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Social comparison in learning analytics dashboard supporting motivation and academic achievement

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ABSTRACT

A promising contribution of Learning Analytics is the presentation of a learner's own learning behaviour and achievements via dashboards, often in comparison to peers, with the goal of improving self-regulated learning. However, there is a lack of empirical evidence on the impact of these dashboards and few designs are informed by theory. Many dashboard designs struggle to translate awareness of learning processes into actual self-regulated learning. In this study we investigate a Learning Analytics dashboard based on existing evidence on social comparison to support motivation, metacognition and academic achievement. Motivation plays a key role in whether learners will engage in self-regulated learning in the first place. Social comparison can be a significant driver in increasing motivation. We performed two randomised controlled interventions in different higher-education courses, one of which took place online due to the COVID-19 pandemic. Students were shown their current and predicted performance in a course alongside that of peers with similar goal grades. The sample of peers was selected in a way to elicit slight upward comparison. We found that the dashboard successfully promotes extrinsic motivation and leads to higher academic achievement, indicating an effect of dashboard exposure on learning behaviour, despite an absence of effects on metacognition. These results provide evidence that carefully designed social comparison, rooted in theory and empirical evidence, can be used to boost motivation and performance. Our dashboard is a successful example of how social comparison can be implemented in Learning Analytics Dashboards.

1. Introduction

The field of Learning Analytics (LA) consists of "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs'' ([70], p. 1). Learning data is processed with the help of data science tools (e.g. machine learning, process mining) and reported to stakeholders in the form of text or visualisations [46,78]. LA has the potential of becoming a key enabling technology in modern education [1,23,45]. For instance, it has been harnessed for supporting educators in guiding educational practices and management [77], and in better understanding learning trajectories (e.g., [63]). An alternative and also promising direction is the development of learner-centred LA Dashboards (LAD) which aim to foster Self-Regulated Learning (SRL; [46]). LAD can be defined as "a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualisations" ([67], p. 37). LAD as a field of research emerged and has been rapidly growing in the last decade and investigates the type of information, visuals and interfaces that are best suited to support learning [67].

Centring LA around learners is important as it can help foster SRL which is an essential component of 21st-century skills [10] and life-long learning [3,38]. Despite the early enthusiasm for LAD research, recent reviews have questioned their effectiveness [37,46]. The issue of effectiveness has also been stressed for LA research at large. A recent review by Viberg et al [79] revealed that only 20% of the reviewed papers demonstrated improvements in learning outcomes and that 70% of the studies did not even try to assess them. In the particular case of LADs, research currently faces three main challenges. Firstly, few studies have empirically evaluated the effects of different LAD designs on learning

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behaviour, motivation and learning outcomes. Strong evidence of benefits for learning remains scarce [46]. Secondly, face-to-face education typically goes hand in hand with limited data on learning activity. Hence, researchers have favoured developing LADs for online education which generates large amounts of data (for a review, see [82]). Still, investigating LADs for face-to-face contexts is important because this is where most of the learning takes place [55]. In contrast, LA research in higher education has been mainly targeted at teachers and institutions, rather than learners [77]. There is a real need for LADs that are compatible with face-to-face, higher education. Thirdly, researchers have called for designs and interventions that are more rooted in learning theory [37,46,77].

Many dashboards have been designed to elicit awareness of learning with the assumption that such knowledge will naturally result in regulation of learning. However, creating knowledge of learning does not necessarily result in SRL. Research has pointed out that many LADs fail to significantly support self-regulated behaviour in learners [37,46]. In order to translate knowledge of learning into the adoption of learning strategies and behavioural changes, learners must feel motivated to do so [20,25].

In this study, we rely on the concept of motivation as a facilitator of SRL [57], and on social comparison and goal orientation as generators of motivation [29,73]. The study takes the form of two LAD interventions during two higher education courses and empirically assesses the effects on motivation, SRL and academic achievement. The design of the dashboard is guided by SRL theory and the literature on social comparison in social psychology.

1.1. Self-regulated learning and motivation, theoretical foundations

While many models of SRLs have emerged over the years, most of them assume that self-regulated students are learners who are metacognitively, motivationally, and behaviourally active in their own learning. They regulate their learning and adopt strategies to attain their goals [57,86]. For this study, we rely on the model developed by Paul Pintrich and colleagues [57], which puts a particular emphasis on the role of motivation in promoting and sustaining self-regulated learning. From it emerged the widely used Motivated Strategies for Learning Questionnaire (MSLQ; [21]). The model includes three categories of strategies: (1) cognitive learning strategies, (2) self-regulatory strategies, and (3) resource management strategies; and three categories of motivational beliefs: (a) self-efficacy beliefs, (b) task value beliefs, and (c) goal orientation. In particular, this study examines the relationship between goal orientation and metacognition. Goal orientation is defined in terms of being intrinsically motivated (with the goal of self-improvement, using self-set standards) and extrinsically motivated (satisfying the expectations and criteria of others, such as teachers, parents or societal prestige). Making use of self-regulatory strategies is viewed as a form of metacognitive activity. Intuitively, metacognition can be described as thinking about thinking, or the ability to have knowledge of and regulate one's own cognitive processes. [8,43]. Metacognitive abilities are thus categorised into knowledge of cognition, or metacognitive knowledge (the ability to monitor one's own thoughts and reflect on them), and regulation of cognition, or metacognitive regulation (evaluating outcomes, planning, applying strategies). These two components can be viewed as an upward and downward flow of information processing, respectively [53]. In other words, cognition is first processed into metacognitive knowledge, which is thereupon translated into regulation of cognition. Pintrich's model of SRL reduces metacognitive knowledge to "students' knowledge about person, task, and strategy variables," whereas metacognitive regulation, referred to as self-regulation captures the "strategies individuals use to plan, monitor and regulate their cognition ([57], p. 461). Importantly, the model does not include the metacognitive knowledge component. Given that the bulk of LAD studies have been built mainly to foster metacognitive knowledge to indirectly stimulate regulation, though with little evidence for the latter [37], we decided to include Baker and Brown [8] and Livingston's [43] definition of metacognitive knowledge to Pintrich's model of SRL to be able to cast a broader net on the effects of this study on metacognition in learners. This allows us to evaluate the contribution of the current LAD on these two aspects of metacognition separately.

SRL theory argues that goal orientation, and metacognition play an essential role in learning and academic achievement [57,58,65,66]. Indeed, various studies have reported a positive effect of goal orientation on achievement [5,22,50,71]. Under SRL, learners with low levels of motivation will tend to monitor their learning behaviour less, will be less effective at self-regulating — even when they have been taught about learning strategies — and therefore tend to show lower learning outcomes than higher motivated learners [65]. Supporting students' motivation is therefore a critical condition in order to foster SRL and promote academic achievement [60]. Particularly, intrinsic motivation is considered to be related to metacognitive activity. Extrinsic motivation, on the other hand, has been linked to using superficial learning strategies such as rehearsal [84]. Traditionally, extrinsic motivation has been considered to negatively impact learning as it may stir the learner away from deep learning behaviour in favour of more surface learning [12,19]. This view has been challenged by various studies finding a positive relationship with academic achievement [5,6,54]. Overall, it seems that extrinsic motivation may play a positive role when it does not impair intrinsic motivation.

