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ARTICLE

Knowledge-Based Design Analytics for Authoring Courses with Smart Learning Content

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Abstract

Over the last 10 years, learning analytics have provided educators with both dashboards and tools to understand student behaviors within specific technological environments. However, there is a lack of work to support educators in making data-informed design decisions when designing a blended course and planning appropriate learning activities. In this paper, we introduce knowledge-based design analytics that uncover facets of the learning activities that are being created. A knowledge-based visualization is integrated into edCrumble, a (blended) learning design authoring tool. This new approach is explored in the context of a higher education programming course, where instructors design labs and home practice sessions with online smart learning content on a weekly basis. We performed a within-subjects user study to compare the use of the design tool both with and without visualization. We studied the differences in terms of cognitive load, controllability, confidence and ease of choice, design outcomes, and user actions within the system to compare both conditions with the objective of evaluating the impact of using design analytics during the decision-making phase of course design. Our results indicate that the use of a knowledge-based visualization allows the teachers to reduce the cognitive load (especially in terms of mental demand) and that it facilitates the choice of the most appropriate activities without affecting the overall design time. In conclusion, the use of knowledge-based design analytics improves the overall learning design quality and helps teachers avoid committing design errors.

Keywords Design analytics · Blended learning · Concept-level visualization · Knowledge-based analytics · Authoring tool · Learning design · Smart learning content

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Introduction

Data analytics applied to education, especially in the form of learning analytics (LA), has attracted the attention of learning technology researchers and practitioners over the last ten years (Papamitsiou et al. 2020). Learning analytics allows instructors to evaluate how students are learning within a learning context and provides them with data-based evidence to improve the overall quality of the learning experience (Lockyer and Dawson 2011; Joksimović et al. 2019). In comparison with educational data mining, LA presents a more human-led mixed method orientation to explore and inform upon educational data using several data analysis techniques, which goes beyond data mining (Reimann 2016). As the field broadened, it has become customary to recognize different categories of data analytics that can be relevant in the educational domain and to distinguish each category by its targeted group of users or tasks. This paper focuses on design analytics, which is one of the least explored areas within this broad research field.

We adopt the definition of the term "design analytics" as the "metrics of design decisions and related aspects that characterize learning designs" (Hernández-Leo et al. 2019). A learning design (LD) is an explicit representation of a lesson plan created by a teacher (Persico et al. 2013). Authoring tools can assist teachers in the creation of learning designs, which can lead to computational representations of the elements within a learning design that can be automatically analyzed. Some representations are generic or neutral, which are those that enable only some options for structural analysis of a course (e.g. the number of tasks, time planned for a set of tasks, etc.). Other representations are specific to pedagogical approaches or subject matter concepts and enable a more detailed level of analysis. Analyses of these representations can support teachers' awareness and reflection about the accumulated decisions taken along the learning process to inform pending decisions toward completion of the course designs (Hernández-Leo et al. 2019).

This paper proposes an approach for fine-grained design analytics that focus on visualizing critical metadata associated with smart learning content to support its authoring. Our proposed visualization covers various aspects of metadata, such as the type of learning content, the nature of knowledge supported, and a list of specific knowledge concepts that a specific fragment of learning content seeks to reinforce. In Albó et al. (2019), we carried out a first exploration of knowledge-based design analytics with a group of ten participants from a single university. The number of participants in the previous research was a limitation, as it was too small to draw general conclusions. In this paper we have extended the study by doubling the number of subjects and by diversifying the sample population (subjects from two different universities and subjects with different cultural backgrounds). Moreover, we provide more insights regarding users' feedback analysis as well as complementary instruments to gather more data from the participants' performances (the use of a second post-task questionnaire to evaluate the controllability, confidence, and ease of choice levels using the system).

In this experimental study, we aim to explore the value of knowledge-based design analytics of supporting instructors during the design process. Up to now, most studies in the field of design analytics have mainly focused on analysing systems that provide teachers with information at the course and activity levels (using a coarse-grained focus): information about the sequence/structure of the activities within the course, types of learning tasks, learning goals, and use of learning spaces (Cross et al. 2012; Villasclaras-Fernández et al. 2013; Laurillard et al. 2018; Martinez-Maldonado et al. 2017). While considerable efforts were spent on concept-level knowledge visualizations in the field of open learner modeling to help students in tracking their knowledge and selecting relevant activities (Bull 2020; Guerra et al. 2018), very little is currently known about whether (and how) a knowledge-based approach (using a fine-grained focus) applied to design analytics could also serve by informing teachers during the design of their courses, increasing their efficiency and precision in taking design-decisions (e.g. facilitating the selection of the most appropriate activities to ensure that all concepts related to a given topic or learning objective are covered). To provide new insights into this topic, our research aims to study the differences of using versus not using knowledge-based design analytics, in terms of instructors' cognitive load, controllability, confidence, easiness of choice, design outcomes, and user actions within the system. We compare both conditions with the goal of evaluating the impact of using design analytics during the decision-making phase of course design. Although this study is contextualized in a programming course that uses smart learning content, it is hoped that this research will contribute to a deeper understanding of how using information (metadata) that characterizes (open) educational resources could generally be used to support the teachers' course-design process.

The structure of the paper is as follows. Section 2 provides a review of related work about design analytics in learning design authoring tools, and open learner modelling and navigation support for smart learning content. In Section 3, we explain what we mean by knowledge-based design analytics and introduce its implementation in a learning design authoring tool that supports teachers in selecting smart learning content. Sections 4 and 5 present the design and results, and Section 6 details our conclusions and some potential areas for future work.

Related Work

Design Analytics in Learning Design Authoring Tools

The term design analytics, at the intersection of LD and data analytics, was coined and defined in the Analytics Layers for Learning Design (AL4LD) framework proposed by Hernández-Leo, et al. (Hernández-Leo et al. 2019). The framework is built on existing learning design tooling that includes features that align with the concept of design analytics. In contrast to the term "learning analytics," which is focused on measuring learners' behaviour and performance (Joksimović et al. 2019), design analytics measures the characteristics of the pedagogical intent in a learning design (Hernández-Leo et al. 2019). These characteristics or data classes include the goals (i.e., objectives, learning outcomes) of the design, which are usually framed using taxonomies (such as competence frameworks, learning objectives taxonomies, local curriculum); types of learning tasks (Sergis and Sampson 2017); social planes (individual, collaborative, collective) (Dillenbourg and Hong 2008); places and tools suggested to complete the tasks (Goodyear and Carvalho 2014); or the time expected for students to complete the tasks.

