Exploring Interaction Design for Advanced Analytics and Simulation

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Abstract. Enterprise businesses are increasingly using analytics and simulation for improved decision making with diverse and large quantities of data. However, new challenges arise in understanding how to design and implement a user interaction paradigm that is appropriate for technical experts, business users, and other stakeholders. Technologies developed for sophisticated analyses pose a challenge for interaction and interface design research when the goal is to accommodate users with different types and levels of expertise. In this paper we discuss the results of a multi-phase research effort to explore expectations for interaction and user experience with a complex technology that is meant to provide scientists and business analysts with expert-level capability for advanced analytics and simulation. We find that while there are unique differences in software preferences of scientists and analysts, that a common interface is feasible for universal usability of these two user groups.

Keywords: Simulation, modeling, expert, analysis, interviews, disruption, ideation.

1 Introduction

Federal lawmakers want to propose a coast-to-coast high-speed rail transportation system to the public. Being that this is a large investment of taxpayer dollars, they want to make the first proposal the optimal proposal so as not to upset citizens. They also realize many decisions are often made with good information and insight such as future needs, demand, and geographic location. Such information is spread across different sources. Assistance is needed aggregating appropriate data sources and models for a large-scale benefit analysis. What would you recommend for developing a seamless high-speed rail infrastructure that reduces airplane and automobile emissions while being cost-efficient, improving overall quality of life for customers, and that is accessible to customers quickly?

Above is an example of a complex problem for which modeling and simulation can provide a solution. Technologies for advanced analytics and simulation are often very complex, requiring specialized knowledge to use them, and are created for experts in a particular domain (domain expert). As an 'expert', the expectation is that she has

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mastered a set of tasks and activities that are performed on a regular basis, and these tasks often become automatic. In turn, this automation can make it difficult to elicit detailed information from the expert about a set of tasks because she may unintentionally leave out important details or essential steps when describing the tasks [1,2].

The research presented in this paper was conducted within the context of a modeling and simulation (M&S) tool called SPLASH (Smarter Planet Platform for Analysis and Simulation of Health) [3]. Through SPLASH, end users with varying degrees of expertise in analytics and simulation can design simulation experiments to apply in a variety of fields including finance, urban planning, healthcare, and disaster planning. This range of fields and end users poses challenges for how to accommodate a wide array of expertise in M&S – that is, for people with deep domain knowledge about the construction of models and simulations to people with skill and expertise in running the simulation system and analyzing the output within a particular field. In addition, the domain of modeling and simulation tends to emphasize algorithm design and implementation rather than interface and interaction design. Without a body of evidence of how scientists and analysts use modeling or simulation tools, we had to work with a community of our intended end users to identify expectations and interface design features. This paper describes the method and results of using exploratory interviews, disruptive interviews, and participatory ideation to elicit information from experts in the field of M&S to inform the design of the SPLASH interaction.

2 Background

The goal of SPLASH is to facilitate the creation of complex, interconnected system-of-systems to advise and guide ''what-if'' analyses for stakeholders and policy makers. In contrast to the tradition of developing isolated models of phenomena, SPLASH takes a slightly different approach to the question, can we use M&S to help policy makers envision the trades-offs of complex policy and planning problems in a more holistic way? Specifically, SPLASH affords being able to examine real-world complex systems by reusing and coupling models and data of individual systems into a more comprehensive simulation [4]. As such, providing a way to consider the effects of change on the complete system rather than through the independent lens of individual systems models. Smarter Planet Platform for Analysis and Simulation of Health is intended to help the stakeholders consider as much about a complex system as possible to avoid negative unintended consequences by using relevant constituent components (i.e., data, models, simulations) for their desired level of system abstraction and analysis [5]. Our role in the development of SPLASH was to initiate the design of the user interface and end user interaction model.

