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DOI

[10.1016/j.chb.2021.106913](https://doi.org/10.1016/j.chb.2021.106913)

Publication date

2021

Document Version

Final published version

Published in

Computers in Human Behavior

Citation (APA)

Wong, J., Baars, M., He, M., de Koning, B., & Paas, F. (2021). Facilitating goal setting and planning to enhance online self-regulation of learning. *Computers in Human Behavior*, 124, 1-15. Article 106913. <https://doi.org/10.1016/j.chb.2021.106913>

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Facilitating goal setting and planning to enhance online self-regulation of learning

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ARTICLE INFO

Keywords:

Self-regulated learning (SRL)
Motivation
Mental contrasting and implementation intentions (MCII)
Massive open online course (MOOC)
Video-based learning

ABSTRACT

Online learning environments demand learners to self-regulate their learning but many learners are poor at self-regulated learning (SRL). In this paper, two studies were conducted to examine the effect of two SRL supports, i.e., guiding goal setting and planning using an approach known as mental contrasting and implementation intentions (MCII) and prompting SRL using videos, on motivation in the form of task value and self-efficacy, SRL in the form of persistence, task strategies, self-evaluation, and self-satisfaction, student engagement, performance, and goal attainment. In Study 1, a two (MCII, no MCII) by two (prompt, no prompt) between-subjects controlled experiment was conducted in an online video-based learning environment. Results showed that learners who completed the MCII had more sustained task value and higher persistence than learners who did not receive the MCII. Study 2 was conducted in five Massive Open Online Courses where we compared three conditions: MCII, goal only, and control. Results showed that there were no significant differences in SRL activities, course engagement and performance, and goal attainment among the three conditions. Collectively, the results suggest that the task duration in which learners' goals can be attained (e.g., within one short session or over multiple weeks) might influence the effectiveness of MCII.

1. Introduction

Online learning is rapidly becoming a ubiquitous form of learning in many higher education institutions (Dumford & Miller, 2018). The term “online learning” refers to a broad range of technology-enabled learning environments from web-facilitated courses where a proportion of the course content is delivered online (e.g., course content videos) to fully online courses where all course content is delivered online (e.g., Massive Open Online Courses also known as MOOCs) (Allen & Seaman, 2016). While online learning environments offer learners a high level of flexibility to pursue education at any place and any time, it does not have the same spatial, temporal, and intellectual supports as typical on-campus learning environments (Artino, 2008; Artino & Jones, 2012; Broadbent, Panadero, Lodge, & de Barba, 2020). As a replacement for face-to-face lectures, many online learning environments use videos as the main medium to deliver content (Ozan & Ozarslan, 2016). This is also reflected in MOOCs where watching video lectures is a large part of the MOOC learning experience (Guo, Kim, & Rubin, 2014). When

learning online with videos as the main instructional format, learners have control over their learning not only at the course level (i.e., when to watch a video), but also at the activity level (i.e., when to pause a video). Researchers have argued that learners in online learning environments need to self-regulate their learning to a large extent in order to succeed (Artino & McCoach, 2008; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018; Wang, C. H., Shannon, & Ross, 2013).

Self-regulated learning (SRL) can be broadly defined as the extent to which learners are active participants of their own learning process by means of monitoring and controlling their motivation, metacognition, cognition, and behavior towards achieving their learning goals (Boekaerts & Cascallar, 2006; Zimmerman, 1989). Research shows that engaging in strategies related to SRL, such as goal setting, strategic planning, time-management, and effort regulation, positively influences success in online learning environments (Broadbent & Poon, 2015; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). However, despite the importance of SRL many learners do not spontaneously self-regulate

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<https://doi.org/10.1016/j.chb.2021.106913>

Received 18 April 2021; Received in revised form 8 June 2021; Accepted 9 June 2021

Available online 18 June 2021

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their learning, do not know how to self-regulate their learning, or self-regulate sub-optimally (Azevedo & Feyzi-Behnagh, 2011). Therefore, to enhance academic success for online learners, there is a need to provide support for SRL in online learning environments (Lee, Watson, & Watson, 2019; Wong et al., 2019).

In the current study, we examined an approach to engage online learners in the process of goal setting and planning, namely mental contrasting and implementation intentions (MCII), to enhance SRL and learning performance. The study contributes to research on SRL by examining whether MCII as an approach to facilitate goal setting and planning affects SRL behavior and learning performance. Another contribution of this study is that the effect of MCII is examined in two online learning environments: a controlled experiment in a video-based learning environment and a field experiment in Massive Open Online Courses. By doing so, we aim to provide a broader perspective of the effectiveness of MCII in online learning environments.

