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IguideME: Supporting Self-Regulated Learning and Academic Achievement with Personalized Peer-Comparison Feedback in Higher Education

Damien S. Fleur[1], Max Marshall[2], Miguel Pieters[3], Natasa Brouwer[4], Gerrit Oomens[5], Angelos Konstantinidis[6], Koos Winnips[7], Sylvia Moes[8], Wouter van den Bos[9], Bert Bredeweg[10], Erwin A. van Vliet[11]

Abstract

Personalized feedback is important for the learning process, but it is time consuming and particularly problematic in large-scale courses. While automatic feedback may help for self-regulated learning, not all forms of feedback are effective. Social comparison offers powerful feedback but is often loosely designed. We propose that intertwining meaningful feedback with well-designed peer comparison using a learning analytics dashboard provides a solution. Third-year bachelor students were randomly assigned to have access to the learning analytics dashboard IguideME (treatment, n=31) or no access (control, n=31). Dashboard users were asked to indicate their desired grade, which was used to construct peer-comparison groups. Personalized peer-comparison feedback was provided via the dashboard. The effects were studied using quantitative and qualitative data, including the Motivated Strategies for Learning Questionnaire (MSLQ) and the Achievement Goal Questionnaire (AGQ). Compared to the control group, the treatment group achieved higher scores for the MSLQ components "metacognitive self-regulation" and "peer learning," and for the AGQ component "other-approach" (do better than others). The treatment group performed better on reading assignments and achieved higher grades for high-level Bloom exam questions. These data support the hypothesis that personalized peer-comparison feedback can be used to improve self-regulated learning and academic achievement.

Notes for Practice

- Learning analytics dashboards have the potential to promote self-regulated learning by giving learners (visual) feedback on their learning behaviour.
- A challenge of such dashboards is not only to raise awareness but also to motivate students to effectively regulate their learning.
- This study presents IguideME, a dashboard that offers the following features: 1) timely feedback on learning activities, 2) grade prediction, 3) comparison to peers with similar goals for their grades, and 4) a message framing the feedback.
- Results indicate that IguideME motivates learners, fosters self-regulated learning, and promotes academic achievement.

Keywords

Learning analytics dashboard, self-regulated learning, social comparison, motivation

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Corresponding author [1] Email: d.s.fleur@uva.nl Address: Faculty of Science, University of Amsterdam, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands. ORCID ID: https://orcid.org/0000-0003-4836-5255

[2] Email: m@zmarshall.nl Address: Faculty of Science, University of Amsterdam, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands.

[3] Email: miguelpieters@me.com Address: Faculty of Science, University of Amsterdam, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands.

[4] Email: n.brouwer-zupancic@uva.nl Address: Teaching and Learning Centre, Faculty of Science, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands. ORCID ID: https://orcid.org/0000-0001-6258-5639

[5] Email: g.oomens@uva.nl Address: Faculty of Science, University of Amsterdam, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands.

[6] Email: a.konstantinidis@rug.nl Address: Center for Information Technology, University of Groningen, Nettelbosje 1, 9747 AJ Groningen, the Netherlands. ORCID ID: https://orcid.org/0000-0002-4342-4650

[7] Email: koos.winnips@rug.nl Address: Faculty of Economics and Business, University of Groningen, Nettelbosje 1, 9747 AJ Groningen, the Netherlands. ORCID ID: https://orcid.org/0000-0002-9994-6466
[8] Email: s.moes@vu.nl Address: Vrije Universiteit Amsterdam, University Library, De Boelelaan 1105, 1081 HV, Amsterdam, the Netherlands. ORCID ID: https://orcid.org/0000-0001-9740-4578
[9] Email: w.vandenbos@uva.nl Address: Department of Psychology, University of Amsterdam, P.O. Box 15916, 1001 NK, Amsterdam, the Netherlands. ORCID ID: https://orcid.org/0000-0002-8017-3790
[10] Email: b.bredeweg@uva.nl Address: Institute of Informatics, Faculty of Science, University of Amsterdam, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands. ORCID ID: https://orcid.org/0000-0002-5281- 2786
[11] Email: e.a.vanvliet@uva.nl Address: Swammerdam Institute for Life Sciences, Center for Neuroscience, Faculty of Science, University of Amsterdam, P.O. Box 94246, 1090 GE, Amsterdam, the Netherlands. ORCID ID: https://orcid.org/0000-0001-5747-3202

1. Introduction

Personalized feedback is important for self-regulated learning (SRL) but it is time consuming and particularly problematic in large-scale courses. Learning analytics (LA) dashboards using automated analysis and visualizations have therefore been developed in recent years to scale the provision of personalized feedback. The approach is seen as promising to stimulate SRL by making students aware of their learning process (Matcha et al., 2020). However, despite the substantial number of dashboards proposed and the early enthusiasm for its potential, successful examples of LA dashboards improving SRL and academic achievement are limited (Matcha et al., 2020; Viberg et al., 2020), and their use in standard, higher education remains anecdotal (Tsai et al., 2020). Furthermore, current LA interventions typically focus on either the learning environment, the learning process, or the learning outcome, while an LA dashboard integrating all three is preferable to effectively foster SRL (Knobbout & Van Der Stappen, 2020). Moreover, predictive and prescriptive analytics using machine learning are essential for state-of-the-art dashboards; yet most LA dashboards merely employ surface-level descriptive analytics (Susnjak et al., 2022). We hypothesize that intertwining personalized feedback with proper peer comparison (peers selected based on shared learning goals), as well as providing predictive analytics in the LA dashboard may be an effective way to increase motivation and prompt SRL.

In this study, we explore the effects of IguideME, an LA dashboard aimed at higher education, providing personalized feedback based on learning goals, using social comparison and grade prediction on various learning activities, as well as integrating information for the learning environment, the learning process, and the learning outcome.

The distinctive features of IguideME are as follows:

1. Social comparison is made with peers sharing the same goal for their final grade, rather than with the cohort average, as is often the case (Schwendimann et al., 2017; Viberg et al., 2020). This is done in order to mitigate the potential for neutral-to-negative effects associated with average comparison and instead shift the response towards more intrinsic motivation.
2. The peer group is transparently and faithfully generated; no manipulation has been made to generate a desired form of social comparison (e.g., upward or downward, far or near).
3. Written feedback has been implemented to make certain categories more salient, depending on how students are compared to their peers. The goal here is to make comparisons that are most likely to stimulate motivation and foster more salient SRL in order to increase the positive effects of the dashboard while minimizing those of potentially less positive forms of comparison.

1.1. Theoretical Foundations

From various SRL models, motivation, (meta)cognition, and emotion clearly play important roles in the learning process (Panadero, 2017). A possible explanation for the limited success so far of student-oriented LA dashboards is that most implementations focus on raising awareness but often leave out the motivational component (Jivet et al., 2017). SRL models indeed argue that motivation is critical for translating metacognitive knowledge into actual SRL (Pintrich, 1999; Schunk & Zimmerman, 2007; Zimmerman, 2008). This study operates under the SRL framework developed by Pintrich and colleagues, upon which the widely used Motivated Strategies for Learning Questionnaire (Pintrich et al., 1993) was built (Pintrich, 1999). In particular, this model formalizes the relationship between goal orientation and self-regulation of learning behaviour. Learners are motivated to follow a course with certain goals in mind, which can be externally oriented (set by external parties) or intrinsically oriented (e.g., self-improvement, self-set standards). Following this framework, a highly motivated learner is more likely to engage in self-regulatory and metacognitive behaviour such as monitoring one's knowledge and progress; evaluating outcomes; planning, selecting, and applying learning strategies (Linnenbrink & Pintrich, 2002; Pintrich, 1999). In turn, strong SRL behaviour is associated with higher academic achievement (Trias et al., 2021; Zimmerman & Schunk, 2001).

