UserFlow: A Tool for Visualizing Fine-grained Contextual Analytics in Teaching Documents

Conference Paper · June 2020

DOI: 10.1145/3341525.3387410

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ABSTRACT

The adoption of innovative online teaching tools in Computer Science (CS) courses provides opportunities for data-informed instruction as a regular teaching practice in CS classrooms. In this paper, we present a design study for an interactive visual analytics dashboard, called UserFlow, that supports feedback collection from teaching documents and assists instructors in interpreting feedback and acting on it in a timely manner. The design study is conducted with eight domain experts comprising of four teaching instructors, two learning analytics (LA) experts and two instructional designers. UserFlow offers a set of novel visualization designs for presenting the four interleaving aspects of document engagement (i.e., annotations, document traversal path, reading/focus time and student information). We evaluated UserFlow in an undergraduate computer science course with over 700 students. Our results demonstrate the usefulness and need for such a tool for CS educators to inform teaching approaches and courseware improvement.

CCS CONCEPTS

• **Applied computing → Interactive learning environments**; *Distance learning*; *E-learning*; Collaborative learning.

KEYWORDS

annotations, analytics, digital education, engagement, dashboards

ACM Reference Format:
Shaveen Singh, Bernd Meyer, and Michael Wybrow. 2020. UserFlow: A Tool for Visualizing Fine-grained Contextual Analytics in Teaching Documents. In *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education (ITiCSE '20), June 15–19, 2020, Trondheim, Norway*. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3341525.3387410

1 BACKGROUND

The education literature [10, 18, 26] is unanimous that teaching practices will change from module to module and from semester to semester in order to better address the needs of students. Educators need to understand how students are engaging with the course, how they respond to teaching practices and materials, and how these elements can be improved for current or future cohorts [17, 22]. This is particularly applicable to computer science education, which is greatly concerned with student retention, diversity and rapidly changing curricula [3].

Most CS courses employ the "flipped" teaching model [9], whereby students are expected to do readings before class and the actual problem-solving activities are performed in the presence of an instructor. Students work through educational materials in isolation and have very little support in understanding concepts and few mechanisms for registering their difficulties. Obtaining their reactions to this material and presenting it effectively to instructors would be extremely valuable in inform teaching decisions [17, 21].

Dashboards that monitor the activity and performance of students are becoming a standard feature of many VLEs [17]. However, the literature has reported inflexibility of most existing dashboards, particularly their difficulty to access data, and limited actionability [12], resulting in lack of widespread adoption of analytics dashboards [15]. Furthermore, there is lack of tools for monitoring reading behaviors ("reading analytics") in teaching documents (prescribed reading material, lecture notes, tutorial problem sets and assignment handouts).

To address these needs, we developed an instructor-facing visual analytics system, called UserFlow, that allows for effective discovery and understanding of dynamic patterns in document usage data. UserFlow offers a set of novel interactive visualizations for presenting different types of document usage data, including user information, annotations, document traversal paths and reading-time information. Instructors can explore data from multiple levels of perspective (macro-, meso- and micro-level), identify anomalies, and explore their own conjectures.

To create UserFlow, we employed a user-centred iterative approach [25], where we elicited domain-specific questions and tasks through multiple interviews with CS instructors. We selected the data sources and analytics prioritized by the use cases, grounded in educational theories [4, 13] and informed by findings of research in learning sciences [1, 6, 23].

The contributions of this paper are: 1) a set of domain-specific goals and design rationales derived through our interviews with CS instructional staff, 2) a scalable and generalisable visualization technique integrating elements of automated data analysis and mining techniques to support deeper exploration and reasoning, 3) a visual analytics system, called UserFlow, for interactive exploration of dynamic patterns in fine-grained and contextual document usage data, and 4) an in-depth case study comprising think-aloud sessions offering direct observation and evaluation of the effectiveness and

ITiCSE '20, June 15–19, 2020, Trondheim, Norway

ACM ISBN 978-1-4503-6874-2/20/06…$15.00
https://doi.org/10.1145/3341525.3387410

usefulness of UserFlow in an authentic setting. A video demonstration of UserFlow can be found at: https://userflow-tool.github.io/.

