Open Social Student Modeling for Personalized Learning

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Abstract—*Open Student Modeling* (OSM) is an approach to technology-based learning, which makes student models available to the learners for exploration. OSM is known for its ability to increase student engagement, motivation, and knowledge reflection. A recent extension of OSM known as *Open Social Student Modeling* (OSSM) complements cognitive aspects of OSM with social aspects by allowing students to explore models of peer students and/or an aggregated class model. In this paper, we introduce an OSSM interface, MasteryGrids, and report the results of a large-scale classroom study, which explored the impact of the social dimension of OSSM. Students in a database management course accessed nonrequired learning materials (examples and problems) via the Mastery Grids interface using either OSM or OSSM. The results revealed that OSSM enhanced learning, especially for students with lower prior knowledge, compared to OSM. It also enhanced user attitude and engagement. Amount of student usage, efficiency of student usage, and student attitude varied depending on the combination of interface condition (OSM/OSSM), gender, and student social comparison orientation.

Index Terms—Adaptive Hypermedia, Personalized E-Learning, Visualization, User issues

1 Introduction

Adaptive educational systems [5; 16] have the potential to improve learning by personalizing learning content and performance feedback. The National Academy of Engineering named personalized learning among fourteen grand challenges for Engineering [21].

The core of every adaptive educational system is a student model (known also as learner model), which represents the current state of the student's domain knowledge. Depending on the system, the student model may also represent other information about the student such as learning goals, personal traits, and/or preferences. Using the student model, an adaptive system can support a range of adaptive learning interventions such as mastery learning, scaffolding, adaptive sequencing, or adaptive navigation support [5; 15; 16]. In most personalized learning systems, the student model is unobservable by the student; however, it has been suggested that allowing students to view aspects of their model might improve student self-reflection and self-regulated learning, better personalization transparency, and user motivation [8; 9; 27; 30]. The approach of allowing students to see aspects of their model is known as open student modeling (OSM). Currently, OSM is used in many adaptive educational systems and portals including Khan Academy.

This paper investigates the value of a less explored recent extension of OSM known as *open social student modeling* (OSSM). The idea of OSSM is to enhance the cognitive aspects of OSM with social aspects by allowing students to explore each other's models or the aggregated model of the class. While several pioneering projects demonstrated the feasibility of this approach and reported positive results [7; 26], the value of adding social dimension to the classic OSM requires further investigation. In this paper we present an implementation of OSSM in MasteryGrids, an open source adaptive learning portal developed in the context of the Personal Assistant for Learning project (PAL) [17]. The PAL aims to to develop support for lifelong learning through intelligent recommendation of learning resources, both within and across domains. To assess the added value of OSSM in comparison with more traditional OSM, we performed a large-scale classroom study comparing an OSSM version of MasteryGrids with a baseline OSM version. The results of the study reported in the paper indicate a number of benefits that could be provided by OSSM.

2 Background

2.1 Open Student Models

An OSM was originally suggested as an innovation in the area of personalized learning systems. While in traditional personalized systems, student models were hidden "under the hood" and used to personalize the educational process, the pioneers of open student modeling argued that the ability to view and modify the state of their own knowledge could provide additional benefit to students. A typical OSM displays the modeled state of student

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knowledge, although examples of models displaying interests [1] or learning styles [32] are also known. A common way to display a state of knowledge is a set of skillometers that show the mastered subset of expert knowledge [30; 35; 37] or the probability that a learner knows a concept [12]. More complex OSMs could display misconceptions, the size of topics, and other factors [8].

The idea to make OSM social was originally suggested and explored by Bull [7; 8]. The idea of OSSM is to enhance its cognitive aspects with social aspects by allowing students to explore each other's models or an aggregated model of the class. In our earlier work, we explored several approaches to combining OSSM with adaptive navigation support in an adaptive system for Java programming. Our preliminary single-classroom studies demonstrated that OSSM increased learner motivation to learn and enhanced the impact of adaptive navigation support [26; 28]. The study presented in this paper differs from earlier studies by its more formal nature, larger scale and different domain (Structured Query Language -- SQL).

While originating from research on adaptive systems and OSM, OSSM is similar in some ways to gamification. Gamefication is the use of game-like techniques in non-game contexts. In particular, the technique of gamification in education similar to OSSM is the use of "leaderboards" [11; 14]. Leaderboards allow an opportunity for students to see the top performers in the class, and compare their own performance to them. Gamification is currently driven by the success and momentum of videogames; however, its benefits to educational outcomes have not been firmly established [10; 25].

2.2 Individual Differences

Students differ in their perceptions, motivations, and judgments about themselves, which can affect their approach to mastering different types of challenges. In particular, students' tendency to compare themselves with others may be a critical characteristic influencing the impact of OSSM.

Social compasiron orientation is focused on habits of users to compare themselves with others [24]. Festinger's [22] social comparison theory claims everyone has a fundemantal drive to compare themselves with others in order to evaluate their own capabilities and opinions. This tendency is seen as an "almost inevitable element of social interaction" [4, p. 150]; however the need and frequency for comparison can be different from one person to another [24]. In the area of learning, these ideas are captured in the distinction between a "mastery orientation" and a "performance orientation." Students with a dominant mastery orientation are motivated primarily by a desire for personal improvement and mastery, whears students with a dominant performance orientation are motivated primarily by comparison with peers – either to outshine them, or to avoid underperforming the norm [2; 18; 19; 20]. Within this context, gender has garnered a good deal of interest as a possible corrleate of competitiveness and the tendency to be motivated by social comparison; however, research addressing this issue suggests that this association is not clear cut [3; 23;13; 31; 36].