Although most LADs display information relative to individuals' own learning behaviour (so-called individual reference frames; [46,67]), research has shown that social norms play an important role in everyday life, including education [7,47]. This suggests that social comparison could be a key feature in LADs to successfully support motivation, metacognition and academic achievement. The current challenges regarding comparative LADs (i.e., presenting social reference frames) are (*i*) designs informed by social comparison theory and empirical literature, and (*ii*) the relationship between motivation and academic achievement as a result of dashboard use. It is reasonable to assume that the effects of LAD exposure on achievement are not direct. Rather, exposure may lead to behavioural, metacognitive and motivational changes that do affect academic achievement (Fig. 1). The goal of this study is to investigate the relationship between motivation, metacognition and academic achievement as a result of exposure to a LAD informed by empirical evidence on social comparison. Specifically, we expect that our LAD increases motivation and metacognition resulting in higher academic achievement overall.

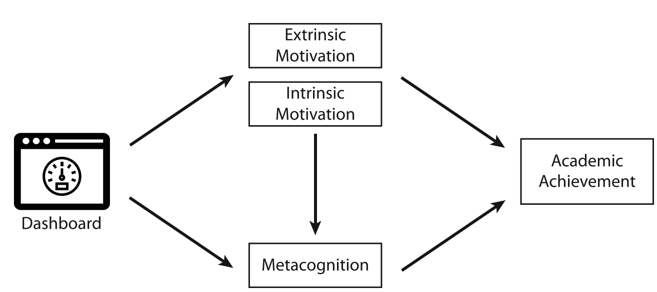

Fig. 1. Diagram representing the potential role of LADs on academic achievement under SRL. Academic achievement is affected by both motivation and metacognition. High intrinsic motivation is necessary for the learner to engage in metacognitive activity. While extrinsic motivation may not affect metacognition, it does play a role in academic achievement. Overall, motivation seems to play both a direct and indirect role in achievement. A dashboard may therefore benefit academic achievement in two ways: (*i*) Raising awareness in already highly motivated learners, and (*ii*) motivating learners to promote metacognitive activity and/or behavioural changes linked with academic achievement.

1.2. *Effects of comparative LADs on motivation and performance*

To date, there is mixed evidence on how LADs can support learners' motivation and how this affects SRL and academic achievement. For the scope of this study, we focus our overview of LAD literature on studies that implement a form of comparison between the user and others (henceforth referred to as *comparative dashboards*) and measure the effects of the dashboards on motivation. The few studies investigating these elements suggest that comparative dashboards may both increase learners' motivation [16] and decrease it [42]. Other studies have found links between comparative dashboards and SRL [18,32]. Interestingly, Russel et al., using self-report questionnaires, found that a comparative LAD displaying the assignment grades and predicted grades of the user and the class average did not have adverse effects for at-risk students but even helped them to persevere in the course. Corrin and De Barba [16] performed an intervention with a comparative LAD in which the performance of higher education students and their engagement in a course was shown against that of the class average. Using interviews to assess motivation and SRL, their results suggest that the LAD positively affected motivation and SRL. Students often reported the desire to work harder as a result of the intervention. However, whether this actually translated into behavioural change and higher academic achievement is unclear. The study points out that comparison to the average of the class may have undesired effects such as shifting the goals of ambitious students from top performance to slightly above class average. This suggests that absolute standards such as class averages may not be ideal and that alternative standards should be explored. For instance, standards could be set individually and relative to the learner's activity or performance

In a study by Lim and colleagues, a majority of participants reported negative affect in response to a comparative LAD during interviews, although many participants also reported positive affect [42]. The dashboard showed course compilation and study time and compared it to the average of the class. Again, this suggests that class average may not be an optimal comparison standard. Interestingly, quantitative measures of motivation did not differ significantly from the control group who were not exposed to social comparison. Furthermore, the study found that baseline metacognition did not affect motivational changes, but this does not rule out that increased motivation may support metacognition.

When it comes to performance, Davis and colleagues [18] found that learners in a Massive Open Online Course (MOOC) who were exposed to a comparative LAD had a significantly higher completion rate and were more active in the MOOC, compared to a control group. The authors viewed it as an indication that the LAD helped users learn in a more self-regulating fashion. Lastly, Günther [32] implemented a LAD into a MOOC that showed how a learner's study time was fairing in comparison to the class average and the most active students. The author found that the intervention had a positive impact on SRL, which was devised based on users log data reflecting learning behaviour.

The contradicting evidence on the benefits of comparative LADs on motivation may be explained by differences in the type of information presented to the learner and the way comparison with peers is presented. While people have an inherent drive to compare themselves to others [24], the nature, direction and distance of the comparison seem to affect motivation differently, which may explain why high achievers seemed to lower their ambitions when they are compared to a less performing class average in Corrin and De Barba [16].

1.3. *Social comparison, evidence from psychology*

Social comparison theory spans from the work of Festinger [24]. The practical usefulness of social comparison with similar people is the idea that it enables individuals to generate accurate evaluations about their aptitudes and opinions. Multiple models have been developed to specify to what extent similarity with peers and the (preferred) direction of comparison (upward or downward) play a role in an individual's self-assessment and self-worth (for a review, see [73]). For this study, we rely mainly on the work of Gerber and colleagues [29] who performed a large-scale meta-analysis covering the selection of a comparison target (i.e., which people are selected for comparison) and reactions to comparisons. They included studies from a wide range of models that operationalise social comparison in various ways. Their findings are therefore not tied to one specific theory but to the concept of social comparison at large, with findings supporting different aspects of different frameworks.

The meta-analysis reveals that the effect of social comparison on motivation varies depending on its orientation. Upward comparison (i.e., with better-off peers) seems to be generally favoured over downward comparison (i.e., with worse-off peers) by individuals overall, especially in the absence of threat to self-esteem [29]. In addition, upward comparison tends to pressure individuals towards conformity with the compared group. At least three factors seem to modulate motivation in the context of upward social comparison. Firstly, motivation is stronger when the compared entity is perceived as similar and relatable [14,15,29,74,85], such as peers, part of one's social and professional circles, or with similar socio-economic background, age or political views. Secondly, motivation seems to increase with the degree of proximity to a standard (S. M. [27,29]). Studies have also found that comparison with slightly, rather than greatly, better-off peers has a positive effect on students' academic achievement [11,34,35]. In other words, matching the performance of peers appears more achievable when they are only slightly ahead than when they seem to be far and potentially out of reach. Thirdly, the effect of social comparison on motivation seems to be inversely related to the number of peers. The higher the number of peers, the less people are interested in comparison (S. M. [27]). A low number of peers is therefore desirable. Note that, to the best of our knowledge, this last factor has so far only been studied in the context of competition. Competition is a form of extrinsic goal orientation that results from social comparison in which one desires to outperforming others (see S. M. [27]). For this study, we operate under the assumption that the number of peers also plays a role on motivation in comparison settings that do not prime towards competition. these effects can also be observed in other contexts in which motivation is relevant.