As with the broad desire of the artificial intelligence (AI) community for providing transparency into decision-making processes, design analytics can be useful in providing awareness about the properties of the learning design; for example, to support the authoring process. For instance, by monitoring the accumulated design decisions made during the authoring of a learning design, design analytics can inform the pending design decisions during the authoring process (Hernández-Leo et al. 2019). Also, in alignment with proposals that connect learning design with learning analytics (Sergis and Sampson 2017; Michos and Hernández-Leo 2020; Milligan et al. 2020), design analytics can offer frameworks for interpreting learning analytics.

An example of design analytics is provided by *Web Collage*, which analyzes the accumulated design aspects specified by the teacher when completing a template that is based on a collaborative learning flow pattern (Villasclaras-Fernández et al. 2013). With this analysis, the tool computes and visualizes alerts that point teachers to pending actions needed to complete the design, as required by the design guidelines that underpin the pattern (Villasclaras-Fernández et al. 2013).

The idea of learning design analytics can be also observed in the *Activity or Pedagogy Profile* tool, which enables the creation of a bar chart representation to help teachers describe the distribution of tutorials and directed study modules (Cross et al. 2012). The profile represents tasks across six activity types in a detailed unit-by-unit or week-by-week analysis. The tool was created to be helpful at different stages within the design process, from first ideas through evaluation and review. Moreover, the analytics bar charts can be shared with learners and other stakeholders to express how learners are expected to spend their time in terms of balance and shape of the expected learning activity.

Another example is the *Learning Design Support Environment* (LDSE or the Learning Designer). The LDSE provides an analysis of the properties of the designs being created by the teacher with the environment as a learning design tool (Laurillard et al. 2013; Laurillard et al. 2018). In particular, it generates charts that visualize the proportion of time that students are expected to spend on the diverse types of tasks that are planned in the design, from "acquisition" to more active forms of "inquiry, discussion, production and practice". This information serves as feedback to teachers about the nature of the learning experience that the learning design proposes.

The *Educational Design Studio* (Martinez-Maldonado et al. 2017) is a physical environment for multiple designers working in teams that is equipped with wall projectors, whiteboards, a digital tabletop, and other tools. These various displays allow for several representations of the designs being created. The environment collects data from the designs and generates various charts; for example, the proportion of learning tasks distributed in the learning spaces (for example, tasks occurring at the lecture room, at the lab, or online). This information enhances awareness of the broad view and the progress of their designs while building and editing individual tasks, as well as facilitating comparison between designs.

The concept of design analytics has been more extensively exploited in the *edCrumble* learning design tool. edCrumble is a pedagogical planner that provides a visual representation of the learning designs, strongly characterized by data analytics, that can facilitate the planning, visualization, understanding, and reuse of complex blended learning designs (Albó and Hernández-Leo 2018). Specifically, the decision-making that occurs during the design process is supported by design analytics that result from the design of the activities sequenced in a timeline. The design analytics provided give more information about the following categories: in-class/out-of-class time analytics, tasks' cognitive process, type of student work, teacher presence, and task evaluation mode. In each category, it is possible to have different visualizations: global time analytics, analytics that depend on the activities' type (in or out-of-class), and analytics that depend on the overall learning objectives.

In this paper, we present our attempt to further expand the design analytics component of edCrumble in order to support teachers at an extremely fine-grained knowledge-based design level, which refines the "goals" data class of the AL4LD framework (Hernández-Leo et al. 2019). The new design analytics proposal will account for the metadata that comes from the new integration of smart learning content into the resources' panel.

Concept-Level Open Learner Modelling and Navigation Support

Blended learning approaches usually attempt to focus each of their different learning contexts on the activities that could be performed most efficiently in this context. For example, lecture classroom time could focus on the explanation of complicated topics and discussions and a lab session could focus on solving sample problems during which the help of a human teaching assistant might be necessary, while online learning might be devoted to self-study, self-assessment, and practice. As the complexity of learning tools increases, the online component of blended learning is increasingly focused on practicing with so-called *smart learning content* (Brusilovsky et al. 2014). Each element of this smart content is a relatively complex interactive activity, which engages students in exploration and provides real-time performance feedback. For example, in the area of computer science education, some previously explored types of smart content included interactive animations, worked examples, parameterized semantics questions, Parson's puzzles, and programming problems. As each smart learning content item is relatively complex and advanced, it usually allows a student to practice a number of different course concepts or skills, which could be introduced in different lectures or course units. This complex nature of smart learning content makes it hard for the student to accurately track progress and to select the most relevant learning content item for further practice.

To improve student knowledge-tracking ability during their work with smart learning content, several researchers have suggested concept-level *open learner models (OLM)* (Bull and Kay 2007; Bull 2020). A concept-level OLM recognizes the presence of multiple domain knowledge components (KC), such as concepts and skills, and visualizes student knowledge progress separately for each of these skills. Made popular by the field of intelligent tutoring systems as *skillometers* (Corbett et al. 2000), concept-level OLMs have become popular in other types of e-learning systems. While the primary focus of such OLMs is student knowledge visualization, many existing concept-level OLMs directly or indirectly support learners in selecting the most relevant learning activities (Bull et al. 2016). A brief review of different concept-level OLM visualizations on which we focused can be found in Bull et al. (2018).

More recently, a similar research stream on student-facing dashboards has been established within the field of learning analytics (Bodily and Verbert 2017). Typically, student-facing dashboards visualize learning progress in terms of learning activities rather than on the level of concepts and other units of domain knowledge, which makes them considerably different in nature from OLMs (Bodily et al. 2018). A notable exception are several projects that attempt to visualize learner progress on the level of relatively coarse-grained domain knowledge units, such as top-level learning objectives (Grann and Bushway 2014; Papanikolaou et al. 2003; Loboda et al. 2014). Yet, even these projects offer no support for selecting most relevant learner activities. A good analysis of similarities and differences between OLMs and learner-facing dashboards is provided in Bodily et al. (2018).

Our own work has prompted us to explore visual interfaces, which combine topic-level open learner modeling with navigation support in order to help learners in selecting the most relevant learning content (Sosnovsky and Brusilovsky 2015). Most recently, we explored student-focused concept-level knowledge visualization to help students in tracking their knowledge and selecting relevant smart content (Guerra et al. 2018). In this paper, we attempt to further expand the application area of concept-level knowledge visualization by exploring its value in a different context—helping instructors select appropriate learning content in a blended learning context.

Knowledge-Based Design Analytics for Blended Learning

The key concept behind knowledge-based design analytics is to visualize the concept coverage of individual learning activities, as well as learning sessions (such as a lecture, a lab, or at-home practice), to help instructors in creating balanced learning designs. A learning activity is usually associated with metadata, which describes its type, engaged concepts or learning objectives, expected time to complete, and other aspects. This metadata is critical to create balanced learning designs. For example, learning practice prepared for a specific lecture should offer a balance of examples and problems, rather than over-focusing on only one of these types of activities, and should cover all critical concepts introduced during the lecture, rather than over-focusing on some of them. Such a balance is usually difficult to achieve without supporting the instructors with appropriate design analytics.

