An Intelligent Interface for Learning Content: Combining an Open Learner Model and Social Comparison to Support Self-Regulated Learning and Engagement

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ABSTRACT
We present the Mastery Grids system, an intelligent interface for online learning content that combines open learner modeling (OLM) and social comparison features. We grounded the design of Mastery Grids in self-regulated learning and learning motivation theories, as well as in our past work in social comparison, OLM, and adaptive navigation support. The force behind the interface is the combination of adaptive navigation functionality with the mastery-oriented aspects of OLM and the performance-oriented aspects of social comparison. We examined different configurations of Mastery Grids in two classroom studies and report the results of analysis of log data and survey responses. The results show how Mastery Grids interacts with different factors, like gender and achievement-goal orientation, and ultimately, its impact on student engagement, performance, and motivation.

Author Keywords
Open Learner Model; Achievement-Goal Orientation; Self-Regulated Learning; Social Comparison

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; K.3.1. Computers and Education: Computer Uses in Education

INTRODUCTION
In many courses offered by modern universities, mastery of a subject comes only after considerable practice. Subjects like college-level mathematics, physics, chemistry, or computer science expect students to work with simulations, examine worked-out examples, and practice their skills by solving a large number of problems. Only a limited amount of this practice (typically problems) is usually assigned to students as a part of course requirements; the rest is recommended for students to complete as practice. This division is well-justified, since different students need considerably different amount of practice. Historically, practice examples and problems were provided by textbook authors at the end of every chapter, and teachers recommended them as practice assignments when this chapter is assigned for reading. However, the increased use of computers as learning tools has gradually led to creation of large numbers of computer-based practice systems oriented toward student self-study. For example, in the area of learning programming, we can distinguish several types of practice content that is now supported by many practice-oriented systems: worked-out examples that allow students to examine meaningful problem-solving approaches [6]; program animations that visually demonstrate program behavior [15]; program tracing exercises that engage students in understanding language semantics [5]; and program construction exercises that allow students to practice their composition skills [26].

Years of studies have demonstrated the strong educational benefits of each of the listed kinds of practice content. Moreover, the recent advancement of Web technologies has led to the steady transition of many practice-oriented systems from stand-alone to Web-based, with solid volumes of practice content accessible online. Surprisingly, these shifts have not led to a similar revolution in the use of this practice content. As observed by a recent report [3], overall student exposure to this content is low.

In this work, we present the Mastery Grids system, an intelligent interface for online learning that attempts to resolve this unfortunate situation and considerably increase student work with several types of practice content, from examples to problems. The Mastery Grids interface combines several

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design decisions to address several known obstacles to work with practice content: all types of content are accessible from the same integrated interface, avoiding the need to log into different single-content systems; student-changing state of knowledge is visualized in the form of an open learned model (OLM) to support self-regulated learning and guide students to the most appropriate practice topics and content; social comparison in the form of peer and class progress is offered to provide additional motivation and navigation support. We grounded the design of Mastery Grids in self-regulated learning and learning motivation theories, as well as in our past work in social comparison, OLM, and adaptive navigation support. The force behind the interface is the combination of adaptive navigation functionality with the Mastery-oriented aspects of OLM and the Performance-oriented aspects of social comparison. To assess the value of our approach, as well as specific design decisions, we examined different configurations of Mastery Grids in two classroom studies and report the results of analysis of the log data and survey responses. The results show the overall impact of our technology on student engagement, performance, and motivation, as well as insights in the ways in which Mastery Grids interacts with different factors, like gender and achievement-goal orientation.

BACKGROUND

Open Learner Model and Open Social Student Modeling

Open learner models (OLMs), which are also referred to as open student models (OSMs), are an important kind of educational interface that has emerged in the area of personalized learning systems. While in traditional personalized systems, student models that represent the current state of student knowledge are hidden from students and are used solely to personalize the educational process, more recent open student model interfaces introduced the ability to view, explore, and even modify the state of a student's own knowledge [8]. Typically, the state of knowledge is displayed using some form of visualization, such as a set of skillometers [19] or a knowledge map [16]. By visualizing, and sometimes, interacting with her own learning or achievement representation, the learner is given a powerful feedback tool that is known to impact her metacognition and self-regulated learning strategies [9].

Recent projects attempted to enhance the value of OLMs in several ways. The most popular among these efforts is integrating OLM with interfaces to access learning content [18, 25, 22]. In this way, an OLM provides personalized navigation support that helps students to select the most appropriate content for their skill levels. Studies show that this kind of personalized support could increase the efficiency of student work and also increase their motivation to work with learning content [18, 25].

Other researchers have attempted to enhance the engagement power of OLMs by using ideas of social comparison; namely, by allowing students to explore each others' models [7] or to view a cumulative model of the class [13, 4], thus triggering social comparison effects. This approach, which has been referred as Open Social Student Modeling, has demonstrated a considerable positive effect on engagement and efficiency, causes students to complete more practice content, and allows them to move quickly to the next content items [13, 4].

Self-Regulated Learning and Achievement-Goal

Self-regulated learning (SRL) defines the learner as an active participant who monitors and applies strategies to control her own learning process cognitively, metacognitively, and emotionally [29]. A key aspect in SRL is the interdependence between motivation and self-regulating processes [29]. For example, self-efficacy, an element of self-regulation, is viewed as the force behind learning motivation [2] and has a strong influence in goal-setting [23]. Moreover, a self-regulated learner, "who proactively seek[s] out information when needed and take[s] the necessary steps to master it" [28], is closely related to the Mastery-Approach orientation defined by the Achievement-Goal Orientation framework [11]. This framework argues that students' motivation while facing a learning situation translates to different types of goals, and defines a 2x2 classification of goal orientations: *Mastery-Approach* oriented students pursue learning, while *Performance-Approach* oriented students pursue achievement and are usually more sensitive to comparison and scores. *Mastery-Avoidance* students avoid not to learn or learn too little, and *Performance-Avoidance* students avoid to perform worse than others or receive low scores. Relationships between SRL and achievement goals are well studied. For example, students who present high levels of mastery goal orientation and who are intrinsically motivated to learn also present higher levels of SRL elements, including higher self-efficacy and the use of self-regulatory strategies [27].

