Evaluating the Effect of Uncertainty Visualisation in Open Learner Models on Students' Metacognitive Skills

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Abstract. Self-assessment is widely used in open learner models (OLMs) as a metacognitive process to enhance students' self-regulated learning. Yet little research has investigated the impact of the visualisation when the OLM shows the conflict (i.e., uncertainty) between the system's beliefs about student knowledge and students' confidence in the correctness of their answers. We deployed such an OLM and studied its use. The impact of the uncertainty visualisation on student learning, confidence gains and actions was determined by comparing these measures across two treatment conditions and a control condition. Those who accessed the OLM performed significantly better on the post-test, and those in the treatment group who could see both sets of beliefs separately showed greater confidence gains and used the system more.

Keywords: Open learner models · Uncertainty · Self-confidence · Visualisation · Metacognitive skills · Learning dashboards

1 Introduction

Lifelong learning requires improved knowledge monitoring skills [1] that allow students to accurately evaluate their own knowledge. These monitoring skills are a prerequisite metacognitive process that is essential to self-regulated learning. Studies have shown the importance of metacognitive confidence and its relation to decision making and academic achievement [2]. It has been claimed that giving students feedback that contains the relationship of their performance to the students' estimate of achievement may be more effective than providing only outcome information [3]. It is argued that the greater the discrepancy between students' confidence about the correctness of the answer and their response, the more motivated the student is to reveal this discrepancy and more time is spent processing the feedback [4].

Research into student metacognitive skills within intelligent tutoring systems (ITS) has explored varied aspects of metacognition which include student reflection, help-seeking, self-awareness and self-assessment [5]. This, however, is not the main

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goal of ITSs. Rather, they aim to provide effective personalised learning experiences that fit the needs of the individual learner and thus improve learning [6]. ITSs provide personalisation using a learner model that represents student's knowledge, interests, affect, or other cognitive dimensions [6]. The contents of the learner model are inferred based on the learner's interactions with the system. The evidence used to infer student knowledge may come from consistently demonstrated skills or a lucky guess. This variability poses challenges to model accuracy and is one of the many forms of uncertainty within the modelling process [7, 8]. Other forms include imprecise assessment of learner knowledge and a lack of information. Uncertainty related to students' diagnoses within the learner model has been managed using different methods such as Bayesian networks [9], fuzzy logic [10] or verification procedures [11]. However, learners are not usually made aware of the uncertainty in the model [7].

The visual representation of these learner models are called open learner models (OLMs). Students can be given access to system information about their knowledge through OLMs to help improve their metacognitive skills [12]. Open learner models support improved student self-assessment accuracy [13, 14] and student learning [13, 15, 16]. Some OLMs also show the discrepancy between students' confidence about the correctness of the system's automated assessment and their level of knowledge which provides an opportunity to increase the accuracy of the learner model [9, 14, 17]. These systems present the learner model as two separate visualisations which can allow learners to compare directly between their self-perceptions and the system's beliefs of their knowledge. However, these studies did not use an experimental control condition in order to test the impact of the OLM visualisation method on students' self-assessment accuracy or interactions with the system.

In this work, we focus on visualising model uncertainty within OLMs in terms of the conflict between the model developed by the system (how well students perform on the system's automated assessments) and student confidence about the correctness of their answers. The visualisation of the learner model used a skill meter that indicated the conflict of the two beliefs by manipulating the opacity of the skill meters' fill colour and including an option to expand the model to view two separate skill meters. Opacity is rarely used within OLM, but it has been commonly used to indicate uncertainty in non-educational fields [18], where opacity has been shown to effectively communicate data limitations [7]. This augmented visualisation of the learner model may motivate students to reconcile any conflict shown in their OLM and thus, promote metacognitive awareness. We conducted an experiment in a real class setting to test our hypothesis that uncertainty visualisation in OLMs will impact students' learning, their confidence judgments and behaviour in using the system, such as the number of times the OLM was viewed and the number of questions answered.