In this section, we present the design of a knowledge-based design visualization component that extends the design analytics offered to the users of edCrumble. To demonstrate the power of this concept-based approach, we apply it to a relatively challenging design context: developing lab and practice sessions for an introductory programming course that uses smart learning content. This context is challenging, since these kinds of smart content are of a different nature (examples vs. problems) and cover different kinds of programming knowledge (program comprehension vs. program construction). Moreover, each content item engages students in practicing a number of different programming concepts.

To support teachers in adapting this complex context, our designed visualization offers a knowledge-based visualization of a learning session being arranged and allows teachers to compare the constructed session on the concept-level by using a mirrored bar chart visualization (i.e., balance of concepts between problems and examples). First, we chose a bar graph because early research in human perception has shown that length (as used in bars) is one the graphical representations of numerical data that leads to fewer biases in judgment (Cleveland and McGill 1984) in comparison to other visual features, such as angle or area. This has been confirmed by later research, which has shown that basic information-seeking tasks (e.g. finding max./min. values) are generally better supported by using bar charts than radar charts, despite perception differences among users (Toker et al. 2012), or that bar charts are visual representations that allow users to complete different tasks (e.g. characterize data distribution or finding clusters) in the shortest time and with the most accuracy in comparison to other visualizations, like pie or line charts (Saket, Endert and Demiralp 2018). Furthermore, the bar chart approach for showing the distribution of concepts in a programming domain was defined after a previous series of user studies (Guerra et al. 2018). Second, the mirrored layout was grounded by previous findings in information visualization research, which show that correlation tasks (i.e. easily detecting if two data distributions were similar or not) are better supported when presented through graphs with a mirrored layout (Ondov et al. 2018) and that the visual system's capability for detecting differences between two regions is more efficient when they are shown as mirror images of each other, as compared to repeated translations of each other (Treder 2010).

We explain the behavior of this visualization with the following scenario. The process of adding a new activity to a learning session starts with selecting the type of learning activity to add. To support the programming context, six types of smart learning content for introductory programming (Table 1) have been integrated into the resources panel of the design tool (Fig. 1 A).

By clicking on each resource tab, the system shows a list of the corresponding activities available for this content type. Users can select the preview button to open and try each activity and thus make an informed decision when selecting activities for a new session. When an activity is judged to be suitable to be used in the design, users can drag and drop the activity's icon to the open session (lecture, lab or practice) in the editor (Fig. 1 B). Once an activity has been aggregated into the design, the design analytics panel (Fig. 1 C) offers a short animation that allows the user to visualize the activity's contribution, in terms of concept-level knowledge coverage (knowledge gained upon its completion).

Each bar on the concept-level knowledge visualization chart (Fig. 1 C) represents a domain concept, and its length represents how frequently the concept will be practiced by the learner when working with the selected session content (which could be also considered to be an estimation of knowledge gained after completing the session). The name of concepts that the instructor should target when designing for a specific lecture (such as lecture 4, with its subsequent lab-4 and practice-4 sessions) are highlighted in yellow for facilitating their coverage (see the seven concepts highlighted in Figs. 1 and 2). The concepts shown to the left of the highlighted concepts are those that were targeted by the previous lecture, whereas those placed to the right are the ones that have not yet been introduced in past lectures. The system also offers the possibility of previewing the contribution of a candidate activity to the overall design by situating the mouse over it, before dragging and dropping it into the selected session. The system then shows the preview of its contribution to learning different concepts by adding striped bars to the visualization, as a short animation is shown when bars are added (Fig. 2 left).

In the analytics panel, we can find three tabs that offer different types of concept-level comparisons, depending on the sessions and the activities' types and knowledge. These comparisons help to balance the concept coverage of selected content by content type, session type, or covered knowledge. The first tab, "Type of session" (Fig. 2 left)

Table 1 Smart learning content integrated into the learning design tool, distinguishing between examples and problems and construction and comprehension types

ID	Title	Type	Description
WebEx	Annotated Examples	Example Compr.	Annotated program examples. Students can click each line of code to see the related explanation for that line (Brusilovsky, 2001).
AnimEx	Animated Examples	Example Compr.	Animated program execution examples, which visualize line-by-line execution of a piece of code (Hosseini et al., 2016).
PCEX	Program Construction Examples	Example Constr.	Interactive program construction examples. Each example provides a goal that specifies the given example's functionality. Users can click on each line of code to see explanations (Hosseini et al., 2018).
PCEXch	Program Construction Challenges	Problem Constr.	Small problems to help students develop program construction skills. Each challenge is a code example with 1-3 removed lines. Students need to drag and drop candidate lines to complete a program to achieve the provided goal (Hosseini et al., 2018).
Quizjet	Parameterized Problems	Problem Compr.	Parameterized problems for self-assessment of student knowledge of programming semantics. Students are asked to predict the final value of a program output (Hsiao et al., 2010).
PCRS	Programming exercises	Problem Constr.	Coding exercises with automatic assessment. The system asks the user to complete a partial code skeleton and then checks the submitted answer using a set of tests (Zingaro et al., 2013).

allows a user to compare the overall concept-contribution of the activities selected, depending on which type of session they have been placed. It also offers the possibility of switching among three comparisons (Lecture/Lab, Lecture/Practice, and Lab/Practice sessions). The second tab 'Examples/Problems' (Fig. 2 right) offers a unique comparison between these two types of activities, but gives the option of filtering the results by visualizing only Lab, Practice, or both. The same applies for the third tab, 'Comprehension/Construction'.

Exploring the Value of Knowledge-Based Design Analytics

Participants and Sample

It is challenging to evaluate a system focused on instructors as users, due to the limited availability of qualified participants. For our study, we recruited a total of 20 domain experts (12 female) who were sufficiently qualified as introductory programming instructors. All the instructors were computer or information science PhDs or postdoc students from two public universities in the United States (10) and Spain (10). Eligibility criteria required individuals to have knowledge in programming languages and experience as instructors or teaching assistants. Their ages ranged from 24 to 36 (M = 30.5, SE = 0.81) and they had between 1 and 13 years of teaching experience (M = 3.70, SE = 0.81). The scores (on a six-point scale) of how often their teaching tasks had implied in selecting what activities and what type of teaching resources would be used during the course were (M = 4.0, SE = 0.33; M = 4.1, SE = 0.35), respectively. The scores (on a five-point scale) related to the instructors' background knowledge of programming in general, in Java, and interpreting graphs were (M = 4.30, SE = 0.15; M = 3.60, SE = 0.20; M = 4.0, SE = 0.13) respectively. In addition to the 20 instructors, two teaching assistants were recruited as pilot users to test and refine the procedure; however, their work has not been considered in our final analysis. All 22 subjects were compensated for their participation in the study.

