Fostering learners' performance with on-demand metacognitive feedback

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Abstract. Activating learners' deeper thinking mechanisms and reflective judgement (i.e., metacognition) improves learning performance. This study exploits visual analytics to promote metacognition and delivers task-related visualizations to provide on-demand feedback. The goal is to broaden current knowledge on the patterns of on-demand metacognitive feedback usage, with respect to learners' performance. The results from a between-group and within-group study (N=174) revealed statistically significant differences on the feedback usage patterns between the performance-based learner clusters. Foremost, the findings shown that learners who consistently request task-related metacognitive feedback and allocate considerable amounts of time on processing it, are more likely to handle task-complexity and cope with conflicting tasks, as well as to achieve high scores. These findings contribute to considering task-related visual analytics as a metacognitive feedback format that facilitates learners' on-task engagement and data-driven sense-making and increases their awareness of the tasks' requirements. Implications of the approach are also discussed.

Keywords: feedback usage patterns · learning analytics · metacognitive feedback · performance · visual analytics

1 Introduction

Assisting learner during her learning is an important part of the cognitive process [36]. Contemporary learning theories highlight the significant role of feedback on the learner's personal development [8, 17]. Feedback can be provided in different forms (e.g., oral, written) of (physical/digital, teacher/peer) tutor's response to learner's needs, actions, emotions, intentions, etc. It is assistive to the learner, either to motivate and reward her, or to help her deal with stressful/ conflicting learning conditions [17, 14]; it is a key tool for guiding and sustaining learner's involvement in the self-regulated learning process and goal attainment [34, 48].

The most common formats of feedback delivered to the learner are prompts, cues and/or questions, to help her to reason, think, understand and reflect about success or failure concerning the task at hand, and allowing her to engage in self-regulatory learning mechanisms [8, 29]. However, feedback on its own might not impact learning as expected, unless the learner is willing to use it [17]. To enable learner to use feedback efficiently, she needs to possess sufficient knowledge about how to use it [43], and feedback should be provided regularly during the learning tasks [48] so as the learner can practice with it [45]. Therefore, the challenge is to design learner-centered feedback, aiming at motivating learner to request for it at the moment she actually needs it, as well as at efficiently supporting her self-regulation [11, 37]. In other words, the goal is to deliver meaningful information to the learner, and promote her metacognition. This increases learner's awareness and sense-making, and finally, her evidence-based decision and actions [39].

The importance of metacognition has been acknowledged in studies that attempt to improve learning in digital learning environments [37, 4, 26, 22, 21, 12, 13]. Metacognition is related to the ability to monitor and control one's own knowing, and comprises the executive processes of reflective judgment and regulation of one's own deeper thinking; in simple terms, it is "thinking about thinking" [15]. Through those processes, the learner acquires her metacognitive knowledge from metacognitive monitoring, and controls her learning using the metacognitive knowledge [30]. Activating learner's metacognition with appropriate feedback is expected to improve learning performance [26, 21, 23, 38].

However, previous studies demonstrated that engaging the learner in metacognitive processes is not a straightforward task, unless she is explicitly encouraged to do so through specialized instructional activities [16, 25].

The rapid developments of different forms of visual analytics have opened new perspectives and opportunities on the design of metacognitive feedback [13]. Specifically, learning analytics dashboards are instruments intended to increase awareness of learning goals [40, 10], to foster self-regulation [4, 12], and to improve decision-making [47, 6] by capitalizing on human perceptual capabilities.

This paper examines the potential of providing task-related visual analytics as task-specific metacognitive knowledge extracted from all learners' interaction trace data (i.e., learner-centered), that would reinforce the learner to complete a task. Thus, this study investigates visual analytics as a metacognitive feedback mechanism, and associates its usage patterns with learners' performance.

2 Related Work

Visual analytics, such as dashboards, pose novel feedback opportunities that enhance learning [10, 12, 20, 40]. Previous works explore the effects of visual analytics on student performance outcomes through self-reflection, awareness, and self-assessment [5, 10, 20]. In fact, the process of providing students with "self-knowledge" has been outlined as key to developing metacognitive skills for self-regulated learning [13, 44]. Information visualization is an effective sense-making tool due to its ability to synthesize complex data in a way for viewers to quickly understand, compare, reflect and ultimately decide [18].