A way to support motivation and enable SRL in LA dashboards is to show information that helps students with achieving their learning goals. Importantly, the social nature of SRL is often underestimated, despite being already noted by early theoreticians (Hadwin & Oshige, 2011; Williamson, 2015; Zimmerman, 1995, 2002). In everyday life, people tend to compare themselves to others to assess their abilities, a phenomenon formalized in Social Comparison theory (Festinger, 1954; see Suls et al., 2002). Research indicates that individuals prefer comparison with better-off peers (upward comparison), which pressures them towards conformity, rather than worse-off peers (downward comparison), especially when there is not a threat to self-esteem (Gerber et al., 2018). Moreover, motivation strongly increases when the peers are viewed as similar and relatable (Gerber et al., 2018; Summers et al., 2003; Zell & Alicke, 2010). In the context of education, this would mean classmates with comparable attitudes. Lastly, the distance between the individual and the peer also has an influence on motivation; the closer the peers are in terms of attitude or performance, the more attainable their status seems, which increases motivation to get closer to them (Blanton et al., 1999; Garcia et al., 2013; Gerber et al., 2018; Huguet et al., 1999, 2001).

1.2. LA Dashboards and Social Comparison

In this study, we define comparative LA dashboards as those that compare a learner's learning behaviour to that of related peers. The (often implicit) idea is that such comparisons put one's own learning into perspective and informs on whether sufficient work is being done to reach a goal. For instance, it can give insights into what to focus on. Empirical research on the effects of LA dashboards that deploy social comparison is scarce (Viberg et al., 2020). In most of these studies, student learning activities and performance are compared to an absolute standard, namely the class average, with mixed results (Schwendimann et al., 2017; Viberg et al., 2020). One pitfall is that such social comparison may be either upward or downward, depending on whether the learner's performance is below or above average. Absolute standards also imply that the distance to the norm varies from one learner to another. In other words, there is a risk that a significant segment of learners will be neutrally or negatively prompted by social comparison. Furthermore, the type of data (e.g., grades) provided in comparative LA dashboards and the way they are presented may promote competition and other forms of extrinsic motivation to the detriment of intrinsic motivation. Previous research indicates that, when comparison is mainly upward, an LA dashboard designed around social comparison and goal orientation can be successful at increasing motivation and learning outcomes, both in Massive Open Online Courses (MOOCs; Davis et al., 2017; Günther, 2021) and in higher education (Duan et al., 2022; Fleur et al., 2020; Russell et al., 2020).

Davis et al. (2017) designed a dashboard that showed a learner's activity in a MOOC against that of the "average graduate" from the current and previous weeks, labelled as "role models." They found that students with access to the LA dashboard had higher completion rates and were more engaged, based on activity data. An LA dashboard designed by Günther (2021) compared a user to the class average, as well as to the most active students in terms of study time, which was coloured in green, making it the most salient component of the dashboard. In line with Davis et al. (2017), log data revealed a positive effect on SRL. The LA dashboard in Russell et al. (2020) compared a user's assignment scores and predicted final grade with the class average. Based on the responses to self-report questionnaires, this intervention helped students to persevere in the course. In the LA dashboard of Duan et al. (2022), performance and learning activity were compared to the top 25% of learners in a higher education course. A survey question asking how the participants felt after viewing the dashboard showed that 65% of emotions were negative (including anxiety, hopelessness, confusion, and boredom), while 35% of the reported emotions were positive (including pride, relief, motivation to improve, hope, and enjoyment). Notably, only 7.4% of students reported feeling motivated to improve. Lim et al. (2019) found that exposure to an LA dashboard displaying course compilation and study time against the class average led to negative reported effects, with some positive effects.

Lastly, Fleur et al. (2020) investigated an LA dashboard that showed the learner's current average grade against that of a small group of anonymous classmates with similar goals. The group of peers was generated by the dashboard so as to perform slightly better, on average, than the learner. The dashboard also showed an estimate of the student's final grade in the course. Both components were routinely updated every time a new grade was entered. This dashboard intervention supported extrinsic motivation but did not show any impact on intrinsic motivation. Moreover, while students who used the dashboard obtained higher grades than those who did not, there was no significant effect observed on SRL (measured with self-report questionnaires). These results indicate that social comparison, and stimulating extrinsic motivation in general, may benefit learners if it is not detrimental to intrinsic motivation. This potential beneficial role of extrinsic motivation, under conditions, has also been observed in other studies (Pintrich & Garcia, 1994; Wolters et al., 1996). Taken together, these studies suggest that social comparison can have positive or negative effects on learners depending on the peer group, the object of comparison, and/or the direction and distance of the comparison (upward or downward). This is in line with Social Comparison Theory (Festinger, 1954; see Suls et al., 2002).

One challenge of comparative dashboards is thus to offer social comparisons that maximize its benefits and minimize its risks. Yet, maintaining transparent visualizations with little-to-no manipulation is equally important. Fleur et al. (2020) decided to control the peers presented to the users to better understand how a certain type of comparison can benefit learners. One issue is that the effect is likely to reduce if the user becomes aware of the manipulation. Therefore, its implementation is less likely to be suitable in a context involving multiple courses. Such a manipulation may also have ethical implications if the LA dashboard is deployed beyond purely experimental settings. Most studies did not manipulate the peer group and simply offered comparison with either the average of the whole cohort or the score of the top students. The issue with this approach is that it makes it more likely to generate detrimental comparisons with potential negative effects on motivation.

1.3. Research Aims

We designed the LA dashboard "I guide My Education" (IguideME) around the following features: 1) the student sets a goal for their course grade that 2) is used for relevant peer comparisons, while 3) personalized, real-time automated feedback about the learning environment, the learning process, and the learning outcome is provided via the LA dashboard, including personalized messages and predictive analytics. The aim of this study is to assess to what extent IguideME supports learner motivation, SRL, and academic achievement. To do so, we compared students who had access to the dashboard (treatment group) versus those who did not (control group).

2. IguideME

IguideME collects and processes data from the learning management system (LMS) as well as the connected tools. It presents the resulting information in a dashboard that can be accessed via a link in the LMS. IguideME is developed as open-source software (https://github.com/UvA-FNWI/IguideME). Students used IguideME freely and as they saw fit; they were not directed towards the dashboard by the lecturer or by reminders.

Students can use the dashboard in two viewing modes: "Radar" (default; Figure 1) and "Grid" (selected by a tab; Figure 2). The Radar view provides a spiderweb-like overview, including activities (attendance, study time, summative and formative assessments such as quizzes, practice sessions, and reading assignments), predictive grade, preparation time, and attendance in comparison to peers. The peer group is generated by IguideME based on the course grade goal set by the student (the first time they open the dashboard) and consists of classmates with a similar goal (n=10–12 students per group). The Radar view allows students to gather information quickly about their learning activities and that of their peers and identify aspects of learning that may require attention. Students can then obtain more information about their learning activities (e.g., progress, scores) by clicking on one of the categories in the Radar view or selecting the Grid view, which shows more detailed data about all learning activities.