2.1 Composite Modeling Methodology

Modeling and simulation is a complex research area that typically draws from mathematics, statistics, and business [6]. The process to create models and simulations tends to be subjective and dependent on the stakeholders, the model scope, level of detail of model content, and data requirements [6, 7]. A typical approach to examining a complex problem is for the modeler to use the individual components they are familiar with (i.e., as data, statistics, models, or simulations) to model and simulate a system. The modeler then uses output from these components as analysis of the individual pieces of the larger system. This would include working with key stakeholders to make assumptions about the impact of changes on the overall system using the individual pieces, resulting in an informed but fragmented system perspective [8].

Creating complex system simulations by coupling models and data sources is not a brand new area for the M&S community. There are a number of ways to create complex simulations through model integration, and these can be classified into three types: (1) integrated and uniform modeling framework, (2) tightly-coupled modeling framework, and (3) loosely-coupled modeling framework (see [3] for additional detail about each type of modeling framework). However, unless designed to accommodate one of these three frameworks from the beginning, the coupling of component models typically requires systems development work to integrate independent data sources and/or to re-code models and simulations so they can conform to a particular protocol or standard. By contrast, SPLASH enables the creation of composite models by automatically translating data from one component model into the form needed by another model to create a composite system model. In doing so, SPLASH also helps to alleviate the guesswork and assumptions about impact of changes and the potential for unintended consequences [3].

This suffices from a systems engineering perspective, but how is the stakeholder supposed to actually use such a complex technology? What complicated our role of designing an interface and interaction model for composite modeling is that there is not a standard process for building individual models or simulations to help inform expectations through a set of current conventions. This left us with little interaction guidance to begin prototyping an interface design for SPLASH.

2.2 Expert Elicitation

An expert can be defined as "an individual that we can trust to have produced thoughtful, consistent and reliable evaluations of items in a given domain" [9]. Because experts have, in essence, 10,000+ hours of experience [2], they are very familiar with a particular process and pattern to perform a task or activity. Therefore, it may be easy for the expert to recall the process for performing a particular activity or sequence of tasks but difficult to express the process to a novice. To study expert activities, many routine tasks are documented using some form of observation [10,11]. However, the tacit knowledge and reasoning may not be apparent to the observer when experts are performing a routine task [12].

There are two intended user groups of SPLASH, both of which are considered to be experts: scientists and analysts. The descriptions of our population were that *scientists* typically design, build, and run models and simulation experiments. *Analysts* run experiments after a model has been built and/or analyze results of the simulation run to aid in further decision-making. Both scientists and analysts are experts in performing analytical tasks that we needed to better understand. To design an interface for SPLASH, it was fundamental to understand what processes, tools, and techniques our target users employ to build and run simulations to model and understand potential system behavior.

For this study, we decided to use a series of three interview techniques to elicit expert knowledge in a relatively short period of time – being sensitive to work schedules and volunteer participation of our pool of professionals. Interviewing is a common HCI technique for eliciting information from stakeholders for rich qualitative analysis. Interviews can take many different forms including unstructured, semi-structured, and structured [13]. We started our investigation with semi-structured exploratory interviews to gain an understanding of what it is to do M&S work and to further structure the remaining two investigation phases of disruptive interviews and participatory ideation.

Disruptive interviews are derived from semi-structured interviews and can aid in the recall of past steps to complete a process that may have become automatic and taken for granted [12,14]. The interview technique uses a specific scenario that is then constrained over time by placing limitations on the options available to the participant. The constraints of the scenario are iteratively refined so that the participant must reflect on the processes and their reasoning. This technique borrows from condensed ethnographic interviews [12] that transform discussion from broad issues to detailed steps [15]. It is critical that disruptive interviews consider the context of the interviewees' processes. Understanding such context allows the researcher to design interview protocols appropriate to the constraints a person typically encounters in their work.