Design and Procedure

To assess the value of the design analytics that were provided, we compared the interface without the visualizations (baseline interface) to the one with the visualizations (visualizations interface). Due to the size of our sample, we used a within-subjects design. Instructors were asked to perform two different tasks with the system and all of them experienced both treatments. The order of treatments was randomized to control for the effect of ordering (half of the instructors started the study using the baseline interface) and each participant did each task with just one treatment. The tasks were designed within the context of a higher education programming course (JAVA course) of 15 weeks: each week had a lecture and a lab session in class, and practice time at home. Our study was focused on the third and fourth weeks (the editor was prepared with the sessions of these two weeks to allow instructors to design within this framework) and asked instructors to perform realistic design tasks to target concepts explained specifically in Lecture 4, which is described as follows. **Task 1:** Design a Lab session for Lecture 4 using eight (problems) activities in total. a) Try to ensure that the practice session covers key concepts introduced during the class (as shown by lecture examples). b) Try to strike a balance between problems that focus on program

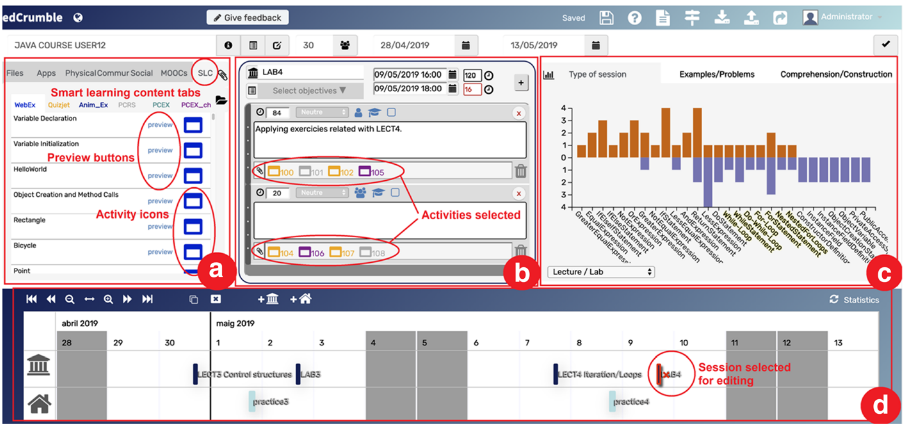

Fig. 1 Screenshot of the learning design tool's editor. (A) Resources panel with the 6 categories of smart learning content; (B) Editor for the selected session in the timeline; (C) Design analytics' visualizations; (D) Timeline with the in-class and out-of-class sessions

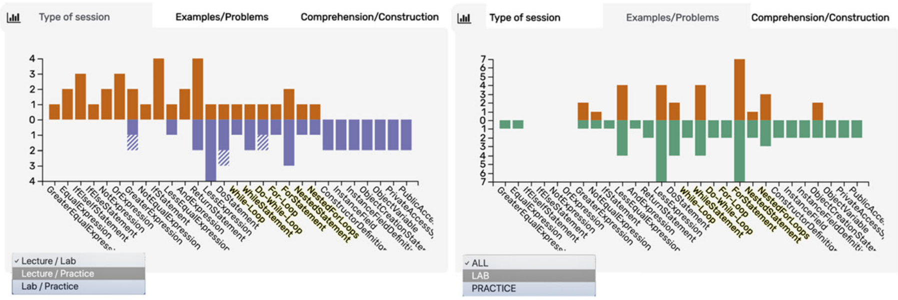

Fig. 2 Design analytics provided in concept-level visualizations. Left: Activity contribution split by the type of session (i.e., lecture on top, lab on the bottom). Right: Activity contribution split by content type (i.e., examples on top, problems on the bottom. Striped bars (left) indicate a preview of the contribution of a potential addition of a new resource

comprehension and program construction. **Task 2:** Design a Practice session for the Lecture 4 using 20 (examples and problems) activities in total. a) Try to ensure that the practice covers key concepts introduced at the class (as shown by lecture examples). b) Try to ensure a balance of examples and problems. c) Make sure that the student will have a chance to practice both program comprehension and program construction skills. The order of the tasks was not randomized, since we considered the second task to be an extension of the first (albeit one with a higher difficulty). Instructors received two training sessions, one about the use of the design tool itself and the other about the use of the visualization. The group that started the study with the baseline interface received the tool training before the first task and the visualization training before the second task, while the group that started with the visualization received both training sessions before the first task. During the tasks, instructors had access to help files on the six types of activities, with a short description of each one that indicated the categories to which they belonged, such as examples/problems and construction/comprehension. After each task, we asked instructors to complete a post-task questionnaire. At the end of the study, instructors filled out a final questionnaire.

Data Collection and Analysis

We collected the action logs of the instructors while they interacted with the system. Above all, we focused on the actions that took place within the resources panel and the visualizations tabs. Moreover, we also gathered the learning design outcomes generated during the study to assess the instructors' performance on the tasks. After each task, we used two questionnaires. The first one was the NASA-TLX questionnaire (Hart 2012) which aimed to measure the instructors' cognitive load of the tasks' performances. We used a paper version of the questionnaire that included both known parts (rating and weights). The second post-task questionnaire had the objective of evaluating and comparing the controllability, confidence, and ease of choice levels using the system with the two treatments (see questions in Table 2). On the other hand, the final questionnaire asked instructors to provide their feedback about the use of visualizations and the design tool. It had two open questions to ask instructors about their preferences between the two treatments, as well as which interface they found to be more efficient in performing the given tasks and why. The third question asked instructors to order the three types of visualizations by their level of usefulness. Next, seven items were presented to instructors for gathering their feedback about the visualizations (all of them were on a seven-point Likert scale: strongly disagree: 1, strongly agree: 7). A final open question gave instructors the opportunity to provide general suggestions or comments.

Internal consistency reliability (Cronbach's alpha) was calculated for each of the three scales in the post-task questionnaire: controllability was 0.697, confidence was 0.743, and choice was 0.657. These correlation coefficients indicated that the scales exhibited acceptable internal consistency reliability with a sample size of 20 participants. In the case of the final questionnaire, the internal consistency reliability was 0.781. T-tests analysis were performed comparing both treatments in doing each task (between-subjects) and comparing both treatments considering both tasks together (within-subjects) to explore for significant differences. All the qualitative data (open questions) were coded with inductive thematic analysis driven by our research aims. Finally, codes of instructors were used for reporting the results (e.g., U1: instructor/user 1).