3 MasteryGrids, an Open Social Student Modeling Interface

To evaluate the effectiveness of OSSM we used MasteryGrids, an open source OSSM interface developed by our group [29]. MasteryGrids uses a social visualization approach pioneered in an earlier system Progressor+ [26], which allows easy comparison of the progress of the student against peer students or against the aggregated progress of all students of the class. MasteryGrids uses cells of different color saturation to show knowledge progress of the target student, her reference group, and other students over multiple kinds of educational content organized by topics. Figure 1a shows MasteryGrids' interface for a database management course. Left to right, the first column of the grid ("OVERALL") shows student average progress, and the remaining columns show student knowledge progress topic by topic starting from the first topic of the database course: "Table Creation". The OSSM grid includes 3 rows. The first row of the grid (Me) presents the topic-by-topic knowledge progress of the *current student* and uses green colors of different saturation to represent the level of progress (the darker is the color, the higher the progress). The third row (Group) shows the aggregated topic-by-topic progress of the reference group (in this case, the whole class) using blue colors of different saturation. The second row (Me vs. Group) presents a topic-by-topic difference between the student progress and the class progress. The cells in the second row are green if the student knowledge progress is higher than the class, blue if the class is ahead, and gray when both the student and the rest of the class have the same progress. Higher color saturation indicates a larger difference. MasteryGrids can be configured to disable the OSSM features turning it into a standard Open Student model (OSM), as it can be seen in Figure 1b. In the OSM version only the first row with the progress of the current student is shown.

By clicking on any topic cell, the student can access learning content associated with the topic. For example, in Figure 1a, the student has clicked in a cell of the topic SELECT-FROM-WHERE and the system displays two rows of content items represented as colored cells: problems (called quizzes) and examples. By clicking in the content cells, the content (problem or example) will be loaded in an overlaid window. The student can access the content by clicking on any of the three rows of the topic (i.e., Me, Me vs. group, or Group). The row clicked defines whether the colors of content cells (Quizzes/Examples) will represent individual progress, comparison between the individual and the group, or the group progress. For example in Figure 1a, the student clicked in the second, differential progress row. Thus, the colors of the content cells also show differential progress (resulting in both green and blue cells.)

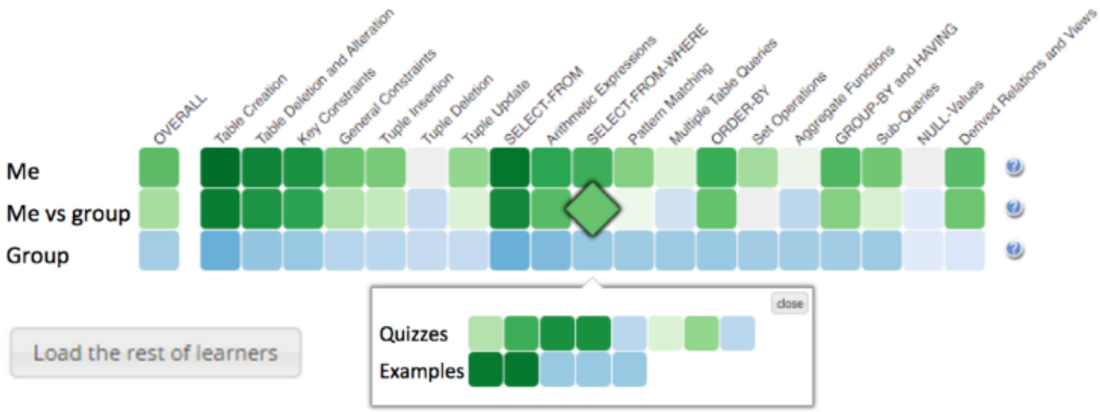

Fig. 1a. MasteryGrid interface with social features (OSSM)

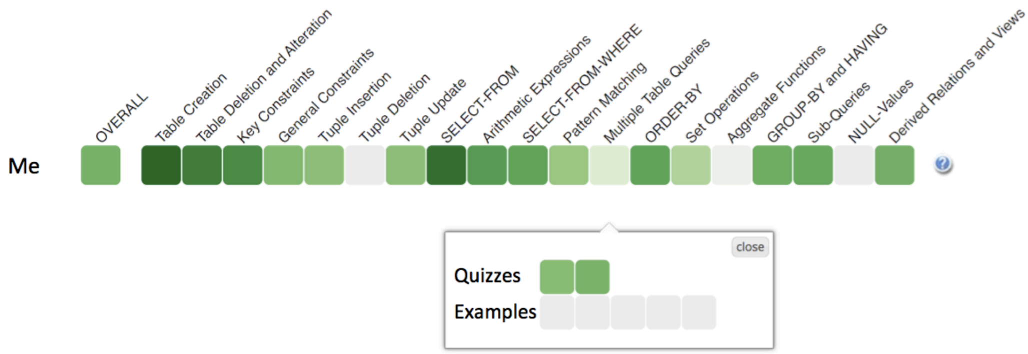

Fig. 1b. MasteryGrid interface withour social features (OSM)

In addition to displaying the overall class progress, MasteryGrids can display an anonymized ranked list of individual student models as shown in Figure 2. To save time and space, this list has to be requested by clicking "Load the rest of learners" button (bottom left part in Figure 1a.) The position of the current student in the list is shown in green.

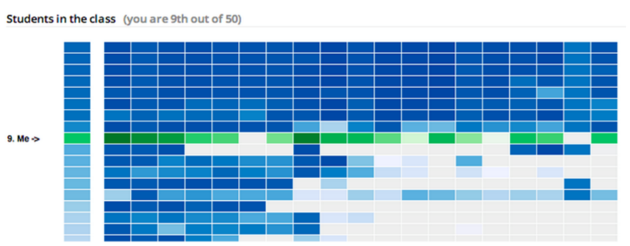

Fig. 2. Sorted list of peers. The current student can find her position, but no names are shown.