Although potentially beneficial for self-esteem, downward comparison may have neutral-to-negative effects on motivation and performance, because it may not pressure towards self-improvement [48,68]. In LAD research, the majority of comparative dashboards use the class average as the norm [67]. This can be problematic because learners may be positioned differently with regards to this norm; high performing learners are given downward comparison, low performing learners are given upward comparison. Additionally, while proximity to the norm would be moderate for most learners (assuming a normal distribution of the learners in terms of performance), best and worst achievers would sit much further from the norm.

In short, learners are affected differently when exposed to the same norm, which could in part explain the contrasting results on motivation in previous LAD research. In this study, we investigate a LAD that is based on social comparison theory to optimise its effect.

1.4. *The current study*

The evidence discussed above suggests that a comparative dashboard can successfully support motivation, and by extension metacognition and academic achievement, when carefully designed. We therefore included the following elements in our LAD design: (*i*) slight upward comparison to increase motivation; (*ii*) relevant and low number of peers to improve proximity which has an impact on motivation; and (*iii*) feedback on progress to make users aware of their learning and achievement (i.e., metacognitive knowledge). To further increase the relevancy of the presented peers and justify their small number, the LAD displays peers who want to achieve a similar course grade as that of the user. This is determined by a goal grade set by the learner at the beginning of the intervention.

The goal of our study is to investigate in two randomised controlled experiments whether interventions using such an upward-oriented comparative dashboard leads to increases in motivation, metacognition and academic achievement. We also investigate to what extent these factors influence each other. In particular, we examine the hypotheses that (*i*) LAD use results in higher motivation, (*ii*) higher academic achievement, and (*iii*) higher metacognitive abilities. Additionally, we expect a relationship between motivation, achievement, and metacognition (see Fig. 1). This study extends on a previous conference paper [87].

2. Experiment 1

2.1. Methods

2.1.1. Research model and procedure

The dashboard itself is composed of two diagrams designed around social comparison and goal orientation (Fig. 2). The first diagram (Fig. 2, Left) follows from the evidence discussed earlier on social comparison, showing peers positioned slightly upward on average compared to the learner. This was done to increase motivation and inform the learners – albeit in a biased way – about the desired trajectory in order to achieve their goal grade. Here, subjects see the average of their grades obtained so far (current average) as well as the current average grade of 9 anonymous peers following the same course (and who gave consent to their data being processed). These peers are presented to the subject as "students with similar goal grades." The sample of peers is selected from the pool of students whose goal grade is equal to that of the subject within a tolerance margin and using a variation of the 'knapsack algorithm' [17] and satisfies the following criteria. First, the average grade of the sample must be 0.5-1.5 points higher than the average grade of the subject. Second, 20-40% of the sample must have a lower average grade and 30-50% must have an average grade higher than or equal to that of the subject. The margin is increased until such a sample can be generated. If no sample could satisfy the criteria – typically applying to top-9 and bottom-9 performers – or if the sample-generation algorithm has timed out, the comparison sample is instead composed of the 9 closest peers in terms of average grades. Importantly, the subjects were not aware of the manipulation.

The goal of the second diagram (Fig. 2, Right) is to raise additional awareness of one's trajectory, such that actions can be taken to achieve one's goal grade. The diagram shows a prediction of the student's final grade in the form of a normal distribution. Details on the implementation and accuracy of the grade-prediction algorithm can be found in the supplementary materials (Section 1.1).

At the beginning of the course, subjects set a goal grade for the course (1-10, passing grade at 6) and fill in the first round of questionnaires. They were afterwards randomly assigned to the treatment or control group. The control group was told that a sufficient number of subjects was reached for testing the dashboard but that we were interested in their learning behaviour and would compensate them for filling out the questionnaires. The course lasted 8 weeks. The second round of questionnaires was filled out during the last class of the course, in week 7.

Every time a subject's grade is entered in the LMS, the dashboard recomputes the visual (Fig. 3). As the course goes on and more assignments are graded, the final grade prediction of the second diagram becomes more accurate and the normal distribution narrower. Details on the infrastructure and algorithms of the LAD can be found in Section 1 of the supplementary materials.

During the study, the LAD was accessible from the course details of the subjects' Learning Management System (LMS; Canvas in this case), via a link on the homepage of the course or via a button in the menu. Fig. 1 illustrates the architecture of the LAD. The full integration was enabled through the use of the Canvas API and Learning Tools Interoperability (LTI) libraries for python. The source code of the LAD can be found on the Github repository of this project (https://github.com/UvA-FNWI/coach3).

2.1.2. Research context and sample

79 first-year bachelor's students in the Netherlands partaking in their very first course voluntarily participated in the experiment. The students were unrolled in an informatics-related programme and the course was part of the main curriculum. The subjects were randomly assigned to the treatment group (LAD access) or the control group (no LAD access). The course lasted 8 weeks and consisted of on-location lectures and seminars. Students were assessed with one quiz, two homeworks (open-ended questions on the course material), two midterm exams, one essay and two group presentations. Each assignment was graded and counted