However, most current visual analytics (e.g., dashboards) are based only on learner performance-oriented indicators (e.g., where a learner is doing well/poor, how much time was spent, how learners' progress compares to teacher specified and/or peer scores) that do not seem to contribute to learners' motivation and engagement [44]. Being performance-oriented, those implementations decrease learner mastery orientation [27]. Seminal research [40] demonstrates that effective feedback needs to be grounded in the regulatory mechanisms underlying the learning processes. This is particularly important when the learner is the main end-user of visual analytics, with a central goal to reinforce self-reflection and self-regulation [20]. Contemporary visual analytics, like dashboards, appear to promote antagonism between learners rather than chasing knowledge mastery [20], and there is always a concern that the learners might not know how to make-sense of this information [28]. Nonetheless, feeding this information to the learner encounters the danger that she may focus too much on her own self (ego), with unwanted effects on the learning (e.g., might lose motivation if the performance indices are low, or stop trying if the indices are high, just to preserve her reputation and avoid failure).

This raises the question of how to provide meaningful metacognitive feedback to the learner, to encourage efficient feedback usage, to shift her focus on the learning task (rather than feeding the self), as well as to help her master the skill/ knowledge. To address this issue, this study suggests and explores the use of task-related visual analytics.

3 The task-related visual analytics

During the design of task-related visual analytics as on-demand metacognitive feedback, two design models were considered: (a) the metacognitive computational model of help-seeking [2] for guiding the desired feedback seeking behavior (i.e., the learner should ask for feedback only when she really needs it, and receives meaningful information), and (b) the Contextualized Attention Metadata schema [46] for providing coordinated views over the data. Based on these principles, the content and the format of the on-demand feedback were decided.

Regarding the content, what task-related information should be provided to the learner was determined so as this knowledge to activate learner's monitoring, reflection and judgment (i.e., metacognition) about the tasks, with an ultimate goal to help the learner to meet the requirements of each task, i.e., the actual difficulty, the actual effort needed to deal with each task, and the time required to allocate on each task. Providing this information *per se* could easily be perceived as the typical performance-oriented indicators (see previous section). Indeed, although those indexes have similarities with typical performance-oriented indexes computed per learner, however, they facilitate different goals: (a) since they are calculated from all learners' data when dealing with a specific task, the aggregated information describes the task and not the learner, (b) the accumulative information about the tasks is more action-oriented and aim to trigger deeper evaluation of the actual requirements of the tasks and guide learner's judgment and metacognitive inference, than the abstractly deduced "user-model" values, commonly delivered to learners. In a sense, those indexes do not intent to inform the learner (who requested this information) about how well all other students are performing, but rather about what one can infer about the real requirements of the task, and to engage with it in a ”solution-behavior” manner.

Next, concerning the presentation of this information, it was decided to be delivered in three simple (easy-to-read) bar/column charts, including: (a) the number of correct vs. the number of wrong solutions submitted for this task (for inferring its difficulty), (b) the average students' effort expenditure vs. their average performance (i.e., correctness of solutions) for this task, and (c) the average time spent to solve this task correctly vs. the average time spent to solve the task wrongly vs. the average time spent to solve the task. Figure 1 illustrates the task-related visual analytics delivered as metacognitive feedback.

Every time the learner needs (or believes she needs) additional information about a task, i.e., beyond cognitive clarifications, she has the option to ask for the above analytics. Using properly this information is expected to support the learner to efficiently regulate herself, i.e., to improve her effort allocation, time-management and help-seeking skills, and metacognitive inference-making [27]. Previous research has shown that visualization of aggregated temporal indexes increases the teachers' awareness on students' progress and helps them revise their considerations about the actual requirements of the assessment tasks [31].

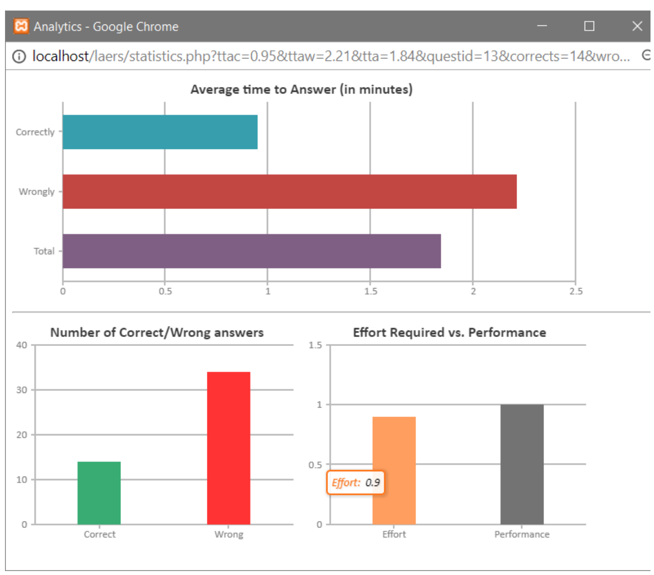

Fig. 1. The task-related visual analytics.