4 The Study

4.1 Study Design

To assess the added impact of the social features of OSSM, we ran a classroom study where we compared two different versions of MasteryGrids, one nicknamed *OSSM* contained both the OSM and OSSM features (as shown in Figures 1a and 2), and another, nicknamed *OSM* with OSM features only, i.e. only showing first row of the grid as in Figure 1b and no access to peer data. The study was performed in the context of a masters-level database management class at the School of Information Sciences, University of Pittsburgh. The class was divided into two comparable sections taught by the same instructor using the same approach. Sections had different class meeting times. One section was assigned to work with the OSM version of the system and another section with the OSSM version. Both versions provided access to the same educational content. The only differencce was the lack of group row, comparison row, and peer table in the OSM interface (Figure 1b). Peer data visualization in the OSSM group was based on the progress of this group alone.
MasteryGrids was introduced to both sections in the 3rd week of the course right before the start of the SQL part supported by the system. The students were informed about the study and received a quick introduction to the MasteryGrids interface used in the group and the learning content available in the system. Then students were given a pretest to check their SQL knowledge. The pretest included ten questions that required writing SQL statements. After the introduction, each student received e-mails with a link to access the system, individual login and password. The use of the system was not mandatory in the course; however, to motivate students to try the system, one extra credit point was offered to students who solved at least 10 problems in the system. All user

interactions with the system were logged. At the end of 11th week of the course, the participants took a posttest and filled in a questionnaire about usefulness and usability of the system.

4.2 Participants

The total number of students in the two sections of the course was 103, however, 14 students never logged in and were excluded from the analysis. Of the remaining 89 students, 47 (52.8%) worked with the OSM and 42 (47.2%) worked with the OSSM interface. Most of the participants (77%) were graduate students in the Information Science program. All students were familiar with information technology in general; however, as shown by the pretest, most students were not familiar with SQL. The majority of the students were 22 or 23 years old (OSM mean=24.17; OSSM mean=23.82). The ages of other students ranged from 20 to 32. The descriptive statistics for gender distributions across groups are shown in Table 1.

TABLE 1
THE DESCRIPTIVE STATISTICS OF OSSM/OSM GROUPS BY GENDER

Systems/gender	OSSM		OSM	
	#	%	#	%
Female	26	55.3	21	50
Male	21	44.7	21	50
Total	47	100	42	100

4.3 Learning Content and Log Data Collection

MasteryGrids allows students to access two types of content: parameterized *problems* and *examples*. We used a set of SQL problems and examples developed for an earlier system Database Exploratorium [6]. Each problem asks the student to write a SQL statement to retrieve a subset of data from a predefined database. Problems are parameterized, which means they are generated using a template in which different specifics (parameters) are inserted each time a new problem is generated. The same problem can be attempted multiple times, but will appear to the student as different, with different correct answers each time. Examples present various SQL statements with explanations for each line. All explanations are originally hidden; the student can explore line explanations one by one by clicking lines of interest, allowing the system to keep track of which line has been viewed. All student activity with the system was logged with a time-stamp. The collected logs included every attempt to open a topic or a content item through the MasteryGrid interface, every attempt to solve problems, and every example line viewed.

4.4 Social Orientation Scale

To collect data about student tendency to compare themselves with other people, The Iowa-Netherlands Comparison Orientation Measure (INCOM) developed by [24] was administered. This Likert-type questionnaire includes 11 items such as “I often compare myself with others with respect to what I have accomplished in life”. Participants rated each statement on a continuum from “I disagree strongly” (1) to “I agree strongly” (5). The scale consists of two factors: Ability and Opinion. In the current sample, the internal consistency was acceptable (Cronbach’s alpha = .78).

5 STUDY RESULTS

In accordance with the research questions introduced above, the independent variable of the study was the type of interface used by the group (OSM or OSSM) and the dependent variables were student engagement, system usage, instructional effectiveness, impact on learning, and students’ opinions about usability and usefulness.

5.1 Student Engagement and Retention

In our past work, we observed that the use of OSSM increases the number of students who were motivated to work with non-mandatory learning content [27]. To investigate whether OSSM differed from OSM in this respect, we compared the percent of students who engaged with OSM and OSSM at six different levels. In total there were 42 students in the OSM group and 47 in the OSSM group who logged into the system at least once, i.e., had a chance to see the system and to make an informed decision whether to use the system or not. In Figure 3(a) we compare the percentage of students who logged in at least once, according to whether they made one to ten, 11-19, 20–29, 30-39, 40-49, or more than 50 attempts on problems. A difference emerged between the groups early and then persistend. For OSSM, almost 70% of the students decided to explore the system further attempting at least one question. In contrast, for OSM, less than 30% of them did so. At the level of 30+ questions that we could consider as a serious engagement with the system, the OSSM group still retained more than 50% of its original users while OSM engagement was below 20%.

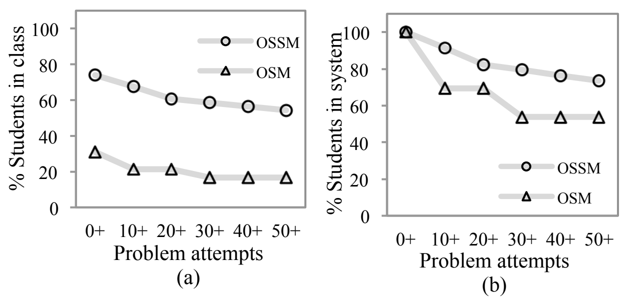

Fig. 3. Students according to number of problem attempts in the OSM and OSSM groups: (a) as percent of students who ever logged in; (b) as percent of students who attempted at least one problem.

Figure 3(b) provides an alternative look at the student engagement by considering only those students who attempted at least one problem. Still, we see that the OSM group is loosing students at a higher rate than the OSSM group, even with this adjustment. These observations demonstrate that the OSSM interface was much more successful than the OSM interface in engaging and retaining students.