Researchers have also studied how different goal orientations can be fostered, a finding that suggests that mastery oriented environmental factors (such as learning autonomy) can promote the adoption of mastery goals [10], while performance-oriented elements, like score rankings, can account for the adoption of performance goals, such as competition to score higher than other students [20]. While mastery and performance orientations seem to represent opposite values, they can coexist: a student can present high levels of performance- and mastery-oriented goals at the same time [1]. Our system follows these ideas by integrating mastery orientation provided by OLM, which allows the learner to monitor her own learning progress, and performance orientation is provided by social comparisons features.

MASTERY GRIDS: AN INTELLIGENT INTERFACE FOR PRACTICE-ORIENTED LEARNING CONTENT

The Mastery Grids system is an attempt to design an intelligent interface for accessing learning content that provides support for SRL and allows learners to monitor their course progress. In its core, it follows our earlier work that integrated content navigation with OLM-based knowledge progress visualization [13]. To complement the benefits of OLM, Mastery Grids (MG) also engages the power of the Open Social Student Model by incorporating visualization based on the models of other students. The MG interface presented below adds several features to its first version presented in [17].

The interface of the Mastery Grids system (Figure 1) is composed of several grids showing different aggregations of progress information. In all grids, columns represent topics and rows represent different types of content (such as problems, examples, or animations). The first grid shows an extended OLM that visualizes the learner's own progress over several kinds of practice content. Each cell shows knowledge progress, with one kind of content for one topic using a different density of green color. The third grid (number 2 in Figure 1) represents the average progress of the *reference group* using a varying density of blue color. A combo box in the menu bar allows the student to use the whole class, or just the top students, as a reference group (number 7 in Figure 1). Different colors were used to represent the group average and the learner (blue and green, respectively) in order to implement the differential comparison in the second grid (number 3 in Figure 1). When the group has a higher progress than the learner on a specific kind of content in a specific topic, the corresponding cell in the second grid becomes blue. Otherwise, it becomes green. The intensity of the color represents the intensity of the difference, and a gray color means there is no difference.

In the bottom part (number 4 in Figure 1), a progress grid for each of the students in the group is shown (with the top progressing students shown first). The list does not show the names of the students. To be consistent with the colors used in the first grid, each peer grid is represented in shades of blue and the learner is represented in shades of green, which also facilitates locating the learner in the list. Figure 1 shows the learner in the 3rd position of the list. To speed up the interface loading, the ranked list of peers is only shown when clicking in the button "Load the rest of the learners," which is located below the 3rd grid and does not appear in Figure 1.

By clicking on any topic cell, the user can access the practice content of this topic, shown as activity cells organized in rows by content type (number 5 in Figure 1). By clicking in the activity cells, the content is loaded in an overlaid window. Mastery Grids integrates different types of online "smart" content from different content providers. "Smart" content [3] interactively engages students, provides mechanisms to store and retrieve student activity data, and ultimately, incorporates feedback mechanisms. The captured activity data are processed by MG's back-end services to compute knowledge progress. For example, each programming problem included in the Mastery Grids system shows the correct answer to the student and logs the student response in a User Model server, which can provide summaries of this data back to Mastery Grids. The version presented in this paper includes three types of smart content for a Java programming course: programming problems [14], interactive examples [6], and program animations [24].

To allow for the exploration of a broader design space, different interface components can be loaded in different combinations. A selector widget in the menu bar allows students to select among different progress visualizations for the different content types (number 8 in Figure 1). The user can choose a *full* view in which each grid has separate rows for each content type (as shown in Figure 1), and can also select to display averages by the type of content (for example, showing only progress in examples), or an *overall* view where all the three first grids are collapsed in one grid with one row for the learner progress, one row for the comparison, and one row for the group progress, as shown in Figure 3. The *overall* view mode is set as the default view. In addition, all comparison features can also be completely hidden by clicking the button "Individual" (number 6 in Figure 1), which leaves only the personal part of the interface visible, as shown in Figure 2.

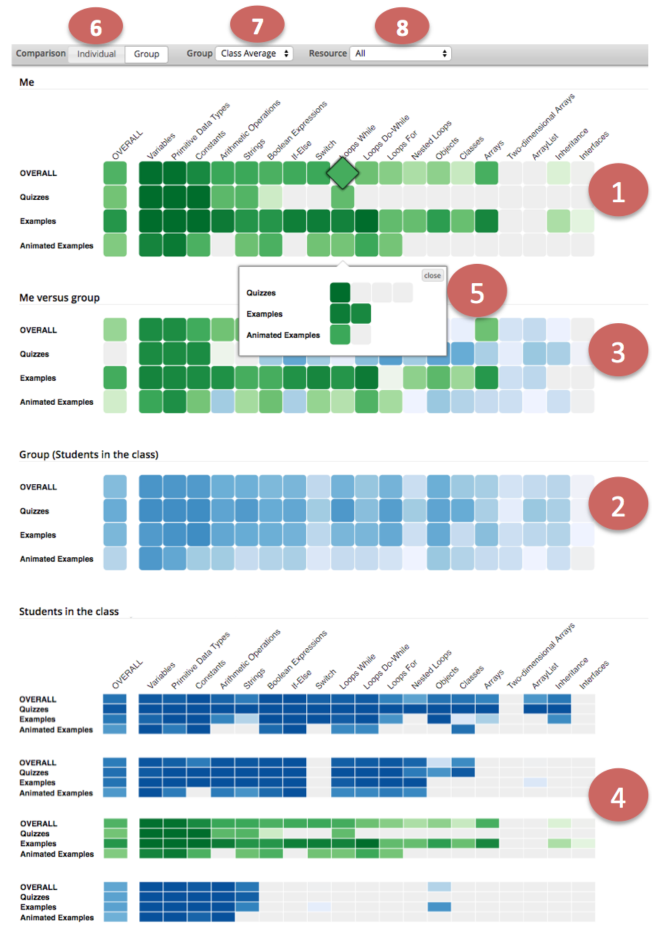

Figure 1. The full Mastery Grids interface. A menu bar contains controls to change the view of the group or the details shown. Circled numbers have been added in the image to support explanations.

The Mastery Grid interface can be configured to hide or show the menu controls (numbers 6, 7, and 8 in Figure 1), as well as to enable or disable the OSSM features for a specific group or for individual users. For example, this allows us to show social comparison features only to some students, or to enable all features for the instructor. Figures 2 and 3 show different configurations of Mastery Grids both with and without social-comparison features, respectively.