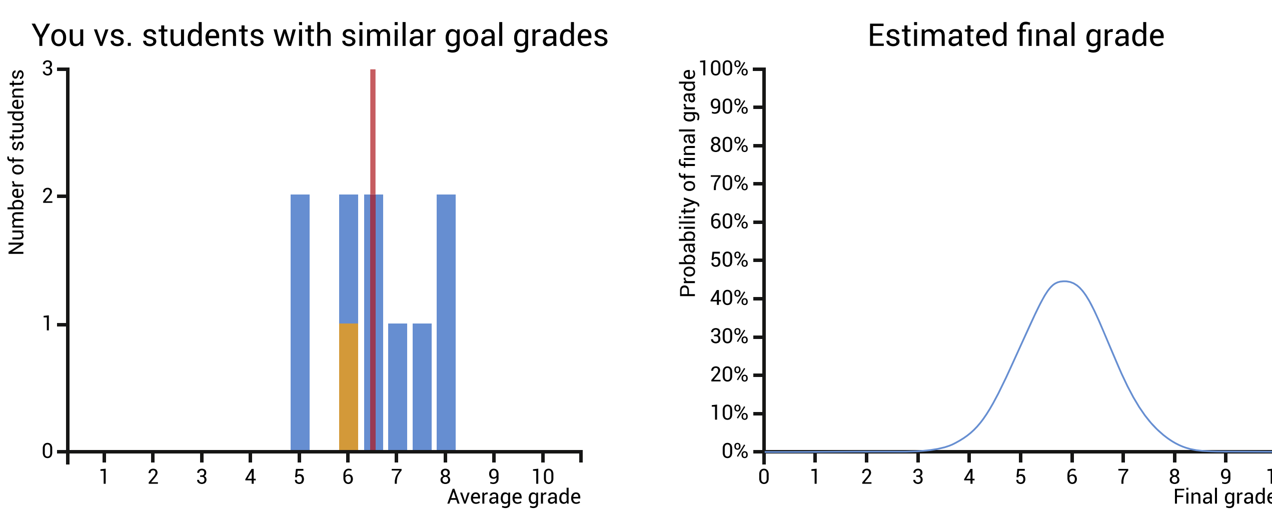

Fig. 2. Example visualisation in the LAD used in this study (at the beginning of the intervention). Left: the subject's average grade (6 in this example; in orange) is shown against that of 9 selected peers who have similar goal grades (in blue). The x-axis represents the average grades and the y-axis the number of people with a given grade. The average grade of the peers is represented by the red vertical line. Right: prediction of the subject's final grade based on the grades obtained thus far. The prediction takes the form of a normal distribution. The x-axis represents the range of possible grades in the course (0-10). The y-axis represents the probability of obtaining a grade. Grades at the centre of the curve are predicted to be the most likely. Grades at the tails are the least likely. As more grades are entered in the LMS during the course, the normal distribution becomes sharper and the prediction more accurate.

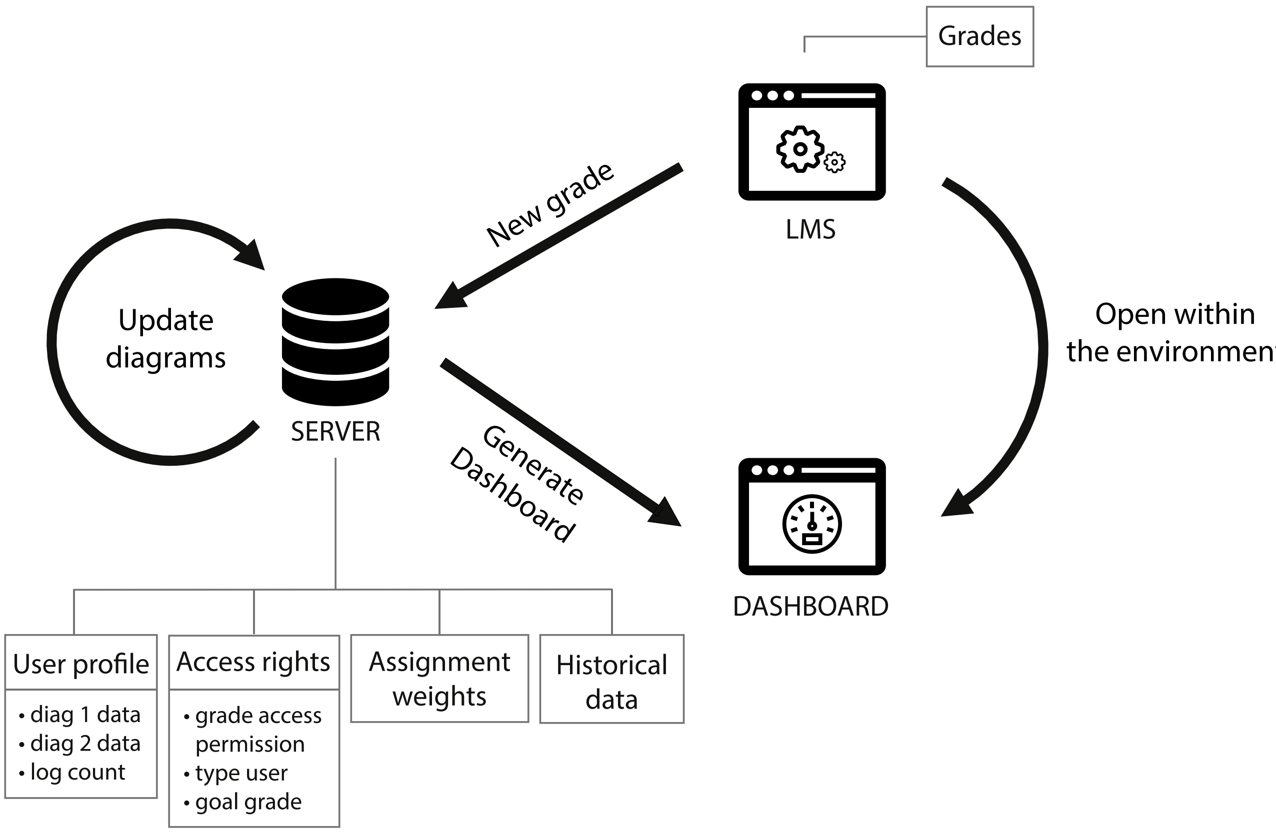

Fig. 3. Architecture of the LAD. In the database are stored a user profile for all users using the app, three static datasets containing information 1) user access rights, system permissions for access student data on the LMS and the goal grade set by students in the course, 2) The weights of all graded assignments in the course to compute average grades, and 3) grades of anonymous students in the previous years of the course, which is used to generate the grade prediction. The user profile consists of the LMS user id, in order to collect user data from the LMS, data to generate the diagrams of the dashboard and log counts. The user's assignment grades are stored on the LMS. When new grades are entered on the LMS, the server updates the user information and generates new diagrams. The dashboard is accessible from the course homepage of the LMS.

towards a course final grade, with each type of assignment given a different weight.

7 subjects were removed from the analysis because they retracted themselves from the experiment or stopped the course. In addition, 46 subjects did not fill in either or both rounds of the self-report questionnaires and were therefore excluded from the self-report analysis. As a result, 72 subjects (treatment: 34) were included in the achievement analysis and 26 subjects (16 treatments) were included in the self-report analysis. Here we assume that there is no role of the dashboard on students quitting the course and that, therefore, those who quit were missing at random. We refer to the supplementary materials for analyses of the excluded participants. The subjects received a monetary reward if they completed all the required questionnaires. This study was approved by the IRB of the University of Amsterdam (case number 2019-DP-10483).

2.1.3. Instruments used and their validation

We collected the grades of the subjects for all individual assignments and computed the weighted average of the individual assignments (henceforth referred to as *final grade*) to measure the impact of the treatment on academic achievement. The group assignments were not included in the analysis because they do not reflect individual achievement, and thus cannot be used to measure the effectiveness of the intervention. Indeed, many groups were composed of both control and treatment subjects, and different members of the group may have contributed differently to the quality of the assignment.