5.2 System Usage

To further compare the ability of the two system versions to engage students, we examined the variables in Table 2. Since the data were not normally distributed, Mann Whitney U, a nonparametric statistical test was used to compare system usage between OSM and OSSM groups. The Table 2 shows the results of Mann Whitney U tests.

TABLE 2
SYSTEM USAGE BY OSM AND OSSM GROUPS

Variable	OSM Mean	OSSM Mean	U
Sessions	3.93	6.26	685.50*
Topics coverage	19.0%	56.4%	567.50**
Total attempts to problems	25.86	97.62	548.50**
Correct attempts to problems	14.62	60.28	548.00**
Distinct problems attempted	7.71	23.51	549.00**
Distinct problems attempted correctly	7.52	23.11	545.00**
Distinct examples viewed	18.19	38.55	611.50**
Views to example lines	91.60	209.40	609.00**
MG loads	5.05	9.83	618.50**
MG clicks on topic cells	24.17	61.36	638.50**
MG click on content cells	46.17	119.19	577.50**
MG difficulty feedback answers	6.83	14.68	599.50**
Total time in the system	5145.34	9276.58	667.00**
Time in problems	911.86	2727.38	582.00**
Time in MG (navigation)	2260.10	4085.31	625.00**

*Significant result (p<0.05) ** Significant result (p<0.01)

The results indicated that students who used the OSSM interface were significantly more engaged with the system. The difference is not only significant, but shows double, triple, or even larger increases in student activity. The number of attempted problems more than tripled and the number of problems solved correctly quadrupled in the OSSM group. OSSM students viewed twice as many examples and example lines and covered three times as many topics. The OSSM group also worked more extensively with the MasteryGrids interface, and overall spent almost twice as much time in the system.

5.3 Impact on Learning

To see the effect of the social interface on students' learning, we measured the normalized learning gain of students using their scores on the pretest and posttest (ngain= (posttest-pretest)/ (maxscore-pretest)). For this analysis we considered only students who answered both pretest and posttest. To increase our confidence that the difference in learning gain could be attributed to the use of the system, we excluded students who made less than five problem attempts. After this filtering, there were 12 students in the OSM group and 30 students in the OSSM group. Comparing learning gains of these students, we found no significant difference (p=.173) between groups, although the mean learning gain of students in OSSM group (M=0.47, SD=0.11) was higher than in the OSM group (M=0.41, SD=0.17).

It is, however, quite common than innovative technology most significantly affects weaker students. To check whether this was true in our case, we measured the learning gain for weaker and stronger students separately. If a student achieved under 25% correct on the pretest we classified the student into the weak group otherwise into the strong group. Altogether, this split placed 70 students into the weak group (score below 25%) and 14 students into the strong group (score at or above 25%). Among 42 students who made five or more problem attempts there were 35 weak and 7 strong. Table 3 summarizes learning gain for these 42 weak and strong students. The mean learning gain was higher for both weak and strong students in the OSSM group compared to the OSM group and the difference was significant for weak students (according to the results of independent samples t-test (t=-2.22; p=.033).

TABLE 3
THE RESULTS OF T-TEST ABOUT NORMALIZED LEARNING GAIN OF WEAK AND STRONG STUDENTS IN THE OSM AND OSSM GROUP

	OSM)		OSSM		p-value
	n	ngain	n	ngain	
Weak (n=35)	9	0.35±0.15	26	0.45±0.1	.033
Strong (n=7)	3	0.57±0.14	4	0.6±0.13	.824

We also examined the association between number of activity attempts in each group and the final grades of the students in the class. We fitted a mixed model with group (G), number of attempts on problems (NP), examples (NE), and example lines (NL) as the fixed effects and the final grade as the response variable. We found that the group (G), number of examples (NE), and lines (NL) were not significant predictors of the final grade, however number of attempted problems (NP) significantly predicted the final grade. We obtained the coefficient of 0.09 for NP, meaning that attempting one problem in the system was associated with an increase of 0.09 in the final grade ranging from 0 to 100 (SE=0.04, p=.017). In other words, attempting 100 problems will increase the final grade by 9. This implies that in both groups, more attempts on problems was associated with gaining a better grade in the final exam. Therefore, the better ability of the OSSM interface to engage students in problem solving might be a reason for the higher learning impact of OSSM.

5.4 Efficiency and Instructional Effectiveness

As could be observed in Table 2, the increase of the number of performed activities (both, examples and problems) is larger than the overall time increase. This observation hints that students work with content more efficiently in the OSSM group. The results of an efficiency analysis are shown in Table 4. To avoid an impact of users who did too little work with the system, we excluded from calculations users who explored less than five examples (Table 4, first two lines), solved less than five problems (Table 4, 3rd line) and explored less than five examples or solved less than five problems (Table 4, 4th line).

The table shows that time per line, time per example and time per activity of students in OSSM group were significantly lower than in the other group, i.e., students who used the OSSM interface worked more efficiently. We believe that this is a result of the social navigation support provided by the OSSM interface guiding students to the right content at the right time. We can't rule out another possible reason – students may rush to move ahead of their classmates in the OSSM group where class progress was visible. In this rush, they may skim examples too faster. Their work on questions was as competent as the work of OSM group, however. No significant difference for the success rate (percentage of correct attemps) was found (median OSM =61%; median OSSM =64%)

TABLE 4
THE RESULTS OF MANN WHITNEY U TEST ABOUT PRODUCTIVITY SCORES

Variable	OSM Mean	OSSM Mean	U
Time per line	22.93	11.61	570.00**
Time per example	97.74	58.54	508.00*
Time per problem	37.96	29.72	242.00
Time per activity	47.92	34.33	277.00*

