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Davis, D.J.; Jivet, Ioana; Kizilcec, René F.; Chen, Guanliang; Hauff, Claudia; Houben, Geert Jan

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Follow the Successful Crowd: Raising MOOC Completion Rates through Social Comparison at Scale*

Dan Davis†
Delft University of Technology
Delft, the Netherlands
d.j.davis@tudelft.nl

Ioana Jivet‡
Open University of the Netherlands
Heerlen, the Netherlands
ioana.jivet@ou.nl

René F. Kizilcec
Stanford University
Stanford, CA, USA
kizilcec@stanford.edu

Guanliang Chen§
Delft University of Technology
Delft, the Netherlands
guanliang.chen@tudelft.nl

Claudia Hauff
Delft University of Technology
Delft, the Netherlands
c.hauff@tudelft.nl

Geert-Jan Houben
Delft University of Technology
Delft, the Netherlands
g.j.p.m.houben@tudelft.nl

ABSTRACT

Social comparison theory asserts that we establish our social and personal worth by comparing ourselves to others. In in-person learning environments, social comparison offers students critical feedback on how to behave and be successful. By contrast, online learning environments afford fewer social cues to facilitate social comparison. Can increased availability of such cues promote effective self-regulatory behavior and achievement in Massive Open Online Courses (MOOCs)? We developed a personalized feedback system that facilitates social comparison with previously successful learners based on an interactive visualization of multiple behavioral indicators. Across four randomized controlled trials in MOOCs (overall $N = 33,726$), we find: (1) the availability of social comparison cues significantly increases completion rates, (2) this type of feedback benefits highly educated learners, and (3) learners' cultural context plays a significant role in their course engagement and achievement.

CCS Concepts

•**Applied computing** → **Collaborative learning;**

Keywords

Learning Analytics; Massive Open Online Course; Feedback; Social Comparison; Framing; Cultural Differences

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1. INTRODUCTION

A mechanism for increasing access to higher education content, Massive Open Online Courses (MOOCs) have afforded millions of people worldwide the opportunity to learn for little or no cost. To achieve this unprecedented scale, MOOCs provide the same material to all learners, no matter what background, motivation, and skill set they possess. Yet this approach falls short of leveraging the technical possibilities of contemporary educational resources to offer learners personalized support, such as giving guidance to learners who are less adept at regulating their learning process over several weeks to achieve mastery. Low course completion rates (typically between 5-10%) highlight the need for additional support in MOOCs. While many learners have no intention to complete MOOCs and instead use them to fulfill alternative needs (e.g., to refresh their memory of a specific topic or to meet new people), the majority of learners who are motivated and committed to complete the course still fail to achieve their goal [25, 26]. Most learners report that they could not find the time to keep up with the course, a challenge that is related to insufficient self-regulatory abilities [44, 23]. Self-regulated learning (SRL; i.e., the ability to plan, monitor, and actively control one's learning process) is associated with a higher likelihood of achieving personal course goals in MOOCs, including course completion [24, 29]. However, the current design of MOOCs does not support learners to engage in SRL [34]. In particular, most MOOC platforms do not provide learners with personalized feedback beyond grades [7], and thus, learners may not know if their engagement in the course is conducive to achieving their learning goals.

We propose a technological solution that facilitates social comparison to help learners regulate their learning behavior to support course completion. According to social comparison theory [8], people establish their social and personal worth by comparing themselves to others. Offering learners the opportunity to compare their behavior with that of their peers promotes increased student achievement in formal learning environments [2, 15, 36]. Students in in-person classrooms can easily identify role models and regularly monitor these role models' behavior and compare it to their own. However, this affordance of social comparison is missing in most online "classrooms." Instead, online learners need to be self-directed and regulate their learning process independently with sparse social and normative signals.

In addition to evaluating the impact of providing learners with personalized feedback, we further examined the potential of adjusting the framing of the feedback to match learners' cultural context. Framing feedback in a way that is consistent with the norms and achievement-based motivation of learners' cultural context is expected to support internalization and behavior change. Prior work has observed differences in the way learners from different countries and cultures interact with MOOCs [11, 23, 30]. We define cultural context based on two established country-level cultural dimensions: *individualism* by Hofstede et al. [14] and *tightness* by Gelfand et al. [9].

We explore the extent to which insights from the social comparison and cultural psychology literature can be translated to support learners in MOOCs. We evaluate how to offer feedback based on social comparison in an online learning environment. To this end, we design, develop, and empirically evaluate a personalized and scalable feedback system that presents MOOC learners with a visual comparison of their behavior to that of their "successful" peers, that is, those who completed the course in the past. We deployed the system in four edX[1] MOOCs offered by the Delft University of Technology with a total of $N = 33,726$ learners. In each deployment we drew on research findings across multiple domains including learning analytics, educational psychology, and social & cultural psychology to inform the design on both the feedback we provide (i.e. the behavioural metrics shown to the learners) and how the feedback is framed (e.g., individualistic- or collectivist- oriented framing).

Our work extends prior research by testing a theory-informed technological solution in a large and diverse population (i.e., MOOC learners) for a prolonged period of time. These are our main findings:

- Personalized social-comparison feedback increases course completion rates.
- Only highly educated learners benefit from this kind of feedback.
- Course engagement and achievement varies by cultural context: learners in countries with a "loose" culture outperform those in countries with a "tight" culture.

