Measuring effects of technology-enabled mirroring scaffolds on self-regulated learning

Nikola Milikić, Dragan Gašević, and Jelena Jovanović

Abstract—Learning design in a Massive Open Online Course (MOOC) intends to promote creativity, autonomy and social networked learning, amongst other things. Students in a MOOC are required to self-regulate their learning to properly self-monitor their learning process and effectiveness of the adopted learning strategies. This paper presents the results of a study among 279 students enrolled in a MOOC that was enriched with a set of scaffolding interventions for social mirroring. The mirroring interventions supported social awareness and social embeddedness of learners. Associations between the use of the interventions and micro-level self-regulated learning processes were measured and analyzed. The extent to which those associations are affected by learner demographics and motivational characteristics was also investigated. Findings show that interventions that provide students, throughout the course, with learning updates and progress of peers are associated with the students' engagement with learning tasks and applying changes in strategies for completing those tasks. Social awareness scaffold influenced more students low in need for cognition, with a higher education degree, high in performance-approach orientation and low in grit, to engage with their learning tasks, while its effect on the change in learning strategies was higher with those early and towards the end of their careers and high in performance-approach strategy. The social comparison scaffold affected more students low in mastery goal orientation and high in grit to work on their learning tasks.

Index Terms— Correlation and Regression Analysis, Education, Learning Management Systems, Learning Technologies, Scaffolding, Mirroring Scaffolds, Social Technologies

1 Introduction

ONLINE education opportunities have grown significantly with the proliferation of online courses offered by universities, companies, and other organizations. Online education enables learning to shift from traditional classrooms to digital space. This trend has been further strengthened by massive open online courses (MOOCs) that are reshaping access to learning opportunities. MOOCs have brought about learning opportunities and support to vast numbers of learners, at no or low cost. Like students in other online learning contexts, MOOC learners need to make learning decisions and to self-regulate their learning [1]. This involves monitoring and adjusting learning behaviour and actions in relation to the specificities of the learning context [2]. Several studies have shown that learners who are able to self-regulate their learning are more successful than others who lack such skills (see e.g. the review by Bernacki, Aguilar, and Byrnes [3]), and learning environments ought to enable them to develop and use their self-regulation skills [3]. However, it is less understood the extent to which self-regulated learning (SRL) can be effectively supported in MOOCs.

Social context and social interactions are important for the development and use of self-regulation during learning [4]. We base our research on the socially shared regulation model that acknowledges that learner actions and behaviour do not occur in isolation, but as a reflection of activities of the whole learning community [5]. Accordingly, to support students in self-regulating their learning within a MOOC, we have designed a set of scaffolding interventions that promote socially-based mirroring. The aim of mirroring interventions is to support social awareness and social embeddedness of learners, thereby allowing the learners to monitor, evaluate, interpret, and act on the information provided to them [6]. These mirroring interventions are integrated in a learning workflow and are associated with different micro-level processes of self-regulated learning. In the study reported in this paper, we examine the existence and the extent of these associations. Also, we examine the variations in these associations for learners of different demographics, but also with different intrinsic motivation and personal traits.

To conduct this research, we have proposed and implemented mirroring scaffolding interventions in a competency-based learning platform deployed in a MOOC course. In our study, participants have completed a pre-course survey capturing their demographics, but also their motivational characteristics. We have also applied a trace-based methodology [7] to collect the traces of learners' actions as they navigated through the learning environment and made use of the mirroring interventions in various learning situations.

According to the literature review on SRL in MOOCs by Lee, Watson, & Watson [8], only few studies examined the use of interventions to promote SRL in MOOCs. None of the existing studies have focused on using socially-based mirroring techniques. Actually, to date, only a limited

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number of small-scale lab studies (e.g. [9]) have used mirroring tools to support and study socially shared regulation of learning in computer-supported collaborative learning [10]. Accordingly, the main contribution of the present study is the analysis of association between the mirroring interventions and SRL. The novelty of our research is also the use of a broad scope of variables our study (trace data, demographics, and motivational characteristics).

2 Supporting self-regulated learning processes in MOOCs

2.1 Self-regulated learning

Self-regulated learning is a process through which learners transform their mental abilities to task-related academic skills [11]. SRL is viewed as a proactive process that learners perform for themselves, for acquiring academic skills (such as setting goals, selecting and deploying strategies) [11]. SRL also considers learning as a self-monitoring process where a learner monitors the effectiveness of their learning methods and adapts their learning accordingly. The adaptation is mostly in the form of regulation of certain aspects of their own cognition, motivation, and behavior [12].

This research examines SRL as a process [13]. SRL is viewed as a process consisting of three phases that cyclically repeat and influence each other, starting with the preparatory, planning phase, followed by the task performance or engagement phase, and ending with the self-evaluation and reflection phase [14]. These phases are also called macro-level SRL processes and can be further divided into micro-level processes [15]. In the planning phase, learners define and set learning goals to pursue, and choose appropriate strategies for achieving them. The planning phase is followed by the engagement, or enactment, phase where learners apply their learning strategies, observe their performance, compare it with learning standards set for their learning goals, and, if needed, apply appropriate changes based on the perceived differences [16]. Finally, the self-evaluation and reflection phase occurs after learning tasks are completed. Here, learners self-evaluate their performance and compare it with their prior performance, performance of other learners, and/or the reference performance set for a particular learning goal (e.g., the criteria established for a specific course).

Socio-cognitive models of SRL place social context to be central in framing and influencing student's self-regulation, with the underlying goal to enhance the individual's regulation of cognition, metacognition, behavior, and motivation [4]. During the learning process, learners monitor their progress towards learning goals and adjust their learning based on changed internal and external conditions [17]. Among different socio-cognitive models of SRL, important to our research is socially shared regulation model. Jackson, Mackenzie & Hobfoll [5] call it self-in-social-setting regulation. Seen more from a collectivist perspective, it refers to the processes by which multiple learners regulate their collective activity [4]. This form of regulation acknowledges that individual actions and behavior do not occur in isolation, but people look to others to make sense of their personal situation. Jackson et al. [5] suggest that personal learning goals are inseparable from social goals and are achieved through social interaction. Two distinct categories can be observed here: a) individual regulation targeted to the social good, and b) collective regulation where groups share awareness of learning goals and progress, thereby regulating together as a collective [4].