Participatory ideation (PI) is a mash-up of two existing techniques, participatory design and social ideation. Participatory design is often described as 'design-by-doing' [16] to assist researchers in the design process. This method is often used when researchers and designers want to accurately design a tool for an audience they are not familiar with [17]. Complementary to this, social ideation is the process of developing ideas with others via a web-enabled platform and utilizes brainstorming techniques to generate new ideas [18]. Both participatory design and social ideation are intended for early stage design and to engage with the users of the intended tool.

We interviewed professional scientists and analysts to investigate their expectations for the design of a technology such as SPLASH. The research questions we aimed to address were:

- RQ1: What are people's expectations for a complex cross-disciplinary modeling and simulation tool?
- RQ2: How should usable modeling and simulation interfaces be designed for non-technical audiences?

3 Methods

To address the above research questions we began with exploratory interviews. We then used the findings from the exploratory interview to design business-relevant scenarios, conduct disruptive interviews, and structure a participatory ideation phase.

We worked with 15 unique participants through the three phases of investigation. Of the 15 participants, nine were scientists, four were analysts, and two held both scientist and analyst roles. (Referred to as scientific analysts here on in, this hybrid categorization included participants who have experience with building models and with analyzing simulation results.) The range of modeling, simulation, and/or analytical domain expertise included atmospheric modeling, healthcare, manufacturing, polymer science, physics, statistics, social analytics, supply-chain management, and text analytics. Participants were recruited opportunistically as references and by snowball sampling.

3.1 Exploratory Interviews and Scenario Design

The first stage of this work was to understand our participant's work context, the type of modeling and/or simulation work that they perform, and their process for building a model and/or running a simulation. We began by interviewing five people, of which four were scientists and one was an analyst. The exploratory interviews were semi-structured, lasted approximately 30 minutes, and were conducted both in-person (for local participants) and by telephone (for remote participants). The results were used to help gauge the level of self-reported expertise of each participant and to develop the scenarios and disruptive interview protocol from the perspective of how M&S activities are performed.

After conducting the exploratory interviews, we aggregated scenario examples provided by participants, examples from our previous publications [3,4,5], and areas of interest to IBM's Smarter Cities initiative [19]. This yielded four scenarios for the disruptive interviews in the fields of transportation, healthcare, disaster recovery, and supply chain. The scenarios are hypothetical contexts in which simulations might be used to help examine a complex business challenge. We used the scenarios developed from the exploratory interviews to scope the disruptive interviews and provide context for the participants of the disruptive interview phase.

3.2 Disruption

Disruptive interviews are "disruptive" in nature because of the ever-increasing constraints placed on a solution set that is available to the participant during the interview itself. In our study, the interviewee was presented a scenario and asked to identify component model and data sources he or she would use to address the challenge highlighted in the scenario. In this phase of the investigation, our participant pool included two analysts, three scientists, and two scientific analysts.

The participants began by describing the models and data sources they thought would be useful in addressing the scenario. This was done without constraint to get the participant engaged in the scenario and to gather thoughts and reasoning of how the participant would approach the scenario challenge. Then, to begin triggering additional and more detailed feedback, the participants were only allowed to choose from a pre-determined list of model and data sources to address the scenario. Lastly, access to component sources was narrowed even further, which required the participant to reflect on the trade-off of potentially not having precisely what component sources they desired and expressing what was important to the design and build of a composite model for analysis. Each interview lasted approximately 1 hour, was transcribed, and then coded for emergent themes using Dedoose [20].

3.3 Participatory Ideation

All of the participants were remote for the participatory ideation phase that was conducted to elicit early-stage interface prototype design ideas. Because all of our participants were remote, we used an asynchronous, online collaboration tool called Twiddla [21] as an aid to collect input. The participants were placed into one of two conditions: individual ideation or group ideation. For this phase we recruited two scientists and one analyst for the individual ideation condition, and two scientists and two analysts for the group ideation condition.