2. BACKGROUND

In this section we provide the theoretical and empirical underpinnings to our work which facilitates social comparisons with personalized feedback. We discuss (i) previous studies on incorporating feedback in online learning, (ii) the theory of social comparison and its application to learning, and (iii) past research on the impact of learners' cultural context on learning behavior.

Feedback.

Providing feedback is one of the most effective teaching strategies to improve student achievement [12]. Given the scale of MOOCs it is impossible for a teacher or teaching assistant to personally monitor and attend to each learner's unique needs. Therefore, up to this point, the majority of feedback solutions developed for MOOCs and other online learning environments have been for the course instructor, typically in the form of a dashboard representing aggregated learner data [27, 33, 43].

While teacher-facing feedback systems can provide key insights for improving the course experience, they are unlikely to address the issue that many learners feel lost and isolated in MOOCs [21]. Personalized feedback promises to promote effective SRL behavior by facilitating self-monitoring of learning processes [18]. One of the most important lines of research which aims to provide learners with personalized feedback is that of Open Learner Models (OLM), an educational interface that gives learners insight into their current knowledge state and activity patterns, which are typically unavailable to them [3]. By allowing learners to visualize and reflect on their own learning and achievements, OLMs have been proven to work as powerful meta-cognitive feedback tools that impact learners' use of SRL strategies [4, 10]. We designed the `Feedback System` informed by prior work on the design of accessible, understandable, and scrutable [20] learner models [5, 19].

There has been little progress in developing and deploying personalized feedback for large-scale MOOC environments, and most work focuses on supporting teachers [40]. In the present research, instead of presenting aggregate data for all learners in a course, we addresses the challenge of delivering individualized, targeted feedback to each learner based on her behavior in the course relative to her peers' behavior to facilitate social comparison. The present research contributes an empirically evaluated scalable and personalized feedback intervention to the literature on learning analytics. Recent studies have begun to run controlled experiments [37], but most feedback system evaluations thus far explain the design, development, and implementation considerations without rigorously testing whether the added support contributes to behavior change or learning gains [43].

Social Comparison.

The feedback learners receive through the `Feedback System` is grounded in social comparison theory, initially proposed by Festinger [8]. The theory posits that, guided by a drive to continuously improve, people evaluate their abilities through comparison to others when they are lacking objective means of comparison. It has received empirical validation and found application in various domains, including marketing, health psychology, interpersonal relationships, and also in education [6, 28]. In one study, social comparison was used to improve the Web search behavior of novice users [1]. The authors found that showing non-expert searchers visual indicators of the search behaviors of expert searchers resulted in closer alignment with effective behavior and, therefore, more successful search task completion among novices.

Social comparison is an inherent phenomenon in traditional classroom environments because of both the visibility and accessibility of similar peers [28]. Multiple studies have demonstrated that comparing oneself to self-selected peers who perform slightly better has a beneficial effect on middle school students' grades [2, 15]. Forced comparisons also have a beneficial effect on performance when the target of comparison is performing slightly better than the learner, although no effects were found when there was a big performance gap between two sides [16].

In the context of a small online learning platform ($N = 55$), Papanikolaou [36] investigated students' attitudes towards viewing the learner model of others. Her results showed that when learners compare their behavior to that of a "desired" one, they are then motivated to recognize and adapt

[1] **https://www.edx.org/**

their learning strategies. She suggests that the "desired" state should be generated based on real data coming from peers who are "worth following." We build on this insight by considering MOOC graduates of previous editions as the basis for creating a role model.

Guerra et al. [10] integrated social comparison features in the form of peer and class progress in the design of an intelligent interface for a learning management system to provide additional motivation and navigation support. This approach showed a positive effect on engagement and efficiency in two studies ($N = 89$), but no significant effects on learner performance in terms of final grades or learning gains. On the other hand, Rogers et al. [38] investigated "discouragement by peer excellence" in a MOOC setting and concluded that learners who are exposed to examples of excellent peer achievements risked feeling less capable of performing at the level of those peers. The `Feedback System` is different in that it shows the *behavior* patterns of the average completing learner, so as not to risk discouragement.

The present research adds to the literature on social comparison in the online learning environments by investigating the effects of forced comparison of learners' performance and engagement in a MOOC setting. With the `Feedback System`, MOOC learners can visualize their behavior compared to that of successful learners, offering them a model against which they can evaluate their own study habits.

Culture.

MOOC learners come from all over the world and cover a profoundly wide range of cultural contexts. Prior MOOC research has observed a learner's culture as affecting behavior within the course. For example, Liu et al. [30] explored patterns in MOOC learner behavior in relation to Hofstede's cultural dimensions [14]. The authors clustered countries based on similarity across four cultural dimensions and found significant variation in learner behavior between the clusters. Moreover, Kizilcec et al. [22] found in two randomized experiments in MOOCs that the effect of a self-regulation intervention depended on learners' cultural context ($N = 17,963$): only learners in individualist countries benefited from the brief writing activity. Thus, prior work supports the hypothesis that cultural factors shape learner behavior in MOOCs. We examine two country-level cultural dimensions: individualism [14] and tightness [9].

Hofstede's dimension of individualism-collectivism characterizes cultural variation around the world. Cultures high in individualism are those which emphasize the individual as an independent actor with loose social relations. Cultures high in collectivism are characterized by tightly-knit social relations and shared responsibility for the collective well-being [14]. Gelfand et al. conceived an index that ranks countries by their cultural tightness: tight cultures are those with "strong norms and a low tolerance of deviant behavior," and conversely, cultures of low tightness (or loose cultures) are those with "weak social norms and a high tolerance of deviant behavior" [9]. The present study attempts to adapt feedback to learners' cultural context so that it resonates with the learner, facilitates internalization of the feedback, and promotes positive behavior change.