** Significant result (p<0.05) ** Significant result (p<0.01)*

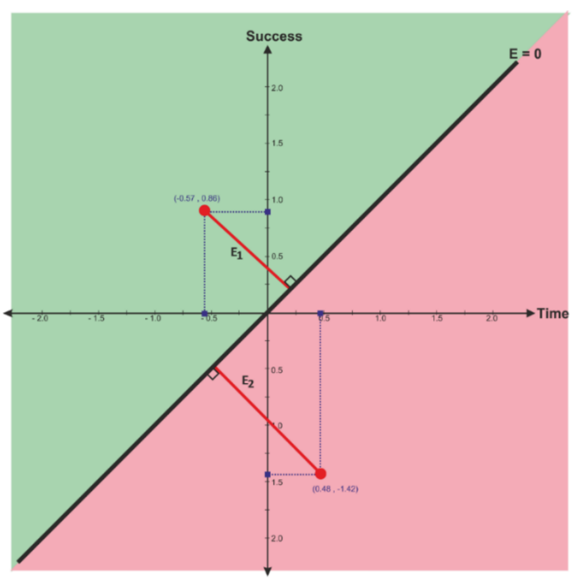

Fig. 4. Instructional Effectiveness Score

Instructional effectiveness could be measured more formally using an approach that takes into account both time and success, such as the computational procedure developed by Paas and Van Merrienboer's [33; 34]. To examine instructional effectiveness following this approach, the performance (correctly answered SQL problems) was combined with time (total time spent to answer SQL problems). The raw scores of performance and time were firstly translated to *Z scores* and were plotted in a Cartesian plane (Figure 4). Then relative instructional effectiveness was computed as the distance between the point (z(p), z(t)) to the line of zero effectiveness (E=0) by using the following formula:

$$E = |z\_success - z\_time\ |/\sqrt{2}$$

$$z_{success} - z_{time} > 0 \quad => \quad E > 0$$

$$z_{success} - z_{time} < 0 \quad => \quad E < 0$$

Relatively higher performance and lower time shows high-effectiveness and is plotted above the line E=0. Low instructional effectiveness is plotted below the line.

To compare instructional effectiveness between groups, we examined students (N=44) who attempted at least 5 problems. According to results of Mann Whitney U test (U=116.000, p=0.045), instructional effectiveness scores of students who studied with the OSSM interface were significantly higher (N=32, mean=0.22) than the scores of students who studied with the OSM interface (N=12, mean=0.03). The effectiveness scores of in OSSM and OSM students who attempted at least 5 problems are shown in Figure 5.

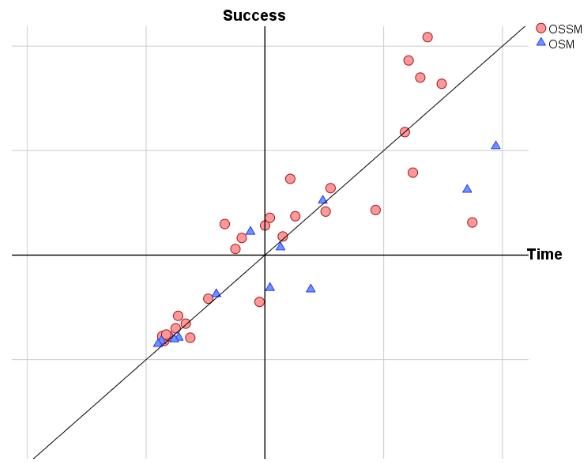

Fig. 5. Instructional Effectiveness Scores of OSM/OSSM students

5.5 Questionnaire Analysis

A total of 81 students (42 in OSSM group, 39 in OSM group) answered the questionnaire about usability and usefulness of MasteryGrids. To focus on more informed feedback, we excluded from analysis students who used the system less than 300 seconds, keeping 53 students' responses for further analysis: 32 in OSSM group (18 females, 14 males), and 21 in OSM group (10 females, 11 males).

Table 5 presents the questions in each part of the questionnaire with mean and standard error of the mean for each group. Values range from 1 (strongly disagree) to 5 (strongly agree). Part 1 was answered by all 53 students; part 2 was answered only by students in OSM group; part 3 was answered only by students in OSSM group. We discarded all answers tagged as "Did not notice", keeping 17 to 26 responses for different questions (some students did not answer all of the questions). In the next paragraphs we refer to the questions in Table 5 as PXQY where X represents the part (1, 2, and 3) and Y the question number.

The general usability and usefulness of the system in **Part 1** were evaluated positively, with values generally above 3.5 and many of them above 4 in OSSM. There was a clear tendency for more positive answers in OSSM group, although the only significant difference observed between groups is in P1Q3: students in OSSM group (N=31) rated themselves as more motivated than students on the OSM group (N=21) by the self-progress features in MasteryGrids, Mann-Whitney U=225, p=.026 two-tailed. We followed this up by contrasting the response of OSSM group in P1Q3 (Seeing *my progress* in the tool motivated me to work on quizzes and examples) with the similar question about OSSM features, P3Q10 (Viewing *my classmates' progress* motivated me to work more in quizzes and examples). We found a significant difference using the Wilcoxon Signed Rank test (z=2.16; p=.031), as we measured answers of students on two questions: while log data shows that students in the OSSM group used the system much more than the students in OSM group, they were also more eager to attribute the motivation to work with the system to the ability of seeing their own progress rather to the ability to see progress of their classmates.

To examine the impact of in-system experience, we clustered students into usage groups, low (N=26) and high (N=27) using two-step clustering over standardized values of the system usage variables: number of distinct problems attempted, number of distinct examples viewed, number of clicks in topics cells and number of clicks in content cells (problems and examples). We expected that students who used the system more would evaluate it higher, as it frequently happens with complicated systems, but we did not find any significant difference here. We hypothesized that the system was sufficiently simple and usable to be sufficiently mastered even by the low group.