2 Methods

To understand better how students respond to being shown the inconsistencies between their confidence in their abilities and their actual answers during learning, we have extended the OLMlets OLM to include the visualisations we previously proposed [19]. This extension uses three versions of the learner model: skill meters that hide learner model uncertainty, a combined model and a version that has the same features of the combined model with the option to expand the model to show two separate models – the expandable model.

2.1 The OLMlets OLM

OLMlets is a tutoring system that provides an open learner model to help students become independent learners. OLMlets identifies students' weaknesses, strengths or misconceptions. The learner model in OLMlets [20] is constructed based on students' responses to multiple-choice questions using the last five questions attempted. Student knowledge can change over time due to learning a new concept, revising previously learnt concepts or simply forgetting an old concept. To manage this temporal uncertainty, the model in OLMlets relies on an algorithm that weighs student responses based on when a question was answered rather than the question's difficulty since questions are expected to have similar difficulty levels within a topic. Thus, it helps to keep the learner model recent. The total weight (t) is calculated iteratively for all questions (q) within a 5-question window, see formula (1). The initial weight (w) of the first question attempted is calculated by applying formula (2). The learner model assigns higher weights to recent responses and lower weights to earlier responses.

$$t = t + (1.3)^q, 0 < q \leq 5 \tag{1}$$

$$weight = \frac{q}{5} * \frac{(1.3)^{q-1}}{t}, 0 < q \leq 5, \tag{2}$$

OLMlets offers a skill meter visualisation that uses different colors to indicate the students' weaknesses (grey), misconceptions (red) or strengths (green) - see Fig. 1. A fully green skill meter shows the student has answered the last five questions correctly. A skill meter that is half green and half grey shows that the student performed some correct answers and the remaining half of the skill meter comprises incorrect answers. Incorrect answers show the learner has some weakness in the topic and needs to invest effort into his or her learning. The skill meter contains a red colour when misconceptions have been detected. A misconception is an answer that shows the student misunderstands a concept. The misconception library used in OLMlets is determined by the teacher. When a misconception has been identified, a link can be clicked to see a description of the misconception.

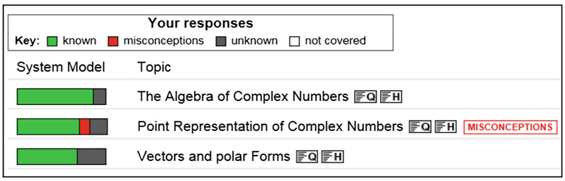


Fig. 1. The standard (skill meter) OLM visualisation within OLMlets. (Color figure online)

To collect the information needed to build the learner model, the answer given to each question is marked as correct, incorrect or a misconception. Also, to collect information to build a model of the students' confidence in their knowledge, students assess their confidence in their responses to multiple choice questions. They are asked "How confident are you that your answer is correct?" and can choose between 'very unsure', 'unsure', 'sure', and 'very sure'. This strategy has been shown to encourage reflection in action, which enhances students' metacognitive awareness by answering questions and thinking about their confidence in their answers at the same time [21].

Uncertainty in the underlying learner model arises when the system's model of student knowledge conflicts with the student-confidence model. For example, when a student selects "very sure" but the answer is incorrect, this shows disagreement between the student's and the system's beliefs. This disagreement is reflected in the model that has been augmented with a specific measure of model uncertainty. In this case, the uncertainty value will be decreased by the weight of the attempted question. The lower the uncertainty value, the higher the uncertainty in the learner model. If the uncertainty value lies between 0.0 and 0.3, the model is considered to be highly uncertain (i.e., Low agreement status). Values between 0.3 and 0.7 are considered to have a medium level of uncertainty, and low uncertainty is defined as values between 0.7 and 1.0. The opacity of the skill meter varies from one uncertainty level to another: high transparency indicates high uncertainty and full opacity indicates certainty or agreement. To study how visualising this uncertainty influences student learning, self-assessment accuracy and actions, three versions of the system were deployed: baseline, combined, and expandable. The two treatment groups (combined model and expandable model) show different amounts of information about model uncertainty.

Baseline (Control Group, Condition 1). The baseline condition used the original visualisation of the OLMlets OLM, where model uncertainty is hidden (Fig. 1).