Prior work suggests that cultural differences shape people's regulatory focus, whether they are motivated by pushing for success (promotion) or by avoiding failure (prevention) [13, 31]. Members of individualist and tight cultures focus more on promotion, while members of collectivist and loose cultures focus more on prevention [31, 35]. We apply this insight in the design of our feedback framing messages to appeal to learners in different cultural contexts.

3. MOOC OVERVIEW

For our experiments, we employed our personalized `Feedback System` to learners across four MOOCs—all of them re-runs (i.e. not in their first edition)—provided by the Delft University of Technology on the edX platform:

`WaterX` The *Drinking Water Treatment* MOOC teaches technologies for drinking water treatment. Its second edition ran between 12 January and 29 March 2016. It is a seven-week course with 63 instructional videos and 42 summative quiz questions. A total of 10,943 learners registered for the course. To complete the course, learners had to gain at least 60% of all scores (i.e. passing threshold $\tau_{pass} = 60\%$).

`UrbanX` The *Urban Sewage Treatment* MOOC learners are taught how to design and manage solutions for urban sewage. The second edition of the seven-week course ran between 12 April and 20 June 2016 with 8,137 learners. There are 272 summative quiz questions ($\tau_{pass} = 60\%$) and 71 videos.

`BusinessX` *Responsible Innovation: Ethics, Safety and Technology* teaches learners how to deal with risks and ethical questions arising from new technologies. 2,352 learners registered to the second edition which ran between 11 April and 14 June 2016. The course has 79 summative quiz questions ($\tau_{pass} = 59\%$) and 54 videos.

`CalcX` *Pre-university Calculus* is the only MOOC in our list that targets beginning Bachelor students and was designed as a refreshment course before entering higher education. The third iteration of this course ran from 28 June 2016 through 27 September 2016 with 12,294 learners, 85 videos, and 327 summative quiz questions ($\tau_{pass} = 60\%$).

We found the `WaterX`, `UrbanX`, and `BusinessX` MOOCs to attract a similar population of learners: two thirds of the enrolled learners were male, the median age was 28, and the majority of learners held a BSc or MSc degree. The learner population in the `CalcX` course was instead targeted at high-school students who were about to enter university. While the gender balance was consistent with other MOOCs (30% female), the median age was only 25, and the most common education level was a high school diploma (45%).

For each learner, we collected all available edX log traces such as the learners' clicks, views, dwell time on the edX platform, and their provided answers to the quiz questions.

4. APPROACH

In Section 4.1 we first introduce the research questions driving our work before detailing the design of our `Feedback System` which was deployed in different instantiations across the four MOOCs just described.

4.1 Research Questions

The first **R**esearch **Q**uestion and **H**ypotheses are based primarily on the social comparison literature in the context of education and learning environments:

RQ1 Does providing personalized social comparison feedback increase learner achievement and self-regulatory behavior in MOOCs?

H1.1 In line with previous findings [1, 36], we expect that providing learners a comparison of their own behavior to that of previously successful peers will increase learner *achievement* (measured in terms of completing/passing the course) and *engagement* (activity levels within the course environment).

H1.2 Learners will change the aspects of their behavior that the `Feedback System` makes them aware of.

H1.3 Certain feedback metrics (and combinations of metrics) will be more effective than others in leading to desirable changes in student behavior.

Based on prior work which has shown that learners from different cultural contexts learn and behave differently in MOOCs [11, 23, 24, 30], we explore:

RQ2 Which learners benefit most from the `Feedback System`?

We also examine the differences in learning behavior according to learners' cultural context. We expected the effects of the feedback to depend on learners' cultural context in terms of individualism and tightness, and moreover, that matching the framing of feedback to learners' culture to be beneficial:

RQ3 Does feedback framed in line with a learner's cultural context lead to increased achievement and self-regulatory behavior compared to a culturally mismatched framing?

H3.1 Learners from individualist cultures will show more engagement than those from collectivist cultures with the individual-promotional framing, while learners from collectivist cultures will show more engagement with the collectivist-prevention framing.

H3.2 Learners from tight cultures will show more engagement than those from loose cultures with the collectivist-prevention framing, while learners from loose cultures will show more engagement with the individual-promotional framing.

4.2 Feedback System Design

Recall, that our design rationale of the `Feedback System` (presented as the "Learning Tracker" to learners in the courses, cf. Figure 1) is to provide learners feedback about their own behavior that enables them to make well-informed decisions about their learning strategies going forward [45] as a result of increased self-awareness. The `Feedback System` can be thought of as a mirror with which learners can view and react to their own, previously-invisible behavior. Since SRL skills are generalizable, the design should be agnostic to the content of each specific MOOC the feedback system is deployed in. We identified three key criteria for our system design:

- *Traceable*: we can only provide feedback on behavior we can extract and derive from edX's log traces[2];
- *Scrutable* [20]: afford learners the ability to intuitively understand and explore the information presented;
- *Actionable*: learners should be able to take action and change their behavior based on what they learn from the presented feedback.