Part 2, answered by the OSM group, presented questions about the *perceived* value of social features. We compared these questions with similar questions in Part 3, answered by the OSSM group wondering whether, students value the social features higher when they actually experience them. P2Q1 was compared to an average score in questions P3Q2, P3Q3, and P3Q5 and the difference was significant, i.e., social features were valued more highly when actually experienced (OSM N=19, OSSM N = 15, Mann-Whitney U=80, p=.0396 two-tailed).

Part 3, answered by the OSSM group, was analyzed in a different way. First we looked at differences across usage clusters (as defined previously) and gender, but found no significant difference between clusters for usefulness or usability questions. Then we looked at possible differences between questions referring to different system features. P3Q2, P3Q3 and P3Q5 refer to *group comparison* features (Figure 1a), and P3Q6 and P3Q8 refer to *peer list* features (Figure 2). We compared these two groups of questions to see if students found more useful one vs. the other. The difference was not significant. This hints that the implementation of social comparison in the system was sufficiently simple to understand even by the low-usage students. In addition, students agreed that the colors of the system used for comparing with others were easy to understand (P3Q4, P3Q9).

Questionnaire responses suggested that students had positive reactions to the social comparison affordances of OSSM. There was a tendency to disagree with P3Q12 (Viewing that others were more advanced than me made me want to quit using MG), and yet to agree that social comparison compelled them (P3Q13, Sometimes I just checked quizzes and examples to catch up with others rather than to learn more). Another interesting finding was the lower scores students gave to the usefulness of showing names (P3Q11). Apparently, the peer comparison is suffucuently valuable even if the names of specific peers are not shown. We further analyzed the relation between P3Q11 (see names of others) and P3Q13 (show my name) by reversing P3Q13 and classifying answers as positive (above 3) or negative (below 3), discarding answers with value 3. We found a significant difference between student answers to these two questions using Wilcoxon Signed-Rank test as we measured answers of students on two questions (z=-2.121 p=.034). Sudents were generally less eager to have their names shown than they were interested to see the names of classmates. Seven out of 20 students who answered both questions thought that they would like to see other names, but would not like to show their own names. Only 1 student would show her name but thought it is not useful to see other names. The remaining 12 students had equal opinion on both questions.

TABLE 5
SUBJECTIVE EVALUATION QUESTIONS

		OSM		OSSM	
Part 1		M	SE	M	SE
1	In general, it was useful to see my progress in Mastery Grids (MG)	3.76	.228	4.03	.145
2	In general, I liked the interface of MG	3.86	.221	3.84	.163
3	Seeing my progress in the tool motivated me to work on quizzes and examples	3.52	.214	4.09	.130
4	The interface helped me to understand how the class content is organized	3.62	.223	3.81	.176
5	The interface helped me to identify my weak points	3.52	.190	3.84	.186
6	The interface helped me to plan my class work	3.33	.211	3.22	.160
7	It was clear how to access questions and examples	3.81	.264	3.56	.190
8	It was useful to see my knowledge progress for each topic [in MG]	3.71	.171	4.03	.135
9	It was useful to see how I am doing with individual quizzes and examples	3.71	.197	4.16	.128
10	Using green colors in different intensity to show my progress was easy to understand	3.90	.217	4.09	.151
Part 2 (only OSM)				M	SE
1	The ability to see the progress of the rest of the group will make MG more valuable for me			3.53	.246
2	The ability to see the progress of the rest of the group will motivate me to use MG more frequently			3.74	.227

Part 3 (Only OSSM)		M	SE
1	It is important for me to see the progress of the rest of the class	3.87	.220
2	It was useful to see the progress of the whole class as it is represented in the Group row [in MG]	3.96	.183
3	It was useful to see the progress of the top students as it is represented in the Group row [in MG]	4.11	.212
4	The comparison between the group and myself [figure] is easy to understand	4.21	.147
5	It was useful to see the comparison between the selected group and myself [figure]	4.14	.151
6	It is important for me to see the progress of individual classmates [in peer list]	3.71	.322
7	In general, it is useful for me to be able to compare my progress with the progress of others	3.88	.185
8	It is important for me to see my position in the class [in peer list]	3.96	.213
9	Visualizing the progress of others using blue colors of different intensities was easy to understand	4.04	.141
10	Viewing my classmates' progress motivated me to work more in quizzes and examples	3.88	.193
11	I think it would be useful for me to know the names of individual classmates in [peer list]	2.68	.230
12	Viewing that others were more advance than me made me want to quit using MG	2.71	.229
13	If names are shown, I will not like to show my name in the list to others	4.15	.120
14	Sometimes I just checked quizzes and examples to catch up with others rather than to learn more	3.35	.264

Part 1 was answered by all students. Part 2 was an-swered only by students in OSM group, and Part 3 by students in OSSM group. Some of the questions refer to figures originally included in the questionnaire (and not reproduced here), and the references were changed to [reference], e.g. [in peer list] in question 6 and 8 in Part 3.

6 Gender Effects

6.1 Gender Effects on System Usage

Two-way non-parametric ANOVAs (Artool) were conducted in order to examine the impact of gender and interface (OSM/OSSM) on students' system usage. The analyses produced significant interactions between the effects of gender and interface type on almost every system usage parameter, as shown in Table 6. The descriptive statistics shown in Table 7 clearly demonstrate the nature of this effect: while the presence of social comparative features in OSSM positively affected usage for both genders, male students were significantly more affected by social comparison. As the data show, female students in the OSM group used the system more than males in almost every aspect. However, in the OSSM group the situation is completely reversed: male students demonstrated much higher system usage in every aspect.