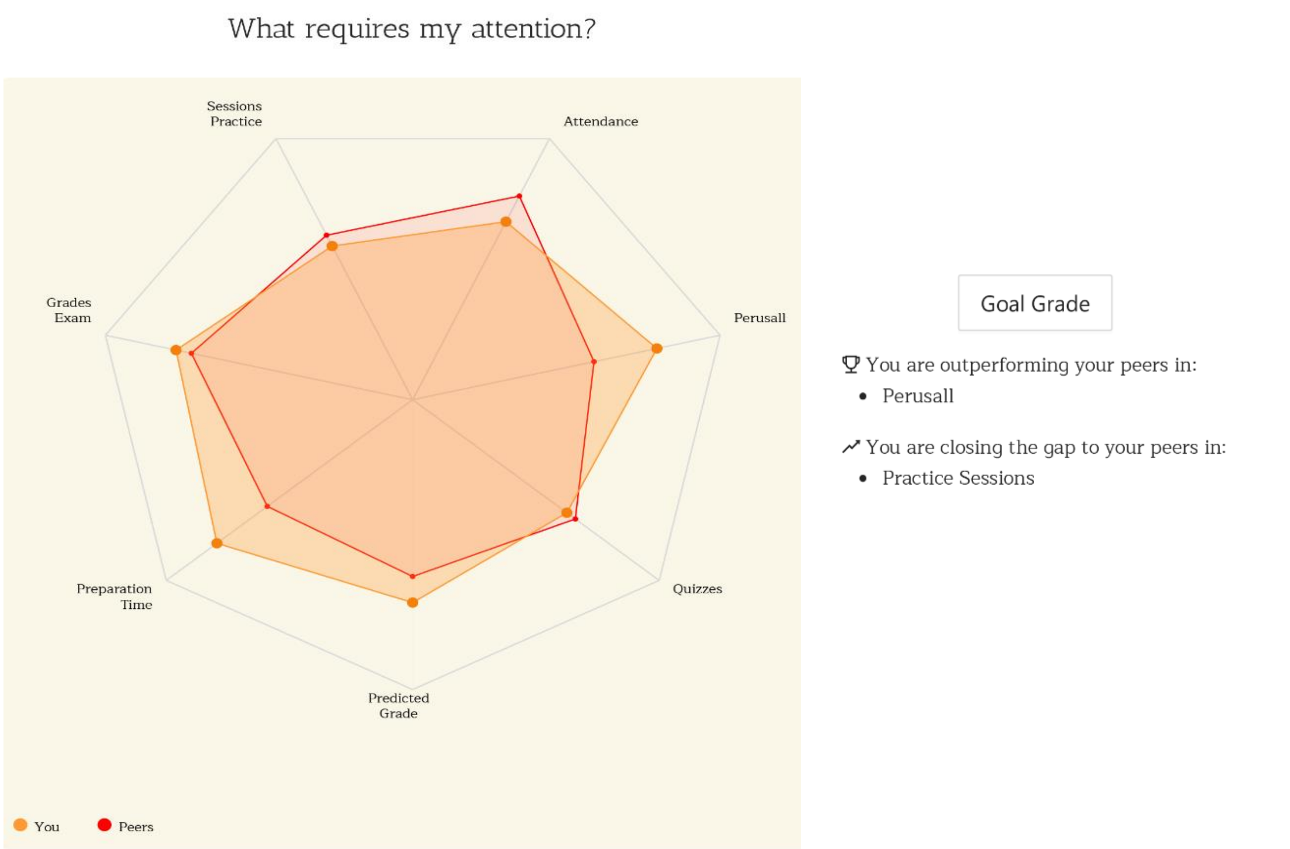

Figure 1. Radar view of the student dashboard.

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Automated feedback messages are generated and presented in the dashboard based on the student's performance for each activity (Figures 1 and 2). Three feedback types are implemented: positive, encouraging, and critical. When the student scores one point higher, as compared to the peer group, the message "You are outperforming your peers in <activity>" is displayed. When the student scores half a point lower as compared to the peer group, the message "You are closing the gap to your peers in <activity>" is displayed. When the student scores one point lower as compared to the peer group, the message "You have to put more effort into <activity>" is displayed. The goal of these messages was to frame the visualization available and orientate the learner towards comparisons that would best prompt motivation. The goal was also to downplay comparisons that may demotivate learners, such as when the distance to peers is too great (i.e., more than one point lower). Although messages were also generated for activities in which the learner outperforms their peers (i.e., a form of downward comparison), we considered this to be acceptable given that it would be provided together with other, more numerous messages related to upward comparisons. Moreover, such messages can act as punctual positive feedback.

In the Grid view (Figure 2), more detailed and personalized information is provided about the summative assessments, formative assessments, learning outcomes, and predicted grade, including a peer comparison. Further information can be obtained by clicking on a tile. The predicted grade is calculated using multiple linear regression, based on all formative and summative assignments during the course. The model is trained using historical data; for each component (activity) a weighing factor is calculated. The predicted grade is calculated with the following formula:

$$Predicted\ grade = e + \beta_0 + \sum_{n}^{i=0} \beta_i * W_i$$

where e is the expected error, β_i is the achieved grade, i is the number of assignments and W_i is the weighing factor. As more assessments are graded and added to the regression, the prediction becomes more accurate.

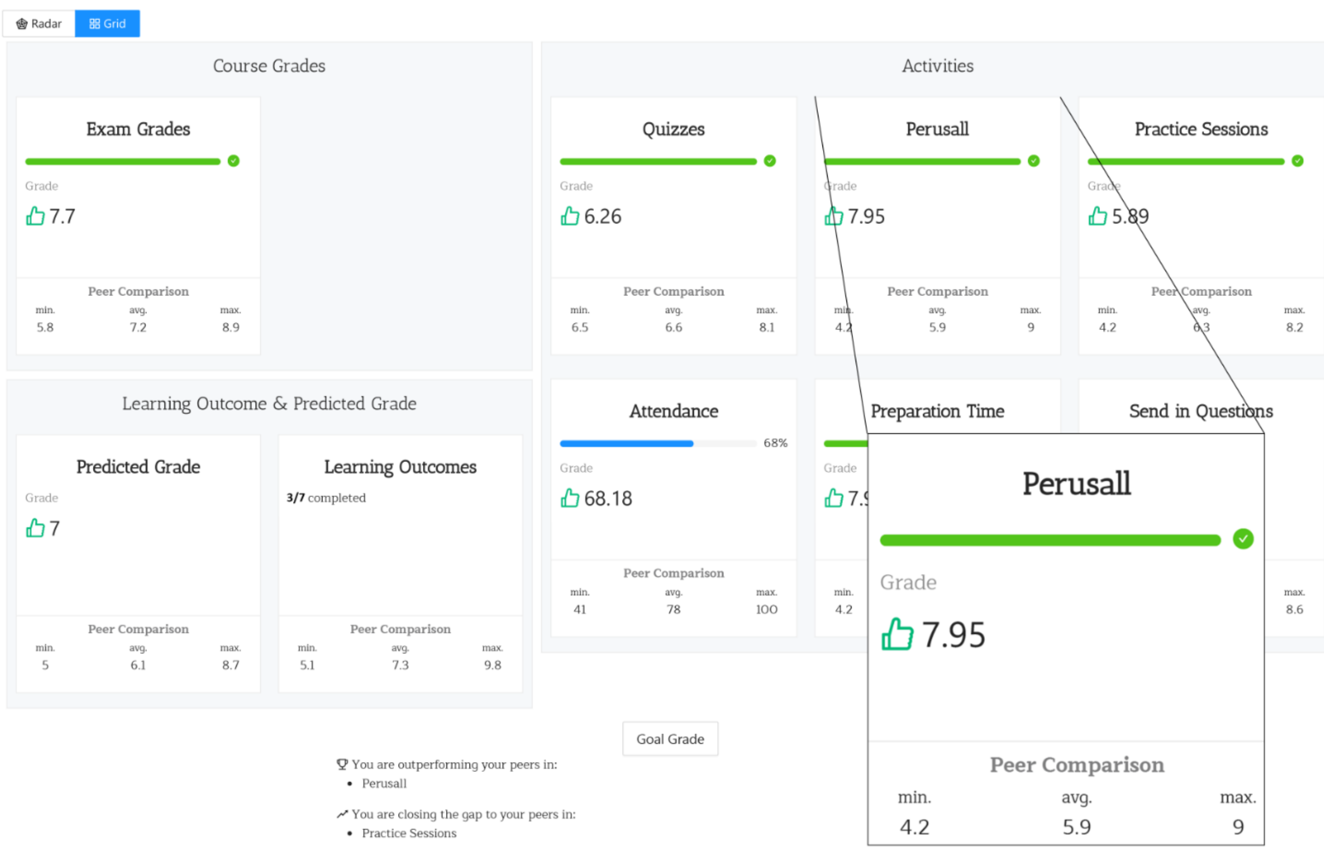

Figure 2. Grid view of the student dashboard with personalized information about summative assessments, formative assessments, learning outcomes, and a predicted grade. A peer comparison is shown on each tile (see enlarged tile). More detailed information can be obtained by clicking on a tile.

