

A Formative Usability Study to Improve Prescriptive Systems for Bioinformatics Big Data

Kanupriya Singh⁺, Shangman Li⁺, Isa Jahnke⁺, Ashish Pandey^{**}, Zhen Lyu^{*}, Trupti Joshi^{*}, Prasad Calyam^{**}
⁺School of Information Science and Learning Technologies, ^{**}Dept. of Electrical Engineering
and Computer Science, ^{*}Dept. of Health Management and Informatics; University of Missouri-Columbia, USA
{kanupriya.singh, sli, apfd6, zl7w2}@mail.missouri.edu, {jahnkei, calyamp}@missouri.edu, joshitr@health.missouri.edu

Abstract—Big data computation tools are vital for researchers and educators from various domains such as plant science, animal science, biomedical science and others. With the growing computational complexity of biology big data, advanced analytic systems, known as prescriptive systems, are being built using machine learning models to intelligently predict optimum computation solutions for users for better data analysis. However, lack of user-friendly prescriptive systems poses a critical roadblock to facilitating informed decision-making by users. In this paper, we detail a formative usability study to address the complexities faced by users while using prescriptive systems. Our usability research approach considers bioinformatics workflows and community cloud resources in the KBCommons framework’s science gateway. The results show that recommendations from usability studies performed in iterations during the development of prescriptive systems can improve user experience, user satisfaction and help novice as well as expert users to make decisions in a well-informed manner.

Index Terms—Usability, User experience, Bioinformatics, Big data, Prescriptive analytics, Cloud solution.

I. INTRODUCTION

With traditional data analytic software systems, computing massive volumes of big data was a daunting challenge [1] [2]. With the advent of advanced analytics comprising of prescriptive systems that use machine learning models, competitiveness in big data analysis is increasing [3]. However, lack of usable prescriptive systems is a critical bottleneck in achieving desired results for users [4]. The usability of prescriptive systems has rarely been studied. In particular no prior study, to our knowledge, has performed a usability study of prescriptive systems in the bioinformatics field. Furthermore, with lack of usable prescriptive systems, there exists a risk that users may misinterpret required input [4] [5].

In this paper, we detail a formative usability study with the goal to apply a usability research approach to support testing and evaluation of a prescriptive system supporting bioinformatics big data analysis. Our approach features iterative phases for detecting and fixing problems during the system design and development process [6]. We demonstrate how an iterative formative usability study during development of a prescriptive system can improve the effectiveness of such system. In other words, our recommendations from iterative feedback

ultimately helps bioinformatics application providers such as KBCommons [7] [8] to support novice and expert users (i.e. frequent users of workflow applications and cloud services) to make informed decisions that improve their productivity.

II. BACKGROUND

A. Biology big data analysis

With the arrival of low-cost high-throughput next generation sequencing (NGS) genomics and multiomics data generation technologies, biologists and life scientists are rapidly moving towards big data to predict trends in regulation of genes and evolution of genomes [9] [10] [11]. Biological scientists show that meaningful big data have the power to guide biological discoveries in plant processes [10] [12]. Data accessibility for genome-wide research is no longer a challenge and the cost of producing, acquiring and disseminating data is decreasing considerably [9] [11]. Multiple research organizations have built systems such as the iPlant Cyberinfrastructure (renamed as CyVerse in recent years) that can make biological big data collection and analytics work together [9] [13] [14].

Facilitating data analysis through traditional software analytic systems becomes a daunting challenge, especially for non-computer savvy users. This is because of the computational complexity involved in data storage, transfer or sharing, access management, and visualization while integrating multiple sources of data [1] [2] [3]. With handling of big data sets, there is an increase in competitiveness of big data analysis and therefore, requirement for advanced analytics which comprises of prescriptive systems with predictive capabilities is increased [3].

Prescriptive systems are adaptive time-based, socio-technical systems that generate strategic recommendations to the users for efficient decision-making [3]. Vater et al. [3] suggest prescriptive systems have two characteristics: first, they deliver optimum recommendations to users for action, and second, quality of their recommendations is measured for its accuracy. According to Frazzetto et al. [4], prescriptive systems can improve user decision making and process effectiveness by helping users choose predicted recommendations for specific situations. Prior research suggests one of the critical roadblocks to achieving effective prescriptive models is the lack of user-friendly tools that can facilitate “self-service” of finding the best solution among multiple possible decisions [4] [5].

This work was supported by the National Science Foundation under award number OAC-1827177. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

B. Usability challenges

While the challenge of scalability and response time for visualizing big data persists [1], there are also usability issues with data analytic systems [15]. Data visualization is created or delivered by machine learning models [16]. Usability studies need to address whether the critical user population understands the data visualization as well as the complexity of underlying analytic process i.e., how the visualized outcome was created with its underlying calculations [15]. With prescriptive systems, the issue becomes further complicated. Advancement of tools and applications for big data analytics have focused more on providing scalable techniques and less on facilitating easy access of these applications for users [4]. For prescriptive systems, efficient decision-making involves users choosing right parameters for computing their data, which if not performed in a well-informed manner may lead to misinterpretation of results or failed experiments [4].