After surveying the literature on learner model visualizations, we settled on employing a single spider chart to visualize six metrics of learners' behavior in relation to that of their successful peers, as shown in Figure 1. The spider chart's key benefits include: (i) a single, embodied representation of multiple metrics, (ii) numerous indicators displayed in a small space, (iii) a simple representation of metrics—data is shown as single points along radial straight lines, and (iv) easily comparable—information is represented as differently colored areas that can be layered [39].

In all four courses, the experimental conditions were not made explicitly known to the learners; the `Feedback System` appeared seamlessly integrated with the rest of the course materials.

We operationalized previously successful students, or "role models", as learners who earned a passing grade in the *previous edition* of the MOOC (note that this setup requires that subsequent editions of the same MOOC have few changes). We updated the `Feedback System` every week (based on the learners' activities on the platform in *all* weeks leading up to the current one) so that the learners could see an up-to-date representation of their activities as compared to that of the role models. The learners' behaviors in the courses were tracked by the standard edX tracking log system.

Table 1: Overview of feedback metrics and alterations presented to learners in each MOOC. A • indicates the presence of the metric/alteration.

	`WaterX`	`UrbanX`	`BusinessX`	`CalcX`
Feedback metrics				
Quiz submission timeliness (days)	•	•	•	•
Time on the platform (in hours)	•			
Time watching videos (in hours)	•			
Number of videos accessed	•			
Number of quiz questions attempted	•	•	•	•
Proportion of time spent on videos while on the platform (in %)	•			
Average time on the platform per week (in hours)				•
Number of revisited video lectures				•
Number of forum visits		•		
Number of forum contributions				•
% of time spent on quizzes				•
Number of sessions per week		•	•	
Mean session length (in minutes)		•	•	
Mean time between sessions (in hours)		•	•	
% of time-on-task - time spent on video-lecture, quiz or forum pages			•	
Alterations				
Interactive visualization		•	•	•
Planning ahead		•	•	•
Feedback framing				•

In each MOOC, the `Feedback System` was placed in the *Weekly Introduction* unit of each course week so that it

[2]edX provides fine-grained log traces of each learner's clicks & views, provided answers to assignments, forum interactions, etc.

would be readily available and immediately visible to learners upon entering the new course week, enabling them to reflect on their SRL behavior so far. With the exception of the `Feedback System`, all learners received the same course materials, independent of the experimental condition.

Feedback metrics.

Table 1 shows an overview of the feedback metrics given to learners in each MOOC. At the end of each week in the course, the metrics were computed based on the log traces of *all* weeks prior. These metrics were chosen based on the following criteria: relevance to self-regulated learning, clarity/intuitiveness to the learner, and availability in the log data. For each metric, all values of previously successful learners were sorted and the top 5% and bottom 5% of values were discarded to remove outliers. The mean of the remaining values was computed, yielding a single value per metric — we consider this mean to be indicative of the tendency of the whole successful group of learners. We operationalize "sessions" as strings of activity with less than an hour gap between two events. As shown in Table 1, we used different feedback metrics in different MOOCs to explore the impact of the choice of metrics (**H1.2** and **H1.3**).

Feedback System Alterations.

Apart from the different metrics, we also explored three refinements of the `Feedback System`:

1. Planning ahead: in `WaterX` the learners only received feedback about their behavior up to now and how it compares to that of successful learners. In this alteration (in `UrbanX` and `BusinessX`), we also provide the learner with a visualization of the role models' behavior (labelled as "Average graduate this week" in Figure 1) in the upcoming week, enabling learners to plan ahead instead of only reflect.

2. *Interactive visualization*: instead of a static feedback image (as provided in `WaterX`), in this alteration, we provide learners with an interactive visualization they can explore, i.e. mouse over the metrics to reveal exact numbers and comparisons (cf. Figure 1), and toggle on/off the metrics of the average successful learner for the upcoming week.

3. *Cultural framing*: in the first three MOOCs, the `Feedback System` provides no written interpretation of the visualization; instead learners are left to draw their own conclusions. In `CalcX` we additionally provide an explanatory text (as shown in Figure 1) that offers a clear interpretation of the learner's "on-trackness".

4.3 Studies

In each MOOC, we deployed a variation of the `Feedback System`. Table 1 summarizes the feedback metrics and variations deployed. For random assignment, we used a between-subjects design, where learners were assigned to either the control or a treatment condition and remained in this condition throughout the study. Table 2 shows a breakdown of the number of learners assigned to each condition for each MOOC. To gather baseline data from the first two weeks of each course, we released the `Feedback System` in the treatment conditions in the third week in each experiment. As noted before, the `Feedback System` is then updated on a weekly basis to reflect the updated learner activity data.

In the control condition across all experiments, learners did not receive the `Feedback System`. However, the edX platform offers a very basic form of learner feedback: a learner can visit her "progress" page and view the number of points scored so far in the course. This progress page is available to all learners, independent of their condition assignment. In the treatment condition, learners received the `Feedback System` in addition to edX's progress page.