CLASSROOM STUDIES

In this work, we reported the analyses and results of two semester-long classroom studies in an introductory Object-Oriented Java programming class during 2014-2015. Classes were taught by the same instructors and had the same setup.

Figure 2. Mastery Grids with minimal features or individual view (all social comparison features have been disabled).

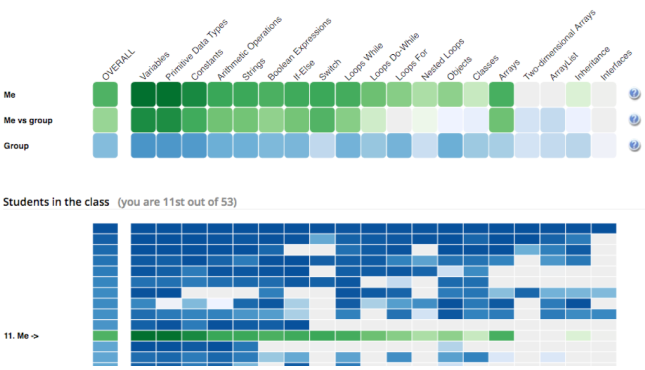

Figure 3. Mastery Grids with social comparison features and collapsed grids, averaging the progress across types of resources.

The studies were designed to explore the engagement effects of the system features, especially the social comparison elements presented in Mastery Grids, and to examine the mediating impact of the learner's motivational characteristics. To support this goal, different features of the system were enabled or disabled to different student groups, which is explained in detail in the next section.

To characterize learners' motivation, we choose the Achievement-Goal Orientation Framework [11] because of its strong relations to Self-Regulated Learning as depicted in the Background section. To measure goal orientation, we use the Achievement-Goal orientation questionnaire [11], which contains 12 questions in a 7-point Likert scale, which corresponds to 3 questions for each of the Achievement-Goal factors: Mastery-Approach ("My goal is to learn as much as possible"), Mastery-Avoidance ("My aim is to avoid learning less than I possibly could"), Performance-Approach ("My goal is to perform better than the other students"), and Performance-Avoidance ("I strive to avoid performing worse than others").

Classroom setup and data collection

Each classroom study was divided into 2 parts. Part 1 started at the beginning of the term, when some details of the study and the Mastery Grids system were introduced to the students with a live demonstration. The Mastery Grids system was initially set up with minimal features, as shown in Figure 2. Instructors offered around 1% of extra credit for participating in the study, including solving at least 10 problems in the system. A pretest was applied in conjunction with an initial measure of the Achievement-Goal questionnaire.

Part 2 started in the fifth week, 3 weeks before the midterm. At this time, students were randomly classified in 4 groups, according to the presence of social features (*social* factor) and/or the presence of the resource selector component (*resource* factor). Pretest scores also balanced the assignment to groups. The four groups are named as follows: *control* or *C* (keep the individual view), *resources-on* or *R* (add the resource selector feature in the menu), *social-on* or *S* (add the social comparison features), *social-resources* or *SR* (add both social comparison features and resource selector). At the beginning of Part 2, an email was sent to all students with a reminder of the study, a reminder of instructions to access the system, and a brief explanation of the new features introduced (for the control group, the email contained only the reminders). A week before the midterm, the Achievement-Goal questionnaire was applied again. At the end of the term and the end of Part 2, a post-test, the achievement-goal questionnaire, and a usability/usefulness survey of the Mastery Grids system were administered. Consent forms were also collected in order to use the data from questionnaires. The three moments wherein the achievement-goal factors were measured are referred to as *initial*, *middle*, and *final* measures.

Table 1. Number of students participating in the studies. Number of female and male students in parentheses.

		Resources		
		Resources On	Resources Off	Total
Social	OSM	23 (12, 10)	20 (8, 12)	43
	OSSM	22 (11, 11)	24 (7, 15)	46
	Total	45	44	89

Activity on the system occurring during Part 1 of the study is referred to as activity *before conditions were introduced* or simply, *Part 1*. Similarly, activity during Part 2 is referred to as activity *after conditions were introduced* or *Part 2*. Recall that during Part 1, all students had access to the same basic features of the system (Figure 2).

The system usage data includes logs of sessions (different log-ins into the system), problems attempted and solved, examples displayed, animations displayed, and other interface interactions, like changes on the resource selector or group selector menu and clicks on the button "load others" (see description of Mastery Grids and Figure 1). Time spent on activities was also recorded. Engagement is measured in absolute scores of system activity and relative scores of activity or time by session in the system.

In total, 89 students who logged into the system at least once (38 female, 48 male; 3 students did not provide gender information) out of 114 students enrolled were used for the analyses in this paper. The number of students in each of the groups can be seen in Table 1. Female and male student counts are shown in parentheses.

In the next sections, we first present analyses on the difference between OSM and OSSM interfaces; i.e. the *OSM* group includes *C* and *R* groups; the *OSSM* group with social features enabled is the combination of groups *S* and *SR*. Then, we briefly analyze the resource selector feature on system usage.

ASSESSING THE OVERALL VALUE OF THE INTERFACE

To explore the value of both the OSM and OSSM, we compared the usage statistics of our classroom studies using the Mastery Grids system to a previous classroom study offered

Table 2. **The Mean±SD of system usage statistics: comparison between a portal of course materials and the Mastery Grids system across all groups (MG), the OSM group, and the OSSM group.**

Parameters	Portal	MG	p-value	OSM	p-value	OSSM	p-value
Logged-in students	17	89	-	43	-	34	-
Active students	14 (82%)	80 (90%)	-	40 (93%)	-	30 (88%)	-
Sessions	2.71±1.49	7.54±6.05	.000 ***	7.45±5.76	.000 ***	9.37±6.49	.000 ***
Distinct topics	9.21±4.85	9.4±5.6	.97	9.3±5.71	.89	11.47±4.75	.192
Problem attempts	72.36±67.25	78.88±62.18	.556	76.45±54.33	.534	100.83±69.51	.07 .
Distinct problems	32.79±21.67	43.74±28.26	.21	43.6±28.25	.15	53.2±25.86	.01 *
Distinct problems solved	28.43±19.2	41.92±28.13	.126	41.88±28.7	.152	50.77±25.57	.003 **
Success rate	.707±.147	.648±.144	.182	.639±.147	.153	.627±.127	.094 .
Repeats per problem	2.52±1.81	1.8±0.77	.318	1.83±0.84	.402	1.85±0.74	.579
Success per problem	1.8±1.36	1.11±0.35	.1	1.11±0.33	.139	1.12±0.39	.098 .
Failure per problem	0.72±0.61	0.69±0.56	.534	0.72±0.67	.418	0.73±0.45	.338
Examples viewed	13.27±9	32.52±26.23	.019 *	31.02±26.67	.035 *	41.57±24.67	.000 ***