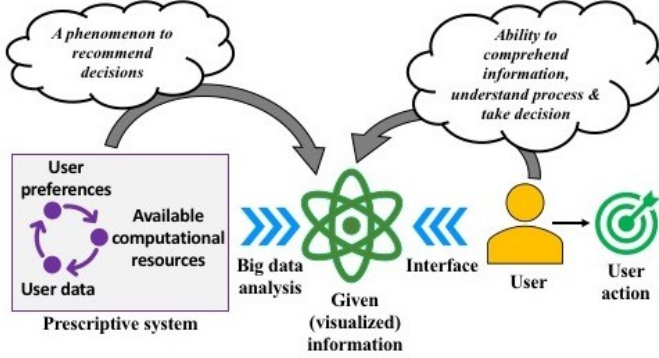


Fig. 1. Conceptual model of usable prescriptive systems for big data analysis. To make informed decisions for computing big data, users should be able to understand the process and information for meaningful user actions.

Studies have discussed challenges with implementation of prescriptive systems [17], with usability being a major challenge [18]. Prior research suggests that ease of use, interpretability and the ability to understand the underlying process of data analysis are important usability metrics to consider for supporting the user experience when performing tasks with prescriptive systems [18]. Fig. 1 represents a conceptual model of our understanding of prescriptive systems.

Literature reports the need for a usability framework to study big data applications [19]. Our work builds upon these prior works to create a formative usability research approach for studying the design and development of prescriptive systems for bioinformatics big data analysis. In iterative steps of design, testing, evaluation and further development, we worked with KBCCommons framework’s science gateway [7] [8] developers to identify usability problems and implemented design improvements for improving the user experience. Following research questions guided the study:

RQ1: What is the current practice of genomic big data computation and visualization with existing software in the organization?

RQ2: To what extent does the new prescriptive system support the users to make informed decisions (and do the predicted recommendations work?)

RQ3: What can be a usable solution to improve the user experience?

III. RESEARCH DESIGN

This research took place at a large mid-western university’s Life Sciences Center in 2019-2020. The existing system, known as SoyKB [20] [21] [22], supports users to browse and retrieve information about soybeans. To address the need of managing large-scale multi-level data and perform complex computational analysis of soybeans and other organisms data, the research team expanded SoyKB, i.e., the *Baseline System*, to a newly developed web application called Knowledge Base Commons, KBCCommons (KBC), i.e., the new *Improved System* [7] [8]. The main purpose of the new system was to provide the users with an easy-to-use web-based platform integrated with ready-made data analysis workflows and cloud solution provider choices to predict computation solutions to users based on their preferences of performance, agility and cost [23]. This new prescriptive system predicts optimum cloud solutions to users in real-time based on a machine learning model to compose cloud solutions for better computational performance [23] [24]. We first studied the Baseline System with five participants comprising of two application providers and three users. Next, we conducted iterative usability studies of three KBC prototypes, read Table I.

TABLE I
STUDY ITERATION DETAILS

Sr. No.	Iteration	Instruments	Participants
1	Baseline System User’s perspective of existing process Summer 2019	Semi-structured interviews; Participant observation; Document analysis	6 [Female:3; Male:3]
2	Improved System Prototype 1 Usability Study, October 2019	Task-based Usability Test with SEQ & Think-Aloud; Semi-structured interviews; Participant observation; SUS Survey	7 [Female:3; Male:4]
3	Improved System Prototype 2 Usability Study Spring 2020	Task-based Usability Test with SEQ & Think-Aloud; Semi-structured interviews; Participant observation; SUS Survey	17 [Female:6; Male:11]
4	Improved System Prototype 3 Usability Study Summer 2020	Task-based Usability Test with SEQ & Think-Aloud; Semi-structured interviews; Participant observation; SUS Survey	11 [Male:8; Female:3]

Participants included: a) users, and b) application providers, who constituted of faculty and research scientists as bioinformatics experts, responsible for user management, communication and providing results to users. The user group were novice and expert users who were mainly graduate and doctoral students and accessed the application to gain analytical insights into genomic database while communicating back-and-forth with the application providers to receive the results, see Table II for the demographics information.

TABLE II
PARTICIPANT DEMOGRAPHICS

Participants descriptive demographics	
Participant Characteristics	Total study sample (n = 40)
Age (years)	
Mean	29
Range	23-43
Gender (%)	
Male	64.1
Female	35.9
Educational Level (%)	
Bachelor	47.5
Master	37.5
Doctoral	15
Current Role (%)	
Doctoral Student	87.5
Postdoc Researcher	7.5
Research Professor	2.5
Research Scientist	2.5

Data Collection (Data Sources): We applied multiple research methods. For iteration 1 conducted in summer 2019, we applied methods to understand the work processes of users with the Baseline System and potential challenges in completing the tasks. We adopted the Sociotechnical Walkthrough (STWT) methodology [25] that is useful for an integrated view of the multiple perspectives of human work procedures related to the technical system. We developed a semi-structured interview protocol [27] using open-ended questions and prompts for elicitation of details organized in four parts: a) current user interaction and task flow, b) user experience, c) participant opinion and reflection, d) additional comments. We also observed the interaction of the participants with the Baseline System. Each session lasted for 40 to 60 minutes and was conducted by a lead interviewer in presence of an observer.