The Combined Model (Treatment Group A, Condition 2). The combined model shows the levels of agreement between students' answers and their confidence by increasing or decreasing the opacity of the skill meter's colour. The skill meter's fill colour becomes increasingly transparent as the level of agreement decreases (Low agreement). In Fig. 2, topic 1 and topic 3 show high agreement (are fully opaque), whereas topic 2 (Point Representation of Complex Numbers) shows low agreement (the green is less opaque), which indicates that the uncertainty value for the known concept was decreased to a value less than 0.3. The unknown (grey colour) in topic 1 and topic 2 is more transparent indicating the student was confident that the answer was correct when answering the question incorrectly. The opaque grey shown in topic 3

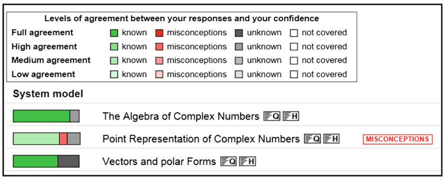
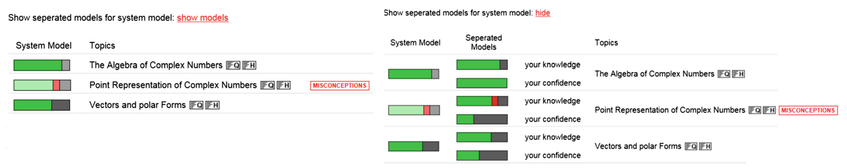


Fig. 2. An example of the OLM for the combined model group. (Color figure online)

(Vectors and Polar Forms) indicates the student fully agrees with the system that his answer was incorrect. The misconception (red) in topic 2 shows that the student may not have the misconception the system has diagnosed because he lacked confidence in his answer, which means he may have guessed incorrectly.

The Expandable Model (Treatment Group B, Condition 3). The base visualisation presented in this condition is the same as that of the combined model. This OLM differs in that students can see more information about model uncertainty by expanding the OLM to view the two models separately (system, student confidence). This expansion allows the learner to compare directly between the two models. The student can expand the model by clicking on "show models" (Fig. 3a). After selecting this option, the model is expanded (Fig. 3b).



(3a) Combined model (3b) Expandable model

Fig. 3. An example of the OLM visualisation for the expandable model group.

2.2 Experimental Design, Participants, Instruments and Analysis

To study the influence that the system has on learners in real settings, OLMlets was integrated into an undergraduate mathematics course. Questions related to three topics from the existing curriculum were added to OLMlets. Approximately 25 multiple choice questions were added for each topic. A pre-questionnaire was distributed at the start of the study to explore students' metacognitive skills before using the system. A post-questionnaire was used to explore their perceptions and metacognitive skills following OLMlets use. In addition to students' perceptions, paper based pre- and post-tests were used to measure students' knowledge and the accuracy of their self-confidence in their knowledge. The post-test and the post-questionnaire were conducted at the end of the third week of the study. Students were given OLMlets user accounts and were introduced to OLMlets by the researcher. A user manual was also given to all students. The system was accessible online at all times. Students were randomly divided into three groups. The control group used the original skill meter (Fig. 1). The second group used the combined model (Fig. 2) and the third group used the expandable model (Fig. 3).

Instruments. The pre-questionnaire had two sections. The first section focused on how students plan and monitor their learning and the second section related to students' confidence level while learning. The pre-test used the same self-assessment procedure as that used in OLMlets. The post-questionnaire had four sections. The first two sections (planning and monitoring learning, and student's confidence) were the same for all groups. The third section contained statements about the open learner model visualisation: only students from the combined and expandable models groups answered these questions. The fourth section was given only to the expandable model group; questions related to how seeing the different levels of agreement in a separated model view influenced their behaviour and their self-assessment skills.

Analysis. To calculate student scores for the pre- and post-test, a skipped question was considered an incorrect answer as this method is followed in class settings. Kruskal-Wallis tests were conducted on questionnaire data to identify any significant differences among the groups. After conducting the post-test, student Confidence Gain from the pre- to post-test was calculated to investigate the impact of the OLM on students and the impact of the different versions of the visualisation on its users. Pearson's correlations were used to identify the relationships between students' system usage (numbers of questions answered, number of times the model was viewed) and their pre- and post-confidence.