It has been shown by various studies that many learners lack the self-regulatory skills required for complex solo and collaborative tasks and often fail to interact productively in groups [18], [19]. Although there has been an extensive research in the area of computer-supported collaborative learning (CSCL), a limited number of studies focused on how to leverage the use of technology to support learners in regulating their own and the group's collaborative processes in socially-regulated learning contexts [10]. The focus of this paper are technological scaffolding interventions related to social awareness and social embeddedness of a learner, and associations of these interventions with different SRL micro-level processes. One of the roles technology can have to reinforce CSCL is by providing mirroring or visualization support [6], [10]. The goal of this type of support is to make learners aware of individual or collective actions of other learners, thereby inviting them to monitor, evaluate, interpret, and act on thus obtained insight [6]. Tools with mirroring support target social awareness of a learner, such as knowing team members' perceptions, ratings, or knowledge [20]. Such tools can also impact change in learner's metacognitive strategies by allowing and promoting comparisons between team members and across teams [10].

2.2 Massive Open Online Courses

Massive Open Online Courses (MOOCs) have received substantial interest by media, researchers, and educational practitioners in the last few years. They were announced as a new, disruptive, and transformative concept in online learning [21]. There are two major types of MOOCs: xMOOC and cMOOC. In an xMOOC (from edX MOOC), coined by Downes [22], courses are usually run on a specially designed software platform, where content is centralized and typically available in the form of online video lectures combined with automated testing [23]. Students are provided with a discussion space, often in the form of online forum.

cMOOCs are based on social learning, and contributing to the collective knowledge [24]. MOOCs of this type focus on resource and knowledge sharing and co-creation. Students are encouraged to collaboratively create new knowledge, and recommend, discuss and use any learning resource they find useful [25]. Learning content is not centralized and course is designed to promote the use of diverse kinds of tools and services.

We use a MOOC as the environment for our study because learner population is considerably more diverse in MOOCs than in typical college courses and data could be obtained in the form of fine-grained records about individual learners' interactions with content and other students [26].

2.3 Self-regulation of learning in MOOCs

The core feature of MOOCs to allow anyone to enroll, has generated a variety of engagement strategies students choose to pursue during a MOOC [27]. This variety of strategies, combined with the diverse backgrounds and previous experiences of learners, has spawned a wide range of learning behaviours among MOOC participants [1]. MOOC platforms, that dominate the space, typically involve minimal, if any, direct interaction between instructors and learners. Support and guidance are often missing, as well. Some MOOCs allow learners to interact with learning content in a nonlinear way, and encourage students to suggest additional and/or alternative learning content. These characteristics of MOOCs force learners to self-regulate their learning [28]. Research suggests that in technology enhanced learning environments self-regulation is required when, among other things, learners must engage in planning, monitoring and strategy use, on their own, without guidance or external pressure [3]. This particularly applies to MOOCs, where learners must determine how, when, and what learning content or activity they should engage with [29].

The problem is that many learners have suboptimal skills to self-regulate their own learning in general [30] or within a MOOC [31]. Kizilcec, Pérez-Sanagustín, and Maldonado [32] have performed a study within a MOOC course where they have compiled seven SRL related recommendations based on the interviews with the most successful learners about their learning strategies. Those recommendations were presented to other learners from the same course in the form of message prompts at the beginning of the course. Although other learners rated the recommendations to be helpful, study results showed that this form of intervention provided insufficient support in a MOOC course. Instead, the authors suggest that fully embedded technological scaffolds are required to adaptively support SRL.

We use MOOCs as a context within which we perform our research to explore how our mirroring scaffolds embedded in a MOOC course can influence learners' self-regulation.

2.4 Self-regulated learning and motivation

Knowledge of different self-regulation strategies is usually not enough for learners to successfully apply them; they must also be motivated to use those strategies during the learning process. Motivation is an important factor for successful application of SRL practices [33] and teaching self-regulation strategies has been linked to higher levels of motivation and achievement [34]. In our study, we focus on three motivational facets, namely learners' need for cognition, perseverance and interest to learn (called 'grit'), and achievement goal orientation, and examine if they moderate the associations between the employed mirroring scaffolds and learners' self-regulation processes.

Students' intentions to learn greatly influence what they would actually learn [35]. Cacioppo and Petty [36] observed differences among individuals in their tendency to engage in and enjoy thinking. They labelled this characteristic as 'need for cognition' (NFC), where 'need' is used in the sense of a likelihood or tendency, rather than in a biological sense. NFC reflects a stable intrinsic motivation that develops over time. For learners low in NFC, thinking is often considered a chore that they engage in mostly when some external incentive or reason is present. They are more likely to rely on others, use cognitive heuristics, or social comparison processes to acquire meaning [37]. On the contrary, for learners high in NFC, thinking satisfies a desire and is enjoyable; they are less likely to rely on simple cues and are more likely to consider all of the pertinent information during decision-making [38]. Furthermore, such learners engage frequently in deep learning activities, using strategies such as critical processing, relating and structuring [39].

Learner traits can be an important factor for development of SRL skills. Duckworth, Peterson, Matthews, and Kelly [40] introduced the notion of grit, a non-cognitive trait defined as a perseverance and passion for long-term goals. Their findings suggest that for the achievement of difficult goals one is required to possess not only talent, but also a strong interest in their goals and perseverance to apply their talent in a sustained and focused way over time. It is shown that a student's grit level is associated positively with adaptive motivational beliefs and attitudes towards learning, and is a consistent predictor of application of SRL practices [41]. In the study by Wolters and Hussain [41], students who indicated that they were hard-working, highly engaged in work, and not discouraged by setbacks "expressed greater interest, value, and usefulness for their coursework and tended to express increased confidence that they could successfully complete academic tasks" [46, p. 13].

Achievement goal theory distinguishes between two qualitatively distinct goals for achievement behavior. Although theories differ in number and definition of these goals [42], most focus on two main goals: mastery goals that are focused on developing a specific ability, and performance goals oriented towards demonstrating an ability [43]. One of the key distinctions between the two goals is in how they define success versus failure. Successful attainment of a mastery goal requires meeting either task-based or self-defined criteria, while successful attainment of a performance goal requires outperforming peers [44]. Mastery and performance goals are further divided into approach and avoidance forms [45]. Mastery goals are separated into mastery-approach (i.e., striving to learn or improve skills) and mastery-avoidance goals (i.e., avoiding failure in learning or skill decline). Performance goals are divided into performance-approach (i.e., striving to outperform others) and performance-avoidance goals (i.e., avoiding performing worse than others) [44]. In a MOOC, Littlejohn et al. [1] found that students with high SRL scores have their goals for participation centered around development of knowledge and expertise. Mastery-avoidance goals are linked to high anxiety, low self-efficacy, disengagement, and poor performance [46].