We started with individual ideation, where the participants were given a blank canvas and asked to sketch ideas for model and data source selection, composition, and expected visualization(s) of simulation output based on one of the four scenarios that was created from the exploratory phase. Key interface and interaction features from the individual ideation output were then summarized and displayed as a starting point on the Twiddla drawing canvas for the group ideation participants. We hypothesized that the group ideation would produce more robust ideas because participants wouldn't need to create a new concept, but could simply build upon a set of common ideas [22].

4 Results

The three phases of this work each provided insight towards answering our research questions and built upon the findings of the previous phase(s). Here we provide the key results for each.

4.1 Grounding the Investigation: Exploratory Interview Results

To begin the exploratory interviews, we asked our participants to describe or define a model and a simulation. We received a range of responses for "model". However, the descriptions were all disposed towards being a codified representation (computer program) of a physical process. An example response was:

> *"A model would be a representation of a physical process, but a simplified representation of that process so that a computer can handle the level of detail, computationally, in an efficient manner."*

Similarly, we received a range of responses to describe or define "simulation". The tendency was for both scientists and analysts to define a simulation in the context of their work with modeling, making little or no distinction between a simulation and a model. We provided definitions in the subsequent phases of investigation to overcome any issues with ambiguous use of these terms.

Participants, regardless of their area of expertise, expressed that the software tools used in their daily work were a large source of frustration when building models and running simulations. Software constraints included limitations of existing tools to correctly support and manage the model development and simulation run independent of the problem size and the time trade-off to build custom tools.

We found that all of the scientists had experience using third party tools but would eventually develop customized applications, program extensions to an existing tool, and/or couple multiple third party tools. The main reasons for custom-built tools were: (a) to accommodate legacy models and computer systems, (b) to perform additional analysis of the post-simulation run results, (c) to properly implement error handling during the simulation runtime, and/or (d) to add capabilities to visualize the simulation results.

In addition to frustration with tools used to build models and run simulations, we found that the amount of time to run a simulation was also a critical factor. The main challenges for time were a combination of (a) proper model design, (b) data quality, and/or (c) avoidance of unnecessary runtime delays or re-runs/re-starts. Results from the exploratory interviews were used to scope the four scenarios for the remaining investigations and to define some of the constraints used in the disruptive interviews.

4.2 Revelation through Disruption: Disruptive Interview Results

The disruptive interviews provided insight into the selection and prioritization of model and data sources – a key element to composite modeling. We were able to explore steps taken when options are suddenly limited and how one would work through the challenge. In doing so, there were disruption-based triggers that prompted participants to deliberately reflect on and express how they would complete the scenario – as illustrated in the following statement:

> *"When you build a simulation model you can collect everything in the world and build the most perfect model and you ask what are my 1st order effects? What are the ones I think are most critical? If I don't have them in there, my simulation model would be way off. The second ones are secondary effects... Those are the ones if I don't have enough time, I could drop those."*

By narrowing the selection of available model and data sources available to address a scenario, participants expressed their preferences and expectations for being able to find resources such as data, models, and tools. The research focused on prioritization, selection, and preferences for data sources, type of analysis, kinds of tools, and visualization capabilities. The participants also expressed a preference for a navigational browser to help them visualize data and select the model and data sources to address a scenario. Results from the disruptive interviews were used as guide for a low-fidelity interface design that resulted from this series of investigations.

4.3 Early Design: Participatory Ideation Results

This next phase resulted in sketches of interface ideas generated by the participants. Recall that the participatory ideation phase was designed with two conditions of participation: individual ideation and group ideation. The findings show similarities between the user groups, but also ideas unique to scientists and to analysts. In addition, we unexpectedly found that even though our group ideation participants were provided a sketch to start from (based on the individual ideation results), it was ignored by all of them and each decided to start with a blank design canvas. What follows is a summary of the design ideas that were mutual to analysts and scientists and then those that were specific to each participant group.