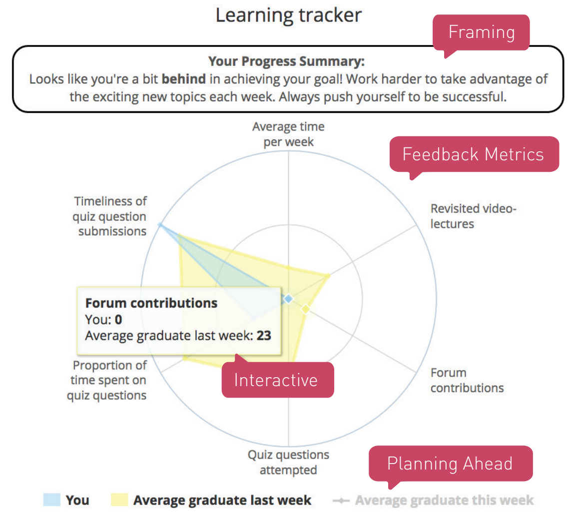

Figure 1: The `Feedback System` as shown in the individualistic-promotional condition in `CalcX`, annotated for clarity.

Table 2: Overview of the number of learners enrolled and assigned to the control and treatment groups respectively. The number of active learners (having spent at least 5 minutes in the course platform) is in the parentheses beneath.

	`WaterX`	`UrbanX`	`BusinessX`	`CalcX`
Enrolled	10,943 (2,519)	8,137 (1,517)	2,352 (324)	12,294 (3,415)
Control Group	5,460 (1,268)	4,038 (771)	1,184 (164)	4,142 (1,150)
Treatment Group 1	5,483 (1,251)	4,099 (746)	1,168 (160)	4,087 (1,147)
Treatment Group 2	–	–	–	4,065 (1,118)

In all but one study there is only one treatment condition. In `CalcX`, we had two treatment conditions, one for each culture-specific framing of the explanatory feedback text:

- `CalcX` *treatment 1* received text with an individualistic promotion-focused framing;

- `CalcX` *treatment 2* received text with a collectivist prevention-focused framing.

We determined each learner's cultural context based on the IP address used to access the course relying on Maxmind's GeoIP lookup database[3], as not all learners self-report their nationality. For learners with more than one IP address used, we consider the first one they used to access the course as their country.

[3]http://www.maxmind.com

We developed a strong manipulation of the culture-specific framing by drawing on the cultural difference in (1) individualistic vs. collectivist appeals (collectivist cultures see the self embedded in a relational network, while the self-concept is more independent in individualist cultures), and (2) prevention- vs. promotion-focus (the prevention of negative outcomes is emphasized over the promotion of positive outcomes in collectivist cultures, and vice versa for individualist cultures) [13, 32, 35]. We designed two texts for each treatment group: one for learners who are "on track" (characterized by exhibiting similar behavior to that of the role model learners) and one for learners who are "behind" (characterized by exhibiting less course engagement compared to the role model learners). The texts (four overall) and how those texts align with a particular framing are shown in Table 3. The learners were evaluated as "on-track" or "behind" based on their *on-trackness score*, OT. The on-trackness score quantifies the similarity between a learner's behavior and that of the previously successful learners: we normalize each metric to a value in the range $[0, 10]$ (chosen for convenience to work well in the spider chart setup) and then compute the difference, d_i, between the learner's score on metric m_i and the previously successful learners' average score on m_i. If $d_i \leq -1 \; \forall m_i, i = \{1, .., 6\}$ the learner is classified as behind, otherwise she is on-track — this is a very conservative classification, the learner has to have a lower engagement level on every single metric before she is considered as being behind.

The study design and all analyses conducted as part of the `CalcX` experiment[4] were pre-registered through the Open Science Framework, vetted, and approved to meet the requirements of the Center for Open Science Preregistration Challenge[5]. All manuscripts, data, and scripts used for analysis are available at: **http://osf.io/ys6au**.

4.4 Measures & Method of Analysis

The primary outcome variable that we targeted with the design of our `Feedback System` is course completion, which indicates that a learner achieved the required minimum passing score on all summative quiz questions and thus earned a certificate. Course completion demonstrates sustained commitment to the course and mastery over the course material. The `Feedback System` is designed to support this type of sustained commitment and learning, even if individual student intentions may vary. The secondary outcome is to promote SRL and meta-cognitive awareness. While many SRL processes are meta-cognitive and remain unobserved, it is possible to infer some of them based on learner's logged actions with the course materials [17, 24, 41, 42]; for example, goal-setting & planning, time management, self-monitoring, and social comparison.

For non-binary measures, to test if differences between experimental conditions are statistically significant, we used the non-parametric Kruskal-Wallis test, because these measures were not normally distributed and exhibited unequal variances across conditions. For binary measures, we tested differences in proportion using a χ^2 test. We present the results of each test by each group's mean and median along with the χ^2 value, degrees of freedom, and level of statistical significance. Due to the commonly high levels of attrition in MOOCs (65%-74% of learners never returned to the course after enrolling in one of our four MOOCs), the subsequent analyses only consider data generated by *active learners*. We define active learners as those having spent *at least five minutes* on the course platform. See Table 2 for the breakdown of registered vs. active learners per MOOC.

5. RESULTS

We present our findings for the **R**esearch **Q**uestions outlined in Section 4.1. We discuss the impact of the `Feedback System` on course completion and engagement in Sections 5.1 & 5.2, heterogeneous treatment effects of the `Feedback System` in Section 5.3, and lastly in Section 5.4, we compare the effects for different cultural framings of the feedback.

5.1 Course Completion

We hypothesized that the `Feedback System` will increase learner achievement in terms of course completion (**H1.1**). Table 4 shows the completion rates in all conditions for the first three experiments. The completion rate is consistently higher in the treatment condition than in the control condition in all experiments. Pooling across experiments, we observed an increase in the completion rate from 15.5% to 18.9% ($\chi^2 = 5.87, p = 0.008$). Thus, regarding hypothesis **H1.1**, we conclude:

> The `Feedback System` significantly increases course completion rates in MOOCs.