Results

Cognitive Load

The first result of the NASA-TLX questionnaire indicates that the second task (TLX index of 52.9) presented more difficulties for the instructors than the first task (TLX index of 42.4). This is an expected result that validates the design of the study, which ordered the tasks by its level of difficulty (not randomized). Table 3 shows the adjusted and weighted ratings for each of the two tasks and for both tasks together. Global TLX indexes indicate that, in both tasks, the perceived

Table 2 Post-task questionnaire items and questions. Seven-point scale (strongly disagree:1, strongly agree:7).Questions (R) are reversed coded

Item	ID	Statement/Question
Controllability	1	It was easy to find and add a proper activity to the design.
	2	It was hard to use the design editor to achieve my design goals. (R)
	3	I feel in control using the design editor to select the most appropriate activity.
Confidence	4	I think that with the activities I have selected, I have successfully covered the concepts of the lecture.
	5	I have little confidence in the design decisions I have made to accomplish the task. (R)
	6	I think I have achieved a very good balance between the activities according to the tasks goals.
	7	I changed my mind several times before making a decision. (R)
	8	I think I chose the best activities from the options available.
Easiness of Choice	9	Selecting the best activity was very easy.
	10	Comparing the different types of activities was very easy.

workload was higher when instructors did not use visualizations. The perceived mental demand (MD) is always higher without visualization, and this difference is significant when comparing all tasks' performances together (Med_{vis} = 150, Med_{novis} = 267.5, p = 0.004, Wilcoxon). According to Grier (2015), the overall range scores observed in the literature regarding the weighted NASA-TLX is 8 to 80 (M = 48.74, SD = 14.88). Thus, our results would be near to the mean score. Even when comparing the literature scores obtained from computer activities related tasks (Grier 2015), the global indexes found in our study can be considered mid-workload levels. The result of the comparison reinforces the importance of balancing the amount of information that the visualization offers to the users, since the results show that they are cognitively loaded in performing the design tasks. Thus, the fact of offering more information through a visualization needs to be carefully balanced and the results show that our visualization accomplishes this goal, since it is not adding more cognitive workload but that it has just the opposite effect.

Controllability, Confidence and Easiness of Choice

The results of the second post-task questionnaire (seven-point Likert scale; see questions in Table 2) are presented in Table 4. The statistical analysis reveals a significant difference in the *Easiness of Choice* item when performing task 2 (Med_{vis}= 5.75, Med_{novis} = 3.30, p = 0.017, Mann Whitney U) and when comparing both treatments that consider both tasks' performances together (Med_{vis} = 5.5, Med_{novis} = 3.4, p = 0.002, Wilcoxon). Visualizations easily facilitated the selection of the best activities and supported the comparison of the different types of activities. For the instructors, it was easier to select and compare the most appropriate activities for their designs by using the visualizations compared with not using the visualizations. Results did not indicate significant differences regarding either *Controllability* and *Confidence* items.

Action Analysis

The click data collected when instructors worked on the tasks provided an objective measure of how the two conditions (both with and without the visualization) affect the way subjects use the system. Results of the action analysis (Table 5) reveal a significant difference between the number of clicks performed for previewing the activities in both tasks. The number of clicks being significantly higher in the case of not using the visualizations (task 1: Med_{vis} = 3.0, Med_{novis} = 19.5, p = 0.003, Mann Whitney U; task 2: Med_{vis} = 2.0, Med_{novis} = 33.0, p = 0.002, Mann Whitney U). When considering the time needed to perform the two tasks, there were no significant differences between the two treatments. The use of the visualization did not significantly increase or decrease the design time compared with the condition without the visualization.

Design Outcomes

The learning designs collected after instructors completed the tasks provide an objective measure of how the two treatments affected the way subjects designed the two sessions (the lab and practice sessions required in the two tasks, respectively). As

Table 3 Results of the NASA-TLX questionnaire. Adjusted ratings considering weights

	Task 1			Task 2			Both tasks		
	Between subjects			*Between subjects*			*Within subjects*		
	Vis. M (SE) n=10	noVis. M (SE) n=10	p	Vis. M (SE) n=10	noVis. M (SE) n=10	p	Vis. M (SE) n=20	noVis. M (SE) n=20	p
Mental Demand (MD)	162.5 (32.9)	**250 (28.8)**	–	175 (36.5)	**265 (38.8)**	–	168.7 (23.9)	**257.5 (23.6)**	*
Physical Demand (PD)	**60 (32.9)**	43.5 (28.9)	–	33 (19.2)	**66 (31.1)**	–	46.5 (18.8)	**54.7 (20.8)**	–
Temporal Demand (TD)	66.5 (24.5)	**79.5 (28.3)**	–	100.5 (43.1)	**117 (34.0)**	–	83.5 (24.4)	**98.2 (21.9)**	–
Performance (OP)	**96.5 (11.4)**	92 (28.2)	–	83.5 (21.0)	**88.5 (19.1)**	–	90 (11.7)	90.2 (16.6)	–
Effort (EF)	**150 (35.6)**	137.5 (18.3)	–	193 (32.7)	**225.5 (41.4)**	–	171.5 (24.0)	**181.5 (24.2)**	–
Frustration (FR)	**73.5 (40.3)**	60.5 (20.4)	–	**130.5 (45.5)**	108 (52.0)	–	**102 (30.3)**	84.2 (27.7)	–
Global TLX index	40.6 (4.8)	**44.2 (2.1)**	–	47.7 (7.0)	**58.0 (5.9)**	–	44.1 (4.2)	**51.1 (3.4)**	–

Higher values in each row/condition are highlighted. *p = 0.004; $p < 0.05$; Wilcoxon Test

Table 6 shows, the presence of visualization slightly increased the instructors' ability to focus on the concepts of the target (statistically significant in task 1) and immediate previous lectures when selecting activities (O*nTopicCurrent* and *OnTopicPrevious*). Notwithstanding the above, the most impressive difference between the conditions was the almost complete disappearance of concepts that had not yet been introduced during the lectures (O*utTopic*). The presence of these "future" concepts in practice and lab sessions is undesirable, since the students have not yet been introduced to them; yet

Table 4 Results of the Post-Condition questionnaire

	Task 1			Task 2			Both tasks		
	Between subjects			*Between subjects*			*Within Subjects*		
	Vis. M (SE) n=10	noVis. M (SE) n=10	p	Vis. M (SE) n=10	noVis. M (SE) n=10	p	Vis. M (SE) n=20	noVis. M (SE) n=20	p
Controllability	5.3 (0.30)	5.3 (0.25)	–	**5.2 (0.32)**	4.2 (0.51)	–	**5.2 (0.05)**	4.8 (0.52)	–
Confidence	4.3 (0.35)	**5.0 (0.23)**	–	**5.0 (0.25)**	4.2 (0.48)	–	**4.7 (0.32)**	4.6 (0.39)	–
Easiness of choice	**4.5 (0.34)**	3.8 (0.36)	–	**5.3 (0.36)**	3.4 (0.55)	*	**4.9 (0.44)**	3.6 (0.18)	**

Higher values in each row/condition are highlighted. *p = 0.017; $p < 0.05$; Mann Withney U **p = 0.002; $p < 0.05$; Wilcoxon Test instructors frequently miss these unwanted concepts when selecting learning content. As our data shows, knowledge-based design analytics did help designers to avoid these future concepts in their designs. When instructors used the baseline interface, they introduced, on average, a significantly higher number of future concepts ($M = 5.7$, $SE = 1.41$, $p = 0.002$ in task 2; $M = 9.2$, $SE = 3.13$, $p = 0.003$ in task 2). When using the visualization, cases of introducing future concepts practically disappeared (0 in task 1; $M = 0.7$, $SE = 0.37$ in task 2).