Students who are performance-oriented try to create an impression on others about their high ability, and strive to avoid being perceived as having low ability. Often, this is done through comparison with others' ability [47]. In a

MOOC setting, learners with low level of SRL skills tend to be more concerned with obtaining a certificate of completion than on gaining new knowledge and skills [1].

2.5 Research Framework

Given that previous research has shown that learning environment can influence the level of engagement in SRL processes [48], we have developed a set of learning scaffolding interventions to support a social component of a learning process within a MOOC environment. The interventions are implemented in ProSolo, a novel online learning platform for self-regulated, competency-based learning.

The conceptual framework used in this research makes distinction between macro- and micro-level processes of SRL (see Section 2.1). Micro-level processes are the central focus of this study and we designed our scaffolding interventions to support them. Relations between macro and micro-level processes, and their descriptions are provided in Table 1 (adapted from [49]). It should be noted that our interventions were designed to support four micro-level SRL processes: Goal Setting, Making Personal Plans, Working on the Task, and Applying Strategy Changes. SRL micro-level processes Task Analysis, Self-Evaluation and Reflection, are thus not included in the study. This is due to the technical capabilities of the learning tool used in our study.

2.6 Research Question 1 and Related Hypotheses

The interventions were designed to be unobtrusive and fully integrated into the learning workflow, so they did not affect the regular use of the learning platform (ProSolo). Our objective was to examine if these interventions were associated with the SRL processes, and to estimate the extent of their association.

RQ1: Are there associations between the use of mirroring scaffolding interventions and SRL processes and if there are, what is the extent of the association?

Some of our interventions were inspired by the interventions from the study presented by Siadaty, Gasevic, & Hatala [49]. Siadaty et al. analyzed the association of scaffolding interventions with micro-level SRL processes in workplace learning context. Our goal is to analyze associations of similar interventions with SRL micro-level processes, but in the context of MOOCs. Our interventions are somewhat similar to functionalities that provide social group awareness tools [50] that provide students with information about group members' participation.

The following subsections describe the four types of interventions we designed (Main Status Wall, Goal Wall, People Suggestions, and Social Comparison), and introduce our research hypotheses related to RQ1 that establish relations between the interventions and specific SRL micro processes (Fig. 1).

2.6.1 Main Status Wall

The Main Status Wall provided a student with an update of all public activities occurring in ProSolo that could be relevant to the student. It allowed students to track learning activities of their peers inside the learning platform, but also outside of it (e.g., Twitter posts related to the course). These included activities related to course enrollment, new activities added, assignments completed, peers followed, etc. Social awareness of other participants in a course could encourage learners' engagement in self-regulated learning [51], especially in a connectivist learning environment [52].

TABLE 1
MICRO-LEVEL PROCESSES INCLUDED IN THE STUDY

Macro-level SRL process		
Planning		
Micro-level SRL process	**Description**	**Examples of SRL events in ProSolo**
Goal Setting	Explicitly setting or defining learning goals	Enrolling a learning goal; joining existing or inviting others to join a goal
Making Personal Plans	Creating learning plans and selecting strategies for achieving a learning goal	Creating/adding competency/activity (from search, recommendation, comparison with others).
Engagement		
Working on the Task	Engaging with a learning task based on the chosen plans and strategies for learning	Requesting /accepting collaboration for working on a learning goal. Interacting with an activity. Completing a learning goal, competency, or activity
Applying Strategy Changes	Revising chosen learning strategies, or applying a change to the current one	Updating a learning goal. Adding new/deleting competency/activity

The Main Status Wall was similar to the Social Wave intervention introduced by Siadaty and her colleagues in [49], which provided updates from colleagues from the same organization. Siadaty and colleagues [49], [53] showed that in a non-formal workplace learning context this kind of awareness can significantly affect the way learners plan their learning and adopt learning strategies. Also, it often results in updates of learning goals, and their components, or users' personal strategies.

We hypothesized that an increased social awareness, achieved through the provision of learning-related updates from a student's social circle inside a MOOC, would have a similar effect on the student's (cognitive and metacognitive) engagement in that MOOC. Thus, we defined the following hypotheses:

The use of Main Status Wall is associated with a student's planning of new learning activities, such as creating new learning goals (association H1.1 in Fig. 1), and making personal plans (association H1.2 in Fig. 1), but will also increase the student's engagement in already started learning processes (SRL process Working on the Task - H1.3 in Fig. 1) and possibly improve them (SRL process Applying Strategy Changes - H1.4 in Fig. 1).

2.6.1 Goal Wall

The Goal Wall was a version of the Main Status Wall displaying only updates about public learning activities of other learners related to a specific learning goal. These were the activities created by all students working on the same learning goal and following each other's learning ac-

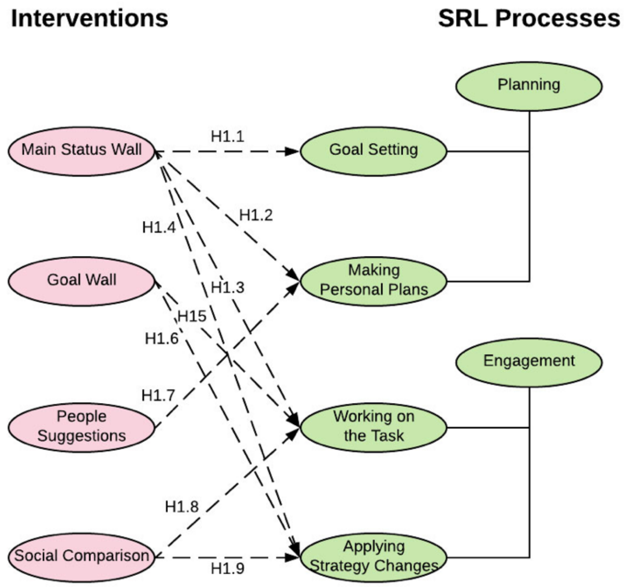

Fig. 1. The hypothesized associations between scaffolding interventions and SRL micro and macro processes related to RQ1

tivities. The Goal Wall was similar to the Social Wave intervention from [49] that provided updates from colleagues working on the same learning goal.

Our assumption was that awareness about activities of learners obtained through the Goal Wall could significantly affect the way the owner of a personal learning goal is attaining it [54], resulting in slight revisions or major updates to the goal or any of its components. Since the Goal Wall was only focused on a specific learning goal, it displayed a subset of updates that can could found on the Main Status Wall. Here we defined hypotheses similar to those for the Main Status Wall:

The use of Goal Wall will be positively associated with a student's engagement in activities of a particular learning goal (association H1.5 in Fig. 1), and with making adjustments to their ongoing learning process in order to have higher goal achievement (association H1.6 in Fig. 1).