2 DESIGN METHODOLOGY

In this section, we describe the method and procedure of extracting user requirements and present our derived design goals.

2.1 Working with Domain Experts

During the design phase of UserFlow, we worked closely with two CS teaching instructors over the course of a semester. The course, ENG1003: Engineering Mobile Apps, was offered over 12 weeks and had a total of 726 students enrolled. It was offered in blended mode, where the students were expected to do their online readings before class and the actual problem-solving exercises were done in the presence of instructors during their studio sessions. The learning material was hosted on a VLE integrated with a document annotation tool with a comprehensive log tracker module. Throughout the semester, we collected fine-grained document usage data and raw annotations created by the students.

Over the course of this design study, we organized three formal interview sessions with the instructors, during which we investigated the data and feedback sources that could inform their teaching approaches and document revision. We also scheduled frequent informal discussions to present the early prototypes to get feedback. Finally, the completed version of UserFlow was evaluated using four concrete use-cases with eight domain experts to assess its usability and usefulness for informing teaching improvements.

2.2 Extracting User Requirements

While there has been some success in informing instructional improvement based on the traditional click-stream data, interpretation and actioning of interventions using such data sources is a major challenge [11, 14, 20]. The experts (instructors) during the interview sessions expressed their need for richer data sources and a visual analytics system specifically designed to achieve the following high-level goals:

- **G1:** To explore annotation data on multiple scales, from the entire syllabi, to module-level, to its location in a document.
- **G2:** To examine the overall pattern of annotation from different perspectives and to compare the nature (categories) of annotations by different user groups.
- **G3:** To explore the document traversal paths of individuals and category of users and see possible deviations.
- **G4:** To reveal engagement data about modules and assist exploration at different levels of granularity (module, page, sections).
- **G5:** Flexibility and extensibility to allow alternative data arrangements within a single consistent user interface.

3 SYSTEM OVERVIEW

The architecture of the UserFlow system consists of three major components: a data pre-processing module, a data analysis module, and a visualization module. Each learning object is a web page in the VLE. The data pre-processing module extracts the page log, and reconstructs the sequence of visits for each user. We then retrieve the annotations from the annotation database, and establish their link with the specific pages (based on visit during which the annotations were posted). The corresponding document usage data (document length, scroll and reading time information) and detailed user information is distilled in this flow sequence. Additional user information such as user achievement records (coursework, grade, etc.) or data acquired externally about student demographics and grades can be imported and used for filtering.

In the analysis module, the main focus is to correctly classify each flow into *intended* and *unintended* pathways based on the preset expectation of the course instructor. *Intended* path is the learning sequence the instructor expects the students to follow based on the structure of the learning material (e.g., from module 1.1 → 1.2 → 2.1 → 2.2 and so on, represented using gray arcs in Fig. 1(c)). Deviation from these paths would be classified as *unintended* (such as a large jump from module 1.1 → 3.1 or a backward jump from Module 5.1 → 2.2, represented using red arcs in Fig. 1(c)). This data feeds into the computation of a *"Stress Index"* of each module. *"Stressed"* modules are those modules with a large number of unintended flows.

The visualization module allows the instructor to explore the data in a single consistent interface with the following four interleaving aspects: annotation data, user information, flow sequence and reading time information. These aspects can be explored at three different scales (Figure 1). At the macroscopic level, the overall dynamics of the entire syllabi is shown (Figure 1(c) and (d)); at the mesoscopic level, a matrix-based visualization supports the comparison of different sub user-groups and their flow trajectory and annotation distribution (Figure 1(e)); and in the microscopic level, the detailed information of each user, annotation or flow can be examined (Fig. 1(a) and (b)). All views in UserFlow are dynamically coordinated via interactive linking, allowing for seamless exploration of the document usage data from different perspectives.

4 USERFLOW DESIGN

In this section, we describe the visual design of the UserFlow interface, which contains five coordinated views to allow the exploration of the document usage data at three different levels of detail.