Consider the overall distribution of the concept coverage from the learning design outcomes. Figure 3 shows how many times concepts have been practiced in the designed sessions, on average, depending on the tasks and the treatments. Results show that using the visualization approach has a positive impact on concept-level balance when it is necessary to select just a few activities (Task 1), as the educator needs to be more precise when selecting the best ones for their class. This is confirmed by the statistical test presented in Table 6 ($Med_{vis} = 12$; $Med_{novis} = 11$; $p = 0.029$; Mann Whitney U). However, when the instructor can select a higher number of activities (Task 2), the probability of covering the necessary concepts by chance is higher and the presence of visualizations has a lower impact on improving the concept-level balance. However, the selection of a higher number of activities in the second task without using the visualizations led users to introduce a higher number of future concepts. In both cases, the number of future concepts selected was reduced drastically when using the visualizations.

Figure 4 presents the balance of concepts from the design outcomes, depending on the characteristics of the smart learning content. Contrary to expectations, the difference for the balance of example versus problem activities between using or not using visualizations is very low, and this balance is also very low in the case of balancing comprehension versus construction activities. We can observe only a moderate improvement of the balance and coverage of the previous concepts in both graphs when using visualizations, as well as a reduction of future concepts, as discussed above. These results are not entirely surprising. As the instructors

Table 5 User actions with the system while performing each task during the two treatments

		With Visualization	Without Visualization	p
Task	Action	M (SE)	M (SE)	
T 1	Total actions	146.9 (27.13)	**166.1 (39.00)**	–
	Click preview activity	6.7 (2.88)	**30.2 (10.37)**	*
	Add activity	12.6 (1.86)	**14.1 (2.64)**	–
	Delete activity selected	4.9 (2.19)	**6.6 (2.96)**	–
	Time Spent (min)	15 (1.78)	**20 (4.81)**	–
T 2	Total actions	**230 (23.24)**	217.1 (14.00)	–
	Click preview activity	5.6 (2.85)	**34 (7.3)**	**
	Add activity	**26.3 (1.67)**	24.1 (1.3)	–
	Delete activity selected	**6.4 (1.84)**	4.7 (1.5)	–
	Time Spent (min)	**22 (3.08)**	19.6 (1.90)	–

Higher values in each row/condition are highlighted. $^{*}p = 0.003$;$^{**}p = 0.002$;$p < 0.05$; Mann Whitney U were domain experts, they were able to understand the type and the most essential concepts of each activity by carefully reviewing its content and were sufficiently successful in balancing the number of activities added to the design (as tasks were required). As the log data shows, by previewing the activities, the instructors were able to achieve a reasonable balance, however, at the price of a higher cognitive load. With the visualization, however, the instructors were able to reach a slightly better balance by using visual previews rather than content previews and with a lower cognitive load.

User Feedback Analysis

In the final questionnaire, 19 out of the 20 instructors stated that they preferred to use the interface with the visualization. Only one participant stated that they preferred the condition without the visualization '*Because with the visualizations I feel very frustrated trying to fulfill all the requirements even when it's impossible to entirely balance everything. I also gave less relevance to the activity itself (almost never checked the example) when using the visualizations, making the entire decision to be based on the visualizations*' (U12). Notwithstanding the above, all 20 participants said that this condition allowed them to more effectively design their sessions. The visualizations were easy to understand and were useful in deciding which activity to choose; they helped instructors to check whether they were doing well enough in designing the course, as well as thinking about how knowledge was balanced. Regarding their preference about the three visualizations' tabs, 12 instructors out of 20 found the "Type of session" comparison to be more useful. However, five instructors indicated the "Construction vs. Comprehension" comparison as their preferred option, and three other instructors selected the "Examples vs. Problems" comparison as their favorite. We can conclude that all three types of comparison were meaningful for the instructors in order to create their course designs. Table 7 shows the user responses to the two open questions of the final questionnaire and the main themes identified from the inductive thematic analysis.

The most frequently identified themes regarding why instructors preferred using the visualization were: first, the provision of topic coverage awareness as well as their ease of comparison and balance (f = 9); second, the easiness of activities' selection process

Table 6 The outcomes of learning designs. Average number of times concepts were selected depending on their type (current lecture-related concepts; from previous lectures or from future lectures) and the tasks performed. *Mann Whitney U

		With Visualization	Without Visualization	p
Task	Selected concepts	M (SE)	M (SE)	
T 1	OnTopicCurrent	**12.4 (0.54)**	10.4 (0.58)	*0.029
	OnTopicPrevious	**9.4 (0.93)**	8.7 (0.88)	–
	OutTopic (future)	0	**5.7 (1.41)**	*0.002
T 2	OnTopicCurrent	**29.2 (1.05)**	28.5 (0.95)	–
	OnTopicPrevious	**27.7 (2.47)**	23.3 (1.49)	–
	OutTopic (future)	0.7 (0.37)	**9.2 (3.13)**	*0.003

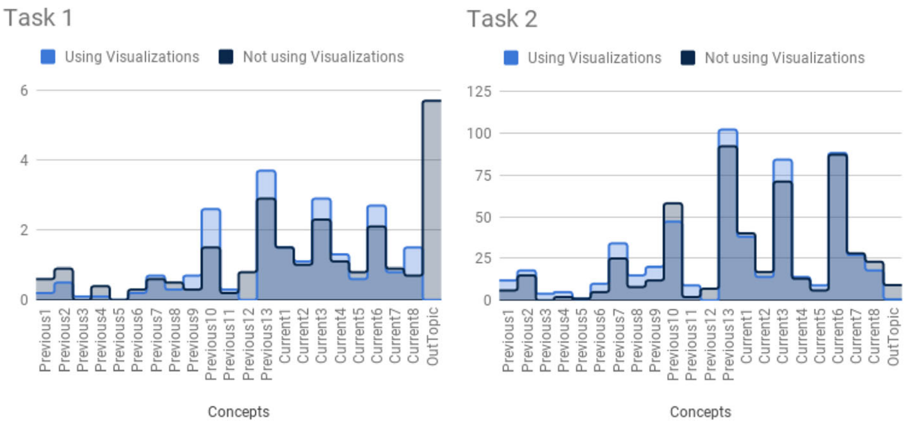

Fig. 3 Average number of times that a concept is practiced during Task 1 (left) and Task 2 (right) (extracted from the learning designs outcomes) depending on the learning design conditions (either using or not using the visualizations). Activities can practice a concept more than once and can practice more than one concept at the same time. Note that there are 13 previous concepts, 8 current concepts, and a counter for future concepts