Once the results of the participatory ideation phase were aggregated, three mutual interaction and interface design ideas stood-out. The first design idea was a feature to support *browsing and exploration* of model and data sources that would afford examination of schemas and/or variables prior to selection for use in a scenario. The second was a feature to *compare the output* of multiple simulation runs for a particular scenario to better understand the trade-offs of selecting one simulation solution compared to another (Fig. 1). The third feature was an *audience-specific dashboard* for making complex decisions that would provide a summary of the model and data sources that were used when running the simulation.

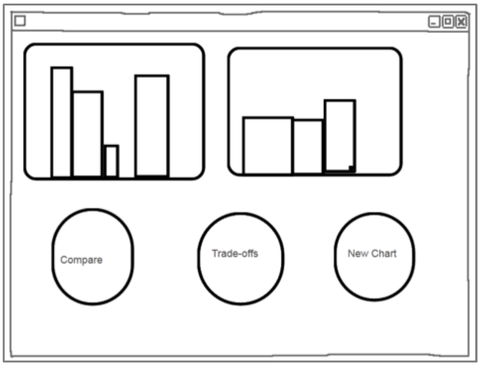

Fig. 1. Example sketch of a simulation output where it would be easy to compare scenarios

Analyst-Specific Design Ideas. Analysts emphasized guidance and recommendation. For example, analysts wanted pre-defined templates for simulation set-up and for analyzing simulation output. They expected the system to provide recommendations for which template to use (similar to the query prediction feature in Google) along with the steps to run a simulation. Also, they did not want technical terms such as "simulation", "model", or "factor" used in the interface. Instead, they preferred words such as "concept" or "category". For visualization, analysts wanted a feature to suggest if one chart style would be better than another style to explain relationships in output data. For example, participants wanted a feature to suggest if a bar chart would be better than a tree map to explain relationships in their data.

Scientist-Specific Design Ideas. Scientists emphasized flow and a rich set of interaction features (Fig. 2). For example, they were consistent in requiring a way to assess the veracity and provenance of model and data sources. This stemmed from past experience with models that did not perform as expected or data that was inconsistent. During this phase, participants were able to query and select curated model and data sources. However, the scientists found the selections to be limiting and wanted to be able to upload their own sources to supplement the existing sources. Lastly, scientists preferred high levels of interaction with the data to examine the source and/or cleanliness of the data, and to determine the appropriateness for their simulation goals when previewing search results *prior* to running the simulation. For example, they wanted to edit parameters of the simulation set-up and interact with the sources before and after they were selected.

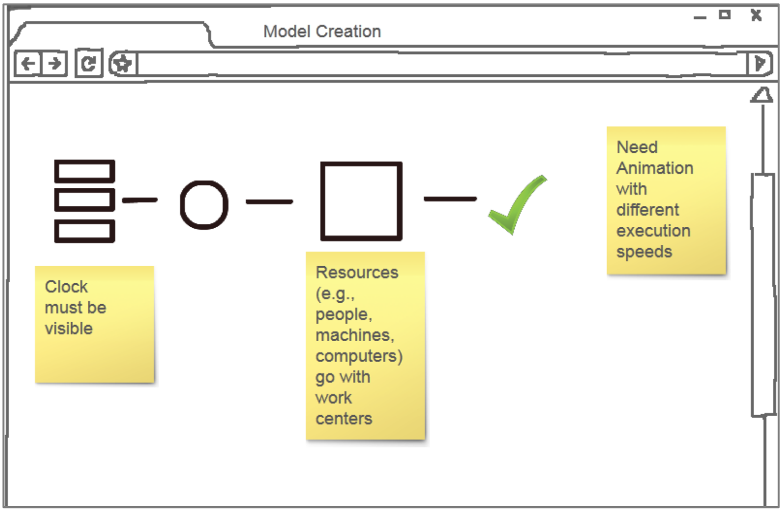

Fig. 2. Example of expected flow and interaction features for composite modeling

5 Discussion

The results of this series of interviews helped us better understand our target users and inform subsequent interface prototype design. Specifically, the use of constraints as disruption in the interviews served as effective triggers, prompting and focusing our experts to provide details about how they would go about designing a composite model. These triggers demonstrated the usefulness of disruptive interviews [12,14,15], and although [9] suggests that experts tend to produce consistent and reliable evaluations of the work that they perform, we found that they are not particularly consistent in the manner that they reflect on their process of doing so. In addition, we were able to efficiently collect interaction expectations and interface design input from the experts we worked with through participatory ideation.