4.1 Minimap View: Summary

The minimap demonstrates a macroscopic level overview of the entire syllabus. This addresses the requirement of displaying the summary view of the distribution of annotations over the syllabi (**G1**). Each rectangle in a minimap (Fig. 1(d)) corresponds to a learning module. Each module is divided into four sections and uses a heatmap to depict the average accumulated time spent on each section. The height of the minimap is proportional to the length of the module so that the educator has a sense of how large or small the module is. The VLE annotation tool allows students to tag their annotations with one of six categories: *Comment, Important, Confusing, Errata, Help, or Interesting*. In the Matrix View, shown in Figure 1(e), the categories are color coded and are shown as a bubble chart. The size of the bubble corresponds to the frequency of annotations made on that module. Hovering over the bubble pinpoints the precise location of the annotation on each module (Fig. 1(d)). Our experts requested a quick way of filtering annotations and seeing their location in the minimap. To address this, we provide a donut chart (Figure 1(b)) to view the location of the annotations in the minimap. The Minimap and Matrix View share the same horizontal axis (module numbers) to allow for direct comparison.

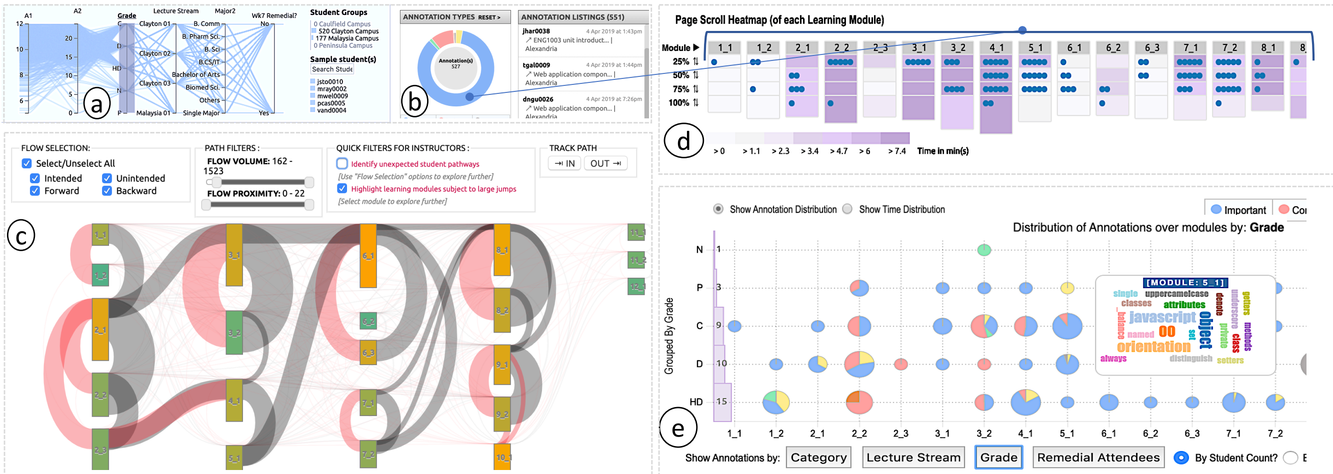

Figure 1: UserFlow tool. (a) The Filter panel supports brushing options to select multi-dimensional data and (b) allows filtering annotations by categories. (c) The Flow View traces intended student pathways and observed deviations navigating course material. (d) The Minimap View shows a heatmap of reading time plus annotation locations within syllabi. (e) The Matrix View displays a comparison of annotation patterns for different user groups.

4.2 Flow View: Investigating User Trajectory

The Flow View (Fig. 1(c)) uses a Sankey diagram [19] to provide a macroscopic view of student trajectory in the syllabi. This choice came out of our participatory design approach and directly addresses the goal of seeing document traversal paths (**G3**). Each node or rectangle on the panel represents a learning module and the arcs represent the trajectory followed by the students. The size of the node is proportional to the length of the module. The nodes are ordered left-to-right in the main sequence that is followed in the course. The thickness of the path connecting the modules is representative of the number of students that followed that path. Forward flow is represented using a gray arc while the red arcs are used to indicate the backwards flow. Analysts can filter flows by their type—intended, unintended, forward or backward—using the checkbox selectors. There is also the option to filter flows by volume and proximity.