TABLE 6
THE TWO WAY ANOVA RESULTS ON INTERACTION EFFECTS OF GENDER AND GROUP

Variable	Group Effect	Gender Effect	Interaction Effect
Topics coverage	0.000***	0.129	0.006 **
Total attempts to problems	0.000***	0.021*	0.002**
Correct attempts to problems	0.000***	0.020*	0.003**
Distinct problems attempted	0.000***	0.129	0.007**
Distinct problems attempted correctly	0.000***	0.133	0.007**
Distinct examples viewed	0.000***	0.342	0.014*
Views to example lines	0.000***	0.017*	0.000***
MG loads	0.001***	0.234	0.032*
MG clicks on topic cells	0.000***	0.039*	0.000***
MG click on content cells	0.000***	0.011*	0.000***
Total time in the system	0.003**	0.122	0.005**
Time in problems	0.000***	0.026*	0.001**
Time in examples	0.307	0.308	0.021*
Time in MG (navigation)	0.002**	0.149	0.007**

*****Significant result (p<0.001), ** Significant result (p<0.01), *Significant result (p<0.05),*

We also compared male and female use of the "load others button" which exists in only OSSM interface. This button was specifically engineered to measure user interest to compare oneself with others. The results of a Mann-Whitney U test showed that males (N=21, mean=9.00) clicked that button significantly more (U=373.000, p<0.05) than females (N=26, mean=4.54). Male students were both significantly more interested to compare themselves with others and significantly more affected by the presence of comparison. This finding is consistent with several previous studies showing that females are often more reluctant to compete than males (Niederle & Vesterlund, 2011).

TABLE 7
THE DESCRIPTIVE STATISTICS ABOUT FEMALE AND MALESTUDENTS SYSTEM USAGE

Variable	Males		Females	
	OSM Mean	OSSM Mean	OSM Mean	OSSM Mean
Sessions	4.05	8.38	3.81	4.54
Topics coverage	12.3%	72.9%	24.8%	43.1%
Attempts to problems	18.24	143.81	33.48	60.31
Correct attempts to problems	11.90	88.19	17.33	37.73
Distinct problems attempted	5.48	30.19	9.95	18.12
Distinct problems attempted correctly	5.43	29.81	9.62	17.69
Distinct examples viewed	13.57	49.29	22.81	29.88
Views to example lines	68.24	297.52	114.95	138.23
MG loads	5.33	12.38	4.76	7.77
MG clicks on topic cells	15.29	90.00	33.05	38.23
MG click on content cells	30.48	172.00	61.86	76.54
Clicks on load others button	NA	9	NA	4.54
Total time in the system	3947.74	11929.92	6342.94	7133.50
Time in problems	660.09	3841.08	1163.63	1827.86
Time in examples	1468.93	2782.90	2178.53	2025.27
Time in MG (navigation)	1634.38	5228.07	2885.82	3162.32

6.2 Gender and Impact on Learning

To analyze gender effects on knowledge gain, a Mann Whitney U test was conducted. The results failed to reveal any significant difference between male and female students in their learning gain (p=.417). A non-parametric two-way ANOVA test also revealed no significant interaction between the type of interface and gender in respect to learning gain.

6.3 Gender and Efficiency

To analyze gender effects on system usage efficiency, a Mann Whitney U test was conducted. As Table 8 shows, time per activity, time per line and time per example scores of female students in the OSSM group were significantly lower than in the OSM group. However, there were no significant differences for time per problem or instructional effectiveness scores between female students in two groups.

TABLE 8
THE RESULTS OF MANN WHITNEY U TEST ABOUT EFFECTIVENESS SCORES OF FEMALE STUDENTS.

Variable	OSM Mean	OSSM Mean	U
Time per activity	56.633	36.813	84.000*
Time per line	23.558	13.024	150.000**
Time per example	108.892	59.217	147.000*

** Significant result (p<0.05) ** Significant result (p<0.01)*

At the same time, a Mann Whitney U test showed no significant difference between time per line, time per example, time per problem, time per activity, or instructional effectiveness scores of male students between the two groups. Together with the data presented in section 6.1, this result reveals an interesting picture. As section 5 discussed, students using the OSSM system showed both significantly higher usage and significantly higher efficiency. The gender analysis, however, points to the asymmetric nature of this increase: while it was mostly males responsible for the remarkable usage increase, it was mostly females responsible for the significant efficiency increase.

6.4 Gender and Student Attitude

Similar to the analysis for gender effects on system usage, two different analyses were conducted to examine gender impact on questionnaire answers. In the first analysis, students were split according to the groups OSM or OSSM. Then for each group, female student ratings about usability and usefulness of MasteryGrids were compared with male student ratings. To perform this analysis, for each usefulness aspect, we combined student feedback on several questions. According to the results, usefulness of one's own progress (P2Q1, P2Q3, P2Q7, P2Q9) was deemed significantly higher (U=12.00, p<0.05) by female students (Mean=3.94) than male students (Mean=3.16) in the OSM condition; however, no significant differences between genders was found in the OSSM condition.

In the second analysis students were split according to their gender. Then within each gender, we compared student ratings between OSM and OSSM groups. As shown in Table 9, several differences were observed between male students' ratings in OSM and OSSM groups: male students in the OSSM group considered the system significantly more useful in all aspects. Here *total usefullnes* includs P2Q1, P2Q4, P2Q5, P2Q6, P2Q9, and P2Q9 while *usefulness of OSSM* combines P3aQ1 for OSM group with P3bQ2, P3bQ3, and P3bQ5 for the OSSM group. No differences were found in female group.

TABLE 9
MANN WHITNEY U RESULTS FOR SUBJECTIVE EVALUATIONS (MALE STUDENTS ONLY)

Variable	OSM Mean	OSSM Mean	U
Total usefulness	3.21	3.94	24.00*
Usefulness of OSM	3.0	4.0	24.00*
Usefulness of OSSM	3.16	4.04	13.50*

** Significant result (p<0.05) ** Significant result (p<0.01)*

These findings are consistent with the Mastery Grid Usage findings, which indicated that the OSSM interface was more engaging for male students while the OSM was more engaging for females.