(f = 4); and third, the possibility of previewing the effects/results of the activity selection before adding the activity into the design (f = 2). Moreover, results indicate that visualizations allowed instructors to more effectively design the sessions by improving the accuracy in making design decisions and by easing the balance of the different types of activities (both with f = 5), together with a better awareness of the knowledge-contribution depending on the types of activities (f = 4). Interestingly, whereas the action analysis revealed no significant differences between the two treatments regarding the time needed to perform the tasks, three instructors expressed *time saving* as a positive aspect in favor of using visualizations. Similarly, three instructors commented that visualizations provided them more *confidence* in making design decisions, while the post-task questionnaire revealed no significant differences between the two conditions regarding confidence items.

Figure 5 presents the response distribution of the nine *agreement* Likert scale items (strongly disagree: 1, strongly agree: 7) that formed part of the final

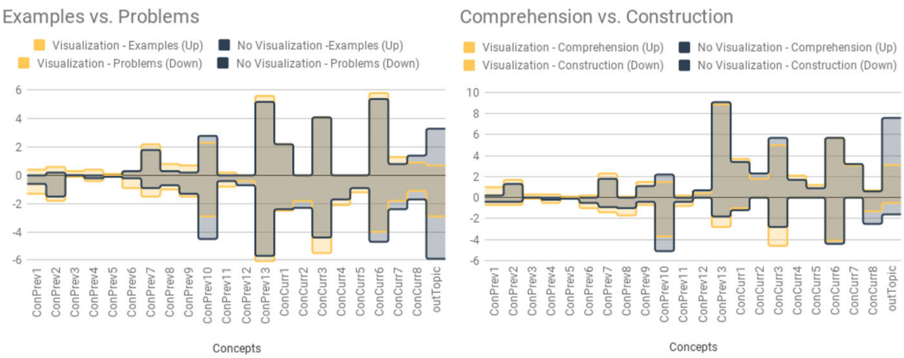

Fig. 4 Average number of times that a concept is practiced during Task 2 (extracted from the learning design outcomes), depending on the learning design conditions (using or not using the visualizations). Note a comparison of example activities versus problem activities (left) and comprehension versus construction (right)

questionnaire. The majority of participants stated that visualizations helped them in thinking about how the knowledge and type of activities were balanced throughout the course, as well as to avoid choosing activities not aligned with the lectures' concepts (70% strongly agreed with these three statements). Strongly agreement percentages were lower when stating that visualizations helped in the awareness of the content involved in each of the topics of the course (45%) and in supporting the decision about which activity to choose (40% strongly agreed and 45% agreed). Overall, participants were satisfied with the visualizations provided (45% strongly agree and 45% agreed).

Finally, the users provided a number of useful suggestions (see Table 8), which we will consider for future work. As the feedback shows, the three most frequently repeated suggestions are: helping to prevent selection of the same activity twice using some visual indication (#1); sorting/filtering the activities in the resources panel (#2); and adding some indicator of complexity to candidate activities (#3). All three suggestions could further reduce users' overall memory load in the process of learning content selection. In particular, the suggestion of providing an explicit indicator of activity complexity correlates well with the results of our earlier studies of concept-level problem visualization with student users. While in both cases a concept profile of a problem provides some indication of activity complexity (the more concepts are involved, the more complex the problem is), processing this information for many problems in a row was a challenging cognitive task. As we discovered, best results were achieved when students received additional support through a" gauge" that directly visualized activity complexity, thus shortcutting the process of complexity estimation (Guerra-Hollstein et al. 2017). We hope to explore similar designs for instructor-facing design analytics in our future work.

Discussion, Conclusions, and Future Work

This paper proposes and studies an approach for fine-grained knowledge-based design analytics that is focused on visualizing critical metadata associated with smart learning content. Among metadata aspects covered by our visualization are the type of learning content, the nature of knowledge supported by it, and the list of specific knowledge concepts that a specific fragment of learning content allows students to practice. The visualization has been integrated into a (blended) learning design authoring tool. We expected that the concept-level design analytics would help instructors in selecting the most appropriate learning content and would result in designing more balanced learning sessions. We performed a within-subjects user study contrasting conditions both with and without the visualization. Our results indicate that the use of knowledge-based design analytics may reduce the cognitive load of design tasks, especially in terms of mental demand. We also demonstrated that the use of design analytics has facilitated the selection of the most suitable activities without significantly affecting the overall design time.

When examining the overall design outcomes, the most prominent finding was an almost complete disappearance of activities that required the use of future (not yet studied) concepts from learning sessions designed with the help of visualization. Selecting content that requires prior knowledge of future concepts is usually a design error, and the presence of concept-level design analytics helped users to avoid these

Table 7 Responses to the open questions of the final questionnaire

Questions (N)	Themes identified	f	Users' excerpts (User ID)
Why do you prefer the condition with the visualization? (N=19)	Topic coverage awareness, easy comparison, and balance.	9	"It was easier to see which topics I was covering, it also contributed to keeping a balance between them." (U15)
	Easy selection of activities.	4	"It helped me with selecting tasks easier." (U1)
	Previsualization of the effects/results of activity selection.	2	"It is quicker and easier to see the results of activity selection than going inside of activities one by one." (U4)
	Provision of extra information.	1	"More information, even if it is not used, is better in my opinion." (U7)
	Overall picture of the design.	1	"I had a better overall picture of my course design and was able to focus on what needs more attention for the student." (U10)
	High level of control for avoiding future concepts.	1	"I felt more in control of not including a topic students will learn later in the course about." (U16)
	Time saving.	1	"There was no need to look at the exercises saving a great deal of time." (U18)
Why do you think that the condition with the visualization allowed you to design the sessions more effectively? (N=20)	Accuracy in making design decisions.	5	"...the design conditions can be met more accurately with the charts." (U12)
	Easy balance of types of activities.	5	"I could keep a balance between the types of activities I could include." (U15)
	Awareness of knowledge-contribution depending on the types of activities.	4	"I could see how examples or problems contribute to different goals of the task." (U1)
	Time saving.	3	"I was more efficient with the visuals because I was faster and more sure about my design." (U10)
	Confidence.	3	
	Easy previsualization of the effect/results of activities selection.	2	"I had to only look at the topics that will be covered to know if this example or problem has to be included in this lecture's lab or practice or not." (U2)
	Awareness of what is missing in the design.	2	"Seeing the distributions of the concepts allows me to determine which concepts I still need to at least provide some practice for." (U7)
	Comfortability.	1	"It was more comfortable and faster." (U19)

errors. In addition, our results hint that the visualization may have a higher impact on the concept-level balance when it is necessary to select just a few activities, as the instructor needs to be more precise in selecting the best ones. In contrast, when the instructor can select a higher number of activities, the probability of covering the concepts by chance is higher and the visualizations have a smaller impact on improving the overall balance among concept levels.