To assist in identifying modules which are subject to large jumps, we have algorithmically computed a *"Stress index"* for each module based on the volume of flow to and from the module, factoring in the deviation from the intended path and flow magnitude. A green-to-orange color gradient is used to highlight this (see Fig. 1(c)), where orange indicates high stress and green low stress.

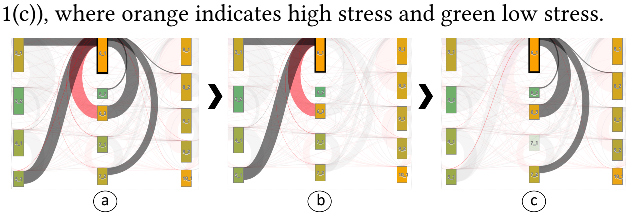

Figure 2: Exploring Flows: (a) Tracing flow for a selected module, (b) Investigating inward flow and (c) Investigating outward flow

The flow view also provides a "Track Path" option (Fig. 2) to trace inward and outward pathways of students when a particular module is selected (Fig. 2(a)). Selecting the "In" option highlights inward pathways, revealing the modules students engaged with prior to arriving at the selected module (Fig. 2(b)). Selecting the "Out" option reveals the subsequent modules the students went to after visiting the selected module (Fig. 2(c)).

4.3 Investigating Engagement

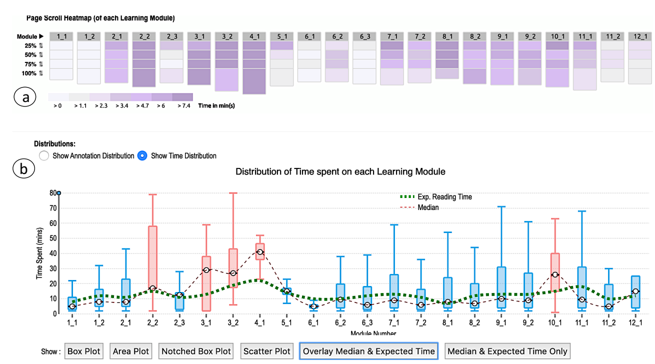

Figure 3: (a) Minimap View together with (b) Color-coded boxplot for each module

To represent engagement information, we use boxplots to show the distribution of the total accumulated reading time for each module in minutes. This addresses the requirement of instructors to have access to granular engagement data to understand the reading strategy of students in different modules (**G4**). We also compute a metric, *expected reading time*—using the word count and the number of images and videos on each page—which is plotted against the boxplot for comparison purposes (represented as a green dashed-line in Fig. 3(b)). UserFlow uses a color-coded boxplot to help distinguish modules where students spend above or below the expected reading time. Modules where the median reading time is higher than the expected reading time are plotted in red, while those modules where the median reading time is lower than the expected time are plotted in blue. The intention is to help instructors easily identify modules which may warrant attention e.g., for reasons such as higher difficulty or being too lengthy.

4.4 Matrix View: Investigating User Groups

To unfold the engagement dynamics of different user groups, we developed the Matrix View that includes a matrix diagram to reveal information at the mesoscopic level (Fig. 4). This addresses the requirement of instructors to be able explore insights about specific groups of users, so that instructional support can be targeted to the sub-group to balance the different needs (**G2**).