In the fourth experiment, which tested two treatment conditions with different cultural framings against the control of not providing the `Feedback System`, we also observed higher completion rates in the treatment conditions (Table 5). However, this difference was not statistically significant ($ps > 0.25$). However, the overall completion rate in the `CalcX` course was extremely low (1.7%). This suggests that the sample is drawn from a population of less committed learners and that potential effects could be obfuscated by high levels of unexplained variance in completion outcomes. Another contributing factor to this rift between `CalcX` and the other three courses is the fact that `CalcX` was self-paced (content released all-at-once), whereas the others were instructor-paced (content released weekly), thus providing less structure/support to the learners.

Moreover, we hypothesized that showing certain combinations of feedback metrics will better promote positive changes in behavior than others (**H1.3**). We explored this by changing the (combination of) metrics in each of the four iterations of the `Feedback System` (see Table 1). Given that the course completion rates increased across all four iterations each with a different combination of feedback metrics (with two of the six metrics—quiz submission timeliness (how far ahead of the deadline responses were submitted) and quiz questions attempted—were present in all four) we conclude:

> Each combination of metrics shown to the learners produced increases in completion.

5.2 Engagement

In light of the positive effect of the `Feedback System` on course completion, we next evaluated specific changes in learner behavior corresponding to the behavioral metrics that were visualized in the `Feedback System` (**H1.1**). These

[4] We pre-registered this experiment because it was the fourth and final study of the present research and included an added manipulated variable in the cultural framing.

[5] **https://cos.io/prereg/**

Table 3: Overview of the supplementary texts the treatment groups received in CalcX, depending on their performance in the course so far (either on track or behind). The alignment of the words and phrases with the intended framing is highlighted. Sentences prefixed by ↱ are directly addressed at the individual (individualistic framing). Best viewed in color.

	Treatment Group 1 (individualistic promotional framing)	**Treatment Group 2** (collectivist prevention framing)
On track	*Looks like you're right on track to achieve your goal! ↱Keep taking advantage of the exciting new topics each week. Always push yourself to be successful.*	*Looks like you're keeping up with the course for now! We're doing our best to introduce you to exciting new topics each week. Please don't let us down now.*
Behind	*Looks like you're a bit behind in achieving your goal! ↱ Work harder to take advantage of the exciting new topics each week. Always push yourself to be successful.*	*Looks like you're a bit behind in the course right now! We're doing our best to introduce you to exciting new topics each week. Please don't let us down now.*

Table 4: Course completion rates across the first three studies among the *active learners*. Overall, the difference in completion rate between the groups is statistically significant ($p = 0.008$).

	Condition	N	# Pass	Pass Rate
WaterX	**Control**	1,268	160	12.6%
	Treatment	1,251	188	15.0%
UrbanX	**Control**	771	136	17.6%
	Treatment	746	165	22.1%
BusinessX	**Control**	164	46	28.0%
	Treatment	160	54	33.8%
Overall	**Control**	2,203	342	15.5%
	Treatment	2,157	407	18.9%

Table 5: Course completion rates in the CalcX course among *active learners*. A binomial test of independent proportions revealed no statistically significant differences between the three conditions.

Condition	N	# Pass	Pass Rate
Control	1,150	45	3.91%
Indiv.-Promotion	1,147	62	5.41%
Collect.-Prevention	1,118	51	4.56%

metrics, which varied across experiments, were most likely to be directly affected through social comparison. Table 6 shows the results of Kruskal-Wallis tests[6] comparing the various feedback metrics between the treatment and control groups in study to test **H1.2**. A common thread across the three experiments was that of the `Feedback System` increased the number of summative quiz questions that learners submitted, which directly promotes course completion.

Looking at each feedback metric individually in Table 6, we observe 15 out of 18 times an improvement from control

[6]While the Kruskal-Wallis test measures the difference between rank orders, the median values are often zero, so in the table we show the mean for better context.

Table 6: Results of the Kruskal-Wallis tests for the behavior metrics (feedback metrics) provided in the Feedback System for WaterX, UrbanX, and BusinessX. Statistically significant differences are in bold.

	Metric	Ctrl $\bar{x}$	Treat. $\bar{x}$	χ^2	p
WaterX	quiz questions attempted	4.2	4.7	4.46	**0.04**
	videos accessed	7.0	7.0	0.01	0.94
	time on platform (hours)	4.5	4.6	0.17	0.68
	time watching videos (hours)	0.8	0.8	0.04	0.85
	ratio video/total time (%)	25.0	25.0	0.11	0.75
	submission timeliness (days)	27.9	31.3	4.20	**0.04**
UrbanX	quiz questions attempted	5.7	6.6	3.16	0.08
	sessions per week	3.8	4.0	2.11	0.15
	avg. session length (minutes)	8.1	8.2	0.18	0.67
	time between sessions (hours)	117.0	120.0	0.29	0.59
	forum visits	2.7	3.0	2.88	0.09
	submission timeliness (days)	28.3	32.0	3.27	0.07
BusinessX	quiz questions attempted	21.4	25.3	3.97	**0.05**
	sessions per week	0.5	0.7	4.89	**0.02**
	avg. session length (minutes)	32.8	46.7	8.42	**0.00**
	time between sessions (hours)	95.9	92.2	1.17	0.28
	time-on-task (%)	64.3	67.5	0.32	0.57
	submission timeliness (days)	19.9	21.4	1.12	0.29

to treatment condition[7]; three times no change is observed. The treatment condition does not lead to a worse effect in any feedback metric. While only a handful of these differences are statistically significant, this consistency lends itself to some explanatory power over the statistically significant increases in course completion rates: while on an individual level, only some metrics show significant increases as a result of the `Feedback System`, on a macro level—that which accounts for a learner's *overall* activity in the course—we infer that these small increases in engagement all effectively coalesce into a boost in desirable behavior that leads to increased completion rates. We draw the following conclusion:

> The `Feedback System` causes desirable changes in learner *engagement*.