To assess intrinsic and extrinsic motivation, we used the *intrinsic goal orientation* (e.g., "In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn"), *extrinsic goal orientation* (e.g., "Getting a good grade in this class is the most satisfying thing for me right now") scales, respectively of the Motivated Strategies for Learning Questionnaire (MSLQ; [21,61]). The MSLQ was chosen because it operationalises the model of SRL developed by Pintrich and colleagues, except for the metacognitive self-regulation component to which we favoured the Metacognitive Awareness Inventory (MAI; [33]; first developped by [64]), as explained in Section 1.1. Specifically, we used a reduced version of the MAI [33] that demonstrated better validity and which consists of the *metacognitive knowledge* (e.g., "I am aware of what strategies I use when I study") and *metacognitive regulation* (e.g., "I change strategies when I fail to understand") scales. This was done to obtain of a more fine-grained understanding of the expected effect of the LAD on metacognition than we would with the MSLQ's self-regulated learning component. Subjects were asked to fill out the questionnaires at the beginning and the end of the intervention. Both questionnaires are validated [28,33,61] and are often used in education research [21,33].

2.1.4. Data analysis

To test the effect of the intervention on final grades we ran a linear regression analysis. We used 'grade' (0-10) as outcome variable and 'group' (treatment vs control) as fixed effect. With regards to testing the effect on intrinsic and extrinsic motivation, and metacognitive knowledge and control, we ran three linear mixed-effect analyses (one per scale), with 'score' as outcome variable, 'group', 'time' (when the measure was performed) and the interaction of 'group' and 'time' as fixed effects and subjects as a random intercept. We also investigated the possible mediation of extrinsic motivation on the effect of the intervention on the final grades. The mediation variable used was the difference of extrinsic motivation scores at the end and beginning of the intervention. We used the R package 'lmerTest' [41] for all tests. Lastly, we performed a mediation analysis to investigate the role of self-reported measures in the relationship between the intervention and academic achievement (final grades). Only self-reported measures that showed a significant interaction effect in the previous test were investigated, using the R package 'mediation' [75]. The full analysis script of both experiments is available on the OSF repository of the study (https://osf.io/tpeu6/).

2.2. Results

2.2.1. Effect on academic achievement

Subjects in treatment condition scored on average 0.45 points higher on the final grade than subjects in the control group ($\beta = 0.45$, $S.E. = 0.21$, $t = 2.15$, $p = 0.03$; Fig. 4Aa). The effect size was moderate (Cohen's d: 0.51). Only 3% of the treatment group got an insufficient grade in the course, while this proportion was 18% for the control group. For more details on the statistical results for academic achievement, see Table S1 of the supplementary materials.

2.2.2. Effect on self-reported measures

At the beginning of the course, both groups showed similar levels of intrinsic and extrinsic motivation, as well as metacognitive knowledge and regulation. By the end of the course, extrinsic motivation had decreased in the control group ($\beta = -0.86$, $S.\ E. = 0.33$, $t = -2.60$, $p = 0.02$), but had remained stable in the treatment group (interaction effect: $\beta = -1.07$, $S.\ E. = 0.42$, $t = -2.54$, $p = 0.01$; Fig. 4B). Intrinsic motivation decreased in both groups similarly ($\beta = -0.62$, $S.E. = 0.19$, $t = -3.27$, $p < 0.01$; Fig. 4B) and neither metacognitive knowledge nor regulation varied significantly between the start and end of the course for either group. For details on the statistical results on self-reported measures, see Table S2 of the supplementary materials.

2.2.3. Mediation analysis

The mediation analysis revealed no role of change in extrinsic motivation in the relationship between the intervention and final grades. In other words, although the intervention had a positive effect on extrinsic motivation and academic achievement, the former did not seem to contribute to the latter.

2.3. Preliminary discussion

The results suggest that the intervention was successful at supporting extrinsic motivation and led to higher academic achievement, but did not seem to affect metacognitive abilities. In addition, there was no convincing relationship between motivation, metacognition, and achievement.

The general decrease in motivation, with the exception of extrinsic motivation in the treatment group, may be attributed to a novelty effect related to the context of the intervention, which has been observed in various instances (e.g., [9,36,51]). Indeed, the intervention took place during the very first university course taken by the subjects. It is reasonable to assume that starting university was exciting for students due to the novelty of the environment.

A potential caveat of the current design of the LAD is that the observed effects may not be (solely) attributed to social comparison. Indeed, the dashboard shows a prediction of the student's final grade (Fig. 2, Right) and this may have affected motivation and achievement, rather than the social comparison (Fig. 2, Left). This issue is addressed in experiment 2.

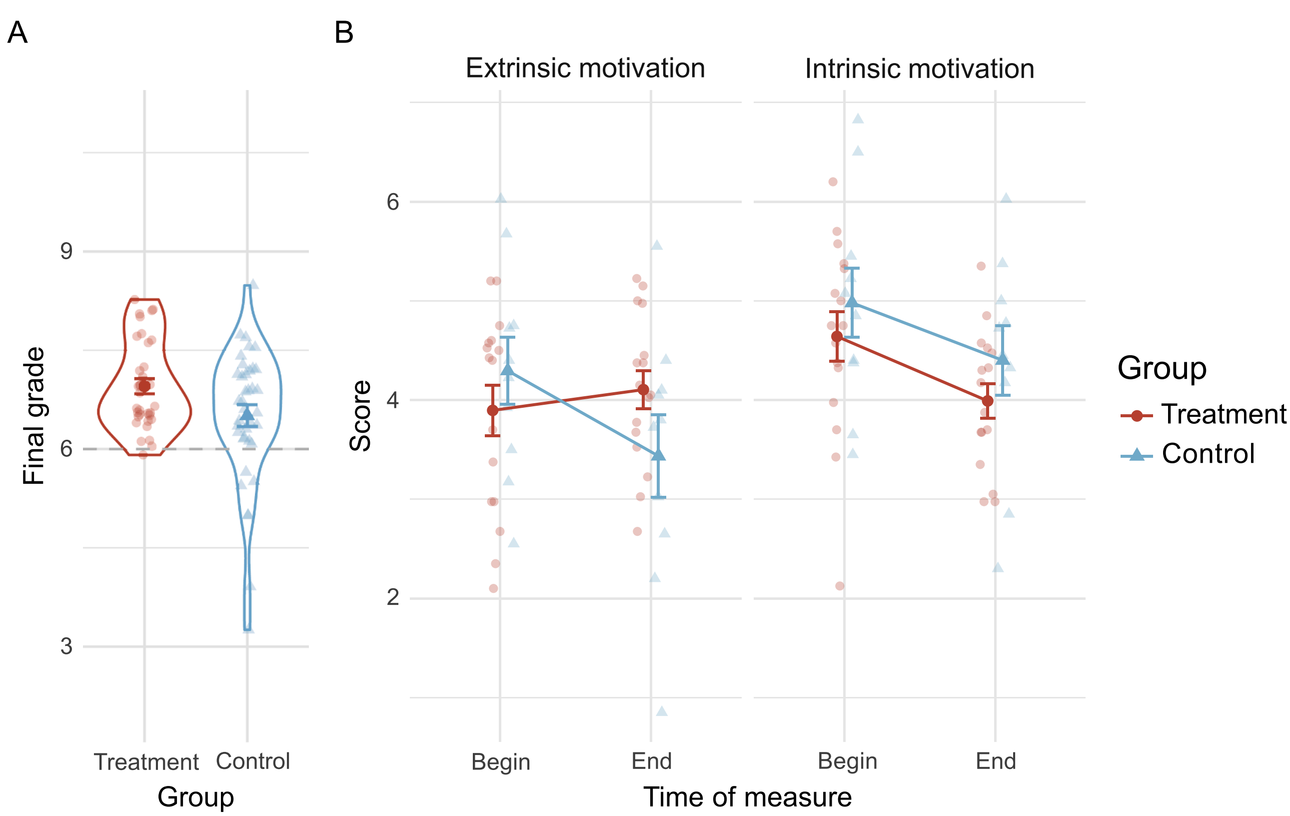

Fig. 4. Results from experiment 1 on motivation and achievement. A) Mean and density of the final grade in the two groups. The dashed horizontal line represents the passing grade. B) Mean extrinsic and intrinsic motivation assessed with the MSLQ at the start and end of the course ('Begin' and 'End', respectively). In both A and B, the bars represent the standard error and the semi-transparent scattered points individual datapoints.