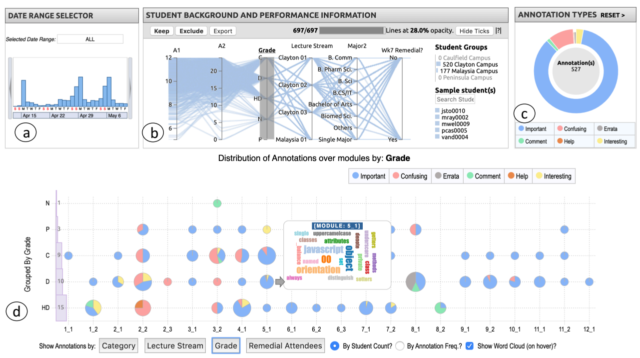

Figure 4: Matrix View: (a) Date-range selector (b) Parallel Coordinate Plot for filtering multi-dimensional student data, (c) Donut Chart to filter annotations by categories and (d) Dynamics of annotations shown in a grid-like matrix

The matrix diagram is a major analytical component in this view, sharing the same horizontal module axis with the Minimap. The y-axis of the matrix diagram (Fig. 4(d)) represents user groups, where the educator can choose to group students by different meta-data attributes, such as grade, lecture stream, those who attended remedials, and so on. Each cell in the matrix diagram indicates the information of one user group (e.g., students scoring High Distinction (HD)) for each module (e.g., module 2.2). The instructor can use the radio button to choose the representation to be *by student count* or *by annotation frequency*. The choice is mapped to the size of a pie chart, where each slice corresponds to the annotation category using the same color-coding in the bubble chart (Fig. 4(d)). A summary of the frequency distribution is further indicated as a sideways bar chart (in purple) on left of the matrix, where the length of the bar maps to the total frequency of students in each group. Further extensions allow filtering/grouping by grade and lecture streams (Fig. 4(d)).

We use a parallel coordinates plot (4(b)) to complement the matrix view and to support multi-dimensional data selection and filtering (**G5**).

4.5 Text View: Examining the Annotations

To enable the instructors to examine the annotation data at the lowest level (**G1**), we designed the Text View that provides a conventional presentation of annotation listing (Fig. 5). Beside the textual content of annotations, we selectively show some important attributes such as the author of the annotation, timestamp, module referenced, and annotation category. The Text View is linked with the Minimap View. Hovering over the annotation text highlights the location of the annotation in the Minimap. Clicking on the annotation message opens the exact location in the document where the annotation was made.

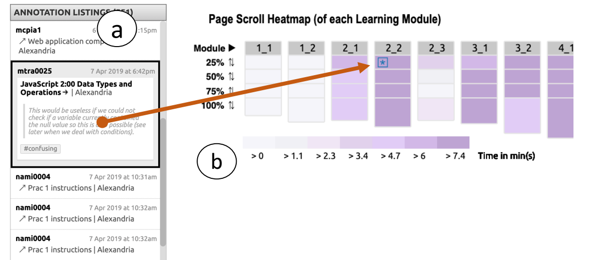

Figure 5: Text View showing (a) the annotation listing in a structured hierarchical format and (b) the location of the annotation in the Minimap when it is expanded for reading

5 CASE STUDY

We conducted semi-structured interviews (1 hour) with eight domain experts comprising of four course instructors, two LA experts and two instructional designers. We demonstrated UserFlow during the first ten minutes, then participants were given four tasks to perform using the tool (see Section 5.1). Participants were given 10 minutes to perform each task, and were free to use their own approach to solve each. We instructed the participants to do the exploration using a think-aloud protocol, encouraging them to speak their thoughts and reasoning during the exploration. We took notes about their feedback. We used two questionnaires: the *Task Load Index* [8] to evaluate UserFlow at task level and the *System Usability Scale (SUS) questionnaire* [2] to quantify the overall usability of tool. Finally, a post-interview discussion was conducted to further discuss the strengths and weaknesses of UserFlow. We recorded the screen and audio of each session for later analysis.

5.1 Tasks

During the interview, we asked the experts to use UserFlow to examine the document usage data generated during the course. The course consisted of 726 students split over two campuses and four lecture streams. There was a total of 83,495 page views and 863 annotations made by the students during the 12 week offering. Each expert was required to perform the following four tasks.

5.1.1 *Task 1: Student Challenge and Difficulty.*

In the first task, the participants were asked to identify possible topics they would choose to discuss in the revision lecture in Week 13 in preparation for their upcoming final examination.