For iterations 2, 3 and 4, we conducted usability studies with the three prototypes of the Improved System [28]. Methods included a semi-structured interview protocol, a usability task-based performance test [28] with Think-Aloud [29], Single Ease Questionnaire (SEQ) [26], participant observation (recorded data and observer notes), and the System Usability Scale (SUS) survey [30] [31]. The interviews gathered demographics, experience with genomic data analysis and prompts such as overall experience with the system, user thoughts about the specific functions, and likes/dislikes. Users chose one of the predicted recommendations for cloud solutions, and we asked them to justify their choice. For the usability test, the participants were asked to think aloud [29], while independently completing the tasks with the prototypes. The tasks included: logging into the system and opening the data request form, creating a data workflow request and reviewing status of submitted request. Sessions were administered using Morae software [32] [33], recorded and transcribed via Zoom. Each session was conducted in the presence of at least two researchers and lasted for 60 to 75 minutes. With multiple methods and multiple data sets, a robust set of triangulated data was used to identify maximum usability problems with certainty.

IV. DATA ANALYSIS

We measured usability in terms of its effectiveness i.e., users being able to complete the task with or without difficulty, and efficiency i.e., time taken by the users to complete the task [34]. Descriptive statistics were used to calculate mean and range values. We analyzed quantitative data for each prototype separately as there were significant changes in functions and the user interface (UI). We performed a two-tailed *t-test* to compare the SUS scores of the three prototypes.

Qualitative data collected in iterations 2, 3 and 4 included observation data and participants' responses of open-ended questions. We used van den Haak et al. [29] method to thematically analyze qualitative data and identify layout, terminology, data entry, comprehensive and feedback problems. The final interpretation of qualitative results was reviewed by the research method expert to ensure interrater reliability. For iteration 1, interview data for the Baseline System was analyzed through a semi-formal modelling notation, known as SeeMe [25]. SeeMe was used to graphically represent the communication and coordination between the multiple stakeholders and the technical system by visualizing human work procedures, related technology functionalities, and social structures of their interaction [25] [35]. Interview transcripts were analyzed by two researchers, including a research method expert. Final results were reviewed through intermittent meeting between the researchers until a consensus was reached.

We used a multiple method approach in each iteration to address validity and reliability of the results. Qualitative data from think-aloud protocol, participant observation and interviews were supported with quantitative data collected from surveys, questionnaire and task performances [36].

V. RESULTS

A. Iteration 1

Fig. 2 shows the users' work process with the Baseline System (SoyKB). Users use the system for analyzing and visualizing their genomic big datasets. According to the participants, the process included following steps (follow left to right): first, to access the computational analytic tools, users create an account in the system. They get an automated username and password. Second, users access analytic tools to compute their own selected biology big dataset. This step includes users creating a work folder in CyVerse to upload their own raw data. During this process, users get stuck with the tools that have a non-intuitive UI design; and they send emails to the providers (third step) to communicate their requirements. Fourth step is from the science gateway provider's perspective, where the issue is identified. For instance, the provider checks if there is a lack of requirement fulfillment from users' end, or if it is a technical system issue. Fifth, providers try to resolve the issue either by communicating to the users to fulfill input data requirements, or debugging the issue at system's backend. Finally sixth step, the providers perform the analytical computations and upload the big data visualization results to the user work folder in the system (i.e.,

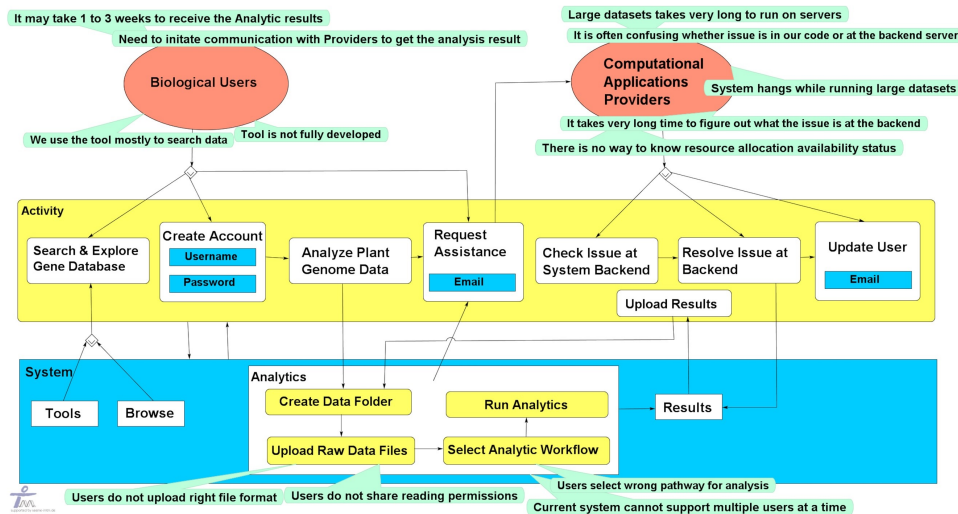


Fig. 2. Visualized diagram showing how genomic big data analysis process with the Baseline System from the user perspective. Red oval= roles (humans), yellow box=activities of the users, blue box=entities (technologies) green bubbles show quotes from users and the challenges with the system; read Activity from left to right

CyVerse). In addition, users can access search and browse features of the system to retrieve information from public repository to check their datasets.