significant level: ***: <.000; **: <.01; *: <.05; .: <.1

in Spring 2008 in which students used a traditional non-adaptive portal to access comparable volumes of the same practice content. The *Portal* presented the content in a simple two-level hierarchy of HTTP links, the first level offered a list of topics and the second level listed links to parameterized problems and interactive examples. Table 2 provides the summary of usage statistics of the *Portal* and the Mastery Grids system across all groups (*MG*), the *OSM* group, and the *OSSM* group. Usage statistics are computed based on the data of *active* users who had at least 5 problem attempts in the portal, whole system (MG), or in a specific condition (OSM or OSSM). Because the OSSM group did not have social features during Part 1, we consider as *logged-in* OSSM users those who logged in during the Part 2 (34 out of 46) and as *active* OSSM users those who have at least 5 problem attempts in Part 2 (i.e, have a reasonable chance to experience "true" OSSM condition). This explains why active users for both the OSM and OSSM groups does not add up to the total active users in the *MG* column: there are 10 students in the OSSM group who had enough activity to be considered as active MG users but did not have enough activity in Part 2 to be considered as *active* OSSM students. In other words, only 30 OSSM students who attempted 5 or more problems during Part 2 are considered as *active* OSSM students. Columns four, six, and eight of the table report the observed significance level (p-values) for the statistical tests that were carried out to compare each usage parameter between the Portal and MG, between the Portal and the OSM group, and between the Portal and the OSSM group, respectively[1].

According to Table 2, the Mastery Grids system performed significantly better than the Portal in engaging students to work with the non-mandatory course materials. The OSM/OSSM interface made the Mastery Grids system arguably more addictive than the basic portal: the average number of sessions and examples viewed were significantly higher in all conditions of the Mastery Grids system (MG, OSM, and OSSM). Progress tracking also allowed students to better distribute their efforts: on average, when using Mastery Grids, students explored and solved more distinct problems. This difference becomes significant for the OSSM group, where they accessed about 1.6 times more distinct problems than in the *Portal*. This indicates that the navigation support available in Mastery Grids decreases students tendency of staying with the same content (for example, repeating problems they have already mastered), and as a result, students moved on to new problems more quickly. This data correlates (but not significantly) with a slightly lower *success rate* in the Mastery Grids system. Our data shows that in the absence of mastery indicators and navigation support offering guidance across course topics, students tended to over-stay within topics repeating the same problems even after solving them correctly, which resulted in a larger fraction of successful attempts on the same problems.

These observations indicate that the Mastery Grids system is more beneficial than a traditional portal, in terms of student engagement and effort allocation. In the next sections, we look beyond the engagement level and explore different aspects of the tool, from its impact on student performance to how it affects student navigation patterns, as well as how it interacts with motivational factors.

ASSESSING THE VALUE OF SOCIAL COMPARISON

Effects of OSSM on engagement

To analyze the value of the social comparison component within the overall context of the Mastery Grids system, we compared engagement differences between OSM (C + R) and OSSM (S + SR) groups by examining usage statistics and patterns both before and after conditions were introduced (Part 1 and Part 2). Table 3 shows statistics of usage during Part 1 and Part 2, and within the OSM and OSSM groups. The first row shows the number of students who logged into the system in the corresponding group and part. The other rows show the average usage parameters per student.

There are no significant differences on usage statistics between social and non-social groups before the OSSM conditions were introduced (Part 1 columns in Table 3), which suggests that groups were balanced. Looking at the OSSM (Social) columns in both Part 1 and Part 2, we note a trend of increase of activity and time on the system, while the OSM group tended to decrease the activity from Part 1 to Part 2.

[1]The One-Way ANOVA or Kruskal-Wallis H test was used, depending on whether the assumptions of the parametric test were met.

Table 3. Mean and Standard Error (in parentheses) of student usage statistics in Part 1 and 2 of the studies for OSM and OSSM groups.

	Part 1		Part 2	
	OSM	OSSM	OSM	OSSM
Students	43	46	35	34
Sessions	3.26 (.49)	3.5 (.49)	4.77 (.58)	4.5 (.68)
Problem attempts	40.7 (6.2)	34.9 (6.0)	37.3 (5.2)	48.4 (7.6)
Problems solved	22.7 (2.99)	20 (3.2)	20.3 (3.2)	24.1 (3.5)
Success rate	.66 (.03)	.694 (.027)	.57 (.03)	.58 (.03)
Examples viewed	16 (2.6)	16.9 (2.8)	16.6 (2.8)	18.4 (2.8)
Animations viewed	4.84 (.94)	4.3 (.99)	5.14 (1.28)	7.62 (1.41)
Time on the system	4905 (1043)	4803 (1136)	6416 (1016)	5955 (984)
Time on problems	1386 (245)	1606 (568)	2317 (406)	2204 (396)
Time on examples	1342 (356)	1239 (278)	1605 (353)	1162 (231)
Time on animations	568 (234)	375 (108)	452 (117)	595 (146)
Clicks group selector				1.15 (.47)
Clicks load others				1.06 (.30)
Time by session	1633 (331)	1328 (230)	1247 (154)	1501 (244)
Activity by session	21.38 (3.49)	17.05 (2.29)	12.87 (1.75)	23.58 (4.96)

Note also how time measures increase in both groups, and that this increase is smaller in the OSSM group. To see the differences in the increase of activity or time, repeated-measures ANOVA on activity statistics measured in Part 1 and Part 2 was performed among OSM and OSSM groups. In these analyses, we also include a measure of the total activity by session (at the bottom of Table 3) which sums problems attempts, examples, and animated examples displayed by each student, and divides this sum by the number of sessions the student has. Only students who have activity in both Part 1 and Part 2 were considered. Additionally, outliers were found and removed for the statistics *time by session* (1 student presented an extremely long session) and *activity by session* (4 students showed 1 session with an extremely high number of activities in either Part 1 or Part 2).