Participants. Undergraduate students ($N = 110$) from Sultan Qaboos University in Oman were enrolled in a mathematics course called Introduction to Complex Variables, where OLMlets was used to complement their course activities. That is, using the system was voluntary. Of those 110, 79 (36 females, 43 males) agreed to participate. These students were randomly divided into three groups: baseline group (n = 27), treatment group A (combined model, n = 27), and treatment group B (expandable model, n = 25). The pre- and post-tests were completed by 54 students, but only 38 logged on to OLMlets. Those who logged on but did not view the OLM (n = 13) were excluded. This meant that 25 students had used the OLM and 29 students had not used the OLM. Of the OLM users, 9 students remained in the baseline group, 9 students in the combined group and 7 in the expandable model group.

3 Results

We investigated the impact of the OLM on student learning and confidence judgment by comparing students who did not use the OLM to those who used it. We also explored how the OLM visualisations impacted student learning for OLM users (baseline group and the two treatment groups) to see the influence of uncertainty visualisation on student learning, confidence-judgment and actions. We divided the results into five sub-sections: student perceptions from the pre- and post-questionnaire, student knowledge on the pre- and post-test, student confidence on the pre- and post-test, system use and the relationship between system use and confidence.

3.1 Student Perceptions: Pre/Post-questionnaire

Students from all three groups showed similar views about their planning for their learning except for two questionnaire items where there were significant differences between the groups (shown in Fig. 4a). Students expressed different opinions ($\chi^2(2) = 8.39$, $p = .015$) when answering "Taking tests helps me to identify gaps in my knowledge", with mean rank ratings of 23.78 for the baseline group, 16.38 for the combined model group, and 29.33 for the expandable model group. Student opinions also differed ($\chi^2(2) = 6.37$, $p = .041$) for "Taking tests helps me to identify my misconceptions", with a mean rank of 23.44 for the baseline group, 16.04 for the combined model group and 27.10 for the expandable model group. We can see that the combined model group had more students who felt that tests did not help them identify their gaps or misconceptions, whereas students in the other groups tended to feel that tests helped them with those tasks. In relation to students' confidence, a group-level difference was found ("I try to increase my knowledge when my confidence is high"), $\chi^2(2) = 7.57$, $p = .023$, shows similar differences between the groups, with a mean rank of 22.85, 16.19 and 29.07 for the baseline group, combined model group and the expandable model group respectively: those in the expandable group claim to always try to learn when they are confident (shown in Fig. 4b).

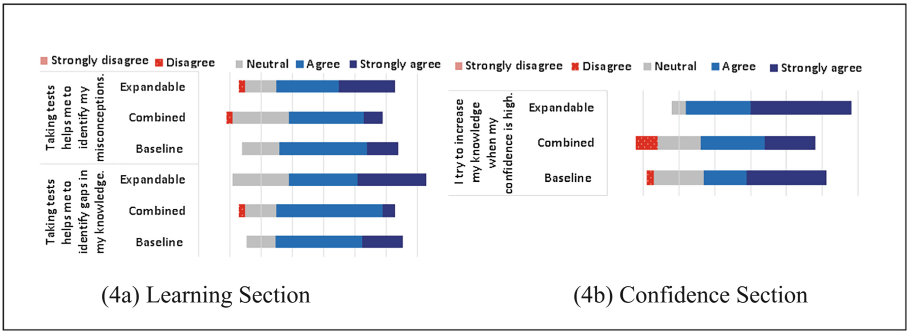


Fig. 4. Pre-questionnaire items where differences were found

Figure 5a, OLM Learning Section, shows the distribution of responses to post-questionnaire items where a significant difference was found between groups. "OLMlets encouraged me to answer more questions" differed significantly ($\chi^2(2) = 7.19$, $p = .027$). The mean rank for the baseline group was 7.39, which indicates that the standard skill meter is less effective at encouraging students to complete more work than the augmented OLMs that were shown to the combined model (mean rank = 14.64) and expandable model (mean rank = 14.00) groups.