The green boxes show the challenges as explicitly pointed out by the users. They illustrate the inability of the system to automatically perform computational analytic jobs, or they point out the cases where there was a lack of a user-friendly and intuitive user interface. According to the users, they struggled to understand different functions and tools integrated in the system and rated the UI as poor. In some cases, the users were not satisfied with the format of the displayed results. There was anxiety among the users when it took several weeks to obtain first set of results as users usually had to tweak the data to re-analyze their datasets.

"I did struggle a bit, initially. I did not understand the full capability of the tool... There are lot of tools in SoyKB which I don't know how to use. There is not really a description for any of those (see Fig. 3) I personally don't want to figure out what each tool does by trial and error." (P2)

B. Iteration 2

Prototype 1 (KBC) the improved and scaled-up version of the Baseline System (SoyKB) was a web application designed to automate the process of genomic data analysis workflows for users by providing them a suite of web-based tools and dedicated computation resources, helping users to achieve results in lesser time [7] [8]. Seven participants, age 26-33 years tested Prototype 1 with five tasks were not satisfied with the format of the displayed results. There was anxiety among the users when it took several weeks to obtain first set of results as users usually had to tweak the data to re-analyze their datasets.

Effectiveness and efficiency: The average time taken by the participants per task was 2.57 minutes. The most difficult task

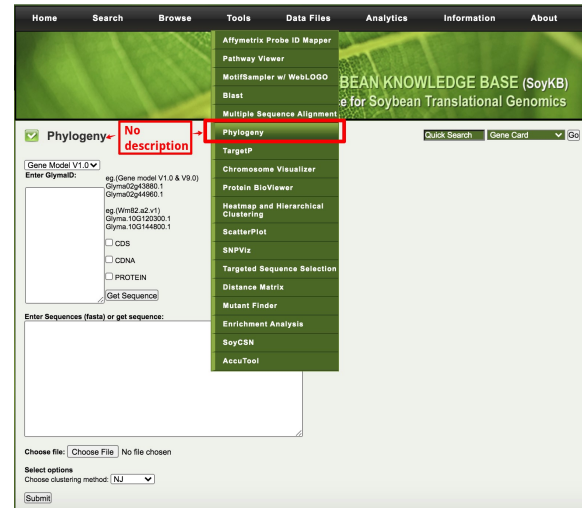


Fig. 3. Screenshot of SoyKB (Baseline System) showing lack of description of tools making it difficult for the users to understand the system capabilities

appeared to be creating the data workflow request into the application. It took participants longest average time (5.22 minutes) to create data workflow request. 43 percent (3/7) failed to complete the task and 43 percent (3/7) completed it with difficulty. It was surprising to note that 57 percent (4/7) rated this task as 'easy,' including the ones who failed to complete the task.

User satisfaction: With an average SUS score of 58.2, Prototype 1 was rated 'marginally acceptable' [30]. While three of seven participants rated Prototype 1 in 'not-acceptable' range (50.0 to 45.0), two participants rated it as 'marginally acceptable' (52.5 and 55.0). According to the participants, Prototype 1 appeared still in development with limited functionalities. Participants did not have much freedom or options to use the web application. In addition to the difficulty in

understanding the terminologies used in Prototype 1, major problems identified by the participants were confusing layout, no help feature, and no notifications for errors or request submission.

“The page is so long...the layout of the page is not good. I mean the imbalance of the layout in the left side and right side of the UI... there are too many descriptions, too many redundant sentences (as shown in Fig. 4) Actually, I don’t like to use this UI.” (P7)

“I guess the Workflow ID is the same as the Workflow name, but I am not sure about this...it was quite confusing.” (P12)

Fig. 4. Screenshot of the webpage of creating workflow request in Prototype 1 of KB Commons (Improved System) which shows layout issues and too many instructions for users to read

C. Iteration 3

To address major user problems, Prototype 2 included changes in layout, concise written instructions, separate instructional videos for different functions, and placeholders in data entry field to hint accepted format of data. A major change in Prototype 2 was the inclusion of the prescriptive ability to guide application users. It featured the addition of an optimum cloud solution provider function which was based on integer linear programming (ILP) optimization. This feature creates the base for the prescriptive system designed to intelligently compose cloud solutions and predict optimum cloud solutions to users in real time for better computation performance [23]. The predicted cloud solutions were categorized as Green/Gold/Red (Green-premium and Red-cheapest) as shown in Fig. 5. Seventeen participants aged 23-36 years, tested Prototype 2 with seven tasks.

