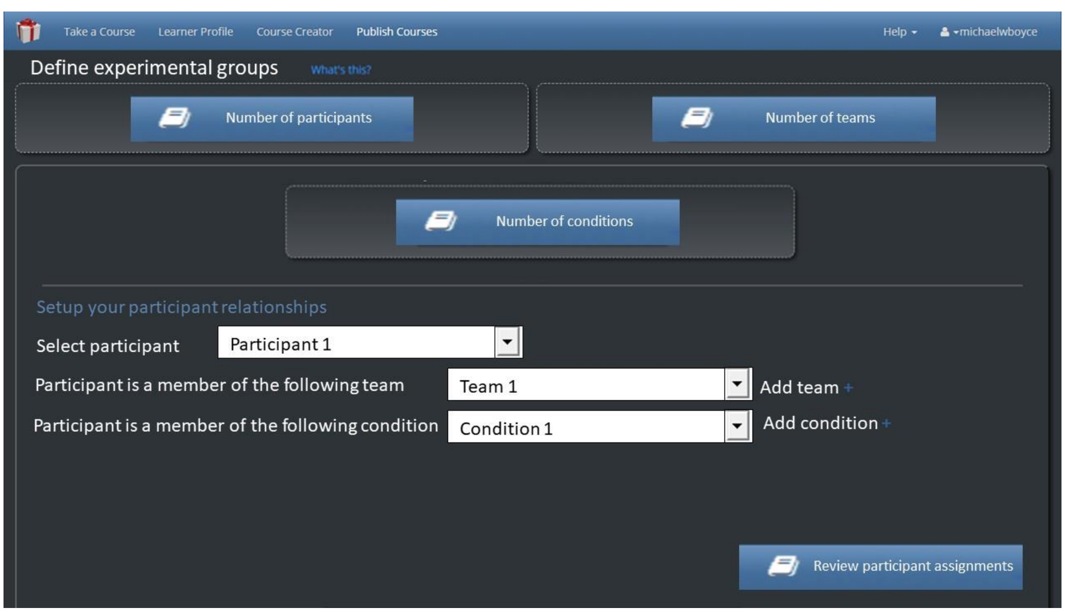

Figure 3. Mockup of the Define Experimental Groups Screen

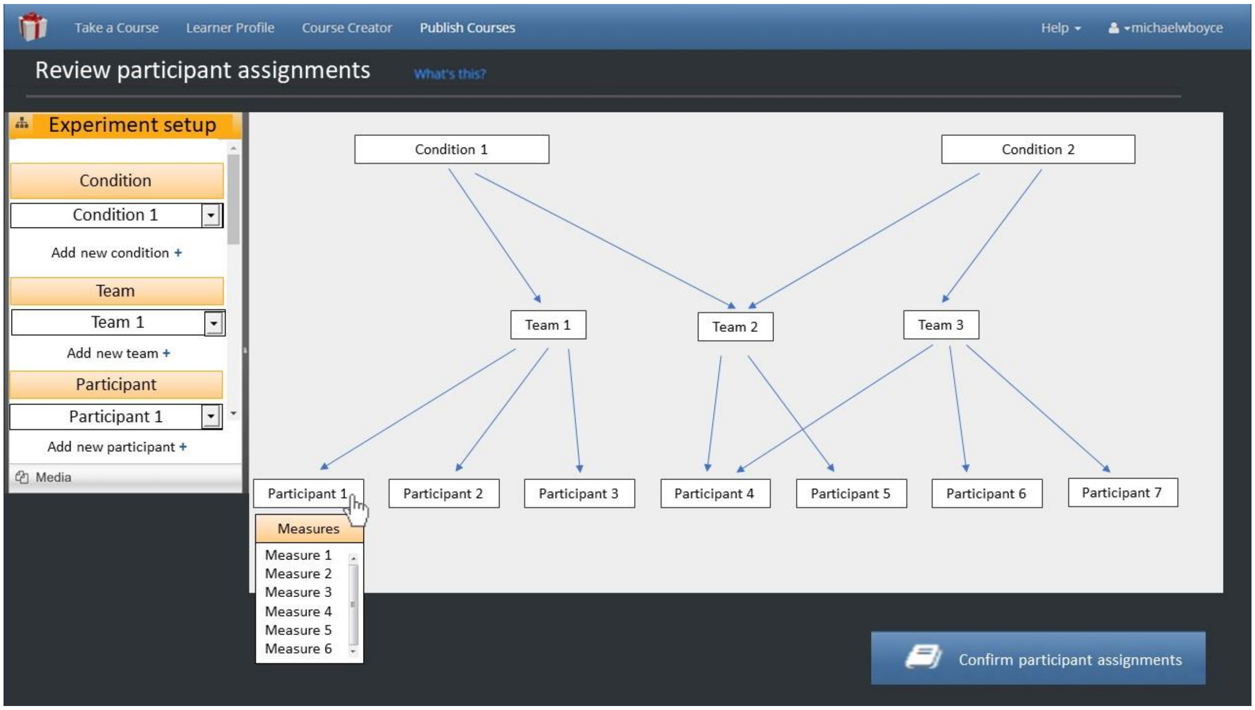

Figure 4. Mockup of the Review Participant Assignments Screen

Then the experimenter would have the chance to review and edit their assignments as necessary, which is shown in Figure 4. This is designed to mimic a flow chart where each relationship is defined by a line connector. Experimenters could add participants, move them between conditions and groups, and have a visual representation of how the experiment is set up. This design could potentially leverage a lot of existing GIFT functionality such as the zoom in and zoom out capability (make the diagram bigger or smaller when there is a need to focus on a specific participant or group of participants) of the authoring tools and the add / delete nodes of GIFT conversation trees. Also relevant here is the experimenter's ability to select each participant and view what measures are associated with them. This measures dropdown could be expanded to create and map measures similarly to experimental groups.

Conclusions and Recommendations for Future Research

This chapter offers suggestions for improving the current data export tools and ERT in GIFT so that they are more efficient and can be used to support team data extraction. The recommendations for updates to the ERT will not only be helpful from a team perspective, but will also provide researchers who are doing non-team research with more power and control over their data which is collected in Cloud GIFT. Improving usability in the ERT's design will ultimately make it more straightforward and result in increased use by the GIFT community. Additionally, allowing for flexibility in the way of defining teams within the ERT can also provide opportunities to leverage the team features for use by instructors in the classroom who are examining subgroups of student answers or in class team assessments. Designing an ITTS framework is a difficult challenge, but by focusing on identifying generalizable elements of team data analysis, and including tools that lessen the burden on the experimenter it is likely to be achieved. Although this is only a mockup, a first step with open questions still to be answered, this chapter could be, in the words of Ben Shneiderman: "A useful starting point for designing advanced graphical user interfaces…"(1996).

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