We found a significant difference on success rate on problems ($p = .007$) between Part 1 and Part 2, which was expected given that Part 2 involves generally more complex problems. A significant interaction between *Time* (Part 1, Part 2) and *Social group* (OSM/OSSM) factors was found on the amount of *activity by session*, $F(1, 55)$ = 4.972, p = 0.03, η_p^2 = .083. As it can be seen in Figure 4, students in the OSSM group increased their number of activities per session, while students in the OSM group decreased it. Another significant interaction was found for the factors Time, Gender and Social group on the number of examples displayed, $F(1, 45)$ = 6.467, p = .014, η_p^2 = 0.126. Female students in the OSSM group tended to increase the number of examples displayed from Part 1 to Part 2, while male students decreased the number of examples displayed, and both female and male students decreased the number of examples displayed in the OSM group (Figure 5).

We compute the total number of activities by summing problem attempts, distinct examples, and animations displayed. A step-wise regression performed on the total activity in Part 2 showed that total activity in Part 1 (β = 0.515, SE = .115) and *social group* factor (β = 30.431, SE = 12.53) are both significant predictors, p <.001 and p=.019, respectively. Being in the OSSM group means an increase of about 30 activities, as compared to being in the OSM group. Other factors

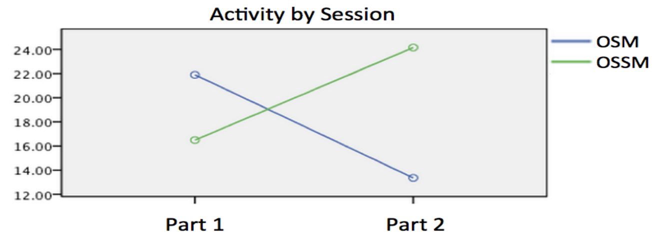

Figure 4. Interaction between Time (Part 1, Part 2) and Social factor (OSM/OSSM).

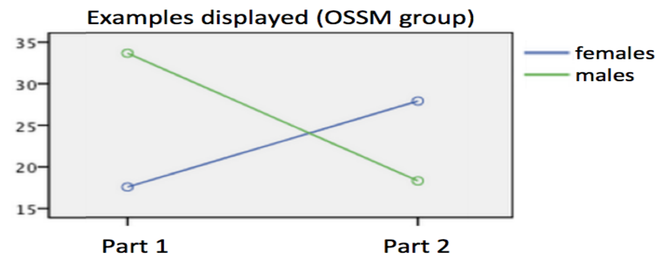

Figure 5. Examples displayed by female and male students in the OSSM during Part 1 and Part 2.

like gender or previous experience did not result in significant predictors and did not enter the step-wise regression model. This confirms the role of social features in engaging students to do more activities.

Effect in performance and instructional effectiveness

We evaluated the effect of the OSM and OSSM on student performance using four measures: (1) *normalized learning gain*, which is defined as the actual gain divided by the possible gain; (2) *course grade*; (3) *success rate*, which is the percentage of correct attempts on problems; and (4) *effectiveness scores*. We conducted several analyses to compare performance differences between the groups (OSM/OSSM). We did not find any differences in the learning gain, success rate, or course grade across the two groups. However, there were some differences in the effectiveness score.

Effectiveness score: To compare instructional effectiveness scores between the OSM and OSSM groups, we looked into instructional effectiveness scores of students, following the approach in [21]. First, we computed $z - scores$ of the performance p_z (correctly answered problems) and time t_z (time spent on problems). Then, the relative effectiveness of a student is computed as the distance between point (p_z,t_z) and the line of zero (0) effectiveness.

For this analysis, we used data from students who attempted at least 5 problems. Although, we did not find a significant difference on the effectiveness scores between the OSM and OSSM groups, differences were found in the change of effectiveness scores among the groups from Part 1 to Part 2. A repeated-measure analysis of variance with both group (OSM/OSSM) and gender as factors showed the main effect of time (Part 1, Part 2) is significant ($F(1, 40) = 27.02$, $p < .001$). The within-subject test indicates that the interaction of time and group is also significant ($F(1, 40) = 4.72$, $p = .036$), in Part 2 the effectiveness scores of the OSSM group ($M = 0.18$, $SE = .426$) were higher than in the OSM group ($M = -2.81$, $SE = .389$). Also, the interaction of gender and group was marginally significant ($F(1, 40) = 3 : 59$, $p = .065$), male students in the OSSM group had higher efficiency scores ($M = 0.12$, $SE = 0.40$) than male students in the OSM group ($M = -0.48$, $SE = 0.37$) during Part 2. In general, we observed a tendency to decrease the effectiveness scores from Part 1 to Part 2, except for male students in the OSSM group.

Effects on navigational patterns

So far, we provided high-level analysis of the intelligent interface in the Mastery Grids system, showed the value of OSSM on engagement, and explored its impact on student performance. In this section, we seek to extend our previous analysis by looking at a micro-level analysis of students' navigation patterns with the goal to understand how the sequence of students' clicks on Mastery Grids cells differs between the OSSM and OSM interface.

We started by classifying students' moves from the current cell to the next cell in the Mastery Grids system into four different groups: (1) *within-topic*, which indicates a move to a cell in the same topic; (2) *next-topic*, which indicates a move from a cell in a topic to the cell in the next topic (according to the sequence of topics in the course), (3) *jump-forward*, which indicates a jump to a cell in a topic that two or more steps further away from the current topic, and (4) *jump-backward*, which indicates a jump to a cell in an earlier topic. A *within-topic* or *next-topic* move represents a sequential navigation, while a *jump-forward* or *jump-backward* move represents a non-sequential navigation pattern. We then computed the ratio of non-sequential navigation for 58 students who had at least one attempt in both Part 1 and Part 2 of the study, and excluded 4 students who had non-sequential navigation scores larger than $2 \times SD$ from the mean. To ensure that these ratios are stable, we considered only 39 (OSM/OSSM : 20/19) students with at least 5 problem attempts in Part 1 and at least 10 problem attempts in Part 2 (the smaller threshold in part 1 is due to the shorter length of the part).