1.1. Self-regulated learning in online environments

A number of SRL models have been developed to describe the processes that self-regulated learners engage in (e.g., Boekaerts & Niemi-virta, 2000, pp. 417–450; Winne, 1996; Zimmerman & Moylan, 2009; for review, see; Panadero, 2017). Despite the differences in underlying theories of the SRL models, there is a consensus that SRL is goal-driven in nature and comprises various phases involving multiple processes that are at play in each phase (Panadero, 2017). According to Zimmerman and Moylan's (2009) model of SRL, SRL occurs in a cyclical manner across three main phases: the forethought phase, the performance phase, and the self-reflection phase. The performance phase builds on the forethought phase, which then influences the self-reflection phase and the subsequent forethought phase. The sequence in which SRL unfolds aligns with how most tasks are performed, and hence, can be applied to various learning contexts (Cleary, Callan, & Zimmerman, 2012). Regardless of learning contexts, self-regulated learners typically engage in processes of self-motivational beliefs (e.g., interest or self-efficacy) and task analysis in the forethought phase prior to performing a task (e.g., learning from videos). Subsequently, as learners proceed to perform the task, they engage in processes of self-control (e.g., self-instruction) and self-observation in the performance phase. Finally, upon completing the task, they engage in processes of self-judgment and self-reaction (e.g., satisfaction) in the self-reflection phase.

In different higher educational contexts, studies have established a positive relationship between SRL and learning outcome, suggesting that successful learners use more SRL strategies (Dent & Koenka, 2016; Kizilcec et al., 2017; Wang, Shannon, & Ross, 2013). Broadbent and Poon (2015) reviewed studies in online higher education and found that time-management, metacognition, effort regulation, and critical thinking are positive predictors of academic success. Apart from SRL strategies, the concept of motivation has also been highlighted as a significant determinant of academic success within SRL. Learners who are motivated to learn are more likely to invest the extra time and effort to self-regulate their learning over the course of learning (Baars, Wijnia, & Paas, 2017; Pintrich, 1999). Results from Sitzmann and Ely's (2011) meta-analysis showed that 17% of the variance in learning was explained by persistence, effort, self-efficacy, and goal level after controlling for cognitive ability and pre-training knowledge. Similarly, in Richardson, Abraham, and Bond's (2012) meta-analysis effort regulation, self-efficacy, and grade goal were identified as the strongest predictors of academic performance at university level. These studies not only provide evidence for the role of SRL processes and strategies (e.g., metacognition and time-management) for student success, but also highlight importance of personal beliefs that generate and sustain motivation (i.e., self-efficacy) to perform a task and regulate one's learning towards personal goals.

1.1.1. Self-motivational beliefs

The decision to invest extra time and effort to self-regulate one's learning depends on one's level and type of motivation that arises from various self-motivational beliefs (Baars et al., 2017; Pintrich, 1999). Two types of self-motivational beliefs that are important for SRL are perceived self-efficacy and task value (Artino & McCoach, 2008; Lee et al., 2020). Self-efficacy refers to the extent to which learners perceive themselves as competent in performing and completing a task. Task value refers to the extent to which learners perceived a task as important, useful, and interesting. Both of these self-motivational beliefs can affect learners' choices, persistence, and performance in the task (Liem, Lau, & Nie, 2008).

Studies showed that learner's level of perceived self-efficacy has an effect on both the goals that learners set for themselves as well as the attainment of these goals (Zimmerman, Bandura, & Martinez-Pons, 1992). Specifically, learners with higher perceived self-efficacy set more challenging goals for themselves (Locke & Latham, 2006). In addition, learners with higher perceived self-efficacy use more SRL strategies such as planning and monitoring than learners with lower self-efficacy (Pintrich, 1999). Perceived task value, on the other hand, provides rationale for performing a task (Wigfield & Eccles, 2000). Learners are more likely to use SRL strategies when taking a course that they believe will be useful (Pintrich, 1999).

Littlejohn, Hood, Milligan, and Mustain (2016) examined the relationship between MOOC learners' SRL and motivation. Results of their study indicated that learners with prior online experience have higher self-efficacy and reported that they know what they need to do to succeed in the course. Moreover, learners with higher levels of SRL placed greater value in mastery of skills and knowledge and connected learning to usefulness for their workplace and future needs. In a recent study, Lee, Watson, and Watson (2020) examined the relationship between self-efficacy, task value, and use of SRL strategies in MOOCs. Results of the study showed that both self-efficacy and task value positively predicted the use of SRL strategies. These findings corroborate results from earlier studies in other online learning environments that showed that self-efficacy and task value promote the use of SRL strategies (Artino & Jones, 2012; Shea & Bidjerano, 2010). Together, studies on self-motivational beliefs and SRL draw attention to the potential of supporting self-efficacy and task value to increase SRL and learning performance in online environments.