The visual analytics tool obtains the necessary temporal and performance indicators from the learning environment, and instantly generates the charts on-demand, by analyzing all learners' logged interactions (i.e., actual usage) with that task. For resolving "cold-start" issues, (i.e., absence of data the first time a task is being viewed by the students) the analytics from former learning procedures are employed. Those analytics are produced during the calibration of the task pool and are updated upon request with the arriving observations.

3.1 Methods

3.2 Participants and Study design

Overall, 174 undergraduate students (93 females [53.4%] and 81 males [46.6%], 19-26 years-old [M=20.582, SD=1.519]) at a European University were enrolled in a self-assessment activity for the Management Information Systems II course (related to databases, e-commerce) at the University computers lab, for 60 mins.

The study reported in this paper followed an experimental design [9]. All students had previously used the self-assessment environment [33], and they were randomly assigned into two groups: 88 students (50.6%) were assigned to the "feedback" group (i.e., the experimental group), and 86 students (49.4%) were assigned to the "no-feedback" group (i.e., the control group). Prior to the self-assessment, the students in the experimental group had a brief introductory presentation of the task-related visual analytics, to explain them what information would be available to them, and how to use it [25]. Those instructions were also available to that group throughout the procedure.

During the self-assessment activity, all students had to answer 15 multiple-choice questions (from now on referred to as "tasks"); each task had four possible answers, but only one was the correct. The tasks were delivered to the participants in predetermined order. The students could temporarily save their answers on the tasks, review them, alter their initial choices, and save new answers; they could also skip a task and answer it later. Moreover, the experimental group could ask for task-related visual analytics for each task.

Prior to the self-assessment, the difficulty of the tasks (easy, medium, hard) was determined using prior assessment results, according to the number of correct answers. Each task's participation in the score was according to its difficulty, varying from 0.5 points (easy) to 0.75 points (medium) to 1 point (hard), and only the correct answers were considered (i.e., no penalizing wrong answers).

The participation in the activity was optional. All participants signed an informed consent form prior to their participation, explaining them the procedure and giving the right to researchers to use the data collected for research purposes. Students were aware that their interactions were anonymized prior to being analyzed, and that the collected data would be stored for 3 years.

3.3 Data Collection

Data were collected with an online self-assessment environment [33]. For both groups, students' performance (i.e., scores) was computed as: $\sum_{i=1}^{k} d_i z_i$ where $z_i \in \{0, 1\}$ is the correctness of the student's answer on task i, and d_i is the difficulty of the task. In addition, for the experimental group, other measurements commonly used in the field of learning analytics, acknowledged to satisfactorily explain students' engagement (e.g., response-times, frequencies) [1, 19, 32], and quantifying how students use the feedback, were computed, as well. Table 1 illustrates the measurements captured and coded for each group.

Table 1. Measurements considered in this study

Variable	Name	Description	Experimental Group	Control Group
TTAV	Time-spent on viewing visual analytics	The average time students spend on viewing the visual analytics	**X**	
FVAR	Frequency of visual analytics request	How many times the students ask for visual analytics	**X**	
LP	Learning Performance	The score the student achieves	**X**	**X**

In this table, Time-spent on Viewing Visual Analytics (TVVA) is the average time all students spend on viewing the visualizations (per task) and engage on reflection, judgment and sense-making (i.e., metacognition). Frequency of Visual Analytics Request (FVAR) is the average value of a counter (per task) that increases every time that the students make the respective request (metacognitive monitoring of tasks) [1].

3.4 Data Analysis

To investigate the effect of task-related visual analytics on learning performance, independent samples t-test was applied between the control and the experimental groups. The minimum required total sample size and per-group sample size, given the probability level ($p<0.05$), the anticipated effect size (Cohen's $d>0.5$), and the desired statistical power level (≥ 0.8), is 128 and 64 respectively. In our study, the sample size is 174, and the subgroup sizes are 88 and 86 respectively. Since, not every significant result refers to an effect of high impact, we calculated the effect size in order to evaluate the strength of the effect. Hedge's g effect size was considered, because the sample size of each sub-group is considered small. Ranges for Hedge's g effect size are small > 0.2, medium > 0.5 and large > 0.8.