3. Methods

3.1. Participants

A cohort of full-time third-year undergrad students (n=62) was followed during an eight-week elective course. Students were randomly assigned to the treatment group (access to IguideME; n=31 in total, 26 females, 5 males) or to the control group (no access; n=31 in total, 27 females, 4 males). The grade point average was not different between groups. Twenty students were excluded from the self-report questionnaire analysis (MSLQ and AGQ, see below) because they did not fully complete the questionnaires at the beginning or end of the course. Thus, 41 students (treatment=23) were included in the questionnaire analysis. Four students were excluded from the learning outcome analysis because they dropped out of the course (sample included in the analysis: n=58, treatment=29). The study was approved by the Ethical Committee of the University of Amsterdam and all students included in the study signed an informed consent.

3.2. Quantitative Measures

The effects of IguideME were studied using the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991) and the Achievement Goal Questionnaire (AGQ; Elliot et al., 2011), which were provided at the start and end of the course. We used the MSLQ to measure motivational and self-regulatory changes. We therefore selected the MSLQ questions related to the following nine components: 1) intrinsic goal orientation, 2) extrinsic goal orientation, 3) task value, 4) self-efficacy for learning performance, 5) metacognitive self-regulated learning, 6) peer learning, 7) time and study environment, 8) effort regulation, and 9) critical thinking. We also used the AGQ to obtain a more fine-grained measure of different aspects of intrinsic and extrinsic motivation. The Achievement Goal model (Elliot et al., 2011) is rooted in the definition and valence components of competence, and is composed of the following six goals:

1. A task-approach goal focused on the attainment of task-based competence (e.g., “Do the task correctly”)
2. A task-avoidance goal focused on the avoidance of task-based incompetence (e.g., “Avoid doing the task incorrectly”)
3. A self-approach goal focused on the attainment of self-based competence (e.g., “Do better than before”)
4. A self-avoidance goal focused on the avoidance of self-based incompetence (e.g., “Avoid doing worse than before”)
5. An other-approach goal focused on the attainment of other-based competence (e.g., “Do better than others”)
6. An other-avoidance goal focused on the avoidance of other-based incompetence (e.g., “Avoid doing worse than others”)

To prevent the questionnaire from becoming too long, we used a subset of questions from the MSLQ (54 out of 81), focusing primarily on motivation and self-regulation components with some additional components we thought important (in total nine out of 15 MSLQ components were used) based on a previous study by van Vliet et al. (2015). From the AGQ, all 18 questions were used. All questions were put together in one questionnaire and randomized. The completion rate was 100%; the response rate was 68%.

We investigated the effects of IguideME on academic achievement from six graded and eight non-graded reading assignments using Perusall (https://perusall.com). Graded and non-graded assignments were alternated. The average grade of the six graded assignments counted for 2% of the final course grade. The grade was based on the value automatically calculated by the Perusall software, using the “holistic” pre-set, considering the following: 1) annotation content score target (60% of the grade), 2) opening assignment target (20%), 3) reading target (20%), 4) active reading target (10%), 5) getting responses target (20%), and 6) upvoting target (20%). These scores add up more than 100%, so students had multiple ways to earn full credit. For the graded assignment, the final score was shown in IguideME to students, while for the non-graded assignments the scores were hidden from students and were only visible to the lecturer.

We also studied the effects of IguideME on the partial exam grades, the final course grade, and the number of students who dropped out. Furthermore, to study the effects of IguideME on the final exam, we scored each exam question according to their Bloom level and categorized them into low-level questions (1 = remember; 2 = understand; 3 = apply) and high-level questions (4 = analyze; 5 = evaluate). In total, 17 exam questions were categorized as low-level questions and three were categorized as high-level questions. Examples of low-level questions include the following: “Which hormone is produced and from which organ?” “Name three lifestyle factors that influence…” “Name three processes that are crucially involved in this disease.” Examples of high-level questions are as follows: “Name two forms of validity established by John Doe et al. (2011) that do not overlap with the forms of validity established by Jane Doe in 1984 and evaluate the effects of these two forms on future experiments.” “Why is the most recent classification an improvement for research and what are the implications for patients?”

3.3. Qualitative Measures

At the end of the term, students had the possibility of evaluating the course anonymously using a standard format provided by the university. To gather some insights on student perceptions of IguideME, we added the following open question: “What is your opinion about IguideME?” Student responses were gathered, and the following categories emerged from their answers:

- I liked the peer-comparison feature.
- IguideME helped me with studying.
- IguideME increased my motivation.
- IguideME provided insights into my learning process.
- IguideME was not interesting.
- IguideME was demotivating.

3.4. Statistical analysis

The Shapiro-Wilk test was used to test if the data followed a normal distribution. Comparisons between the treatment and control groups for normally distributed data were made using Student’s t-test, or else the Kruskal Wallis test was used. $p < 0.05$ was assumed to indicate a significant difference between groups. Effect size was calculated using Cohen’s *d*. The anonymized dataset and analysis scripts are available on the OSF page of the project (https://osf.io/b789s/).

4. Results

4.1. MSLQ and AGQ

At the start of the course, the scores for the MSLQ components did not differ between the treatment group and the control group. In contrast, at the end of the course, the treatment group had a higher score for the MSLQ components “metacognitive self-regulation” and “peer learning” with large effect sizes (Student’s t-test $p = 0.03$, Cohen’s $d = 0.70$ and $p = 0.02$, Cohen’s $d = 0.75$ respectively; Figure 3A and Supplementary Tables 1 and 2).

Similarly, at the start of the course, the scores for the AGQ components did not differ between the treatment group and the control group. However, at the end of the course, the treatment group had a higher score for the AGQ component “other-approach,” also with large effect size (Student’s t-test $p = 0.03$, Cohen’s $d = 0.71$; Figure 3B and Supplementary Tables 1 and 2).