Observation: In this task, the participants all identified that Module 2.2 and Module 4.1 were the most challenging modules in this course. This conclusion was reached by exploring the annotation distribution data as shown in Figure 1(b) (where *confusing* and *help* annotations were high). Three of the eight participants also considered the reading time information (accumulated reading time as shown in Fig 3) for Module 2.2 and Module 4.1, which was beyond the estimated reading time (workload represented using green dashed line graph in Fig. 3(b)) for these modules.

Using these insights, the instructors could action tangible interventions, such as by including more slides on Module 2.2 and Module 4.1 in the lecture material to add explanation to these topics. Alternatively, they could include supplementary reading material in the VLE to support the confused students. Another suggestion that came from the lead instructor was that UserFlow could help identify student sub-groups exhibiting certain behavior and that targeted intervention sessions could be implemented. The participants also acknowledged that the visual presentation was more intuitive than the traditional forms of feedback they received.

5.1.2 ***Task 2:*** *Content Presentation.*

The second task focused on the suitability of the UserFlow tool to help identify issues around the structure or sequence of topics.

Observation: All eight participants used the Flow View panel (Fig. 1(c)) for this task. Most of them focused on the large volume flows and backward flows. They were able to further investigate the flow and modules by tracing the 'Inward' and 'Outward' flows. Three of the participants used the *"Identify unexpected student pathways"* or the *"Highlight learning modules subject to large jumps"* quick filter options to identify the unusual flows. They discovered that there was unexpected high volume flows from Module 4.1 (*JavaScript Functions*) to Module 2.3 (*Debugging JavaScript*) and from Module 3.1 (*Working with Mobile Web Apps*) to Module 6.1 (*Configuration Management*) as shown in Figure 1(c).

The instructors acknowledged that the two modules were related and students could be advised via a forum post to explore some of the future sections in advance. A quick solution to remedy the issue would be to embed a *'Hints and Suggestions'* hyperlink to make the relationship explicit. Alternatively, instructors felt they could potentially merge the two topics.

5.1.3 ***Task 3:*** *Student Engagement.*

The third task was to use the UserFlow tool to identify topics and modules attracting unusual engagement. More specifically, the task asked participants to identify modules and sections where students were spending a lot of time and which modules or sections the students were skimming or not reading?

Observation: To address this task, three of the six participants started their exploration from the Minimap View (Fig. 3 (a)). The experts identified that the engagement pattern (shown in Figure 3(a)) was rather unexpected. The LA expert was quick to comment *"This seems like a course of two halves, there is active engagement from Module 2 to Module 4 and Module 7 to 10." "Seems like the workload or content is too light in the beginning, middle and the end."*, he added. He also inferred that some of these modules may have higher difficulty after jointly exploring the annotations (Fig. 1 (e)) and high volume of flow around these modules (Fig. 1 (b)). The lead instructor also came to the same conclusion regarding the difficulty of those modules and explained that engagement might be affected during the weeks coinciding with assignment deadlines. The color-coded boxplot (Fig. 3(b)) also assisted in identifying the sub-modules 2.2, 3.1, 3.2, 4.1 and 10.1 where students were spending more than the expected allocated time.

The participants suggested that for modules they identified as having high reading time (red boxplots in Fig. 3(b)), the best solution would be to consider splitting them into sub-modules to make it easier for the students to incrementally comprehend concepts.

5.1.4 ***Task 4:*** *Content Adequacy.*

The final task was to use the dashboard for checking if the material was comprehensive/complete, looking for student engagement cues of missing or superfluous (excessive or redundant) content.

Observation: For this task, the participants were able to quickly use the annotation Matrix View (Fig. 1 (e)) to identify *error*, *help* and *errata* annotations to pinpoint specific problematic areas. The reading time information and the boxplot shown in Figure 3 was also helpful. The participants used this information (see color-coded boxplots in Fig. 3(b)) as cues to identify which material may need more content (1.1, 1.2, 6.1 and 11.1) and which modules (2.2, 3.1, 3.2, 4.1 and 10.1) had higher than expected workload (workload represented using green dashed line graph in Figure 3(b)) and needed to be more balanced. The main lecturer also commented:*"I have just revised and moved this course material to another platform. I had limited feedback to work with in regards to where I could improve the material. This tool would have been very useful in identifying modules that needed attention."*

5.2 NASA TLX Ratings

We collected participants' NASA Task Load Index (TLX) ratings on their perceived effectiveness, effort, frustration, confidence and performance using UserFlow for each task. Figure 6 summarizes the results. For performance, effectiveness, and confidence measures, the higher numbers mean they have rater the tool better. Conversely, for effort and frustration measures, lower values are better.