In order to explore potential differences between low, medium and high performers, students of the experimental group were grouped into three clusters according to their performance: High-performers: final grade>7, Medium-performers: final grade≥ 5, and Low-performers: final grade<5. Then, an Analysis of Variance (ANOVA) test was performed to investigate differences in each one of the feedback usage measurements (i.e., TVVA, FVAR) between the different performance-based student clusters. The impact of these parameters was explored as well, and the η^2 effect size was computed for evaluating the strength of each one of these parameters. Ranges for η^2 effect size are small > 0.01, medium > 0.06 and large > 0.14. The decision to use ANOVA test instead of multiple t-tests was because ANOVA controls the Type I error so as it remains at 5%, when the number of groups is higher than two. The analyses were performed with SPSS 25.0 for Windows.

4 Results

Table 2 demonstrates the descriptive statistics for the two groups with respect to the learning performance.

Table 2. Descriptive statistics for performance

Group	N	Mean	Std.Dev (SD)
Experimental	88	6.534	1.735
Control	86	4.372	1.681

Table 3 depicts the independent samples t-test results regarding students' learning outcomes between the experimental and the control groups. In this table, the last column illustrates the Hedge's g effect size. As seen from this table, there were significant differences in performance between the experimental and control groups, and the effect of task-related visual analytics on performance was relatively large (g=0.68).

Table 3. Independent samples t-test results for learning performance (*p<0.05)

				95% CI		
Groups	**F**	**df**	**t**	**Lower**	**Upper**	**Hedges' g**
Experimental vs. Control	0.009	172	5.486*	0.6507	1.6733	0.68

Table 4 presents the results for ANOVA tests for each one of the parameters of visual analytics usage (i.e., FVAR, TVVA). The η^2 effect size was calculated, as well. The Levene's test for homogeneity of variances could not reject the hypothesis of equal variances (sig.>0.05).

Table 4. ANOVA results for the learning analytics factors on the performance-based clusters (*p<0.05)

	F	p-value	η^2
Frequency of Visual Analytics requests	23.002	0.00001	0.351*
Time-spent on Viewing Visual Analytics	19.073	0.00001	0.310*

Since the statistical analysis revealed significant differences in the parameters of visual analytics usage with respect to the performance-based learner clusters, next we looked for specific usage patterns per cluster: we visualized the parameters of on-demand metacognitive feedback-seeking per task, per cluster.

Figures 2 and 3 illustrate the analytics parameters of feedback usage per task, for each one of the performance-based learner clusters (in different shaped lines). In both Figures, on the x-axis are the task, ordered according to their increasing difficulty from easy to hard (as it was initially defined – see section 3.2 – i.e., tasks 1- 8 are easy, tasks 9-12 are medium, and tasks 13-15 are hard).

In Fig. 2, the y-axis corresponds to the average time-spent on viewing the visualizations (in seconds), and in Fig. 3, the y-axis corresponds to the respective average requests for task-related visual analytics.

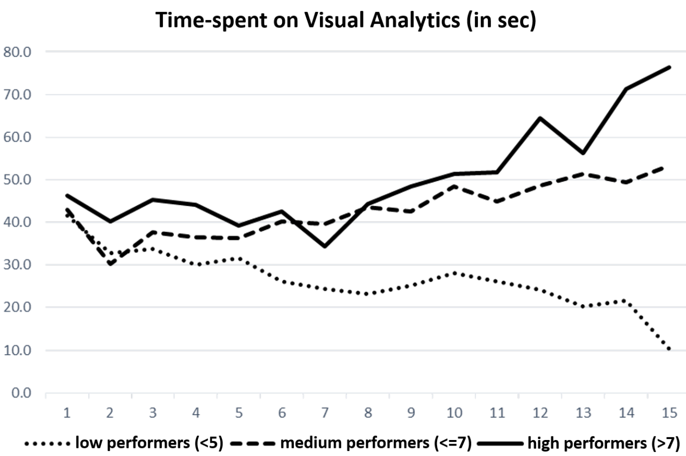

Fig. 2. Average time-spent on viewing task-related visual analytics per task.