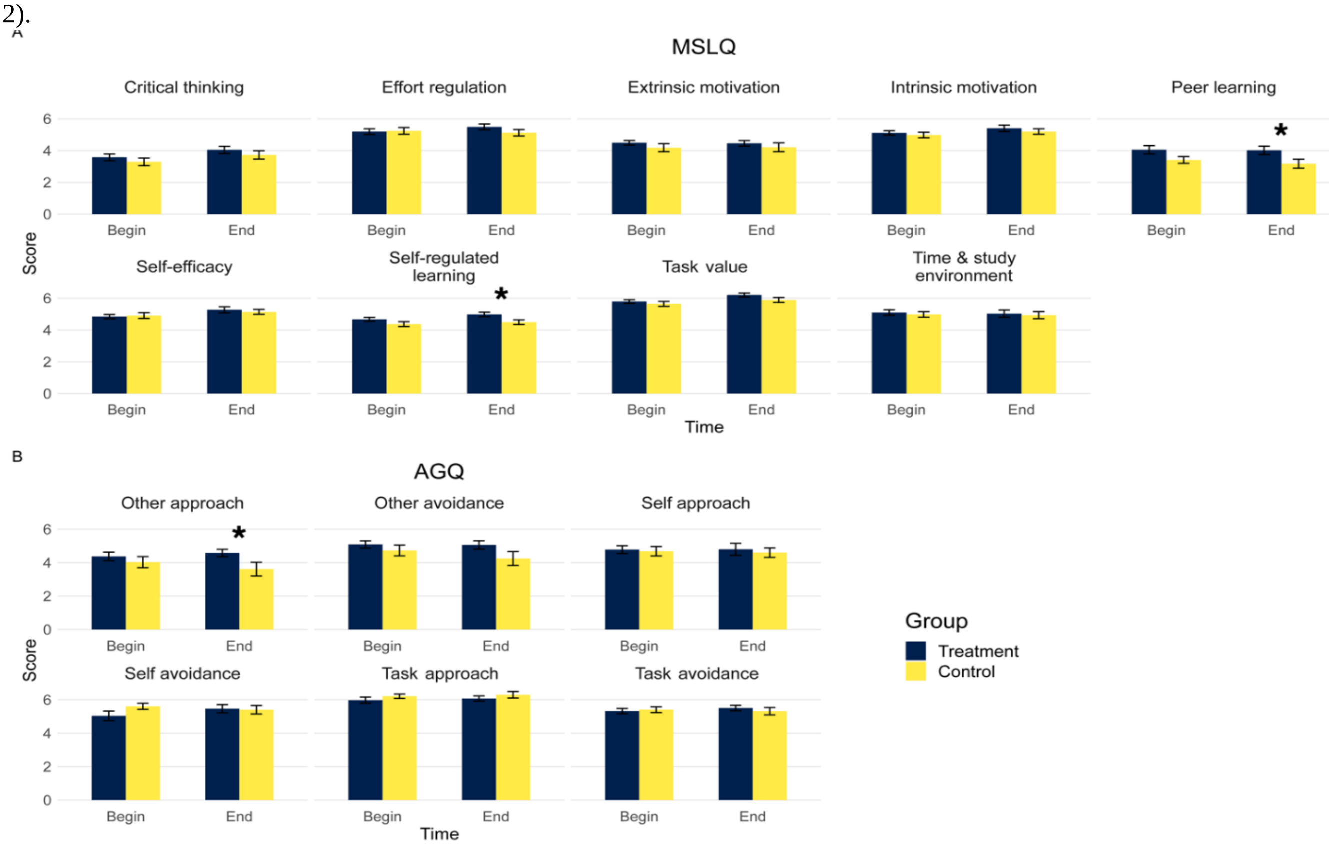

Figure 3. (A) MSLQ component scores for the treatment group (n=23, dark blue bars) and the control group (n=18, yellow bars) at the beginning and end of the course. (B) AGQ component scores for the treatment group (n=23, dark blue bars) and the control group (n=18, yellow bars) at the beginning and end of the course. * Student’s t-test p<0.05 between groups. Bars represent mean±sem.

These MSLQ and AGQ scales were further investigated by comparing scores from the beginning and the end of the course within group using paired t-tests. The results suggest that the effect on "peer learning" is driven by the control group scoring significantly lower at the end of the course than at the beginning (p = 0.03, Cohen's d = 0.54). The other comparisons were not significant (Supplementary Table 3).

4.2. Academic Achievement

We investigated the effects of IguideME on academic achievement from six graded and eight non-graded reading assignments using Perusall. The treatment group showed better performance for both graded and non-graded Perusall assignments as compared to the control group (assignment 3: Kruskal Wallis test p = 0.03; assignment 6: Kruskal Wallis test p = 0.01; assignment 7: Kruskal Wallis test p = 0.03; Figure 4A and Supplementary Table 5), which could be explained by a higher "annotation content score target" (Student's t-test p < 0.05). Furthermore, more students in the treatment group did the assignments (69%) than students in the control group (54%). All other grading parameters (opening assignment target, reading target, active reading target, getting responses target, and upvoting target) did not differ between the groups. Higher scores were obtained when the Perusall assignment was graded (Student's t-test p < 0.05).

The treatment group had a higher grade for high-level Bloom exam questions compared to the control group (Kruskal-Wallis test p = 0.03; Figure 4B and Supplementary Table 5), whereas the grades for low-level Bloom exam questions did not differ between groups (Figure 4B and Supplementary Table 4). Partial exam grades and the final course grade did not differ between the groups. Interestingly, the grade goals set by students correlated to their final grade (Spearman Rank test, r = 0.55, p = 0.01). The number of students who dropped out was low in both groups (control n=1; treatment n=3).

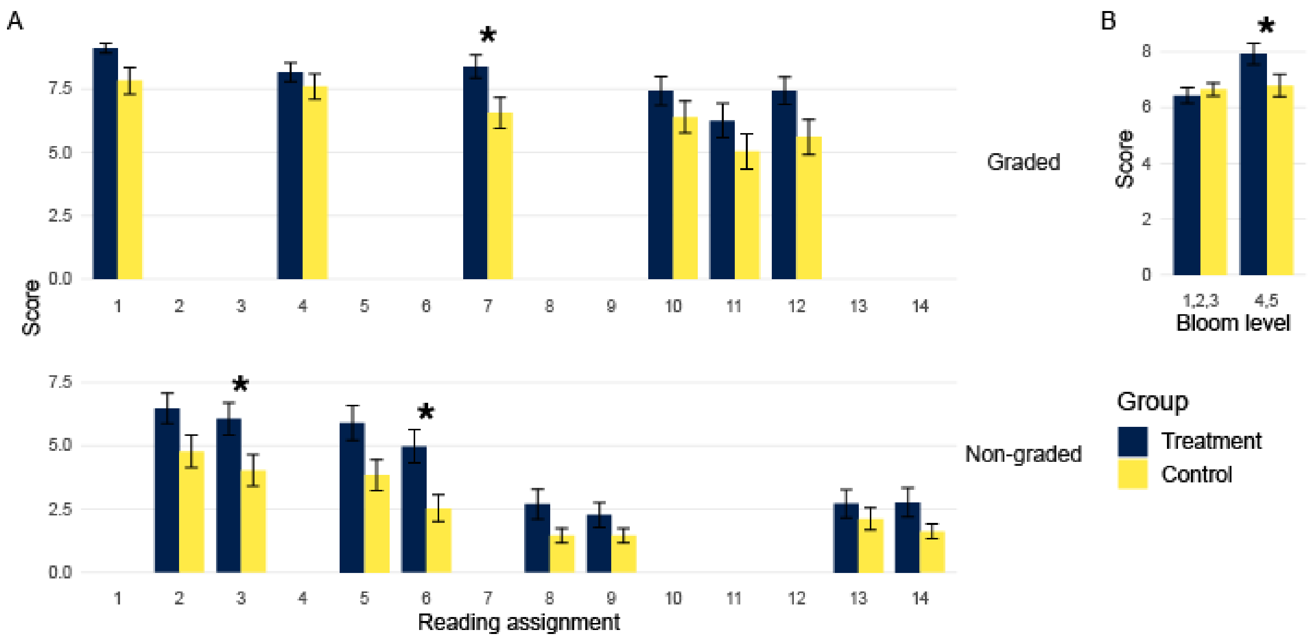

Figure 4. (A) Perusall reading assignment grades for the treatment group (n=31, dark blue bars) and the control group (n=28, yellow bars) for graded assignments (upper panel) and non-graded assignment (lower panel). The order of the assignments is indicated on the x-axis. (B) Grades for low and high-level Bloom exam questions for the treatment group (n=28, dark blue bars) and the control group (n=28, yellow bars). * Kruskal-Wallis test (A) and Student's t-test (B) p < 0.05 between groups. Bars represent mean±sem.

4.3. Qualitative Measure

Seventy-nine percent of the treatment subjects (n=23) answered the question "What is your opinion about IguideME" in the student evaluation. The responses were overall positive. More than half liked the peer-comparison feature, and more than a third found that IguideME helped them with their study, increased their motivation, or helped them understand their learning process. A handful of students found IguideME to be either not interesting or demotivating (Table 1).

Table 1. Responses to the Question, "What is your opinion about IguideME?"

Category	n
I liked the peer-comparison feature	12
IguideME helped me with studying	9
IguideME increased my motivation	8
IguideME provided insights into my learning process	7
IguideME was not interesting	3
IguideME was demotivating	1

5. Discussion and Conclusion

Students who used IguideME had a higher score for the MSLQ components "metacognitive self-regulation" and "peer learning," and the AGQ component "other-approach" as compared to students who did not have access. Furthermore, the treatment group showed better academic performance on both graded and non-graded reading assignments and scored better on high-level Bloom exam questions. Most of the students reported that IguideME helped them with studying, provided insight into their learning process, and increased their motivation. They also liked the peer comparison. These data support the hypothesis that personalized peer-comparison feedback can be used to improve SRL and academic achievement. Moreover, it supports the idea that extrinsic motivation can be compatible with SRL.