To explore the differences in student patterns between the OSM and OSSM groups, we conducted a repeated measures ANOVA on the non-sequential ratios (Part 1 and Part 2) among OSM/OSSM groups. There was no difference in the non-sequential patterns between the OSM and the OSSM group, $F(1, 37) = 0.50, p > .05$. Similarly, there was no difference in those patterns both before and after social features were enabled in the OSSM; namely, in Part 1 and Part 2 of the study $F(1, 37) = 1.61$, $p > .05$. However, there was a significant interaction between *time* (Part1, Part2) and group (OSM, OSSM), $F(1, 37) = 3.01, p < .10$. More specifically, in the OSM group, the ratio of non-sequential navigation was higher in Part 2 ($M = 0.16$, $SD = 0.08$) than in Part 1 ($M = 0.11, SD = 0.08$).

To investigate further the relationship between the non-sequential patterns on the amount of learning, we performed a step-wise regression to predict the normalized learning gain of students in terms of the following factors: number of total activities on problems and examples, pretest group (low or high by median split), gender, group (OSM/OSSM), and total ratio of non-sequential navigation patterns over the whole semester. The results of the regression showed that only the total ratio of non-sequential navigation made a significant contribution to the learning gain ($\beta = 0.66$, $SE = 0.28$, $p < 0.03$). The non-sequential navigation patterns also explained a significant proportion of variance in the learning gain $R^2 = .20, F(2, 30) = 3.65, p < .04$.

By putting all these results together, the non-sequential patterns increased more in the OSM group than in the OSSM group. This could be due to the social nature of the OSSM that makes students more conservative in their navigation – they tend to sequentially follow their peers rather than browsing the content space by their own, which is often a non-sequential process. More interestingly, there was a positive association between non-sequential navigation patterns and learning gain: those who had a higher proportion of non-sequential patterns gained more knowledge. Although the two groups (OSM and OSSM) were not different in terms of the learning gain, this suggests that students in the social group might gain more knowledge if other adaptive features are added to the social interface, such as individual or personalized guidance. Future studies should be conducted to investigate this hypothesis.

The role of the Achievement-Goal orientation

We now analyze how the motivational profile of the students, as characterized by their Achievement-Goal orientation [11], affects overall engagement in the system and learning effectiveness. For each student, the responses of the Achievement-Goal questionnaire were grouped and averaged by each of the factors. As a result, each student has four scores (Mastery-Approach score, Mastery-Avoidance score, Performance-Approach score, Performance-Avoidance score) for the three moments in the term in which the questionnaires were applied: initial, middle, and final measures.

We first analyze differences in usage between low or high achievement-goal students by classifying students using the median of each of the achievement-goal factors. We used the middle Achievement-Goal measures (measures at the middle of the term) because it is more representative of the state of the goal orientation of the students while using the system. Only 54 students who answered the questionnaire and gave consent are included in these analyses. We found a clear difference on usage only among low and high Mastery-Approach students, while other classifications did not show significant differences. Students in the high Mastery-Approach group have a higher level of activity in all the measures during Part 1. In Part 2, this effect disappeared. A 2x2 ANOVA on usage statistics on Part 2 by the Mastery-Approach factor (low/high) and the group (OSM, OSSM) did not result in any significant main effect or interaction. This suggests that the motivational effect that social features have on the increase of activity observed in the OSSM group might be of another nature than Mastery orientation, and are perhaps related to Performance orientation or a change of Performance orientation during the term.

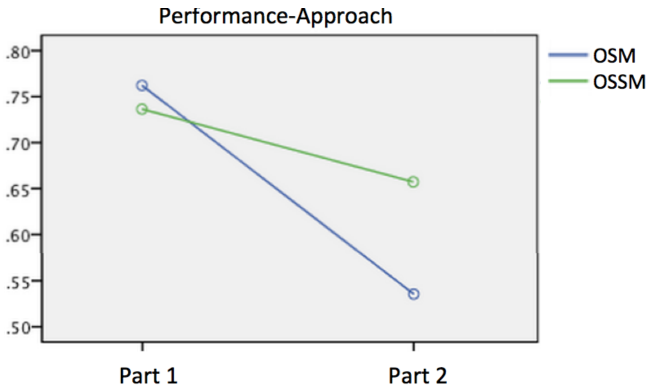

Figure 6. Different decrease of Performance-Approach orientation of students in the OSM and OSSM groups.

We now analyze the change of Achievement-Goal and the interaction with the *Social* factor. Since the literature on Achievement-Goal suggests that Mastery and Performance orientations can be influenced by environmental factors [10], we are interested to see if the use of the system with social comparison features, which are performance-oriented features, has any impact on the change of the goal orientation of the students.

We performed a repeated-measures ANOVA on the initial and final measures of Achievement-Goal orientation between the OSM and OSSM groups. A significant effect on Time (initial, final) exists for all 4 achievement-goal factors, which all consistently decreased during the term. A significant interaction was found for the Performance-Approach orientation and *Social* factor, $F(1, 50) = 7.506$, $p = .009$, $\eta_p^2 = .131$. Students in the OSSM group showed lower decrease of the Performance-Approach level than students of the OSM group (Figure 6). These results suggest either that students who did not decrease their Performance-Approach orientation are becoming engaged by the social comparison features, or that social comparison features are influencing students positively in their Performance orientation. Both of these explanations have support in the achievement-goal literature, and further research is needed to establish a causal relationship. It is interesting to highlight that the Social factor presented no interaction effect, nor a main effect on the change of other Achievement-Goal factors like Mastery-Approach orientation. Even when the social comparison features might foster performance orientation, they are not negatively influencing the mastery orientation.

Now, we look at the relations between Achievement-Goal and the proportion of non-sequential navigation patterns (see previous section for details about non-sequential navigation measures). We consider the Achievement-Goal orientation measures taken in the middle of the term. Only students who answer the questionnaire, gave consent, and present at least 5 attempts to problems in Part 1 and at least 10 attempts to problems in Part 2 are considered, resulting in 29 students, 15 in OSM group and 14 in OSSM group. A significant negative correlation between the proportion of non-sequential patterns and the Mastery-Approach orientation score was found,

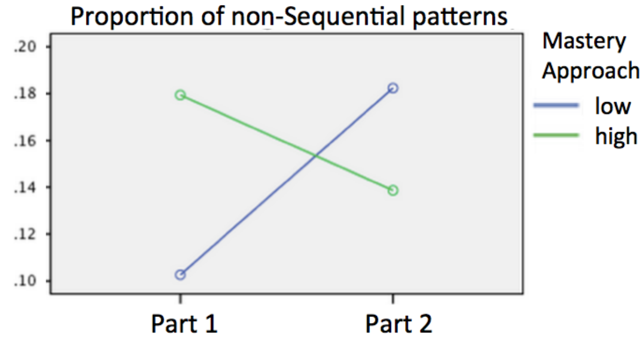

Figure 7. Contrast of the change of the proportion of non-sequential patterns among students in the low and high groups of Mastery-Approach orientation.