2.6.3 People Suggestions

In order to bootstrap social connections necessary for Main Status Wall, we introduced three different people recommendation types. The first type of recommendation was based on the spatial proximity between students. Common socio-cultural background was relevant for establishing social connections, thus contributing to a student's overall social presence [55]. Hence, a student was recommended to follow a peer who lived and/or worked nearby, provided that both students had set their location in their profile. The second type of recommendation favored peers who were the most active on the platform during the course period. The rationale was to recommend students who were active participants in the course and whose activity could motivate other students to engage more in their learning. Finally, the third type of recommendation was based on the similarity between student profiles, namely their learning interest and learning history. We assumed that having been provided with recommended peers to follow, a student would engage in learning goals, competencies and activities the suggested peers had already engaged in. The assumption here built on the literature of social networks in education that indicates that a learner learns by establishing links with those with whom they share similar attitudes and values [56]. Hypothesis we made regarding this intervention is:

The People Suggestions intervention will be positively associated with Making Personal Plans micro-level process (association H1.7 in Fig. 1).

2.6.4 Social Comparison

Finally, we wanted to study the association of SRL micro-level processes and a technological intervention that promotes students' awareness of what their peers are currently learning and how they are progressing. The social comparison intervention allowed a student to compare with a member of his/her learning group. This intervention is similar to *Progress-o-meter* from [49] that allowed comparison of one's progress with that of their colleagues at workplace.

The student's progress on a specific learning goal or a competency was displayed alongside the progress of the chosen peer. It was shown that social comparison could significantly increase course completion rates across different courses [57]. With social comparison enabled, a student gained an insight into how he/she was progressing compared to others, which was expected to be positively associated with their learning task engagement [49], [53], [58]. Unlike quantitative measures commonly used in learning analytics dashboards, our social comparison intervention was qualitative, offering learners an insight into operations performed and products created by peers.

The hypotheses we made for this intervention are:

The Social Comparison feature will positively influence the SRL macro-level process Engagement, i.e. with Working on the Task micro-level process (association H1.8 in Fig. 1) and Applying Strategy changes micro-level process (association H1.9 in Fig. 1).

2.7 Research Question 2 and related hypotheses

Prior research has investigated the relation between individual differences of learners and SRL in MOOCs [28]. Based on the analysis of data of 140,546 students in four edX MOOCs, Guo and Reinecke [59] found that older students are more prone to follow non-linear paths of navigation through the course, which could be a sign of lower SRL skills [28]. Several studies showed that self-regulated behavior is independent of learners' gender [60], [61]. However, the study by Kizilcec and Halawa [62] performed on data from 20 online courses (with over 67,000 participants in total) did find gender difference in developing SRL skills. Their results suggested higher level of persistence among male participants. The same study showed learners with higher education to have higher grades and levels of persistence compared to other students. In our research, we wanted to test whether individual differences between learners affected levels of association between mirroring interventions and SRL processes. We assume that motivation, as a component of internal conditions based on which learners make decisions [17], could moderate the association between the use of social technological interventions and the engagement into micro-level SRL processes.

RQ2: Do individual differences between students affect levels of association between scaffolding interventions and SRL processes?

As already mentioned, in this study we examined the moderation effect of three motivational facets (learners' need for cognition, grit, and achievement goal orientation) to the associations between the employed mirroring scaffolds and learners' self-regulation processes. We make the following hypotheses:

H2.1: Learners low in NFC will be using more mirroring scaffolds that instigate the activation of Planning and Engagement micro-level SRL processes than learners high in NFC.

H2.2: Students high in grit will be using more mirroring scaffolds that are associated with micro-level SRL processes from the Engagement category (Working on the Task and Applying Strategy Changes) than students low in grit.

H2.3: Performance-oriented students will be using mirroring scaffolds that allow them to follow their peers' learning activity, especially peers' progress, and to compare it with their own progress. Similarly, performance-avoidance students are expected to use scaffolds that allow them to compare with other students.

H2.4: Individual characteristics of learners, such as their level of education, gender, and age, can influence the levels of association between scaffolding interventions and SRL processes.

3 Method

In our research, we consider SRL as a process formed of a series of events a learner performs during his/her learning experience. We utilize a trace-based methodology in order to examine the presence of associations between the proposed scaffolding interventions (Section 2.5) and a learner's SRL practices observed at the micro level [49].

3.1 Study context

The data used in this study are obtained from the MOOC "Data, Analytics, and Learning (DALMOOC)". The MOOC lasted 9 weeks, from October 20th until December 15th, 2014. The main topics of the course were learning analytics, educational data mining, text mining, and social network analysis. The delivery of the course was experimental as for the first time the same course content was offered in parallel on two platforms [63]: edX, a typical MOOC learning platform, and ProSolo, a platform designed to support SRL[1]. The edX offering of the course initially attracted more than 23,000 participants, and ProSolo, despite being unknown to the students, attracted 1,600 students to register. The content on both platforms was similar, with the difference in the way learning resources were grouped. In edX, content was grouped by weeks, with each topic being introduced in every two weeks. In ProSolo, resources were organized in nine learning goals (one for each topic), composed of several competencies that were predefined by the course instructors. Students also had the opportunity to create their own personal learning goals and competencies that would complement the official course learning goals. Various types of learning activities were provided to students, such as video and text-based materials and assignments to perform. No formative or summative assessments were supported in the course.

This study uses student log data obtained from the ProSolo platform due to its design to support SRL and features to collect granular digital trace data about SRL micro-level processes of interest for this study (see Appendix A for the list of SRL-related events generated in ProSolo).

3.2 Participants

Although initially 1,600 students registered for ProSolo use in DALMOOC, not all of them were active throughout the course. Thus, we have focused only on the students who were using our mirroring scaffolds and were active. As active is considered a student who, during the course, generated at least two SRL or intervention events over a period longer than a week. The reason for this is based on the fact that the MOOC itself was organized into four two-week long topical sections followed by the final week dedicated to the course synthesis. Thus, we wanted to make sure that the students' participation spanned at least across two weeks as some of the students came to study only some portions of the MOOC rather than to take the entire course. In other words, students who registered just to try the new platform or dropped out after one week of participation in the MOOC were excluded from this study. The number of active students on the ProSolo platform was 314.