A combination of quantitative and qualitative data collected in our study indicated that the most important impact of the provided visualization was a significant reduction of a designer's mental load in the process of selecting the most appropriate activities through visual help in knowledge balancing and preventing activity selection errors (70% of strong positive answers). In contrast, they were only 40–45% of strong positive answers about the value of visualization as a whole, which indicates that other decision-making needs were not

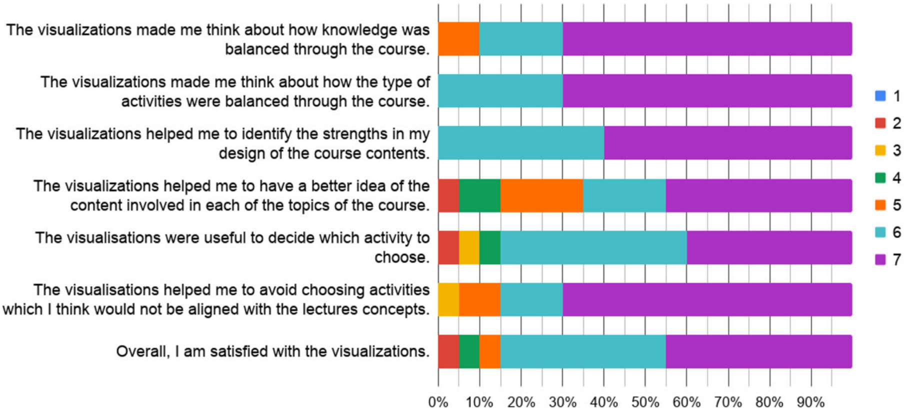

Fig. 5 Final questionnaire ($N = 20$). Items are based on seven-point Likert scale (strongly disagree: 1, strongly agree: 7)

fully supported by the current visualization. The analysis of free-form feedback uncovered some of these needs, such as remembering which activities were already selected and

Table 8 Users' suggestions extracted from the last open question of the final questionnaire

#	Themes identified	Suggestion	f	Users' excerpts (User ID)
1	Prevention of repetition in the selection of activities.	Highlight the activities already selected or/and warning when repetition occurs.	3	"Facilitate the detection of repeated activities." (U14)
2	Sorting/filtering activities in the resources panel.	By alphabetical order, by tags, by concepts related to the design.	3	"...sorting problems with concepts related to design can make it less effort." (U6)
3	Indication of the activities' complexity level.	For instance, by using a star rating mechanism.	2	"There is nothing in the system that shows how hard or easy a certain example is. It would be good to have something like a star rating for each task that shows how hard/easy that task is." (U9)
4	Provision of meaningful labels to the activities.	Labels related to concepts that can be found in the activities.	1	"... labelling activities with respect to key concepts covered in the lecture, such as do while loop, may be helpful (...) for some of them it is not clearly understandable from the label of the activity and you need to go inside and inspect the alternative activities one by one." (U4)
5	Inspection of several activities' codes at the same time.	Mechanism for previewing the codes of several activities on the same screen.	1	"... easy comparison between codes by showing multiple codes in one screen could be awesome to compare how similar and different are 5 while loop codes say." (U5)
6	Recommendation activities to be selected.	Highlight activities that cover concepts that need to be covered in a particular design.	1	"In the future maybe you can suggest or highlight the activity types which are unbalanced within my design." (U13)

assessing difficulty of the learning activities. This feedback provides ideas for future work on improving the visualization of the proposed design analytics.

Interestingly, the presence of the visualizations seems to have changed the behavior of instructors in the process of selecting the activities and has enabled them to focus more on previewing their contribution to the target design using visualization and to spend less time examining their content. While the increased reliance on the visually presented metadata was a positive factor and was the likely reason for improved performance and decreased cognitive load, it might negatively affect the results of the design if the quality of metadata is low, which is a known concern in learning object repositories (Palavitsinis et al. 2014). On the other hand, the expected popularity of the visual metadata-driven design process might deliver a long term positive impact on the quality of learning object metadata. Given that one major cause of poor metadata quality is frequently the low perception of the value of metadata by the instructors who supply but never use it, the increased recognition of medata as a valuable source of design analytics for the instructors themselves could be a “game changer”.

Another interesting observation is an apparent disagreement between log data and user feedback with respect to time spent on task. While we found no significant time-on-task differences between the two treatments, three instructors expressed *time saving* as a positive aspect in favor of using visualizations. We could offer two possible contributing factors. One is a likely difference between instructors in their ability to understand and use visualization, which might stem from individual differences (i.e., spatial ability) and experience with similar interfaces. Indeed, while the average time on task was about one-quarter (5 min) less for the group that used visual analytics, large variability of time spent between instructors along with a relatively small number of subjects prevented this difference to become significant. Another possible source is the possible “flow” effect (Csikszentmihalyi 2008), which could impact skilled instructors for whom the work with visualization will become not just more productive, but more enjoyable. Further studies will be required to investigate these issues in more detail.

Our ability to make these interesting observations stresses the importance of collecting and analysing multiple sources of data - in our specific case, the log data on how the analytics was used, the self-reported questionnaires from users, and qualitative feedback from the users. By triangulating data, we were better able to explore and compare perceptions of the users and their interactions logged by the system.

Despite the fact that this study is contextualized in a programming course that uses specific smart learning content, our findings provide light on how the use of knowledge-level metadata associated with any type of (open) educational resource could be used to support teachers in the course-design process. The results indicate that providing fine-grained design analytics based on the conceptual knowledge of the learning materials can improve the design support. The findings of this study suggest that learning design authoring tools that consider coarse-grained design analytics would benefit from complementing their existing analytics with the fine-grained approach presented in our research.

While the obtained results are encouraging and the prospects for its broader applicability are good, caution should be applied when interpreting and generalizing these results. We remind that our study has been done in a very specific context (a college-level programming course) with a small cohort of instructors. Thus, future research will be necessary to explore and evaluate the use of knowledge-based design analytics in other educational contexts, using a larger sample size, and while comparing different types of visualizations. Moreover, further research may explore the connection of design analytics with learning analytics extracted from the existing usage of smart learning content in real educational scenarios.

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Declarations

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