Effectiveness and efficiency: The average time taken by the participants per task was 26.67 minutes. The most difficult task appeared to be choosing one of the optimum cloud solutions predicted by the system to submit the request. Participants took longest average time (7.98 minutes) to choose an optimum

Cloud Solutions	CSPs	Cost
Gold	AZURE	0.0208
Gold	AZURE	0.0208
Gold	AZURE	0.0208
Green	AZURE	0.0364
Green	AZURE	0.0416
Green	AZURE	0.0416
Red	AZURE	0.0208

Fig. 5. Screenshot of optimum cloud solution provider in Prototype 2. Users enter their preferences in the form and get Gold/Green/Red Templates of cloud solutions. Users are expected to choose a predicted template based on given cost and available cloud service providers.

cloud solution for their workflow request. Average SEQ rating obtained from participants for this task was 4.06 (neutral) where 47 percent (8/17) self-rated this task as ‘difficult’ (range: 1 to 4). However, according to the observers, 82 percent (14/17) completed this task with difficulty (see section III) and 12 percent (2/17) failed to complete. Only 53 percent (9/17) watched instructional video for this cloud solution function.

User satisfaction: With an average SUS score of 75.7, Prototype 2 was rated ‘acceptable’ [30]. In all, 65 percent (11/17) rated Prototype 2 as ‘acceptable’ (range: 100 to 72.5) and the rest as ‘marginally acceptable’ (range: 67.5 to 52.5). Participants pointed out multiple challenges (e.g., confusing instructions, no error notification, lack of intuitiveness, difficulty in understanding terminologies) with UI of Prototype 2 and found the interface confusing.

“I am not sure what numbers to put in the fields... I am just copying the examples.” (P15)

The main problem with cloud solution provider function was that it did not trigger informed decision-making among the participants. According to the participants, they were making decisions based on their imaginations rather than facts. Participants were not sure if they would want to use the system in the future.

“It is easy to fill out the form but then I don’t know what I’m filling out. The numbers that they are showing on the table does not make sense to me.” (P25)

“I don’t really care about the computing resource... I might be confused about whether I need to pay that money?” (P18)

“I feel confused... I do not understand the purpose of Clock Speed. The first impression for me is to select Green not Gold. Gold looks yellow to me just like the traffic light. The user may have a very low possibility to click Red because of the nature

Cloud SOLUTIONS

We provide you optimal cloud solutions to compute your workflow. The solutions are optimized based on available computing resources and your given requirements.

Please read the table below for more information:

Choice	Description	Resource Allocation	Execution Time	Cost
Gold:	- Available resources exceed user's inputs. - Dedicated computing resources provided. - Fully automated processing of workflow.	⚙️ ⚙️ ⚙️	⏱️ ⏱️ ⏱️	\$\$\$
Silver:	- Available resources meet user's inputs with extra computing power. - Dedicated computing resources provided. - Semi-automated processing of workflow.	⚙️ ⚙️	⏱️ ⏱️	\$\$
Bronze:	- Available resources just enough to match user's needs. - No dedicated resources provided. - Manual workflow processing with user's effort	⚙️	⏱️ ⏱️ ⏱️	\$

⏱️ - Shortest execution time; ⏱️ ⏱️ - Medium execution time; ⏱️ ⏱️ ⏱️ - Longest execution time

Show 10 entries

Select	Click for Machine Details*	Cloud Solutions	Server Name	Given Computing power	Given Memory	Given Storage	Estimated Time (Days)	Estimated Cost(\$)
☐	☐	Gold	AWS	4.0	4.0	15.0	5.00	0.51
☐	☐	Silver	AWS	3.0	4.0	15.0	5.83	0.45
☐	☐	Bronze	AWS	8.0	1.0	15.0	11.25	0.47

Showing 1 to 3 of 3 entries

*All unique type of machines used to compose the template solution.

Previous 3 Next

Submit Workflow

Fig. 6. Screenshot of optimum cloud solution provider in Prototype 3 named as 'Ideal Cloud Solution Provider.' Users enter size of their raw data files and how soon they need the results. New users have the option to select 'Recommended' settings. Users are expected to choose one of the predicted cloud solution templates categorized as Gold/Silver/Bronze based on time, cost and agility.

of the color." (P14)

D. Iteration 4

In iteration 4, we recommended necessary changes in the UI for Prototype 3 for improved usability and user-friendliness. Recommended changes included an information button for each data entry field, improved layout alignment and additional instructions in form of images under 'Introduction' tab. Major changes were made to optimum cloud solution provider function. For example, templates were categorized as Gold/Silver/Bronze (Gold-premium and Bronze-cheapest) as shown in Fig. 6, color instead of Green/Gold/Red with detailed instructions in written and as images. New or first-time users had the option to select 'Recommended' input which auto-filled the form. In this iteration, the new features were added by utilizing a machine learning model along with ILP optimization in the previous iteration. Terminologies were simplified (e.g., computing power instead of vCPU) and backend computing related fields were removed (e.g., Clock Speed). Eleven participants with ages 23-37 years, tested Prototype 3 with three tasks.

Effectiveness and efficiency: The average time taken by the participants per task was 29.74 minutes. The most difficult task continued to be choosing one of the optimum cloud solutions predicted by the system to submit the request. Participants took longest average time (13.78 minutes) to choose an optimum cloud solution for their workflow request. While the average SEQ rating obtained from participants for this task was 5.18 (easy), only 18 percent (2/11) self-rated the task as 'difficult' (SEQ rating: 3). However, according to the observers, 82 percent (9/11) completed this task with difficulty and 18 percent (2/11) failed to complete, including the one participant who rated the task as 'easy.'