Before the course started, students were given a pre-course questionnaire aimed at capturing the students' demographics data, and factors related to their motivation, namely need for cognition, grit, and goal orientation. Valid responses to the survey were collected from 940 students. Out of those students, 279 were active ProSolo users. Thus, our study includes the 279 participants who completed the pre-course survey and were active ProSolo users. There were total 101 female and 178 male participants. Regarding the education level, six participants completed a "High School/GED", 11 participants completed "Some College", 8 participants obtained a "2-year College Degree", 89 participants had a "4-year College Degree", 123 participants held a "Master's Degree", 38 participants had a "Doctoral Degree", and six participants had a "Professional Degree (JD, MD)". Participants came from diverse age groups, specifically, there were 28 of them from the "18 to 24" age group, 90 participants from the "25 to 34" age group, 70 participants from the "35 to 44" age group, 52 participants from the "45 to 54" age group, 34 participants from the "55 to 64" age group, and five participants from the "65 or over" age group.

3.3 Variables

Our study dataset consisted of two parts: the records of individual user sessions, and the data collected through the pre-course questionnaire. The first part of the dataset was obtained by processing user session data from the ProSolo platform (see Appendix B). The second part was obtained

[1] Learning in ProSolo is organized around learning goals. A learning goal is composed of a set of related competencies created. Competencies are achieved by completing a set of activities that can be of different type.

from the pre-course survey, providing us with participants' demographics (age, gender, and education level), but also with their motivational state, observed through the three facets. In this section, we explain the variables that were derived from the overall dataset and used in the study.

Counts of events indicative of SRL micro-level processes. We have extracted the trace data for all study participants. The data were analyzed and trace-based measures were calculated. In particular, the extracted trace data were used to compute the number of occurrences of each of the SRL micro-level processes for each student session. This resulted in four variables representing counts of each of the observed SRL micro-level processes: goal_setting, making_plans, working_on_the_task, and applying_strategy_changes. They were used as dependent variables in our models.

Counts of events indicative of scaffolding intervention use. Similar to SRL micro-level process counts, we computed the number of interaction events with each of the mirroring interventions per student session. Since we introduced four scaffolding interventions, usage counts for each of the interventions represented independent variables for our analyses. These variables were: main_status_wall, goal_wall, people_suggestion, and social_comparison.

Demographics variables. Demographics data were collected through the pre-course survey. Three variables were extracted from student responses: gender, age, and education (Table 2). All three variables are categorical and were used for examining their moderating effect on the relation between the intervention variables and the outcome.

Need for Cognition. Pre-course survey contained questions that allowed us to measure the NFC score. The 18-item questionnaire was used from [64]. It produced a single score that measures one's reported tendency to engage in and enjoy thinking. The participants' responses to these questions had Cronbach's alpha score of 0.83, suggesting that the responses were reliable. Our initial analyses using continuous value for the NFC score yielded some models that were not interpretable. For this reason, but also for the reason that this score in literature is mostly observed in the binary, low or high [38], [65], we have discretized the variable. We have converted it into a categorical variable with possible values low and high based on the median split (Md = 16). This variable was added to the final dataset as nfc_score.

Grit-S scale. Our pre-course survey included an 8-item self-report questionnaire for measuring grit score, called Short Grit Scale (Grit-S) [66]. The scale has a two-factor structure, where one subscale measures an individual's consistency of interest, whereas the other measures their perseverance of effort. But, as suggested by Duckworth and Quinn [66], only one score should be calculated from the survey responses. Cronbach's alpha value for the Grit-S survey responses of our study participants was 0.78, suggesting the metric is reliable. The students' Grit-S scores were also converted to a categorical variable (the same rationale for discretizing as used for NFC scores was applied here too) with values true and false based on the median split (Md = 2.375). The discretized variable was added to the final dataset as grit_s.

Patterns of Adaptive Learning Scales (PALS). PALS is based on the goal orientation theory and examines the relation between the learning environment and students' motivation, affect, and behavior [67]. It consists of several scales, among which the following three were relevant to our study: Performance-Approach Goal Orientation, Mastery Goal Orientation, and Academic Efficacy scales. As the name suggests, Performance-Approach Goal Orientation Scale measures students' performance-approach orientation, while Mastery Goal Orientation Scale measures their mastery-approach orientation. The last scale we used is Academic Efficacy Scale that measures how much students think they are competent for their course work. For each of the three scales, an independent variable was created, namely mastery_goal_orientation, performance_approach_goal_orientation, and academic_efficacy, respectively. Values for these three variables among all study participants had Cronbach's alpha scores of 0.87, 0.91, and 0.94, respectively, so we assumed the responses to be reliable. Similar to the previous two variables, all three variables were converted into categorical variables with values true and false based on the median split (for performance goal orientation: Md = 4.2; mastery goals orientation: Md = 4.6; and academic efficacy: Md = 4.2). The discretized variables were used in all models.

Student id. For each user session, we stored the id of a student (variable is called student). This attribute was used to group user session records of one student in order to account for variations between individual students.

Course week. Week of the course (from 1 to 9) in which a student session occurred was also a grouping variable in our dataset (variable is called week). We want to test for variations between user sessions in different weeks of the course.

Note that some participants did not provide responses to all questions of the pre-course questionnaire, leaving us initially with missing data for some motivation facets variables (a total of missing values was less than 2.8% per variable). In these cases, we have used median based data imputation technique as these variables were not normally distributed [68].

3.4 Data Analysis

Since our data were nested in structure (multiple user sessions of students in different course weeks), and also crossed (we have several categorical variables), linear mixed-effect models were used for the data analysis [69]. These models take into account fixed and random effect variables. Fixed effects are variables that are associated with the entire population. Random effects are variables that are associated with individual experimental units drawn at random from a population and quantify the variation among those units [70]. Mixed-effects models can be used to assess the association between the fixed effects and response variables, and account for effects of the random variables. A mixed model without random effects is actually a regular linear model.

In our study, we used mixed-effect models to examine the associations between the use of mirroring interventions and the occurrences of SRL micro-level processes (response variables). We also examined the presence of interactions between the use of a scaffolding intervention and the demographics variables and scores of the motivational facets. We built three models for each of our nine hypotheses related to RQ1: the *null model*, the *full model*, and the *reduced model*. The *null model* included only random effects, namely *student* and *week*. Based on the ICC values[2] [69] of both random effect variables, we decided whether to include both, one or none of random effect variables in our *full models*. In case ICC value for a variable was zero or close to zero, that variable was not included as a random effect in the *full* model. Thus, in such a case, the *full model* was built without random effects included, i.e., as a regular linear model.

Each *full model* included, as a fixed effect, the count of events indicative of scaffolding intervention use corresponding to the hypothesis in question. In order to test our RQ2 hypothesis, each of the nine models included interactions between the count of scaffolding intervention use variable and the three demographics variables, as well as interactions with all three motivation facet variables. The advantage of this approach over evaluating individual differences separately was that the regression coefficients were estimated simultaneously [28]. Some full models also included student id as a random effect (depending on the ICC values, as explained above). For the random variable *week*, the ICC value in all models was zero or close to zero, thus it was not included in our *full* models.