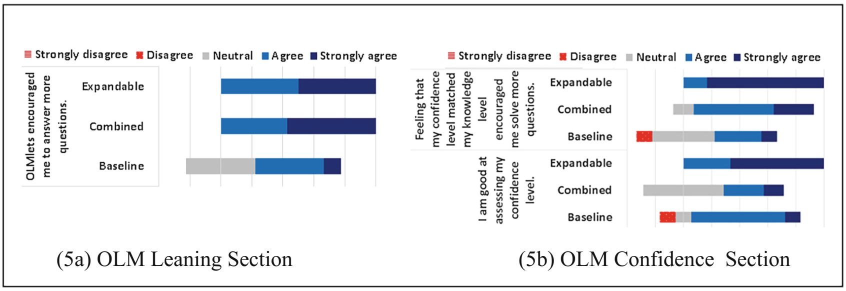


Fig. 5. Post-questionnaire items where differences were found after OLM use.

Group-level differences were also found in two items related to confidence (shown in Fig. 5b), “I am good at assessing my confidence level”, ($\chi^2(2) = 6.80$, $p = .033$) with a mean rank 10.39 for the baseline group, 8.36 for the combined models group and 16.83 for the expandable model group. The second item with differences ($\chi^2(2) = 9.06$, $p = .011$) was “Feeling that my confidence level matches my knowledge level encourages me to answer more questions” which also had the higher mean rank for the expandable model group (mean rank = 17.17) in contrast to the combined model group (mean rank = 11.86) and the baseline group (mean rank = 7.44). Students from the treatment groups (combined and expandable models) seemed to have comparable abilities for interpreting the visualisation: significant differences were not found in the third section of the post-questionnaire that related to OLM uncertainty visualisation. Figure 6 shows students’ perceptions from the expandable model group about the ability to expand the models. Students believed that seeing the two models separated is useful and helped them to be more accurate in assessing their confidence.

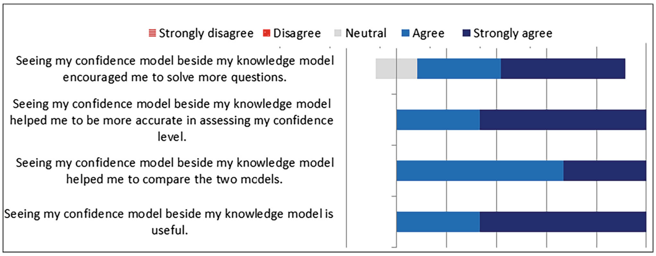


Fig. 6. Students’ perceptions of the option to see the two models separated.

3.2 Student Knowledge on Paper Pre/Post-tests

To analyse the effect of the OLM on student knowledge using their pre-and post-test, we compared students who used the OLM with students who did not use the OLM. There was no significant difference between the two groups on the pre-test using an independent t-test ($t(50.92) = 1.62$, $p = .112$, $d = .04$). The pre-test performance of OLM users was also analysed across the three groups: no significant differences were found ($\chi^2(2) = 1.59$, $p = .452$, $\eta^2 = .07$) with a mean rank of 15, 13 and 10.43 for the baseline, combined model and expandable model groups respectively. Table 1 shows student scores on the knowledge portion of the pre-test and post-test for no-OLM users, OLM-users and the three sub-groups of OLM users. Students’ post-test scores were lower than the pre-test, which indicates that the post-test was more difficult than the pre-test. However, our focus is to compare group scores on each test rather than the amount of learning from the pre- to post-test. The OLM users significantly outperformed the no-OLM users on the post-test, ($t(51.69) = 2.06$, $p = .045$, $d = .56$) equal variance is not assumed, implying that students benefited from using OLMlets. However, there were no significant differences between OLM user sub-groups on the post-test ($\chi^2(2) = .36$, $p = .833$, $\eta^2 = .02$) with a mean rank 12 for the baseline group, 14.06 for the combined model group and 12.93 for the expandable model group.

Table 1. Descriptive statistics for pre- and post-test of knowledge for those who did not use the OLM (no-OLM) and those who did (OLM, including experimental groups).