User satisfaction: With an average SUS score of 73.86, Prototype 3 was rated 'acceptable' [30]. In all, 64 percent (7/11) rated Prototype 3 as 'acceptable' (SUS range: 97.5 to 75.0), 27 percent (3/11) as 'marginally acceptable' (SUS

range: 67.5 to 60) and 9 percent (1/11) as 'not acceptable' (SUS score: 40). The two-tailed *t-test* for SUS scores obtained for the prototypes compared Prototype 1 and Prototype 3, and SUS significantly improved from 58.2 to 73.86 ($p < .05$). Participants appreciated the usefulness of Prototype 3 for novice and expert biological researchers. According to the participants, the instructions were easy to follow, and they were able to understand the data analysis process as well as the working of the application.

"I think it [Prototype 3] is good. Instructions are good and easy to follow and easy to read. I think that people that are not experts in those kinds of analyses can do it... for people who are really working in this field (bioinformatic), it is very useful." (P36)

Participants found the Gold/Silver/Bronze color categorization of cloud solution templates to be more intuitive, and spent time reading the instructions to make an informed decision.

"It (cloud solution function) was very intuitive. When I see the Gold color, I think it is the most expensive because it is of highest quality. And the bronze ones would be, as the name says itself. Right. You don't have to think a lot like what it is. It's a lot like buying schemes from different vendors." (P31)

According to the participants, although the instructions were easy to follow, the UI and layout of Prototype 3 needed improvement. Participants pointed out that they did not receive meaningful error notifications or request submission confirmation. Furthermore, the instructions did not stand out from the background, and it was easy to skip reading it.

"If at any time, I'm submitting my workflow and I have an error... will something show up? Like an error message like, you're filling out this which is not matched... I haven't seen anything like this in this workflow." (P33)

The central feature of Prototype 3 was the prescriptive system recommending optimum set of cloud solutions to the users based on their preference of time, cost and agility. Users chose a Gold/Silver/Bronze solution to compute their data analysis. While Prototype 2 still had usability issues

with the predicted recommendations, Prototype 3 indicates the users' preferences and the decision they made were aligned, meaning they picked the decision that was best suited for their needs. This shows the improved accuracy of the newly developed prescriptive system. Table III lists the data sample of users' preferences and the option they picked based on the prescriptive system.

VI. DISCUSSION

A. What is the current practice of genomic big data computation and visualization with existing software in the organization?

Regarding the current process of analyzing genomic big data with the Baseline System, the results highlighted two important issues. First, there is a gap in understanding the process of analytic execution between application users and science gateway providers. The lack of an interactive and intuitive interface of the Baseline System (with proper layout and documentation) made the underlying process appear as a black box to the users. Users did not understand the functionalities of the different tools integrated in the system. Second, both novice and expert users struggled with the increased amount of manual effort required to achieve desired results because of lack of process automation, and users experienced increase in overall execution time. This corresponds with other studies that a usable system design should enable stakeholders to obtain and interpret system status information in minimum time and execute their actions with minimum effort. Furthermore, usability, scalability and response time continue to be a challenge with traditional big data visualization systems which was found in this study too [1] [16].

An important observation during the study was the need for an interactive communication channel for the users to interact with the providers for help during the process of data analysis. Based on the results, we identify a lack of sociotechnical process design to address user problems of not being able to comprehend the system. This aligns with the observation of Varshney [37] who identified data analytic systems to be "noisy black boxes" which may not always be interpretable by users. Our results suggest a need to bring the 'social' into the 'technical' system and not to rely merely on technical solutions [38]. Sociotechnical data analytic systems can enable users to address their issues, execute analytic requests, view status of their requests, communicate with experts and obtain results in lesser time.

B. To what extent does the new prescriptive system support the users to make informed decisions (do the predicted recommendations work)?

With Prototypes 1-3, an improvement of the user interface was made including layout, terminologies and design comprehensiveness of the application, with improved user satisfaction. Although the time taken to complete the task for creating the system's workflow request and choosing an optimum cloud solution to receiving the analyzed data was significantly longer than in the Baseline System, it was observed that users spent

time reading instructions to understand their next actions. According to users' responses, the Improved System appeared promising for achieving automated workflows with adequate guidance due to the prescriptive nature of the system. Users were able to enter the information in the request form and they followed instructions or watched instructional videos when they got stuck.

TABLE III
USER NEEDS AND CHOICES THEY MADE

User responses in Iteration 4: Prototype 3 of KBC			
Sr. No.	Preferences for big data analysis	Option selected by user	User rationale
User1	Shorter execution time; Low cost or free	Gold	"I choose Gold for relatively lesser time (15 days) and high computing power"
User2	Ease of use; Shorter execution time; Free of cost	Silver	"I choose Silver because it matches my choice of estimated time. Given storage is same for all so it does not make a difference."
User3	Shorter execution time; Low cost	Bronze	"Because my input data is not very big and I don't want to spend much money on this, I will choose Bronze because the pipeline I am working on, I can wait for a day. But if I do not have to pay then I will choose Gold because of the shortest amount of time it takes."
User4	System efficiency; Shorter execution time; Free of cost	Gold	"Because I am not an expert, I will choose Gold - I don't have to put time in it. I am a beginner and it is fully automatic. It is quick and easy. If I have some experience, then I would want to cut down cost and choose Silver. Or Bronze if I am an expert."