As illustrated in Figure 6, the participants found the tool quite useful in meeting their expectation in supporting inquiry-based practice. UserFlow had the highest ranking in fulfilling Task 1 (Identifying difficulty and confusion) and Task 3 (Interpreting Engagement pattern). Task 2 (identify issues around structure and sequence) seemed to be most complex and frustrating for the participants. Two reasons reported during the evaluation were the unfamiliarity of analyzing flow data and the complexity of the interface. The training time of 10 minutes was also not enough. Confidence in answering Task 4 (is the content adequate?) was ranked lowest as the the participants suggested that errors and confusion may be one sign of content inadequacy but students may not have a complete picture of the content at the pre-reading phase.

5.3 System Usability Scale (SUS) Questionnaire

System Usability Scale (SUS) is an effective tool for assessing the usability of a product. It has become an industry standard and can be used on small sample sizes with reliable results [2]. The average SUS score of 74 rates the UserFlow application between 'good' and

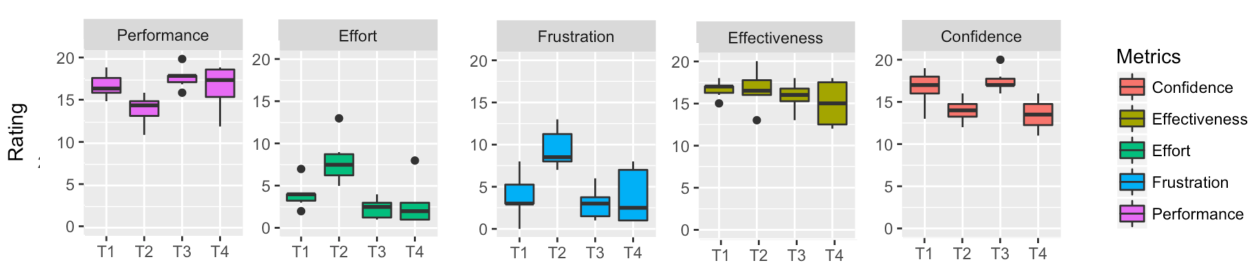

Figure 6: Participants' TLX evaluation of each task. Ratings were on a 1-20 scale.

'excellent' [2]. Looking at the individual questions, as shown in Figure 7, we find some interesting results.

The participants unanimously rated the *Data Quality* and *Human-In-the Loop Approach* adopted in UserFlow very highly. This showed that the insights were meaningful and actionable and the tool is problem-focused and empowering. These sentiments were also echoed by the think-aloud comments and reported in our task evaluation. Nearly all questions also scored well on tool usability with a median of 4 or above where a high score is desirable (Questions 1–5), and a median of 2 where a low score is desirable (Questions 6–10). Question 2, where the instructors were asked if they felt the tool was easy to use, scored positive, yet most answers lay between 3 and 4. This is likely because 10 minutes of training time was not sufficient for all participants. The learning curve of parallel coordinates plot and flow diagram for a few of the participants may have contributed negatively to this rating. This is confirmed by the rating of mostly 2 to 3 for Question 7: ("I need support of a technical person").