$\rho = -.378$, $p = .043$, $N = 29$. This suggests that highly motivated students are more sequential in their patterns of navigation. A significant negative correlation was also found in the difference of the proportion of the non-sequential patterns (Part 2 - Part 1) and Mastery-Approach level, $\rho = -.429$, $p = .02$, $N = 29$. When looking at the OSM and OSSM groups separately, the negative correlation between the difference of non-sequentiality and the Mastery-Approach orientation is stronger in the OSSM group $\rho = -.62$, $p = .018$, $N = 14$, and is not significant in the OSM group. These results suggest that more motivated students become more sequential in their patterns of navigation after being exposed to social features. Step-wise regression analyses showed that other factors, including goal orientation, gender, and *social* factors were not significant predictors of the non-sequentiality proportion in Part 2. However, a repeated measures ANOVA on the proportion of non-sequentiality patterns at Part 1 and Part 2 found a significant interaction of Time and Mastery-Approach group (low/high), $F(1, 27) = 8.135$, $p = .008$, $eta_p^2 = .232$. Figure 7 shows different patterns of the change of the proportion of non-sequential navigation patterns among low and high Mastery-Approach students.

Effectiveness scores (see Section *Effect in performance and instructional effectiveness*) measured in Part 1 and Part 2 did not show any significant correlations with the Achievement-Goal measures (middle). Repeated-measures ANOVA on the effectiveness scores did not show any significant effect of interaction with any Achievement-Goal group (low/high). Regression analyses on effectiveness scores also did not find any significant factor.

The value of peer-level comparisons

The Mastery Grids interface has a number of optional social features that were enabled for the students in the OSSM group: changing the comparison mode through the group selector menu (number 7 in Figure 1), and loading the progress of other students in the class (number 4 in Figure 1) by clicking on the 'load the rest of learner' button in the interface. We analyzed Mastery Grids logs to see how much students clicked on these features. Overall, out of the 34 logged-in OSSM students who logged in the system in Part 2, 18 students clicked at least once on the *group* menu or the *load learners* button, with a median of 2.5 clicks $(Mean =$

$4, Max = 20$). Although students used the social features comparatively few times, there was a statistically significant positive correlation between the number of clicks on these features and overall engagement, ($\rho = 0.41, p < .02$). Those who clicked on these features more had also more activities on problems and examples. Of course, this correlation does not imply causation. The results of the regression analysis also showed that number of clicks on social features had a significant positive impact on the number of activities ($\beta = 5.87$, $SE = 2.25$, $p < 0.02$), which can explain about 18% of the variance ($R^2 = 0.18$, $F(1, 32) = 6.84$, $p < .02$).

THE IMPACT OF INTERFACE COMPLEXITY

To see the value of the resource selector component in the Mastery Grids system, we looked into logs of 45 students who were in the *resources-on* (R) and *social-resources* (SR) groups. In both groups, students were able to switch from the default *overall* view that showed the average progress of content in one row, to the *full* view that showed progress of different content types in separate rows. For example, in the *social-resources* (SR) group, the *full* and *overall* view were similar to those shown in Figure 1 and 3, respectively.

In general, only 11 (24%) students clicked on the resource selector menu, but they did not used it extensively. The average number of clicks on this menu was 1.54 ($SD = 5.33$, $Max = 33$). However, number of clicks on the resource menu was positively correlated with the number of activities that students viewed, $\rho = 0.29$, $p < .06$. Those who clicked more on the resource menu had more problem attempts or example views. This suggests that the presence of a feature alone does not increase students tendency in using it, and that there is a clear trade-off between having a complex interface with different views (the *full* vs *overall* view) and the amount of engagement. Some students might become reluctant to continue working with a complex interface. On the other hand, those who start using such an interface might find it helpful and become even more engaged.

SURVEY ANALYSIS

A usability and usefulness questionnaire was designed to survey student opinion about the system and was applied at the end of the term in both classroom studies. The questionnaire has 2 main sections. Section 1 has 11 questions that refer to the overall usability and usefulness of the OSM features of the system. All surveyed students answered this part. Part 2 contains 14 questions about the usefulness and usability of the OSSM features, which was answered only by the OSSM group. All questions are in a 5-point Likert scale (Strongly Disagree to Strongly Agree). For Section 1, the middle point of the scale (3) is labeled as "No Opinion". In section 2, the middle point of the scale is labeled as "Did not notice". The questions, with their Mean and Standard Error in parentheses, can be seen in Table 4.

Figure 8 shows the distribution of answers. For the analysis and in the figure, questions are grouped by usefulness, usability, and motivation questions. In Section 1, questions 1, 4, 5, 6, 8, 9, and 10 are about the usefulness of the OSM system. Questions 2, 7, and 11 are about usability, and question 3 is about motivation. In Section 2, questions 1, 6, 7, and 8 are general questions about the importance that students give to be able to compare or see others. Questions 2, 3 and 5 are about the usefulness of OSSM features. Questions 4 and 9 are about usability, and questions 10, 12, and 14 are about motivation on OSSM features. Questions 12 and 14 have reversed scales, but are not shown reversed in the figure 8. Finally, questions 11 and 13 ask students about the idea of showing peer names. Some of the question refer to figures showing the features that were included in the questionnaire and are not reproduced here.