With the Prototype 3, there is now a user-friendly tool available that facilitates self-service of finding best decision among possible decisions [5]. According to SUS results, users indicated that they did not need help, which was a significant improvement of the user experience in comparison with the Baseline System. However, users still desire a better visibility of instructions and error notifications with the Improved System.

Prototype 3 of the Improved System comprising of prescriptive system supports the users to make informed decisions. Results indicate that the predicted recommendations work and are rather accurate, as Vater et al. [3] say this is the key of prescriptive systems. In line with [4], the studied prescriptive system improves the user's decision making; it is an effective tool for choosing predicted recommendations for the specific situation of the genomics big data analysis of plants.

C. What can be a usable solution to improve user experience in this process?

Prototype 3 exemplifies a usable UI of a prescriptive system. The results indicate that a formative usability research approach is a fruitful method to iteratively improve ease of use and user satisfaction with complex prescriptive systems, where the goal is to empower the user to make informed decisions. This finding aligns with [18]'s suggestion for the critical need of users to interpret and understand the underlying process of a prescriptive system to feel satisfied. Having a framework to address users' complexities with big data analytic systems will be important to design user-friendly prescriptive systems [19].

VII. CONCLUSION

This study provides evidence that the usability of prescriptive systems is a critical component for complex analytics systems to support users to avoid risk of misinterpretation of information. Such a formative usability research approach using iterative steps and multiple research methods can improve complex software designs by detecting problems and fixing them during the development phases of the system. For example, one of the main challenges in moving to a prescriptive paradigm was in presenting users with relevant user interfaces.

One limitation of our implementation was that we conducted usability studies (iteration 3, 4) as online sessions during pandemic situation which might have an effect on user experience. Session speed was dependent on Wi-Fi connectivity at users' place. We have tried to address the limitation by using multiple data collection methods to create a robust data triangulation and provide reliable results. Future research should further test the guidance strategies to improve prescriptive bioinformatic systems from user's perspective, while facilitating interpretability and understanding of the underlying process of data analysis and visualization.