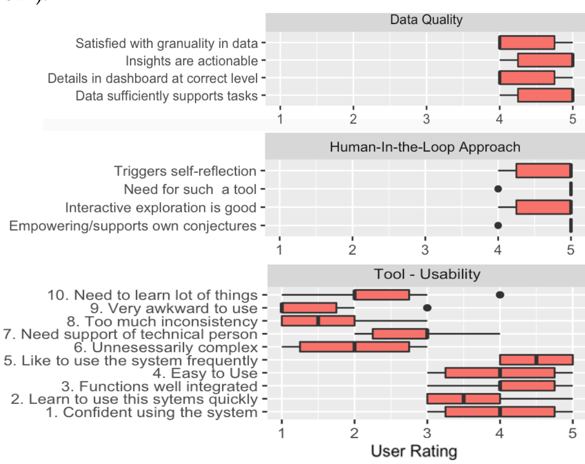

Figure 7: Participants SUS Rating. Ratings were on a 1–5 scale where 5 is *'Strongly Agree'* and 1 is *'Strongly Disagree'*.

6 CONCLUSION AND FUTURE WORK

We presented the design and evaluation of a visual analytics system, named UserFlow, which allows CS educators to effectively discover and understand patterns of engagement in teaching documents. UserFlow enables interactive exploration of complex and heterogeneous datasets at macro, meso and micro level (overall cohort, by user groups and by individual student). Our work addresses the misalignment between the information generated by current analytics dashboards, and the needs, problems, and concerns teachers have with learning design activities [6, 7]. The reason for this misalignment is often the gap between data easily captured from system logs and data that is pedagogically valuable to educators.

Our design study is a step towards fostering clearer connections between analytic data and instructors' teaching concerns by incorporating local instructors' ongoing involvement in the decisions about selecting data input and in the design process. Some of the challenges that appeared in this study mirror issues well known in the fields of human-computer interaction [16, 24]. Drawing on those best practices and from the literature, we have involved the instructors throughout the analytic tool development and conducted early studies of analytics use in-situ to provide important insight into tool design for local actionability. The study reaffirmed that the translation from information to insight to action is not straightforward. However, through the practices of human-centered learning analytics design and by conducting such studies of analytics use in authentic settings, we can develop better analytic tools as a pathway to improving wider analytics adoption and impact in CS education.

Our results have demonstrated the effectiveness and usefulness of UserFlow in exploring real-world document usage data. However, the are some limitations of UserFlow that can be addressed. The parallel-coordinates plot, although very powerful, is not a commonly used visualization. To effectively use this feature requires a certain amount of learning. The same applies to the flow diagram. Although the participants did not encounter any major difficulty understanding these visuals during our study, designing better help or training for them is necessary to increase the use of the powerful features they provide. Secondly, as shown in Figure 1(c), we use various color-coding and flow lines to show the document traversal paths of students in the Flow View. However, for larger classes, this causes visual clutter and becomes quite overwhelming for the users, resulting in complex flow data and courses with many modules. To resolve these problems, we plan to try a click-to-reveal option for the Sankey diagram as well as explore other methods summarized in [5], such as sampling, to illustrate messy lines in a clean and informative way. There are also limitations in our design study. Evaluating a broader sample of CS courses from different streams and specialization could offer additional insight on how document usage patterns and reading strategies may vary among different groups of students in different courses.

There are several promising directions to generalize the current UserFlow design. Although we conducted our design study in the context of analyzing document usage data, UserFlow can also be applied to the exploration of other kinds of teaching material, for example streamed video lectures in lecture-based courses. Individual or collections of videos packaged as a course can be analyzed in a similar manner as documents—as it is now possible to capture and extract granular navigation behavior and annotations made within video files and monitor the order in which videos are watched. Secondly, in this design study, we only collected user information regarding student grade, study major, lecture stream and remedial attendance status. It would be straightforward to expand the data sources in UserFlow to analyze richer user attributes, such as gender, age, and education level, to gain a deeper understanding of the behaviors of these categorizations in the course.

In future, we plan to enhance UserFlow to present social analytics on peer-interactions and group cooperation in collaborative coding environments, such as Google Colab. Moreover, our experts rely on their previous knowledge to interpret the visualization. We plan to integrate course events (assignment date, etc.) into UserFlow to help explain unexpected patterns detected through use of the system. We also hope to support real-time browsing of usage data so that instructors and educational content authors can dynamically adjust learning material and their teaching strategies in classrooms or react more swiftly to notable behaviors exhibited by the students through their flow and annotation data while a course is in progress.

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