In order to reduce the complexity of *full models*, we have applied the backward elimination algorithm [71] and using the corrected Akaike Information Criterion (AICc) we chose the optimal model structure [72] for each of our hypotheses; we refer to these models as *reduced* models.

Finally, each of the nine resulting models used in our analyses was chosen between the *null*, *full* and *reduced* model, based on the AICc criterion; specifically, the model with lower AICc value was used in the analysis [73]. This resulted in the following models, listed with respect to the study hypotheses (Table C1 in in Appendix C):

M1: for the response variable ***goal_setting*** the *null model* was chosen.

M2: for the response variable ***making_plans,*** the *null model* was chosen.

M3: for the response variable ***working_on_the_task***, the *reduced model* was chosen and it included the interaction between the *main_status_wall* and *performance_approach_goal_orientation* variables. The model did not include random effects.

M4: for the response variable ***applying_strategy_changes***, the *reduced model* was chosen and it included interactions between the *main_status_wall* variable and *gender*, *performance_approach_goal_orientation*, and *grit_s* variables. The model did not include random effects.

M5: for the response variable ***working_on_the_task***, the *reduced model* was chosen and it included the *goal_wall* variable, and interactions between the *goal_wall* variable and gender, *age*, *education*, *nfc_score*, *performance_approach_goal_orientation*, and *grit_s* variables. The model did not include random effects.

M6: for the response variable ***applying_strategy_changes***, the *reduced model* was chosen and it included interactions between the *goal_wall* variable and *age*, *education*, *mastery_goal_orientation*, *academic_efficacy*, *performance_approach_goal_orientation*, and *grit_s* variables. The model did not include random effects.

M7: for the response variable ***making_plans***, the *null model* was chosen.

M8: for the response variable ***working_on_the_task***, the *reduced model* was chosen and it included the *social_comparison* variable and interactions between the *social_comparison* variable and *gender*, *nfc_score*, *mastery_goal_orientation*, *academic_efficacy*, *performance_approach_goal_orientation* and *grit_s* variables. The model did not include random effects.

M9: for the response variable ***applying_strategy_changes***, the *reduced model* was chosen and it included the *social_comparison* variable and interactions between the *social_comparison* variable and *mastery_goal_orientation* and *academic_efficacy*. The model did not include random effects.

4 RESULTS

For **M1** and **M2** we accepted the *null models*. For **H1.1**, this indicates that there is no significant association between the *goal_setting* and *main_status_wall* variables. Similarly, for **H1.2** we did not find a significant association between the *making_plans* and *main_status_wall* variables.

The model **M3** revealed a significant interaction effect between the main_*status_wall* and *performance_approach_goal_orientation* variables ($p < 0.05$) on the Working on the Task micro-level SRL process. The intervention was used more by learners with high performance-approach goal orientation while working on their learning tasks. The regression model was statistically significant ($F(2, 1118) = 3.346$, $p < .05$), with adjusted R^2 value of .006.

The model **M4** showed a significant interaction effect between the main_*status_wall* and *performance_approach_goal_orientation* variables ($p < .05$) on the Applying Strategy Changes micro-level SRL process. Specifically, students with low performance-approach goal orientation had higher association between the counts of the Status Wall intervention and changes in their learning strategies than the ones with high performance-approach goal orientation. This contradicts our hypothesis H2.3 where we anticipated the association would be higher for students high in performance-approach goal orientation than the ones with low performance-approach goal orientation. There was also a significant interaction effect between the main_*status_wall* and *gender* variables ($p < .05$), where the association was higher for females than males. The regression model was statistically significant ($F(4, 1116) = 3.346$, $p < .01$), and adjusted R^2 for this model was .014.

The model **M5** revealed that the *goal_wall* variable had a significant association with the *working_on_the_task* variable ($p < .05$). Also, the model revealed a significant interaction effect between the *goal_wall* and *age* variables (p <

[2] The Intraclass Correlation Coefficient (ICC) is a ratio of the between-cluster variance to the total variance. Clusters are groups of similar observations based on random effect variables.

.001). In particular, learners from the 45 to 54 age category tended to have the highest association between the Goal Wall intervention and activities related to the Work on the Task SRL micro-process, whereas learners from the age categories 35 to 44 and 55 to 64 had a lower association between the Goal Wall use and the Work on the Task SRL micro-process than the 45 to 54 age category. A significant interaction effect was also observed between the *goal_wall* and *nfc_score* variables ($p < .001$). Specifically, in the context of working on the learning tasks, the use of the Goal Wall intervention was associated more with learners with low NFC score, than those with high NFC. Similarly, a significant interaction effect was observed between the *goal_wall* and *education* variables ($p < .001$), where the association between the Goal Wall use and Working on the Task SRL micro process was most pronounced in the case of learners who completed some college, and slightly less for those who completed a high school / GED or had a 4-year college degree. Also, a significant interaction was found between the *goal_wall* and *performance_approach_goal_orientation* variables ($p < .001$). The association between the Goal Wall use and Working on the Task SRL micro process was higher for students having high performance-approach goal orientation than those with low performance-approach goal orientation, that is in line with our hypothesis H2.3. Finally, a significant interaction was found between the *goal_wall* and *grit_s* variables ($p < .001$), where the observed association was higher for students low in grit than those having high grit value. This contradicts H2.2 where we anticipated higher association for students high in grit than the ones with low grit score. This regression model was statistically significant ($F(11, 1109) = 45.58$, $p < .001$), and the R^2 value of this model was .311.

The model **M6** indicated that there was a significant interaction effect between the *goal_wall* and *age* variables ($p < .05$) on the Applying Strategy Changes micro-level SRL process. The Goal Wall intervention use was associated the most with learners from the 25 to 34 age category, and slightly less with those from the 55 to 64 age category to apply changes to their learning strategies. There was also a significant interaction effect between the *goal_wall* and *performance_approach_goal_orientation* variables ($p < .01$) that revealed that the counts of the Goal Wall intervention were associated with changes in learning strategy in case of students low in performance-approach goal orientation. This contradicts H2.3 where we anticipated high association for students with high performance-oriented goal orientation. The regression model for this hypothesis was statistically significant ($F(10, 1110) = 2.617$, $p < .01$) with adjusted R^2 having value of .023.

For **M7** the *null model* was chosen, indicating that there was no significant association between the *making_plans* and *people_suggestion* variables.