During the initial process of building a composite model, our analyst community expected a tool that would provide recommendations. These recommendations ranged from an automated reference providing which model and data sources to use for a particular scenario to suggestions for how to then couple the data and models in order to run the simulation. This ran counter to what our scientist community expected. Where, they were familiar with building the models and wanted to be able to interrogate the data and model sources to investigate elements such as provenance, robustness, and limitations prior to selection for use. A compromise that may satisfy both participant groups would be to implement an exploratory search and browse feature where users are not recommended models and data sources, but must prioritize the information needed before beginning the information retrieval process.

An exploratory search and browse feature may be useful for interactive navigation of model and data sources to identify the appropriate elements to create a composite model. For example, take two use cases we found for creating a composite model. The first is that users may know the specific scenario or issue that they want to analyze using a composite model; and to facilitate the identification of appropriate and useful source components, they want to perform a search using specific keywords or questions. The second use case is that users are in the early stages of defining their project scope and want to run a simplified or meta-simulation to explore what is important in order to identify the appropriate source components for the design of the composite model. This loose exploration would be equivalent to browsing content on a system, or browsing a larger set of possible scenarios, and getting approximate output based on approximate inputs. This would allow the user the luxury of having a basic understanding of the model and data requirements to target particular source components.

Implementing an exploratory search and browse would require the underlying systems to have information about the source components (most likely through metadata, e.g., [3]) along with a set of composite model templates to enable this manner of recommendation system. Alternatively, a more manual approach could be taken such as prompting the user to identify known factors to be explored prior to building the simulation, or identify the important relationships between source components. This would lead to the system displaying either a dashboard of specific sources or a catalog of different scenarios to consider. Participants agreed this exploration should include a high level of interaction with different tuning knobs and a visualization recommendation interface. In addition, audience-specific dashboards would be useful for making complex decisions, providing a summary of the simulation models and source components used in the simulations.

For the simulation output, our results show that both user groups want a comparison feature that illustrates trade-offs of important scenario factors used in the final simulation. In addition, they would prefer recommended visualizations for the simulation to best understand and interpret the generated output. Overall, we saw a desire to explore model and data sources before and after use in a simulation.

6 Conclusions

This paper describes the results of the first stages of a research effort to explore interaction expectations for a modeling and simulation technology. The study was set within the context of a composite modeling and simulation technology called SPLASH that enables the coupling of independent models (and their respective data sources) to examine what-if trade-offs for complex systems. Our participant pool included scientists and analysts; both considered experts in the areas of modeling, simulation, and analytics. Without the benefit of interaction conventions for modeling and simulation technologies, we used three techniques (exploratory interviews, disruptive interviews, and participatory ideation) to elicit information from experts in the field of modeling and simulation to inform the interaction design of the SPLASH interface.

Our results show that there are differences in interaction expectations between scientists and analysts. Our scientists wanted considerably more explicit features and functionality to enable deep precision for modeling and simulation tasks; whereas our analysts wanted simplified functionality with intelligent features and recommendation functionality. We also found some common ground between our participants, such as both groups wanting a comparison feature to show trade-offs based on simulation output. Our findings point towards a semi-automated interface that provides a recommended starting point and allows for flexibility to explore component sources of models and data prior to selection for use, along with a pre-screening capability to quickly examine potential simulation output based on an early idea for a composite model.

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