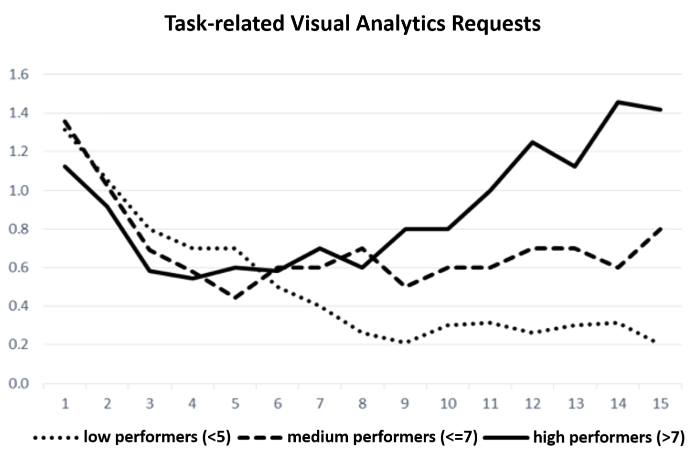

Fig. 3. Average requests for task-related visual analytics per task.

As seen from these figures, there are significant differences in the patterns of usage of visual analytics between high, medium and low performers. For example, as the difficulty of the tasks increases, low-performers tend to gradually use less the metacognitive feedback, both in terms of the average requests for on-demand metacognitive information and of the average time allocated to view and study this information. It is interesting to note, though, that those learners put a lot of effort (in time and requests) to understand the visual information in the beginning of the process, on the easy tasks. Further exploring those patterns of the feedback usage across the performance-based learners' profiles, is expected to provide useful insights regarding the learners' metacognitive skills.

5 Discussion & Conclusions

Despite the concern that learners might not know how to make-sense of learning analytics [28], previous studies argued that learners can interpret their own performance indices, yet they reserve a skepticism on how to practically convert this information into actionable insights [10]. The innovation of this work derives from exploiting easy-to-read task-related visual analytics to provide learners with meaningful information about the tasks, and investigates how they use it and how they adjust their answering behavior. The overall results of this study demonstrate a coherent relationship between the actual use of on-demand metacognitive feedback and learning performance. Additional consistent patterns of feedback usage behavior were identified, as well.

Specifically, the t-test shown a large effect size (Hedge's g=0.68) of the usage of on-demand feedback on learners' performance, between the experimental and the control group. The one-way ANOVA revealed statistically significant differences between the high, medium and low performers with respect to the frequency they requested for visual analytics ($F(2, 85)=23.002$, $p=0.000$), and to the time-spent on viewing the metacognitive information ($F(2, 85)=19.073$, $p=0.000$). The effect sizes of both measurements about the actual usage of feedback were strong ($\eta^2=0.351$ for FVAR; $\eta^2=0.310$ for TVVA), as well.

Combined with the results from the graphical representation of help-seeking behavior with respect to the performance-based learner clusters (Figures 3 and 2), this finding can be interpreted as follows: high performing students use visual analytics more often and allocate considerable time to think and reflect about the received information and infer its implications. On the contrary, low-performers rarely request for analytics about the tasks (probably because they don't know how to use it or feel uncomfortable with this type of information or simply they don't care). This finding provides additional empirical evidence to previously reported results that associated higher learning gains with time allocated on hint reasoning [41, 3]. Furthermore, this finding is in line with prior research works that claim that students in need usually don't ask for feedback, while students who can achieve higher – even without additional support – tend to ask for complementary hints and resources [7, 35, 42].

Beyond confirming previous results, this study is the first one – to the best of our knowledge – that dives into the learners' interactions with the metacognitive support and associates the usage of this feedback type with performance-based learner clusters. From the exploratory analysis Figures 3 and 2, it becomes apparent that most students ask for visual analytics on the first task. From that point on, high-performers seek for additional information mostly on hard tasks, low-performers successively avoid requesting for metacognitive feedback, and medium-performers follow a more stable pattern and ask for analytics on most of the tasks, regardless of their difficulty, but do not allocate significant amounts of time on processing the information. This implies that these students are aware that they need support, they seek for it, but they are uncertain regarding the actions they should take afterwards.

In accordance with the literature [24], this study argues that learner data have the potential to support decision-making and enhance learning (e.g., via quantified-self technologies). Such a support can be transformative for students, especially the ones who are already familiar with such technologies and motivated [24]. Future work needs to collect data from other learning settings (e.g., MOOCs, problem solving), at larger scale and use different and repeated survey data collections. Cross-validating and extending our findings will allow us to generalize them and even identify activities were on-demand metacognitive feedback might be more important (i.e., higher effect). This will allow us to identify why and how on-demand metacognitive feedback can be used to optimize its potential.

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