5.1. Self-Regulated Learning and Achievement

Students who used IguideME displayed higher scores on average on the MSLQ components "metacognitive self-regulation" and "peer-learning" compared to the control group at the end of the course. At the start of the course, there was no difference between the groups. This suggests that the treatment group developed a more metacognitive and strategic approach to learning. Moreover, the effect sizes for these measures are quite large, indicating practical, not merely statistical, significance. These aspects of SRL and peer learning are in line with the learning outcomes in the reading assignments and the final exam. Overall, the treatment group scored better than the control group in both graded and non-graded reading assignments and obtained more points for high-level Bloom exam questions. The higher grade for the reading assignments could be explained by a higher "annotation content score target," meaning that higher quality annotations were made, while all other grading parameters (opening assignment target, reading target, active reading target, getting responses target, and upvoting target) did not differ between the groups.

Furthermore, more students in the treatment group did the assignments (69%) than students in the control group (54%), indicating that they were more engaged. We view this as a sign of deeper learning activity and enhanced SRL. This also reflects engagement and interaction with peers during learning, which may explain why students in the treatment group had higher scores on the "peer learning" component. For instance, in a study by van Vliet et al. (2015), it was shown that flipped-class pedagogy in combination with collaborative-learning strategies enhanced the MSLQ components of critical thinking, task value, and peer learning, as well as improved the exam grade. In line with the SRL theory (Wolters et al., 1996), this deeper form of learning and knowledge acquisition seems to have helped treatment students to better address high-level Bloom questions in the final exam. For low-level Bloom questions, the treatment group did not differ from the control group. Note that partial exam grades and the final course grade did not differ between groups since most of the exam material was on the lower Bloom levels. Similarly, van Vliet et al. (2015) also found that high cognitive level exam questions were answered more correctly, suggesting that SRL not only leads to more engagement, but also to better and deeper understanding.

A closer examination of the reading assignments shows that students who had access to IguideME scored higher on both graded and non-graded Perusall assignments. However, there was a large class-wide drop in scores in the second half of the course. A possible interpretation is that, by the second half of the course, students became busier and had less time to dedicate to the reading materials.

It is interesting to compare the effect on achievement and SRL with those observed in Fleur et al. (2020) who did find an effect of their dashboard intervention on achievement but not on SRL (note that SRL was assessed in the same way as in this study). A notable difference between Fleur and colleagues' dashboard and IguideME is that the former only provided feedback on grades (assignment and predicted grade), whereas IguideME also provides insights into learning activities, such as reading, attendance, and preparation for exams. We speculate that such insights may be actionable in ways that can be captured by the MSLQ, while insights purely based on grades may not. In future studies, it would be interesting to investigate the most optimal conditions for SRL and to disseminate positive as well as negative factors. These insights may guide further development of LA dashboards.

5.2. Motivation

We also used the AGQ to study the effects of IguideME on motivation. The treatment group showed higher scores on the AGQ component "other-approach" at the end of the course, compared to the control group, whereas there was no difference at the start of the course between the groups. Here as well, the effect size was large. This result is partly in line with the outcomes of previous research (Fleur et al., 2020), which found an increase for the extrinsic motivation component of the MSLQ. While this specific component did not change in the current study, the "other-approach" component can be viewed as a sub-component of extrinsic motivation. This suggests that social comparison in IguideME leads to a constructive motivation-behavioural change. Notably, the AGQ component "other-avoidance" (doing worse than others, another type of extrinsic motivation) and the MSLQ did not change in this study, nor did the MSLQ component "extrinsic motivation," as was the case in Fleur et al. (2020). This is a positive result in pedagogical terms, because it shows that the intervention was successful at mitigating potential adverse motivational factors. Evidence suggests that other-avoidance and other-approach goals are negative and null predictors, respectively, of intrinsic motivation (Day et al., 2003; Elliot et al., 2011; Elliot & Harackiewicz, 1996). Similarly, other-avoidance and other-approach goals have been found to be negative and positive predictors, respectively, of exam performance (Elliot et al., 2011) and learning efficacy (Cury et al., 2002; Elliot et al., 2011; Smith et al., 2002). It is important to note here that more than half of the students who filled out the evaluation reported that they liked the peer-comparison feature and that more than a third of them said they felt motivated, indicating a positive affective impact on learners.

Lastly, we note that IguideME did not lead to changes in scores for some MSLQ components (e.g., critical thinking, effort regulation, self-efficacy, task value, and time and study environment) and some AGQ components (e.g., task-approach, task-avoidance, self-approach, and self-avoidance). For some components, this is quite understandable since our course design and LA dashboard design were not specifically aimed to alter these (e.g., time and study environment). For other components, however — such as intrinsic motivation, self-efficacy, task value, and critical thinking — we did anticipate positive effects. While it is difficult to interpret these results, we may speculate that our course design and/or LA dashboard design were not specific enough to target these components, though the positive effect on the AGQ component "other-approach" does indicate that some form of intrinsic motivation was stimulated. In future studies, it would be interesting to investigate whether a more targeted approach for one or more of these components would lead to positive effects.

5.3. Limitation and Future Research

This study was hampered by the context of the course in which it took place. First, due to the size of the cohort, the sample size for this study was relatively low. In addition, a significant number of students did not complete either or both questionnaire rounds. Second, genders were not well balanced (80% female) and the majority was of Dutch origin. Gender balance could not be controlled since the experiment took place in a naturalistic environment (an existing higher education course) with a set number of students. The findings of a recent cross-cultural investigation suggest that the effects of social comparison for SRL may differ depending on the cultural background of the learner (Guimond et al., 2007; Kang et al., 2013; Xu et al., 2023). These factors influence the generalizability of our results.

The design of this study did not allow for clear attribution of the effects on motivation, SRL, and academic achievement from social comparison, nor was it the aim. IguideME also offered a grade prediction component as well as insights on individual progress. These elements are likely to contribute to the effects observed to some extent. The results do suggest, nevertheless, that IguideME, a dashboard with social comparison features, is appreciated by learners and that it benefits them.

We suggest that future studies investigating social comparison in LA dashboards should try to assess their long-term effects. Indeed, little is known about whether the benefits of LA dashboards hold in the long run and transfer to different contexts. More importantly, researchers need to assess if the use of LA dashboards may lead to adverse effects at a later stage, as has been found for gamification designs (Nebel et al., 2016). While it would require large samples sizes, it would be interesting to develop LA dashboards that are highly personalized. For example, different types of social comparison could be used for different personality types.

6. Supplementary Tables

Supplementary Table 1. Questionnaire Data — Student's T-Test

	Component	Time	Treatment		Control					
			M	*SD*	*M*	*SD*	*t*-test	*df*	*p*	Cohen's *d*
AGQ	Other-approach	Begin	4.55	1.31	4.04	1.61	1.1	32.4	0.28	0.35
		End	4.58	1.05	3.54	1.79	2.19	25.91	**0.04**	0.71
	Self-approach	Begin	4.86	1.26	4.81	1.17	0.11	37.75	0.92	0.03
	Task-avoidance	Begin	5.43	0.82	5.43	0.88	0.03	35.4	0.97	0.01
		End	5.51	0.78	5.28	0.98	0.81	31.93	0.42	0.26
MSLQ	Critical thinking	Begin	3.7	1.14	3.33	1.19	1.01	35.84	0.32	0.32
		End	4.04	1.09	3.71	1.16	0.94	35.52	0.36	0.3
	Effort regulation	Begin	5.33	0.92	5.31	1.03	0.07	34.56	0.95	0.02
		End	5.49	0.87	5.11	0.92	1.34	35.66	0.19	0.42
	Extrinsic motivation	Begin	4.55	0.79	4.1	1.21	1.39	27.85	0.18	0.45
		End	4.46	0.84	4.22	1.24	0.69	28.61	0.5	0.22
	Intrinsic motivation	Begin	5.18	0.68	5.07	0.86	0.47	31.91	0.64	0.15
		End	5.4	0.96	5.17	0.76	0.88	38.99	0.38	0.27
	Peer learning	Begin	4.12	1.43	3.61	0.93	1.37	37.92	0.18	0.42
		End	4.01	1.26	3.09	1.21	2.38	37.35	**0.02**	0.75
	Self-efficacy	Begin	4.98	0.61	4.78	0.85	0.82	29.66	0.42	0.26
	Self-regulated learning	Begin	4.76	0.64	4.31	0.76	2	32.92	0.05	0.63
		End	4.98	0.69	4.5	0.67	2.24	37.08	**0.03**	0.7
	Task value	Begin	5.88	0.46	5.69	0.77	0.93	26.31	0.36	0.3
		End	6.2	0.59	5.85	0.7	1.71	33.23	0.1	0.54
	Time and study environment	Begin	5.22	0.84	5.1	0.78	0.47	37.78	0.64	0.15
		End	5.03	1.08	4.93	1	0.3	37.86	0.77	0.09