Among surveyed students, 63 answered Section 1 and between 20 to 26 students answered Section 2 (only within the OSSM group). In general, the evaluation of the OSM interface, Section 1, is positive in terms of both usability and usefulness. Students also agreed that Mastery Grids motivated them to work in problems and examples. The lower score was given to question 6 ("The interface helped me to plan my class work"), which might has been interpreted as the overall class work plan. We may need to re-phrase the question to stress the idea of planning the work within the system. We further average usefulness questions, usability questions, and motivation questions and test their differences among low and high Achievement-Goal orientation (using the middle measure of the achievement-goal survey). A Krustal-Wallis non-parametric test found a significant difference of usefulness responses among low and high Mastery-Approach students, $\chi^2 = 5.699$, $p = .017$. Other scores (such as usability and motivation) and other achievement-goal measures did not result in significant differences. High Mastery-Approach students were more positive towards the usefulness of the system. A similar analysis was performed for Section 2 within the OSSM group. Questions were classified and 4 scores computed: value (questions 1, 6, 7, and 8), usefulness (2, 3, and 5), usability (questions 4 and 9), and motivation (questions 10, 12 reversed, and 14 reversed). A Krustal-Wallis non-parametric test found significant differences on the value score $\chi^2 = 4.071$, $p = .044$ among Mastery-Approach groups. High Mastery-Approach students value the interface more. A marginally significant difference ($p = .071$) was also found for usability scores, with the same trend: high Mastery-Approach students think the system is more usable.

CONCLUSIONS

This paper presented the Mastery Grids system, an intelligent interface for accessing several kinds of practice content for an introductory programming course. To address several known obstacles to the broader use of valuable practice content, we combined an open learner model, adaptive navigation support, and social comparison technologies. Based on the analysis of literature on learning motivation and self-regulated learning, we expected OSM and social comparison features to provide different motivational dimensions to the tool.

The analyses of data from several classroom studies confirmed the overall engagement impact of our interface and provided important insights about specific interface components such as social comparison and content-level progress

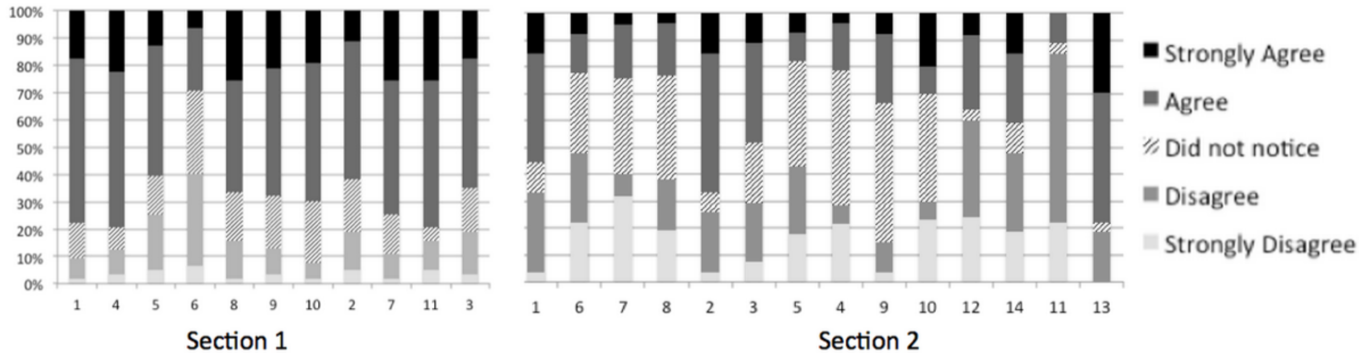

Figure 8. Distribution of responses of Sections 1 and 2 of the Mastery Grids Survey.

Table 4. Questions included in the Mastery Grids Survey. Some of the questions refer to images contained in the survey that are not reproduced here.

	Section 1 questions	M (SE)
1	In general, it was useful to see my progress in Mastery Grids	3.84 (0.11)
2	In general, I liked the interface of Mastery Grids	3.49 (0.13)
3	Seeing my progress in the tool motivated me to work on quizzes and examples	3.60 (0.13)
4	The interface helped me to understand how the class content is organized	3.86 (0.12)
5	The interface helped me to identify my weak points	3.43 (0.14)
6	The interface helped me to plan my class work	2.89 (0.13)
7	It was clear how to access problems and examples	3.87 (0.12)
8	It was useful to see my knowledge progress for each topic (figure 1, A)	3.75 (0.13)
9	It was useful to see how I am doing with individual quizzes and examples (figure 1, B)	3.73 (0.13)
10	The timeline (figure 1, C) was useful	3.79 (0.11)
11	Using green colors in different intensity to show my progress was easy to understand	3.84 (0.14)

	Section 2 questions	M (SE)
1	It is important for me to see the progress of the rest of the class	3.44 (0.19)
2	It was useful to see the progress of the whole class as it is represented in the Group row in Mastery Grids (A)	3.50 (0.18)
3	It was useful to see the progress of the top students as it is represented in the Group row in Mastery Grids (A)	3.30 (0.19)
4	The comparison between the group and myself (B) is easy to understand	3.61 (0.18)
5	It was useful to see the comparison between the selected group and myself (B)	3.33 (0.18)
6	It is important for me to see the progress of individual classmates (C)	3.30 (0.20)
7	In general, it is useful for me to be able to compare my progress with the progress of others	3.44 (0.22)
8	It is important for me to see my position in the class (D)	3.53 (0.20)
9	Visualizing the progress of others using blue colors of different intensities was easy to understand	3.94 (0.17)
10	Viewing my classmates' progress motivated me to work more in quizzes and examples	3.34 (0.22)
11	I think it would be useful for me to know the names of individual classmates in (C)	2.18 (0.17)
12	Viewing that others were more advance than me made me want to quit using Mastery Grids	2.71 (0.24)
13	If names are shown, I will not like to show my name in the list to others	3.91 (0.18)
14	Sometimes I just checked quizzes and examples to catch up with the progress of others rather than to learn more	2.79 (0.24)

visualization. Most importantly, the study demonstrated a significant positive impact of navigation-oriented social comparison interface on student engagement, efficiency, and effectiveness. A more detailed analysis also revealed interesting interactions of social comparison interface with motivational factors. While all achievement-goal orientations tend to decrease during the term, students exposed (and engaged by) social features in the system do not decrease their performance orientation. Student feedback indicated that students find the OSM and OSSM features useful and usable, and that highly motivated students have more positive opinions of these features. These results provide sufficient ground to recommend further exploration and practical use of social comparison technology as a component of interfaces for accessing practice content.

On the other hand, the study has provided some evidence that social comparison could negatively affect the diversity of student navigation, causing students to behave more alike one another. To decrease the unifying effect of social comparison while retaining its engagement value, it might be advisable to combine social comparison and personalized recommendation technologies. Our pilot study of this combination brought positive results [12]. In future work, we plan to further explore the value of OSM and OSSM in the context of practice content access examining different kinds of OLM, different approaches to present social comparison, and different combinations with other navigation support technologies.

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