Groups		Pre-knowledge		Post-knowledge	
	n	*M (SD)*	95% *CI*	*M (SD)*	95% *CI*
no-OLM	29	6.21 (2.53)	[5.25, 7.17]	5.52 (1.99)	[4.76, 6.28]
OLM	25	7.32 (2.51)	[6.28, 8.36]	6.52 (1.58)	[5.87, 7.17]
Baseline	9	8.25 (1.75)	[6.78, 9.72]	6.63 (1.06)	[5.74, 7.51]
Combined model	9	7.5 (2.20)	[5.66, 9.34]	6.5 (1.31)	[5.41, 7.59]
Expandable model	7	6.12 (3.87)	[2.11,10.23]	6.5 (2.07)	[4.32, 8.68]

3.3 Student Confidence on Paper Pre/Post Tests

Students' self-assessed confidence in their mathematical knowledge on the pre-test was reliable (α = .88). There was a strong positive relationship between students' confidence on the pre-test and students' pre-test score (r = .80, p < 0.001). Table 2 shows students' pre- and post-confidence scores. A difference in student confidence on the pre-test was observed between the no-OLM group and OLM users (U = 230, p = .021, r = .31). There was also a significant difference between the no-OLM and OLM users' confidence on the post-test (U = 176, p = .001, r = .44), with a mean rank of 21.07 for no-OLM users and 34.96 for OLM users. The post-test effect was stronger than the pre-test one, which reflects that using OLMlets influenced student confidence: those who used OLMlets experienced a small confidence gain (M = 0.25, SD = 0.78, 95% CI = [−0.07, 0.57]) in contrast to the no-OLM users who experienced almost no confidence gain (M = 0.06, SD = 0.76, 95% CI = [−0.23, 0.35]).

Table 2. Descriptive statistics for pre- and post-test of confidence for those who did not use the OLM (no-OLM) and those who did (OLM, including experimental groups).

Groups		Pre-confidence		Post-confidence	
	n	*M (SD)*	95% *CI*	*M (SD)*	95% *CI*
No-OLM	29	2.76 (0.64)	[2.52, 3.00]	2.82 (0.68)	[2.56, 3.08]
OLM	25	3.15 (0.65)	[2.89, 3.42]	3.40 (0.42)	[3.23, 3.58]
Baseline	9	3.41 (0.37)	[3.12, 3.69]	3.20 (0.45)	[2.85, 3.55]
Combined model	9	3.24 (0.47)	[2.88, 3.60]	3.38 (0.34)	[3.12, 3.65]
Expandable model	7	2.71 (0.94)	[1.85, 3.58]	3.69 (0.33)	[3.38, 4.00]

Analysing the three sub-groups of OLM users, no significant differences were found in student confidence on the pre-test ($\chi^2(2) = 2.94, p = .230, \eta^2 = .12$ with a mean rank of 15.78 for the baseline group, 13.00 for the combined group and 9.43 for the expandable model group. There was also no significant difference in their confidence on the post-test $\chi^2(2) = 5.28, p = .068, \eta^2 = .22$ with a mean rank of 9.44 for the baseline group, 12.67 for the combined model group and 18 for the expandable model group. However, there was a significant difference in their confidence gain from the pre- to post-test $\chi^2(2) = 7.58, p = .023, \eta^2 = .32$ with a mean rank of 8.39 for the baseline group, 13.28 for the combined model group and 18.57 for the expandable model group. Both the combined model group ($M = 0.14$, $SD = 0.42$, 95% CI = [−0.18, 0.46]) and the expandable model group ($M = 0.98$, $SD = 0.98$, 95% CI = [0.07, 1.9]) experienced gains. In contrast, students in the baseline group had a small loss in confidence as shown through their negative gain score ($M = -0.21$, $SD = 0.46$, 95% CI = [−0.56, 0.14]), indicating the standard skill meters did not enhance student confidence in comparison to both treatment conditions. There was no correlation between student confidence in their pre-test and their confidence in the post-test for sub-groups of OLM users ($r = -.01$, $p = .948$) or between students' pre-test score and their post-test score ($r = .01$, $p = .967$), but there was a correlation between students' confidence in the post test and their post-test score ($r = .61$, $p = .001$).