Supplementary Table 2. Questionnaire Data — Kruskal-Wallis Test

	Component	Time	Treatment		Control				
			M	*SD*	*M*	*SD*	c^2	*df*	*p*
AGQ	Other-avoidance	Begin	5.28	1.02	4.74	1.6	1.39	1	0.24
		End	5.06	1.2	4.2	1.84	2.3	1	0.13
	Self-approach	End	4.8	1.72	4.54	1.25	0.57	1	0.45
	Self-avoidance	Begin	5.12	1.55	5.83	0.66	1.58	1	0.21
		End	5.46	1.17	5.35	1.11	0.08	1	0.77
	Task-approach	Begin	6.07	0.97	6.28	0.64	0.12	1	0.72
		End	6.07	0.75	6.26	0.87	0.52	1	0.47
MSLQ	Self-efficacy	End	5.27	0.92	5.09	0.66	1.7	1	0.19

Supplementary Table 3. Paired T-Tests Comparing Scores in a Given Scale Within Group Between the Beginning and End of the Course

	Component	Group	Begin		End					
			M	*SD*	*M*	*SD*	*t*-test	*df*	*p*	Cohen's *d*
AGQ	Other-approach	Treatment	4.55	1.31	4.58	1.05	0.09	22	0.93	0.02
		Control	4.04	1.61	3.54	1.79	-1.79	17	0.09	-0.42
MSLQ	Peer learning	Treatment	4.11	1.43	4.01	1.26	-0.56	22	0.58	-0.12
		Control	3.61	0.93	3.09	1.21	-2.31	17	**0.03**	-0.54
	Self-regulated learning	Treatment	4.76	0.63	4.98	0.69	1.69	22	0.10	0.35
		Control	4.31	0.76	4.5	0.67	1.51	17	0.15	0.37

Supplementary Table 4. Assignment Data — Student's T-Test

Assignment	Treatment		Control					
	M	*SD*	*M*	*SD*	*t*-test	*df*	*p*	Cohen's *d*
Bloom level 1–3	6.43	1.48	6.65	1.23	-0.6	51.88	0.55	-0.16

Supplementary Table 5. Assignment Data — Kruskal-Wallis Test

	Assignment	Treatment		Control				
		M	*SD*	*M*	*SD*	c^2	*df*	*p*
Bloom	Level 4–5	7.92	2.03	6.79	2.09	4.46	1	**0.03**
Graded Perusall	Assignment 1	9.12	1	7.83	2.9	1.75	1	0.19
	Assignment 4	8.16	1.98	7.6	2.77	0.11	1	0.74
	Assignment 7	8.4	2.39	6.57	3.35	4.51	1	**0.03**
	Assignment 10	7.44	2.97	6.41	3.44	0.97	1	0.32
	Assignment 11	6.26	3.59	5.05	3.81	1.57	1	0.21
	Assignment 12	7.45	2.84	5.61	3.83	2.08	1	0.15
Non-graded Perusall	Assignment 2	6.48	3.21	4.66	3.48	3.43	1	0.06
	Assignment 3	6.07	3.36	3.94	3.38	4.97	1	**0.03**
	Assignment 5	5.91	3.62	3.75	3.35	3.71	1	0.05
	Assignment 6	4.98	3.5	2.49	2.89	6.29	1	**0.01**
	Assignment 8	2.69	3.17	1.44	1.55	2.72	1	0.1
	Assignment 9	2.26	2.58	1.43	1.53	1.72	1	0.19
	Assignment 13	2.71	2.91	2.08	2.38	1.74	1	0.19
	Assignment 14	2.76	3.04	1.6	1.57	2.04	1	0.15

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

Blanton, H., Buunk, B. P., Gibbons, F. X., & Kuyper, H. (1999). When better-than-others compare upward: Choice of comparison and comparative evaluation as independent predictors of academic performance. *Journal of Personality and Social Psychology*, *76*(3), 420–430. https://doi.org/10.1037/0022-3514.76.3.420

Cury, F., Da Fonséca, D., Rufo, M., & Sarrazin, P. (2002). Perceptions of competence, implicit theory of ability, perception of motivational climate, and achievement goals: A test of the trichotomous conceptualization of endorsement of achievement motivation in the physical education setting. *Perceptual and Motor Skills*, *95*(1), 233–244. https://doi.org/10.2466/pms.2002.95.1.233

Davis, D., Jivet, I., Kizilcec, R. F., Chen, G., Hauff, C., & Houben, G.-J. (2017). Follow the successful crowd: Raising MOOC completion rates through social comparison at scale. *Proceedings of the 7th International Conference on Learning Analytics and Knowledge* (LAK '17), 13–17 March 2017, Vancouver, BC, Canada (pp. 454–463). ACM Press. https://doi.org/10/gk84vr

Day, E. A., Radosevich, D. J., & Chasteen, C. S. (2003). Construct- and criterion-related validity of four commonly used goal orientation instruments. *Contemporary Educational Psychology*, *28*(4), 434–464. https://doi.org/10.1016/S0361-476X(02)00043-7

Duan, X., Wang, C., & Rouamba, G. (2022). Designing a learning analytics dashboard to provide students with actionable feedback and evaluating its impacts. *Proceedings of the 14th International Conference on Computer Supported Education* (CSEDU 2022), 21–23 April 2022, Online (Vol. 2, pp. 117–127). ScitePress. https://doi.org/10.5220/0011116400003182

Elliot, A. J., & Harackiewicz, J. M. (1996). Approach and avoidance achievement goals and intrinsic motivation: A mediational analysis. *Journal of Personality and Social Psychology*, *70*(3), 461–475. https://doi.org/10.1037/0022-3514.70.3.461

Elliot, A. J., Murayama, K., & Pekrun, R. (2011). A 3 × 2 achievement goal model. *Journal of Educational Psychology*, *103*(3), 632–648. https://doi.org/10/ch6d89

Festinger, L. (1954). A theory of social comparison processes. *Human Relations*, *7*(2), 117–140. https://doi.org/10.1177/001872675400700202

Fleur, D. S., van den Bos, W., & Bredeweg, B. (2020). Learning analytics dashboard for motivation and performance. In V. Kumar & C. Troussas (Eds.), *Proceedings of the 16th International Conference on Intelligent Tutoring Systems* (ITS 2020), 8–12 June 2020, Athens, Greece (Lecture Notes in Computer Science, vol. 12149, pp. 411–419). Springer. https://doi.org/10.1007/978-3-030-49663-0_51

Garcia, S. M., Tor, A., & Schiff, T. M. (2013). The psychology of competition: A social comparison perspective. *Perspectives on Psychological Science*, *8*(6), 634–650. https://doi.org/10.1177/1745691613504114

Gerber, J. P., Wheeler, L., & Suls, J. (2018). A social comparison theory meta-analysis 60+ years on. *Psychological Bulletin*, *144*(2), 177–197. https://doi.org/10.1037/bul0000127

Guimond, S., Branscombe, N. R., Brunot, S., Buunk, A. P., Chatard, A., Désert, M., Garcia, D. M., Haque, S., Martinot, D., & Yzerbyt, V. (2007). Culture, gender, and the self: Variations and impact of social comparison processes. *Journal of Personality and Social Psychology*, *92*(6), 1118–1134. https://doi.org/10/fdjrvk