3. Experiment 2

3.1. Methods

3.1.1. Research model and procedure

To determine whether the social comparison component on its own is sufficient positively impact motivation and achievement, we performed the same intervention in another course but this time removed the grade-prediction diagram, such that treatment subjects only had access to the social comparison diagram.

The procedure was overall the same in experiment 1, with a few changes. First, additional questionnaires measuring metacognition and motivation were used on top of those of experiment 1 to determine whether effects observed on these two factors are dependent on the way they are operationalised (see section 3.1.2). The analysis of the intervention was pre-registered (https://osf.io/tpeu6/). Second, subjects filled in the questionnaires in week 2 instead of week 1. This was done to allow subjects sufficient time to familiarise themselves with the course so that they could answer the questionnaire relying on experience specific to the course, rather than on previous experience. Third, a major difference with experiment 1 was that due to the COVID-19 pandemic, the course had to take place entirely online. As a result, we were able to have the subjects fill out the second round of questionnaires at the very end of the course, instead of during the last class.

3.1.2. Research context and sample

83 second-year bachelor's students in the Netherlands, all partaking in the same course, voluntarily participated to the experiment. As in experiment 1, the students had a background in informatics. The course lasted 8 weeks and was part of the main curriculum. Due to the COVID-19 pandemic, the course, consisting of lectures and seminars, had to be given entirely online and the assignments were adapted to the circumstances. The assignments consisted of 3 quizzes, 3 individual computer assignments and 3 group computer assignments, all graded and counting towards the final course grade. Quizzes and computer assignments were given different weights.

As in experiment 1, the subjects were randomly assigned to the treatment or control group. 7 subjects were excluded from the analysis because they either retracted from the experiment or did not complete the course (i.e., not enough assignments were submitted; see supplementary materials for more details). In addition, 14 treatment subjects were excluded because they never used the LAD (note that the final grade of these subjects did not vary from that of the rest of the cohort, treatment or control, see the supplementary materials, see supplementary materials). We also excluded subjects from specific analysis if they did not fill either or both rounds of questionnaires. Thus 6 and 18 subjects who did not fill out both rounds of the motivation questionnaires and metacognition questionnaires, respectively, were excluded.

As a result, 62 subjects (treatments: 22) were included in the final grade analysis, 56 subjects (treatments: 21) in the self-reported motivation analysis and 46 subjects (treatments: 17) in the metacognition analysis. This time, filling in questionnaires was a mandatory part of the course. Therefore, the students did not receive a monetary reward for their participation. This study was approved by the IRB of the University of Amsterdam (case number 2020-DP-11942).

3.1.3. Instrument used and their validation

To measure the effect of the intervention on academic achievement, all individual assessments were collected and the final individual grade was computed. Two types of assessments were made in the course: computer assignments (3 assessments) and online quizzes (3 assessments). The three group assessments were not included in the analysis because, as in experiment 1, they are confounded by the fact that classmates contributed to it. In other words, the grades do not accurately reflect individual academic achievement.

As in experiment 1, the extrinsic and intrinsic goal orientation scales of the MSLQ were used, as well as the metacognitive knowledge and regulation scales of the MAI. Since it is possible that students regulated their learning in a way that the MAI did not capture in experiment 1, we also included the *metacognitive self-regulation* scale of the MSLQ (e.g., 'If course materials are difficult to understand, I change the way I read the material.') as an additional assessment of metacognition. This way, experiment 2 more closely operates under Pintrich's theoretical framework. As pre-registered, measures of participants' effort in the course were collected in the form of student reports on weekly study time and time spent on individual assignments. Unfortunately, due to technical errors, only data for the first assignment is usable, such that the analyses investigating the role of effort could not be performed.

3.1.4. Data analysis

To replicate the findings in experiment 1 on final grades and extrinsic motivation (MSLQ) we performed a one-tailed linear regression analysis and a one-tailed linear mixed model analysis, respectively, with the same outcome variables, fixed effects and random intercept as in experiment 1. The same statistical tests as in experiment 1 for self-reported measures were also performed to test the effects on intrinsic motivation (MSLQ) and metacognition (MAI: metacognitive knowledge, metacognitive regulation; MSLQ: metacognitive self-regulation). In total, five linear mixed model analyses were done, one for each self-reported measure. Exploratory statistical analyses announced in the pre-registration can be found in the supplementary materials (Section 3.2). Lastly, we repeated the mediation analysis of the role of extrinsic motivation on the effect of the intervention on the final grades.

With regards to testing the effect on intrinsic and extrinsic motivation, and metacognitive knowledge and regulation, we ran three linear mixed-effect analyses (one per scale), with 'score' as outcome variable, 'group', 'time' (when the measure was performed) and the interaction of 'group' and 'time' as fixed effects and subjects as a random intercept.

3.2. Results

3.2.1. Academic achievement

The same statistical models as in experiment 1 were performed. Similar to the previous intervention, subjects in the treatment group on average achieved 0.42 points higher final grades than the subjects in the control groups ($\beta = 0.42$, $S.E. = 0.24$, $t = 1.78$, $p = 0.04$; Fig. 5A). The mean difference between the two groups was similar to that of experiment 1. The effect size was moderate (Cohen's d: 0.49) and comparable to experiment 1. No student in the treatment group obtained an insufficient final grade, whereas 2 students in the control group did, following the pattern observed in experiment 1, albeit to a lesser degree. Also similar to experiment 1, there was no significant difference between the two groups in assignment grades overall (see Section 3.1 and Table S3 of the supplementary materials for details).

3.2.2. Self-reported measures

The interaction effect observed on extrinsic motivation replicates experiment 1 ($\beta = 0.62$, $S.E. = 0.33$, $t = 1.91$, $p = 0.03$; Fig. 5B). Both groups showed similar scores at the start, but while extrinsic motivation had not varied significantly for the control group by the end of the course, it did increase for the treatment group ($\beta = 0.58$, $S.E. = 0.25$, $t = 2.32$, $p = 0.02$). As in experiment 1, the two groups did not differ significantly in terms of intrinsic motivation. Interestingly, there was no general decrease between the beginning and the end of the course. Lastly, there was no significant change in metacognition overall for either the metacognitive knowledge and regulation scales of the MAI or the metacognitive self-regulation scale from the MSLQ (see Table S4).