3.4 System Use

Using the log data, we investigated the impact of the visualisation on the behavior of each group in terms of number of questions answered and number of times they viewed the model. Table 3 shows the descriptive statistics for the number of questions answered and the number of times the model was viewed between the groups.

Table 3. Descriptive statistics for number of questions answered (No. Q. Answered) and number of times the model was viewed (No. Model Views) by OLM condition.

Groups		No. Q. Answered		No. Model Views	
	n	*M (SD)*	*95% CI*	*M (SD)*	*95% CI*
Baseline	9	23.00 (6.20)	[18.23, 27.70]	3.11 (5.25)	[−0.93, 7.15]
Combined model	9	37.56 (25.26)	[18.14, 56.98]	3.78 (5.09)	[−0.14, 7.69]
Expandable model	7	59.29 (23.75)	[37.32, 81.25]	8.86 (10.33)	[−0.70, 18.42]

We found a significant difference between groups for the number of questions answered, $\chi^2(2) = 7.62, p = .022, \eta^2 = .32$, with a mean rank of 8.44, 13.28 and 18.50 for the baseline group, combined group and expandable model group respectively. This shows that adding information about the level of agreement between their confidence and their knowledge encouraged additional learning activity. We also found a significant effect on the number of times students viewed the model $\chi^2(2) = 8.74, p = .013, \eta^2 = .36$, with a mean rank of 9.11 for the baseline group, 11.89 for the combined model group and 19.43 for the expandable model group. This shows that students who had the option to expand the model were more motivated to know how close their level of knowledge was to their confidence. The log data shows that students from this group expanded the model an average of 4.86 times ($SD = 5.79$) while viewing their OLM.

3.5 Relationship of System Use to Confidence

To determine whether students' willingness to use OLMlets may have been linked to their confidence, we tested for relationships between students' activities within

OLMlets and their pre-test confidence. No relationship was found between their confidence at the beginning of the study and the number of questions that they answered within OLMlets ($r = -.16$, $p = .437$). Similarly, no relationship was found between their score on the pre-test and their OLMlets usage ($r = -.21$, $p = .303$). In contrast, a moderate relationship ($r = .51$, $p = .009$) was found between their post-test confidence and the number of questions answered in OLMlets suggesting that their OLMlets use positively influenced their confidence.

4 Discussion and Conclusion

Our evaluation showed OLMlets use had a moderate effect ($d = .56$) on student knowledge as measured by their post-test performance. While prior findings show that less able students benefit from OLM use [13, 15], few empirical studies show all OLM users benefit when compared against a non-OLM control group [16]. Our findings contribute to the literature by showing how those who used the OLM learned, regardless of prior knowledge. Although, we did not find a significant difference among the sub-groups for students' knowledge, the large effect of the OLM visualisation ($\eta^2 = .32$) was visible in student confidence gains, with those who used the expandable model benefitting the most. A moderate positive relationship between students' confidence and students' knowledge in the pre- and post-test was observed, confirming previous findings [2] within a new instructional domain. This shows that the group who was able to see the expandable models benefited the most. The expandable (separated) model view has been shown in previous studies to allow students to compare directly between the two beliefs (system, student) which can promote their metacognitive skills through negotiation [14, 17].

Our findings imply showing model uncertainty that is due to a conflict between the system and student's beliefs had an impact on students' confidence which in turn impacted their interaction with the system. It has been claimed that showing students information about their confidence in their correctness of answers with their actual answers influences students to try to align their confidence with their knowledge when inconsistencies are present [3]. This supports our finding that both treatment groups answered significantly more questions than the control group. Also, the expandable model treatment group, who could view the model separately or combined, was more motivated to view the OLM than the other groups. This suggests that students benefited from the two ways of viewing the model (combined and expanded). In conclusion, our study supports the claim of the benefit of OLMs on students' learning activities. Also, measures of their confidence and system-logged activities show that adding additional information in the OLM visualisation can impact student confidence and behavior within an ITS. We are completing studies that explore the impact of uncertainty visualisation on metacognitive skills (comparing visualisation against textual description). Future studies could explore the role that negotiation (between learner and system) could play in the interactive maintenance of learner models.

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