Günther, S. A. (2021). The impact of social norms on students' online learning behavior: Insights from two randomized controlled trials. *Proceedings of the 11th International Conference on Learning Analytics and Knowledge* (LAK '21), 12–16 April 2021, Irvine, CA, USA (pp. 12–21). ACM Press. https://doi.org/10.1145/3448139.3448141

Hadwin, A., & Oshige, M. (2011). Self-regulation, coregulation, and socially shared regulation: Exploring perspectives of social in self-regulated learning theory. *Teachers College Record*, *113*(2), 240–264. https://doi.org/10.1177/016146811111300204

Huguet, P., Dumas, F., Monteil, J. M., & Genestoux, N. (2001). Social comparison choices in the classroom: Further evidence for students' upward comparison tendency and its beneficial impact on performance. *European Journal of Social Psychology*, *31*(5), 557–578. https://doi.org/10.1002/ejsp.81

Huguet, P., Galvaing, M. P., Monteil, J. M., & Dumas, F. (1999). Social presence effects in the Stroop task: Further evidence for an attentional view of social facilitation. *Journal of Personality and Social Psychology*, *77*(5), 1011–1025. https://doi.org/10.1037/0022-3514.77.5.1011

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough: Pitfalls of learning analytics dashboards in the educational practice. *Proceedings of the 12th European Conference on Technology Enhanced Learning* (EC-TEL 2017), 12–15 September 2017, Tallinn, Estonia. (Lecture Notes in Computer Science, vol. 10474, pp. 82–96). Springer. https://doi.org/10/gg4jzv

Kang, P., Lee, Y., Choi, I., & Kim, H. (2013). Neural evidence for individual and cultural variability in the social comparison effect. *Journal of Neuroscience*, *33*(41), 16200–16208. https://doi.org/10/gjjt7p

Knobbout, J., & Van Der Stappen, E. (2020). Where is the learning in learning analytics? A systematic literature review on the operationalization of learning-related constructs in the evaluation of learning analytics interventions. *IEEE Transactions on Learning Technologies*, *13*(3), 631–645. https://doi.org/10.1109/TLT.2020.2999970

Lim, L., Dawson, S., Joksimović, S., & Gašević, D. (2019). Exploring students' sensemaking of learning analytics dashboards: Does frame of reference make a difference? *Proceedings of the 9th International Conference on Learning Analytics and Knowledge* (LAK '19), 4–8 March 2019, Tempe, AZ, USA (pp. 250–259). ACM Press. https://doi.org/10.1145/3303772.3303804

Linnenbrink, E. A., & Pintrich, P. R. (2002). Motivation as an enabler for academic success. *School Psychology Review*, *31*(3), 313–327. https://doi.org/10.1080/02796015.2002.12086158

Matcha, W., Uzir, N. A., Gašević, D., & Pardo, A. (2020). A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies*, *13*(2), 226–245. https://doi.org/10.1109/TLT.2019.2916802

Nebel, S., Beege, M., Schneider, S., & Rey, G. D. (2016). The higher the score, the higher the learning outcome? Heterogeneous impacts of leaderboards and choice within educational videogames. *Computers in Human Behavior*, *65*, 391–401. https://doi.org/10.1016/j.chb.2016.08.042

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00422

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research*, *31*(6), 459–470. https://doi.org/10/dwqb9s

Pintrich, P. R., & Garcia, T. (1994). Self-regulated learning in college students: Knowledge, strategies, and motivation. In P. R. Pintrich, D. R. Brown & C. E. Weintein (Eds.), *Student motivation, cognition, and learning: Essays in honor of Wilbert J. McKeachie* (pp. 113–133). Lawrence Erlbaum.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the motivated strategies for learning questionnaire (MSLQ)*. The University of Michigan. https://eric.ed.gov/?id=ED338122

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*(3), 801–813. https://doi.org/10.1177/0013164493053003024

Russell, J.-E., Smith, A., & Larsen, R. (2020). Elements of success: Supporting at-risk student resilience through learning analytics. *Computers & Education*, *152*, 103890. https://doi.org/10/gjk2jr

Schunk, D. H., & Zimmerman, B. J. (2007). Motivation and self-regulated learning: Theory, research, and applications. Routledge.

Schwendimann, B. A., Rodríguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., Gillet, D., & Dillenbourg, P. (2017). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE Transactions on Learning Technologies*, *10*(1), 30–41. https://doi.org/10/f9t33q

Smith, M., Duda, J., Allen, J., & Hall, H. (2002). Contemporary measures of approach and avoidance goal orientations: Similarities and differences. *British Journal of Educational Psychology*, *72*(2), 155–190. https://doi.org/10.1348/000709902158838

Suls, J., Martin, R., & Wheeler, L. (2002). Social comparison: Why, with whom, and with what effect? *Current Directions in Psychological Science*, *11*(5), 159–163. https://doi.org/10/cwtnsg

Summers, J. J., Schallert, D. L., & Muse Ritter, P. (2003). The role of social comparison in students' perceptions of ability: An enriched view of academic motivation in middle school students. *Contemporary Educational Psychology*, *28*(4), 510–523. https://doi.org/10.1016/S0361-476X(02)00059-0

Susnjak, T., Ramaswami, G. S., & Mathrani, A. (2022). Learning analytics dashboard: A tool for providing actionable insights to learners. *International Journal of Educational Technology in Higher Education*, *19*, 12. https://doi.org/10.1186/s41239-021-00313-7

Trias, D., Huertas, J. A., Mels, C., Castillejo, I., & Ronqui, V. (2021). Self-regulated learning, academic achievement and socioeconomic context at the end of primary school. *Revista Interamericana de Psicología/Interamerican Journal of Psychology*, *55*(2), e1509. https://doi.org/10.30849/ripijp.v55i2.1509

Tsai, Y.-S., Rates, D., Moreno-Marcos, P. M., Muñoz-Merino, P. J., Jivet, I., Scheffel, M., Drachsler, H., Delgado Kloos, C., & Gašević, D. (2020). Learning analytics in European higher education: Trends and barriers. *Computers & Education*, *155*, 103933. https://doi.org/10/gg2v3t van Vliet, E. A., Winnips, J. C., & Brouwer, N. (2015). Flipped-class pedagogy enhances student metacognition and collaborative-learning strategies in higher education but effect does not persist. *CBE—Life Sciences Education*, *14*(3), ar26. https://doi.org/10.1187/cbe.14-09-0141

Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK '20), 23–27 March 2020, Frankfurt, Germany (pp. 524–533). ACM Press. https://doi.org/10.1145/3375462.3375483

Williamson, G. (2015). Self-regulated learning: An overview of metacognition, motivation and behaviour. *Journal of Initial Teacher Inquiry*, *1*, 25–27. http://dx.doi.org/10.26021/851

Wolters, C. A., Yu, S. L., & Pintrich, P. R. (1996). The relation between goal orientation and students' motivational beliefs and self-regulated learning. *Learning and Individual Differences*, *8*(3), 211–238. https://doi.org/10/bhggr3

Xu, K. M., Cunha-Harvey, A. R., King, R. B., de Koning, B. B., Paas, F., Baars, M., Zhang, J., & de Groot, R. (2023). A cross-cultural investigation on perseverance, self-regulated learning, motivation, and achievement. *Compare: A Journal of Comparative and International Education*, *53*(3), 361–379. https://doi.org/10.1080/03057925.2021.1922270

Zell, E., & Alicke, M. D. (2010). Comparisons over time: Temporal trajectories, social comparison, and self-evaluation. *European Journal of Social Psychology*, *40*(3), 375–382. https://doi.org/10.1002/ejsp.737

Zimmerman, B. J. (1995). Self-regulation involves more than metacognition: A social cognitive perspective. *Educational Psychologist*, *30*(4), 217–221. https://doi.org/10.1207/s15326985ep3004_8

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, *41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, *45*(1), 166–183. https://doi.org/10.3102/0002831207312909

Zimmerman, B. J., & Schunk, D. H. (Eds.). (2001). *Self-regulated learning and academic achievement: Theoretical perspectives* (2nd ed.). Routledge.