3.2.3. Mediation analysis

As in experiment 1, we found no evidence supporting a mediating role of extrinsic motivation on the effect of the intervention on academic achievement.

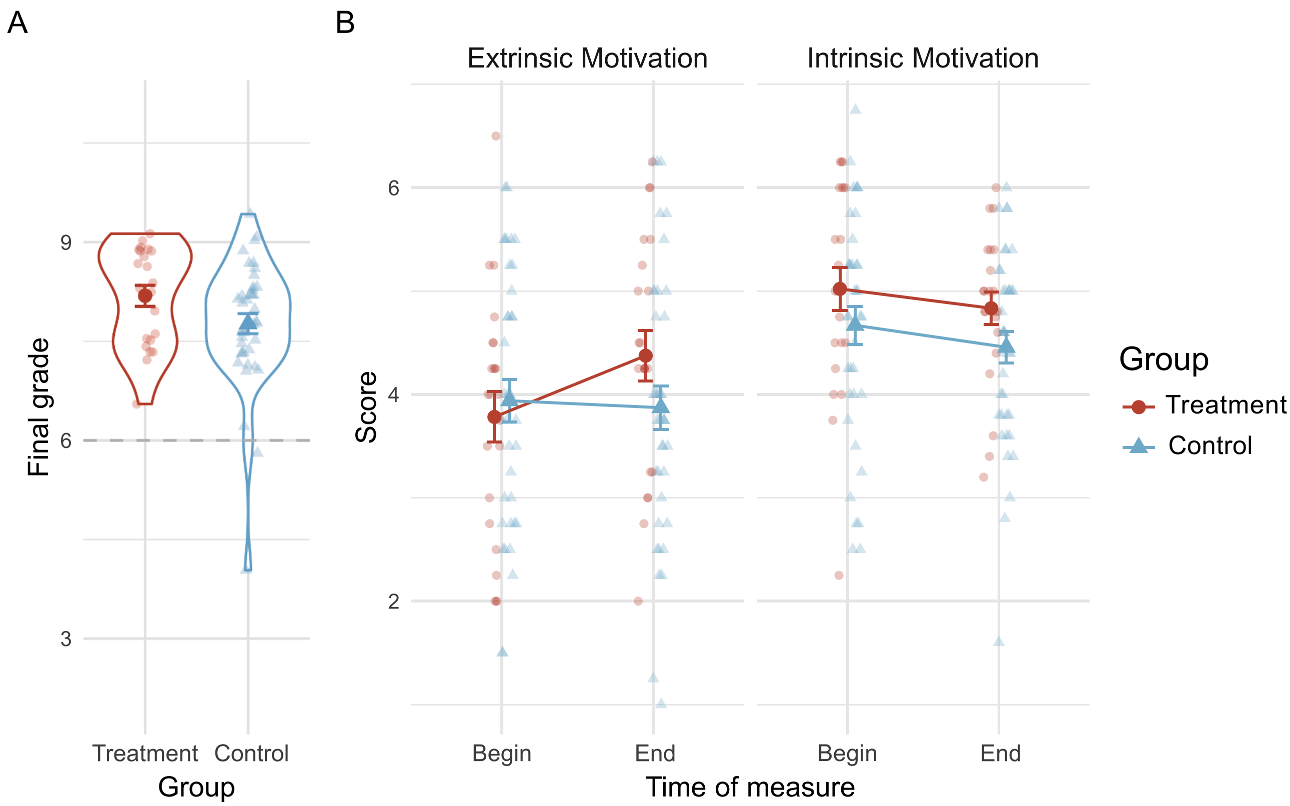

Fig. 5. Results for experiment 2 on motivation and achievement. A) Mean and density of the final grade in the two groups. The dashed horizontal line represents the passing grade. B) Mean extrinsic and intrinsic motivation assessed with the MSLQ at the start and end of the course ('Begin' and 'End', respectively). In both A and B, the bars represent the standard error and the semi-transparent scattered points individual datapoints.

4. Discussion

In both experiments we found that our LAD implementing a slight upward comparison successfully supported motivation and academic achievement. The main differences between the two experiments were the learning contexts (different courses, one of which moved online due to the COVID-19 pandemic) and the absence of the grade prediction diagram in experiment 2. In experiment 1, extrinsic motivation was maintained in the treatment group whereas it decreased in the control group; in experiment 2, extrinsic motivation remained stable in the control group and increased in the treatment group. Given the comparable findings in both experiments, we argue that the social comparison component is sufficient to generate these effects and that the grade-prediction component does not offer additional benefits when provided in combination with the social comparison component. The unique contribution of grade prediction was not explored in this study.

We found no significant effect on metacognition nor a mediating role of extrinsic motivation. Nevertheless, the overall positive impact of the intervention on achievement is encouraging and is in line with previous research implementing some form of upward comparison [18,32], as opposed to an average indicator. Indeed, treatment subjects achieved higher grades and fewer students failed the course. The absence of effects on our measures of metacognition may be explained by the fact that intrinsic motivation did not vary as a result of the intervention. Indeed, SRL researchers have highlighted the strong link between intrinsic motivation and metacognitive engagement [59]. The fact that the intervention did increase academic achievement but not metacognitive abilities does, however, indicate that students did adapt their learning behaviour in some way that was not captured in this study. The validity of the metacognitive self-regulation factor of the MSLQ has been recently challenged, as pointed out by an anonymous reviewer. Indeed, whereas time and study environment management and study time, have been found to be positively affected by comparative LADs [32,42], confirmatory factor analysis have indicated a poor fit of the measure with these two variables, as well as with performance [76]. Besides, while SRL theory and educational scientists at large typically associate metacognition with an explicit, strategic level of cognition characterised by planning, monitoring and regulation, cognitive neuroscience researchers have argued that metacognitive activity can operate on an implicit level [4,26,40,69]. It is therefore possible that in our study the LAD contributed to more implicit metacognitive processes that may have played a role in achievement. Whether or not these forms of implicit processes truly qualify as metacognitive is still being debated. One might argue, however, that under Pintrich's model of metacognition, students exposed to the LAD likely resorted to more cognitive learning strategies, rather than metacognitive ones. Nevertheless, this suggestion may generate interesting research questions for SRL theory. Is learning behaviour self-regulated only when it is strategic (i.e., explicit)? Does increased engagement suffice to qualify self-regulated learning (as it is often inferred in studies analysing trace data in MOOCs)?