The model **M8** revealed a significant main effect of the social_comparison variable on the working_on_the_task variable ($p < .05$). Also, the model revealed a significant interaction effect between the *social_comparison* and *mastery_goal_orientation* variables ($p < .001$). Specifically, the students low in mastery goal orientation when using the Social Comparison intervention tended to engage more in the work on their learning task SRL process. There was also a significant interaction effect between the *social_comparison* and *academic_efficacy* variables ($p < .01$), where the intervention was used more by learners low in academic efficacy to engage in the work on the task SRL micro-level process. Finally, there was a significant interaction between the *social_comparison* and *grit_s* variables ($p < .01$), where students high in grit tended to engage more with the work on the task SRL micro process when using the Social Comparison intervention, which is in line with H2.2. The regression model was statistically significant ($F(7, 1113) = 6.271$, $p < 0.001$) and adjusted R^2 value was .038.

Finally, the model **M9** showed a significant main effect of the *social_comparison* variable on the *applying_strategy_changes* variable ($p < .05$). The model also revealed a significant interaction effects between the *social_comparison* and *academic_efficacy* variables ($p < .01$). Specifically, the use of the intervention was associated with the strategy changes in case of learners with high academic efficacy score. The regression model was statistically significant ($F(3, 1117) = 3.305$, $p < 0.05$) and adjusted R^2 value was .009, indicating rather a small effect size.

5 Discussion

5.1 Discussion of the Results in Relation to the Research Questions

The results presented in the previous section suggest that certain types of mirroring interventions can have a significant association with SRL micro processes in a MOOC-based learning environment (RQ1). We have found several cases where individual differences between students moderated associations between our scaffolding interventions and SRL processes (RQ2).

We found no effect of our mirroring interventions on the observed Planning micro-level SRL processes, namely Goal Setting and Making Personal Plans (we have accepted null models M1 and M2). The reason for this can be found in the very design of the course where learning goals were predefined by the course instructors before the course had started. Students did not diverge from those goals by making additional learning goals, but instead stuck with the predefined ones throughout the course.

Here we should also note that the third micro-level process from the Planning phase, namely Task Analysis, was not observed in our study. Even though the platform we used in the study enables students to examine learning tasks (e.g. to view a competency description and its structure, read an activity description, etc.), no specific mirroring scaffolds were designed to invoke this process as the whole course structure was predefined by the course instructors and was the same for all students.

The engagement into the micro-level SRL processes related to the Engagement macro-level process, namely Working on the Task and Applying Strategy Changes, were significantly associated with the use of the interventions that enabled awareness of learning updates and progress of peers. The Main Status Wall was shown to have had only an interaction term associated with these SRL micro-level processes, while the Goal Wall and Social Comparison interventions had significant main and interaction effects on both of these processes.

The Main Status Wall had a significant effect on learners with high performance-approach goal orientation to engage with their learning tasks (H2.3). This is somewhat expected since those learners tended to try to outperform others and thus were interested in activities and performance of other learners. Conversely, the Main Status Wall affected learners with low performance-approach goal orientation to change less their learning strategies. This was likely due to the fact that learners were not so much focused on the social comparison. The Main Status Wall intervention was associated with lower engagement in the change of learning strategies for male learners in contrast to that of their female peers (H2.4). This was likely caused by the fact that men are often found to be more confident (i.e., higher self-efficacy) than women in academic areas related to mathematics, science, and technology [74]. Several authors posit that this difference in self-efficacy between genders may be due to the factors such as previous achievement, exposure to course content, response biases, measurement practices, or gender orientation beliefs [75]. Also, as found by Kizilcec et al. [28], female MOOC participants are reported to have higher SRL skills related to task strategies than males. We have to note here that models revealing these findings had a low R^2 value, which means they explained only a small portion of the variability in the data and additional variables should be included [76].

The reason why Main Status Wall did not show any significant main effect to any of the SRL processes might be due to its very design. In order to overcome the cold start problem, where learners had their accounts just created and they initially do not explicitly follow other learner's updates, the default setting for the Main Status Wall was to display learning activities from all learners in a course. And that could possibly have been an overwhelming number of updates to consume. In our study, we had 279 active course participants and displaying learning updates from each of them can easily get unmanageable to follow, leading to information overload [77]. Although several studies have shown that awareness of peers' learning updates can significantly affect different phases of students' learning [49], [51], [53], those studies included either small sample of course participants, or the participants were clustered in groups and thus were exposed to learning updates from a small number of peers.

The Goal Wall intervention was by design similar to the Main Status Wall, but it actually solved its limitation by narrowing the circle of peers from whom learning updates were received. The Goal Wall was implemented to display learning updates from peers working on the same learning goal and who have agreed to be a part of the circle of peers following each others' updates. It enabled a peripheral awareness of those who are working with a learner. Implemented in this way, the intervention was shown to have a significant main effect on the Working on the Task. This finding is in line with existing findings that awareness of activities of other learners on the same learning goal can significantly affect the way a student is working towards the goal [54]. The model that revealed these results had R^2 of .311. There are also several interesting interaction effects that this model revealed.

The Goal Wall use was found to be associated the most with the engagement of mid-aged students (H2.4). This can be explained by the fact that those students were potentially more interested in the course and its topic since learning analytics and educational data mining are hot topics in the educational space and learning them can contribute to one's overall lifelong learning process and professional development. This is also confirmed by the analysis of variance (ANOVA) on responses of learners from different age groups to a pre-survey question "*Can you tell us why you want to enroll in this course? Supplement other college/university class*" where answers were on a 5-point Likert scale (from "Not at All True" to "Very True"). We found a significant variations in responses between different age groups, $F(5, 1118) = 19.832$, $p < .001$. A post hoc Tukey test showed significant differences in responses between students from mid-aged groups ('35 to 44', '45 to 54' and '55 to 64') and younger students ('18 to 24' and '25 to 34'), at $p < .001$, where mid-aged groups answered this question with higher scores. This indicates that those students self-reported a much higher interest in completing the course and improving their knowledge than their peers in the course from other age groups.

Our analyses also revealed that the association between the Goal Wall and working on learning tasks was more pronounced for students low in NFC, than students high in NFC (H2.1). This can be explained by the fact that students who have low NFC were socially adept and were concerned with their affiliation, while those who had a high NFC were low on affiliative needs and were unconcerned about fitting into their social environment [78].