REFERENCES

- [1] C. L. P. Chen and C. Zhang, "Data-intensive applications, challenges, techniques and technologies: A survey on Big Data," *Information Sciences*, vol. 275, pp.314-347, 2014.
- [2] E. E. Schadt, M. D. Linderman, J. Sorenson et al., "Computational solutions to large-scale data management and analysis", *Nature Reviews: Genetics*, vol. 11, pp. 647-657, 2010.
- [3] J. Vater, L. Harscheidt, and A. Knoll, "Smart manufacturing with prescriptive analytics," 8th International Conference on Industrial Technology and Management (ICITM), pp. 224-228, 2019.
- [4] D. Frazzetto, T. D. Nielsen, T. B. Pedersen et al., "Prescriptive analytics: a survey of emerging trends and technologies," *The VLDB Journal*, vol. 28, issue 4, pp. 575-595, 2019.
- [5] J. Glassman, B. Shao, and R. St Louis, "Don't get the cart before the horse: There are no shortcuts to prescriptive analytics," *Proc. of Hawaii International Conference on System Sciences*, 2019.
- [6] B. Albert and T. Tullis, *Measuring the User Experience*. Burlington, MA: Morgan Kaufmann Publishers, 2013.
- [7] S. Zeng, Z. Lyu, S. R. K. Narisetti et al., "Knowledge base commons (KBCommons) v1.0: A multi 'OMICS' web-based data integration framework for biological discoveries," *IEEE International Conference on Bioinformatics and Biomedicine*, 2018.
- [8] S. Zeng, Z. Lyu, S. R. K. Narisetti et al., "Knowledge base commons (KBCommons) v1.1: a universal framework for multi-omics data integration and biological discoveries," *IEEE BIBM International Conference on Bioinformatics and Biomedicine*, vol. 20, issue 11, pp. 1-16, 2019.
- [9] C. Ma, H. H. Zhang, and X. Wang, "Machine learning for big data analytics in plants," *Trends in Plant Science*, vol.19, issue 12, pp. 798-808, 2014.
- [10] UF Petrillo, M Sorella, G Cattaneo, R Giancarlo and SE Rombo, "Analyzing big datasets of genomic sequences: fast and scalable collection of k-mer statistics," *BMC bioinformatics*, vol. 20, issue 4, pp.1-14, 2019.
- [11] V. Marx, "Biology: The Big Challenges of Big Data," *Nature*, vol. 498, pp. 255-260, 2013.
- [12] E. K. Brauer, D. K. Singh, and S. C. Popescu, "Next-generation plant science: putting big data to work," *Genome Biology*, 15, 301, 2014.
- [13] N. Merchant, E. Lyons, S. Goff et al., "The iPlant collaborative: cyberinfrastructure for enabling data to discovery for the life sciences," *PLoS Biology*, vol. 14, issue 1, 2016.
- [14] S. A. Goff, M. Vaughn, S. McKay et al., "The iPlant Collaborative: Cyberinfrastructure for Plant Biology," *Frontiers in Plant Science*, vol. 2, issue 34, 2011.
- [15] C. Chen, "Top 10 unsolved information visualization problems," *IEEE Computer Graphics and Applications*, vol. 25, issue 4, pp. 12-16, 2005.
- [16] R. Jordan Crouser and R. Chang, "An affordance-based framework for human computation and human-computer collaboration," *IEEE Transactions on Visualization and Computer Graphics*, vol. 18, issue 12, pp. 2859 - 2868, 2012.
- [17] D. den Hertog and K. Postek, "Bridging the gap between predictive and prescriptive analytics-new optimization methodology needed," Technical report. Netherlands: Tilburg University, 2016.
- [18] L. Zhou, S. Pan, J. Wang et al., "Machine learning on big data: Opportunities and challenges," *Neurocomputing*, vol. 237, pp. 350-361, 2017.
- [19] D. Bhatta, A. Hafeez-Baig, R. Gururajan et al., "An investigation into usability of big data analytics in the management of Type 2 Diabetes Mellitus," 24th Annual Conference of the Asia Pacific Decision Sciences Institute. Brisbane, Australia, pp. 22-33, 2019.
- [20] T. Joshi, K. Patil, M. R. Fitzpatrick et al., "Soybean knowledge base (SoyKB): a web resource for soybean translational genomics", the Tenth Asia Pacific Bioinformatics Conference. Melbourne, Australia, vol. 13, issue S1, pp. S1-S15, 2012.
- [21] T. Joshi, M. R. Fitzpatrick, S. Chen et al., "Soybean knowledge base (SoyKB): a web resource for integration of soybean translational genomics and molecular breeding," *Nucleic Acids Research*, vol. 42, issue D1, pp.D1245-D1252, 2014.
- [22] T. Joshi, J. Wang, H. Zhang et al., "The evolution of soybean knowledge base (SoyKB)", in *Plant Genomics Databases*. New York, NY: Humana Press, pp. 149-159, 2017.
- [23] A. Pandey, Z. Lyu, T. Joshi et al., "OnTimeURB: Multi-Cloud Resource Brokering for Bioinformatics Workflows," 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 466-473, 2019.
- [24] K. Lepenioti, A. Bousdekis, D. Apostolou et al., "Prescriptive analytics: Literature review and research challenges," *International Journal of Information Management*, vol. 50, pp. 57-70, 2020.
- [25] T. Herrmann, K. Loser, and I. Jahnke, "Sociotechnical walkthrough: a means for knowledge integration," *The Learning Organization*. Vol. 14, issue 5, pp.450-464, 2007.
- [26] J. Sauro, 10 things to know about the Single Ease Question (SEQ), *Measuring U*, October 2012. Available: <https://measuringu.com/seq10/> [Online] [Last access: 29th August 2020]
- [27] J.W. Creswell, *Qualitative Inquiry Research Design: Choosing Among Five Approaches*. Los Angeles, CA: SAGE Publications, 2013.
- [28] A.W. Kushniruk, V.L. Patel, and J. J. Cimino, "Usability testing in medical informatics: cognitive approaches to evaluation of information systems and user interfaces", *AMIA Annual Symposium Proceedings*, pp. 218-222, 1997.
- [29] M. van den Haak, M. De Jong, and P. Jan Schellens, "Retrospective vs. concurrent think-aloud protocols: testing the usability of an online library catalogue", *Behavior and Information Technology*, vol. 22, issue 4, pp. 339-351, 2003.
- [30] A. Bangor, P. T. Kortum, and J. T. Miller, "An empirical evaluation of the system usability scale," *Intl. Journal of Human-Computer Interaction*, vol. 24, issue 6, pp. 574-594, 2008.
- [31] J. Sauro, *Measuring usability with the system usability scale (SUS)*, *Measuring U*, 2011. Available: <https://measuringu.com/sus/> [Online] [Last access: 29th August 2020]
- [32] Morae Software Available: <https://www.techsmith.com/tutorial-morae-current.html> [Online] [Last accessed: 29th August 2020]
- [33] J. Zhang, V. L. Patel, K. A. Johnson et al., "Designing human-centered distributed information systems," *IEEE Intelligent Systems*, vol. 17, issue 5, pp. 42-47, 2002.
- [34] J. Preece, H. Sharp, and Y Rogers, *Interaction Design: Beyond Human-Computer Interaction*. Danvers, MA: John Wiley Sons, 2019.
- [35] T. Herrmann, M. Hoffmann, G. Kunau et al., "A modelling method for the development of groupware applications as socio-technical systems," *Behavior and Information Technology*, vol. 23, issue 2, pp. 119-135, 2004.
- [36] M. J. Wenge and J. H. Spyridakis, "The relevance of reliability and validity to usability testing," *IEEE Transactions on Professional Communication*, vol. 32, Issue 4, pp. 265-271, 1989.
- [37] L. R. Varshney, "Fundamental limits of data analytics in sociotechnical systems," *Frontiers in ICT*, vol. 3, pp. 2, 2016.
- [38] C. Dremel, E. Stoeckli, J. Wulf et al., "A socio-technical approach to manage analytics-as-a-service-results of an action design research project," 14th Wirtschaftsinformatik Proceedings. Siegen, Germany. pp. 617-631, 2019.