While LAD use resulted in comparatively higher extrinsic motivation, we did not find a similar effect for intrinsic motivation. Intrinsic motivation decreased in both groups in experiment 1 – likely due to a novelty effect – and did not vary between the beginning and the end of experiment 2. Critically, the comparative absence of increase in intrinsic motivation did not preclude achievement. On the contrary, achievement increased. According to SRL theory, intrinsically motivated learners tend to be more (meta-)cognitively active and are more prone to self-regulation than extrinsically motivated ones. It is therefore generally assumed that intrinsic motivation should be promoted and that extrinsic motivation is undesirable. This assumption is nuanced by our results that indicate that enhanced extrinsic motivation can induce cognitive and behavioural changes. In line with our results, Pintrich and Garcia [58] (cited in [59]) observed that learners with low intrinsic motivation but high extrinsic motivation were more cognitively engaged than those with low motivation overall. In other words, fostering extrinsic motivation in learners who have little interest in the course material can have positive effects on their cognitive engagement and subsequently their academic achievement. The fact that the significant difference in achievement between the treatment and control groups seems to be due to the lower number of treatment subjects failing the course supports this view. We might add that this benefit only holds as long as intrinsic motivation does not decrease. Apart from that, setting goal grades and comparing one's grades to those of peers can be viewed as a form of ability or performance goal orientation. In contrast to the theory, Wolters, Yu and Pintrich [81] found that such goal orientation "resulted in positive academic outcomes in motivation, cognition and performance" (p. 233).

4.1. Limitations and future research

The design of this study was constrained by the data available in the two courses and by the fact that it had to minimally intervene with their structures. The sample size was also constrained by the number of students following the courses and the statistical analyses performed may thus be sensitive to the small samples used in the two experiments. Designs that intervene more with the course structure with larger samples may enable researchers to investigate more complex phenomena. We want to stress that the study took place in Dutch higher-education contexts and that similar studies should be carried out for different populations and with bigger samples to evaluate the full generalisability of these findings. Research has shown that behaviour related to social comparison can vary between cultures and genders [31,39,80]. Nevertheless, the fact that we were able to find comparable effect sizes and direction in both experiments provide support in favour of the generalisability of our results. For the purpose of this study, we manipulated the data presented to the learners in a way that prompted slight upward comparison. It is possible that the effects reported in this study would not be observed if the learners were to be aware of this manipulation. Therefore, in its current version, the LAD developed in this study may not be suitable for use by the same learner in different courses through time.

While the design of this study was based on randomised control trial (RCT) methodology to assess the benefits of the LAD on learners, limitation inherent to the discipline and the field of research make it that this study does not fully satisfy the standard RCT requirements, such as used in medical research. Therefore, confounding factors cannot be ruled out entirely (for discussions, see [2,62]). For instance, we cannot exclude that some novelty effect (the boost in motivation generated when interacting with anything new) contributed to the results to some extent. Furthermore, our design does not allow to clearly determine the unique contribution of grade prediction. We view however that this effect is likely to be small, if present at all, given the fact that students kept using the LAD repeatedly over time.

(Upward) social comparison is an inherent aspect of human behaviour [24,29] and might have been a driving force in our evolution as social animals. This can allow individuals to recalibrate their metacognitive biases (i.e. over/under-confidence; [13,56]) and may provide them with pathways towards self-improvement [44,83]. Yet comparing oneself to others to evaluate one's own worth or aptitude can also have strong negative effects for the individual [30,49,52]. The recent testimony of Frances Haugen on the impact of social media, Instagram in particular, on the mental health of young people being relentlessly compared to idealised versions of peers is a clear illustration of this [72]. That these negative effects have been mainly observed on social media regarding body image should not distract researchers from the fact that LADs with social comparison components may carry an inherent risk of negatively affecting their users' self-worth and mental health. It is therefore critical that future research investigates the effects resulting from other manipulations of the social comparison and differentiates different factors playing a role on motivation to obtain a full picture of social comparison in the context of LADs, such as further distance from the norm, different number of peers, and downward instead of upward comparison, as well as the potential long-term effects of LAD interventions. In particular, we encourage researchers to inform their designs with findings from social (media) psychology, social learning and social comparison and investigate to what extent they are applicable to LAD contexts in order to mitigate potential negative effects. To illustrate our point, a recent study by Midgley and colleagues found that extreme upward comparison in social media had an immediate negative impact on users' self-esteem and mental health and this effect was particularly worse in individuals with already low self-esteem [49].

Future research should also attempt to foster intrinsic motivation in particular. A possible account of the non-conclusive results with regards to metacognition is that social comparison was made on the basis of grades which may prime more towards performance, associated with extrinsic motivation, rather than mastery which is more linked to intrinsic motivation.

Lastly, the design of this study was constrained by the data available in the LMS. It would be interesting to investigate designs with social comparison on learning behaviour for contexts where richer data is available such as study time, use of learning strategies, and use of learning materials. Such presentation of data coupled with an emphasis on goal achievement may help learners to gain awareness on learning behaviour that are desirable or undesirable in order to achieve their learning goals, allowing them to regulate their learning efficiently.

5. Conclusion

This study investigated the effects of a comparative LAD on motivation, metacognition, and academic achievement. The design was informed by SRL theory and social comparison theory and the empirical evidence on these two lines of research. The LAD consisted of a social comparison diagram on academic achievement with peers with similar goal grades and a grade-prediction diagram. The social comparison was manipulated to elicit a slight upward comparison such that the relevance and proximity of the peers was high. In contrast to the majority of Learning Analytics research which is carried out in online education, this study was performed as part of a standard, face-to-face higher-education course. The hypothesis was that exposure to the LAD would increase motivation, which would support the activation of metacognitive processes and lead to higher academic achievement. We found that the intervention does overall support extrinsic motivation and academic achievement. However, we did not find any effect on metacognition as measured by the MAI or the MSLQ. These results suggest that carefully designed social comparison, rooted in theory and empirical evidence can be used to create LADs that support both awareness about performance and learning processes and behavioural changes in learners, notably towards higher achievement. Specifically, implementing norms relative to the learner, rather than absolute norms such as class averages, can contribute to more successful LADs. Our design is particularly suited for face-to-face higher education for which the availability of a wide range of data can be a challenge. It is still unclear what type of behavioural changes (metacognitive or not) precisely were elicited by exposure to our LAD and how they exactly relate to increased motivation.

This study provides theoretical and methodological contributions. From a theoretical standpoint, our results are in line with social comparison theory and the empirical evidence gathered in other contexts not directly related to education and technology-enhanced learning, generalising the validity of this theory. From a methodological standpoint, we provide a successful example of how evidence from (social psychology) can guide the design of LADs. It also highlights a set of conditions under which visualisations containing social comparison can benefit learners. Future research should focus on the relationship between motivation, metacognition and achievement, explore this paradigm with data related to learning behaviour, design social comparison, and especially investigate how to foster intrinsic motivation.

Credit author statement

D.S.F., W.vd.B. and B.B. were involved in the conceptualisation, and methodology. D.S.F. programmed the software, performed the investigation, formal analysis and validation, and wrote the original draft under the supervision of W.vd.B. and B.B. W.vd.B. and B.B. were involved in the reviewing and editing of the draft.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2023.100130.

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