[7]A high "time between sessions" score is not better per se, but it indicates a desirable high-spacing learning routine

Table 7 shows the results of the same analysis on the engagement metrics across the three conditions in `CalcX`; the results are less consistent.

In **H1.2**, we hypothesize that learners change aspects of their behavior that are reflected back to them in the `Feedback System`. Since there is no consistency among significant increases in the provided behavior metrics, we conclude:

> Learners do not change specific behaviors based on what metrics are shown in the `Feedback System`.

5.3 Who benefited from the feedback?

Going beyond average treatment effects of the `Feedback System`, we now evaluate heterogeneous treatment effects, that is, how the feedback affects different groups of learners (**RQ2**). Specifically, we focus on heterogeneity by prior education level, as this might determine learners' ability to use the information provided in the `Feedback System`. We gather learners prior education levels from their edX user profile; learners who do not report their education level are omitted from this analysis. We define *high prior education* learners as those with a Bachelors, Masters, or PhD degree, and *low prior education* learners as those with any degree below Bachelors. Table 8 compares the average final grades in the control and treatment conditions of the first three courses separately for high vs. low prior education learners.

In `WaterX`, `UrbanX` and `BusinessX` we observed a consistent increase in final grades for highly educated learners, but not for less educated learners. However, this pattern did not replicate in the `CalcX` course, as education level did moderate the effect on grades ($p = 0.82$)[8]. Nevertheless, the results for `CalcX` are harder to interpret due to the relatively low completion rate in this course. Moreover, `CalcX` stands out in that a majority of low prior education learners were enrolled in this course, while the `WaterX`, `UrbanX` and `BusinessX` courses had a majority of high prior education learners. Based on these analyses, we conclude that:

> The `Feedback System` only helps to improve the *achievement* (final grade) of learners who are already highly educated.

This finding suggests three possibilities: (i) the `Feedback System` is too complex for people falling in the low prior education category to understand, (ii) highly educated learners are better able to synthesize the information offered by the `Feedback System` and translate it into positive behavior as they are already experienced learners (with at least some SRL skills), and/or (iii) less educated learners are not concerned with obtaining a certificate, but rather focus on knowledge acquisition.

5.4 Framing Feedback to Cultural Contexts

In the `CalcX` course, we tested **H3.1** and **H3.2** about supplementing the `Feedback System` with culture-specific feedback. As before, we evaluated each hypothesis both in terms of learner achievement and engagement. All pre-registered analyses for this experiment are reported in Section 5.4.1. Additional exploratory analyses are reported in Sections 5.4.3 and 5.4.2.

[8]Once more we report `CalcX` separately due to the overall difference in completion rate compared to `WaterX`, `BusinessX` and `UrbanX` as shown in Tables 4 & 5.

5.4.1 Pre-registered: Completion & Engagement

We compared the completion rate and six behavioral measures (the ones shown in the `Feedback System`) between the treatment and control conditions separately by learners' cultural context. To address **H3.1**, we segmented learners into three groups of individualism—*high*, *balanced*, and *low individualism*—and compared completion rates of learners in high vs. low individualism cultures in each condition. There was no significant increase in completion rates for either feedback framing, neither for learners in low individualism cultures nor for those in high individualism cultures (all $p > 0.12$). Likewise, we tested for treatment effects in contexts defined by cultural tightness (**H3.2**) and also found no significant increase in completion rates (all $p > 0.29$). Results for learner engagement were also not significant (cf Table 7). Finally, we tested the moderating role of education level, as in the prior experiments (**RQ2**), but found no evidence in support of moderation ($\chi^2 = 0.40, p = 0.82$). We thus conclude that:

> Supplementing the `Feedback System` with feedback framing tailored to cultural tendencies of individualism and tightness does not increase learners' course *achievement* or *engagement*.

5.4.2 Increased "Active" Threshold

From the exceptionally low completion rate of `CalcX`, we gathered that a high proportion of uncommitted learners rendered the data set noisy. Whereas the `WaterX`, `UrbanX`, and `BusinessX` experiments yielded a consistent main effect on course completion, this effect was not detectable in the `CalcX` experiment. To focus our analysis in `CalcX` on more committed learners, we imposed a stricter threshold for "active" learners. Considering only learners who accessed the course platform for at least an average of 1hr/week, we proceeded by analyzing data for *highly active* learners ($n = 658$). This threshold is reasonable given the amount of course content per week (between 6–8 hours). Moreover, the overall completion rate in this sample was 15.65%, a similar rate as in the other experiments.