7 SOCIAL COMPARISON ORIENTATION EFFECTS

This section examines the impact of social comparison orientation on system usage, efficiency, learning gain, and attitude. As explained in section 4.4, the INCOM questionnaire was administered to determine social comparison orientation. In total, 35 students in the OSM group and 45 students in the OSSM group completed the questionnaire. These participants were divided into a low comparison oriented group (M=2.84, SD=0.31) and a high comparison oriented group (M=3.69, SD=0.31) using a median split of the scores of Social Comparison Orientation Scale (median = 3.27). Students who did not complete this questionnaire obviously had to be excluded from the analyses reported in this section.

7.1 Social Comparison Orientation Effects on System Usage and Efficiency

System usage and efficiency differences across groups were analyzed by low and high comparison oriented groups. While we expected that the low comparison oriented group would be less affected by the social comparison features of OSSM, the data did not confirm this expectation. A two-way non-parametric ANOVA test confirmed the significance of the observed main effect for interface condition on usage and efficiency, as already reported; but there was no significant interaction of interface condition and social comparison orientation. In other words, while both groups were significantly affected by OSSM, the impact of OSSM interface on both groups was comparable.

We also compared the use of "load others button" by students with low and high social comparison orientation. The results do show that students in high comparison oriented group clicked this button more frequently (mean=8.04) than in the low comparison oriented group (mean=4.95), however, a Mann-Whitney U test showed that this difference is not significant (p=0.575).

7.2 Social Comparison Orientation and Impact on Learning

The results of Mann Whitney U tests failed to indicate significant differences between low and high social comparison students in respect to learning gain. The results of a two-way non-parametric ANOVA also failed to indicate any significant impact of social comparison orientation and interface (OSM/OSSM) on students' learning gain.

7.3 Social Comparison Orientation and Student Attitude

For the OSSM group, students' ratings for comparison with the group (P3bQ2, P3bQ3, P3bQ5) were significantly higher (p=0.04) for the high comparison orientation group (mean=4.50) than for the low comparison orientation group (mean=3.80).

To compare perception of OSSM between high social comparison orientation groups working with OSSM and OSM, Mann Whitney U test conducted. As it can be seen in Table 10, the real value of OSSM in the high comparison orientation group (i.e., feedback on real comparison features in OSSM group) was significantly higher (p=0.036) then the perceived value of these features (i.e., feedback on *possible* social comparison features in OSM group). In other words, the reality beats the expectation. Suprisingly, high comparison oriented students who used the OSSM interface also rated OSM features significantly higher (p=0.046) then students in the similar category who used the OSM interface. In other words, the presence of social comparison made the traditional OSM part, presentation of one's own knowledge, more valued as well.

TABLE 10

MANN WHITNEY U RESULTS FOR SUBJECTIVE EVALUATIONS IN HIGH COMPARISON GROUP

Variable	OSSM Mean	OSM Mean	U
Usefulness of OSSM	4.50	3.44	14.000*
Usefulness of OSM	4.21	3.44	31.000*

** Significant result (p<0.05)*

8 DISCUSSION AND CONCLUSION

In this paper we presented a visual implementation of an open social student modeling approach and compared it to the traditional open student model without a social component, in a semester-long classroom study. Student answers to the administered questionnaire indicated positive attitudes to both, traditional OSM features and new OSSM various features; however, the OSSM interface had a remarkable engagement power: a much higher ability to engage and retain students than OSM. OSSM motivated students to perform significantly more work with non-mandatory learning content. These features of OSSM make it very attractive for contexts where motivation and retention are critical, such as modern MOOCs. In addition, social visualization enabled students in the OSSM group to work more efficiently, which could be attributed to the navigation support aspect of our OSSM implementation. Working with OSSM also positively impacted student learning, significantly improving the learning gain of weaker students. This could be attributed to the increased work with the content (as shown by the correlation between the amount of work and exam grade). While it is hardly surprising that more work with learning content resulted in better learning, it is impressive that we were able to achieve this effect with non-mandatory educational content, which the students explore at their own will.

The analysis of possible differential impacts of social comparison aspects on males and females revealed a significant interaction between group and gender in respect to student engagement. Male students were significantly more affected by the social comparison affordances. While female students in the OSM group used the system more than males in almost every aspect, male usage grew remarkably from the inclusion of social comparison features in OSSM. The larger impact of OSSM on male students is also confirmed by student feedback analysis. In contrast, the analysis of efficiency showed an opposite trend: only female students demonstrated a significant increase of efficiency with OSSM. In other words, it was mostly males who caused the remarkable usage increase; it was mostly females who caused the significant increase of efficiency.

Analysis of the differential impact of OSSM on students with low and high comparison tendency did not confirm the expected usage differences between these cohorts. The impact of the OSSM interface on high and low groups was comparable. These data suggest that the usage increase in the OSSM group is only marginally related to this scale. On the other hand, we did find some sensitivity of scale values to students' perception of system features. The high comparison oriented group rated the social comparison features of the system higher than the low comparison oriented group. Moreover, comparing the *perceived* value of social comparison features (as rated by the OSM group that had no access to those features) with the opinion about *actual* social comparison features in the OSSM group among high comparison oriented students, we found that reality was significanlty more valuable than expectation.

Taken together, these fundings provide interesting insights on the impact of OSSM features on different kinds of students. The positive nature and the magnitude of this impact encourages us to recommend MasteryGrids-style social comparison interfaces to the developers of practice-oriented systems based on non-mandatory learning content.

In the end, we must acknowledge that the study confirmed the value of OSSM in one specific context – a graduate class in a large US university. The impact of the same interface might be different for other kinds of students and in different countries. We plan to investigate the impact of these factors in future work.

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