The Goal Wall intervention was also found to be associated with engagement with learning tasks, and the association was the highest for students with a college degree, a bit lower in case of students holding a doctoral or 4-year college degree, and even lower for those having a Master degree (H2.4). Previous research has demonstrated that MOOC students with a professional, master's degree or a Ph.D. tend to have high reported levels of SRL, especially in task strategies [28]. In order to explain the difference in the association between students with a college degree and other students, we analyzed variations in responses of students with different education level to the pre-survey question: "Can you tell us why you want to enroll in this course? Subject relevant to my academic field of study". We found a significant variations in responses between students with different education background, $F(6, 1120) = 143.23$, $p < .001$. A post hoc Tukey test showed significant differences in responses between students with a college degree and students with all other education levels, with $p < .001$ (except with education level 'Less than High School' for which we had no participants). This can potentially be explained by the fact that students with a college degree had the highest professional motivation to take the course. As such, they were exploring all opportunities for professional learning, including opportunities to understand how other participants in the course were approaching and progressing with their studies.

When looking at the students' level of performance-approach goal orientation, we can observe that the association between the Goal Wall use and engagement with learning activities was more pronounced with students high in performance-approach orientation, than those low in performance-approach (H2.3). This is potentially due to the fact that students high in performance-approach tried to outperform their peers and were more interested in learning activities of others, and that affected them to engage with their own learning tasks [47].

Finally, our results show that the effect of Goal Wall on the engagement with the learning tasks was higher for students low in grit, than the ones high in grit. This partly contradicts our assumption (H2.2) that there would be a higher association between mirroring scaffolds and micro-level SRL processes from the Engagement category for students high in grit than students low in grit. However, it turned out that social awareness enabled by the Goal Wall, affected more students low in grit to engage with their learning.

The model M6 revealed that the Goal Wall had a significant interaction effect with age. Specifically, the association between the Goal Wall intervention and change in learning strategies proved to be the highest for younger students (age group "25 to 34") and older students ('55 to 64'). This finding suggests that those early and towards the end of their careers tended to engage into the task-related updates from their peers (H2.4). This is consistent with findings by Kizilcec et al. [28] that older students participating in MOOCs tend to report higher levels of SRL. The reason for the high association for young MOOC participants is something to be investigated in the future research. The association between the Goal Wall intervention and the tendency to change one's learning strategy is more present for students high in performance-approach strategy than those low in performance-approach (H2.3). This can be explained, again, by the fact that these students try to outperform others; hence, increased awareness of actions of their peers might incite them to change their learning strategies [47]. We should note that this model had a low R^2 value meaning additional data should be included in the analysis [76].

The People Suggestions intervention showed no association with the engagement into the Making Personal Plans SRL micro-level process (we have accepted the null model for the M7). In addition to the interpretation of the non-significant association given above, there is another possible reason for the observed result. Although research in social networks in education indicates that establishing links with peers who share similar attitudes and values helps a learner to learn [56], our peer recommendations were not found to instigate activation of any of SRL micro-level processes. A possible reason for this can be found in the types of recommendations that were used in our study and the study context itself. Location-based and activity-based recommendations were probably not that relevant for a learner to connect with a peer in a MOOC. Relations between students need to be more related to the learning context, like sharing learning interests, learning problems, as suggested in the mentioned studies (e.g. in [56]). On the other hand, our third type of recommendation, based on student profile similarity, is related to the learning context. However, for this recommendation type to give relevant suggestions, it needs to be based on more robust data regarding students' learning history and competences achieved. Our study participants had created their profiles when the course started, and their learning profiles and interests were based only on their achievements during this course, which were more or less the same for all study participants. Thus, this recommendation type could not provide relevant suggestions and have a bigger impact on the learning process. The improvement of the shared profiles could also improve students' social presence, which could also affect the association of the Main Status Wall with the Planning micro-level process.

The Social Comparison intervention was found to have a significant effect on micro-level SRL processes related to engagement, namely Working on the Task and Applying Strategy Changes. Similar to findings in other studies [49], [53], [58], we found that awareness of the progress of other peers working at the same learning goal, and especially the ability to compare with them, is positively associated with engagement in ongoing learning tasks. The finding that the association between Social Comparison and working on the task was the highest for students with low mastery goal orientation may be explained by the fact that those high in mastery goal orientation tended not to be concerned with the progress of others, but only about their own progress and improvement of their own skills [44]. Similarly, the Social Comparison influenced more students high in grit than the ones low in grit to engage with their tasks (H2.2). Finally, the Social Comparison intervention affected more students with low academic efficacy than the ones with higher values to complete their learning tasks. Social Comparison also affected the ones with high academic efficacy to apply strategy changes during the course. The reasons for all these findings should be studied in the future research. Again, we must note that the models related to Social Comparison intervention had low R^2 values, which indicates that the models explained only a small portion of the overall variability of the response variables and additional data should be included [76].

5.2 Limitations

The results presented in this paper come from a study based on the data collected within one offering of a MOOC course on Technology Enhanced Learning. Being derived from a single case study, the results cannot be generalized [79]. To confirm the validity of our findings, similar analyses should be performed on the data from other courses in other subject areas. Next, our study design allows for measuring only associations between the introduced mirroring scaffolds and observed SRL micro-level processes. Therefore, we cannot establish directional causality in any of the detected associations.

5.3 Implications for Research and Practice

Our findings indicate that scaffolds providing social awareness and comparison had significant main and interaction effects on Working on the Task and Applying Strategy Changes micro-level SRL processes. The social awareness scaffold's effect to engagement with learning tasks was more pronounced with students low in NFC, with a higher education degree, high in performance-approach orientation and low in grit. Its effect on the change in learning strategies was higher with those early and towards the end of their careers and high in performance-approach strategy. The social comparison scaffold affected more students low in mastery goal orientation and high in grit to work on their learning tasks. Other scaffolds had low to none effect on SRL micro-level processes.

In accordance to the previous research that has shown that the learning environment can influence student's level of engagement in SRL processes [48], we have demonstrated that mirroring scaffolds can be an important instructional technique that are associated with this level of engagement in SRL processes. Awareness of learning updates and progress of peers can foster students' actions related to the engagement with learning tasks and applying changes in strategies for completing those tasks. Different demographic and motivational characteristics of students can influence the level of the effect these mirroring scaffolds have on the level of engagement in SRL processes. Learners with high performance-approach goal orientation are especially affected by mirroring scaffolds as insights into what other students are doing and how they are performing motivate them to engage even further with their learning tasks. Similarly, students low in NFC respond more to the mirroring scaffolds (compared to the ones high in NFC) since they are concerned with their affiliation and fitting into the social setting [78].

Practitioners in the area of Technology Enhanced Learning should consider the social nature of learning [24] and design the learning process to utilize features that foster social awareness among learners in order to induce their engagement in SRL processes. Next to providing learning updates and progression of other students, it should be investigated how this process can be further supported by providing visualizations and aggregate representations of social activity within or outside of the learning environment [10].

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