Among highly active learners, we find that the individualist framing increased completion rates regardless of a learner's own cultural context from 12.8% in the control condition to 19.9%, a 7.1 percentage point increase ($t = 2.02$, $p = 0.04$). Moreover, we find that the effect of the individualistic framing was especially large for learners in tight cultures, effectively tripling the completion rate from 12.1% in the control condition to 36.3% ($t = 2.07$, $p = 0.04$). We therefore conclude that:

> The individualist framing was most effective in increasing course completion rates overall, and especially for learners in tight cultures.

The effect of the individualist framing is surprising in terms of its large magnitude and cultural heterogeneity. We expected the individualist framing to resonate in loose rather than tight cultures. Perhaps the individualist framing is more congruent in an environment where learners tend to be anonymous and socially isolated. Learners in tight cultures were also more likely to benefit as there course performance was generally lower, as discussed next.

Table 7: Results of the Kruskal-Wallis tests for `CalcX`. Statistically significant differences indicated in bold.

Metric	Ctrl $\bar{x}$	Treat.1 $\bar{x}$	χ^2	p	Ctrl $\bar{x}$	Treat.2 $\bar{x}$	χ^2	p	Treat.1 $\bar{x}$	Treat.2 $\bar{x}$	χ^2	p
avg. time/week (minutes)	31.9	33.4	1.38	0.24	31.9	33.8	0.11	0.74	33.4	33.8	2.16	0.14
revisited lectures	3.44	3.62	0.59	0.44	3.44	3.42	0.35	0.55	3.62	3.42	1.88	0.17
forum posts	0.34	0.53	0.03	0.86	0.34	0.36	4.01	**0.05**	0.53	0.36	3.31	0.06
quiz questions attempted	31.3	32.4	1.52	0.22	31.3	33.5	0.09	0.77	32.4	33.5	2.24	0.13
time on quizzes (%)	37.0	34.0	5.08	**0.02**	37.0	36.4	0.15	0.70	34.0	36.4	3.30	0.07
submission timeliness (days)	47.48	45.70	1.31	0.25	47.48	46.71	0.84	0.36	45.70	46.71	0.04	0.83

Table 8: Mean final grades (out of a possible 100 points) grouped by prior education levels. The "Prior Education" column indicates the highest degree the learner has earned; "N" is the sample size; and "p" shows the result of a Kruskall-Wallis test. Significant values are in bold.

Course	Prior Education	N	Ctrl $\bar{x}$	Treat. $\bar{x}$	p
`WaterX`	High	2,006	13.2	15.7	0.15
	Low	788	11.8	11.5	0.16
`UrbanX`	High	1,337	17.4	21.3	**0.04**
	Low	438	16.4	14.0	0.66
`BusinessX`	High	299	23.7	29.1	**0.04**
	Low	92	21.4	22.8	0.78
OVR	High	3,642	16.3	19.5	**<0.01**
	Low	1,318	14.4	13.6	0.36

5.4.3 Lower Achievement in Tight Cultures

In the preceding analyses, we observed a notable cultural difference along the tightness dimension. Pooling across experimental conditions in the `CalcX` course, we found for every metric (cf. Table 1) with the exception of *number of forum posts* that learners in tight cultures exhibit significantly higher levels of achievement and engagement than those in loose cultures ($ps \leq 0.02$). We repeated the analysis for the other three courses and found the same cultural differences. We therefore conclude:

> Learners from countries with low cultural tightness significantly outperform their peers from countries of high cultural tightness in terms of both *engagement* (all p-values $p \leq 0.1$) and *achievement* ($p \leq 0.02$).

This cultural difference in performance could arise from the nature of the MOOC learning experience. MOOCs provide significant latitude for different levels of commitment and engagement; in fact, learners can come and go as they please at no cost. This may especially appeal to loose cultures, where there are few strongly-enforced rules and high tolerance for deviation. In contrast, traditional classroom environments with strict attendance and performance policies would align more with the ideals of tight cultures. Alternatively, the current finding may reflect structural differences that are associated with both tightness and performance, such as infrastructure and education levels.

6. CONCLUSION

This research tested the effect of providing online learners with personalized feedback in four large-scale randomized controlled experiments in MOOCs. The `Feedback System` was designed to promote learners' awareness of both their own SRL behavior and that of their successful peers through social comparison. It significantly increased course completion rates across different courses. The combination of behavior metrics that was shown to learners in the `Feedback System` did not determine the significance of the effect on course completion, highlighting a need for further research on the optimal set of metrics to show. Moreover, we discovered that the `Feedback System` primarily benefited highly educated learners, although the system was envisioned to support those who struggle with self-regulation. This suggests a new challenge for MOOC researchers and designers to make targeted interventions that support learners who are less educated and need more support.

As online courses can be culturally diverse learning environments, we investigated how the `Feedback System` could be adapted to resonate with learners from different backgrounds. Our pre-registered analyses yielded no significant effects of changing the cultural framing of the feedback. In exploratory analyses, however, we found strong benefits of framing feedback with an individualistic and promotion focus. This insight warrants further research to establish its generalizability. Aside from our intervention, we found that learners from loose cultures consistently outperformed learners tight cultures in terms of course engagement and final grades. In light of the two sources of heterogeneity we identified, future MOOC interventions may be strengthened by personalization based on learners' prior education level and cultural context.

In future work, we plan test a different feedback interface design that presents a set of different *personas* that learners can identify with, such as person who works a bit every day and one who works a lot over the weekend. We will also evaluate new approaches for feedback messages to better support learners with different cultural and educational backgrounds.

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