1.2. Facilitating self-regulated learning

Review studies indicate that supporting SRL has a positive effect on SRL and academic achievement in online learning environments (Lee et al., 2019; Wong et al., 2019; Zheng, 2016). Wong et al. (2019) reviewed studies that examined SRL supports in online learning environments and concluded that empirical studies in MOOCs are still scarce. Promising approaches to support SRL included prompting SRL, providing feedback, and implementing an integrated support system. Of the approaches reviewed, providing prompts to support SRL, has been the most widely studied approach and has been shown to be considerably effective in enhancing SRL (Wong et al., 2019). Studies suggest that prompting SRL is an appropriate and straightforward way to enhance online learners' SRL in learning environments such as MOOCs where videos are central to the learning experience (Jansen, van Leeuwen, Janssen, Conijn, & Kester, 2020; Wong, Baars, de Koning, & Paas, 2021).

Apart from prompting to support SRL, research findings in MOOCs suggest that providing support for learners to set their personal goals may increase SRL (Lee et al., 2019). Having clear goals can help learners to initiate, orientate, and sustain SRL processes, such as planning, monitoring, and reflecting (Wäschle, Allgaier, Lachner, Fink, & Nückles, 2014). Zimmerman (2008) explained that goals influence students' learning process in four ways: 1) selecting and executing goal-relevant tasks, 2) stimulating one to exert a higher level of effort, 3) sustaining one's persistence overtime, and 4) indirectly enhancing learning

through heightened arousal. There is a small but increasing number of studies focusing on the goal setting and planning aspect of SRL in MOOCs (Lee, Lee, & Watson, 2019). Davis, Chen, van der Zee, Hauff, and Houben (2016) implemented a study planning prompt at the beginning of each week to ask learners to write about their study plan and goals for the week. Results of the study showed that learners who engaged in the study planning prompt had higher course engagement, persisted more in the course, and had higher final grades than learners who did not engage in such prompts. Yeomans and Reich (2017) also reported positive findings of open-ended planning prompts that asked learners to plan when and where they were to work on the course content, specific steps to take, and how they will respond to obstacles. They found that the planning prompt increased completion rates by 29%. The results suggested that open-ended prompts that elicit specific plans for learning are helpful in increasing course completion in MOOCs. However, not all studies that examined planning obtained positive results. Andor, Fels, Renz, and Rzepka (2018) embedded a pop-up window in MOOCs to help learners select a time for their next study session. Results of the study showed no significant differences in course engagement and completion between learners who were prompted to plan a time and learners who were not prompted. Therefore, it appears that having an intervention that is more guided and self-generative (i.e., having learners to write about their plans) was more effective than simply having learners to plan a time for their next study session. The studies suggest that prompting study planning can enhance course completion in MOOCs but the effect of planning support on SRL behavior is less clear.

1.3. Facilitating SRL using mental contrasting and implementation intentions

An approach that has been successfully used to support goal setting and planning is MCII. MCII consists of two complementary strategies: mental contrasting (MC) and implementation intentions (II). While studies provided support for the effectiveness of the two strategies when used independently, research suggest that when combined, MCII, can be even more effective than when the strategies are used in isolation (Duckworth, Grant, Loew, Oettingen, & Gollwitzer, 2011; Duckworth, Kirby, Gollwitzer, & Oettingen, 2013; Kizilcec & Cohen, 2017; Oettingen, Kappes, Guttentag, & Gollwitzer, 2015; Saddawi-Konefka et al., 2017; Wang, Wang, & Gai, 2021). MC involves thinking about the outcome associated with achieving a goal (e.g., better job opportunities) and a current obstacle (e.g., lack of time and other distractions) that prevents one from achieving the goal. Such a thinking process gives learners an opportunity to evaluate the importance of the desired goal and the impact of the obstacle (Oettingen, Hönig, & Gollwitzer, 2000). These MC activities help learners to commit to goals that they view as highly important and achievable. II, on the other hand, involves identifying concrete actions and making specific plans that describe the possible obstacles that one might encounter (i.e., if) and the actions that one will take in the face of the obstacle (i.e., then). The process of II supports goal achievement by providing learners an opportunity to form a strong association between an opportunity to act in the face of the obstacle (e.g., If I think that I do not understand the content) and the responses or actions that they have chosen to execute (e.g., I will play back the video, I will test myself by recall the main ideas) (Webb & Sheeran, 2008).

There are several studies pointing in the direction that MCII has the potential to enhance SRL by initiating goal-directed behavior. In Oettingen et al.'s (2015) study, learners who completed an MCII activity scheduled more time and reported better time management than learners who did not complete the MCII activity. Furthermore, the attendance of learners who had more obstacles to cope with (i.e., more children and longer working hours) was moderated by MCII. Similarly, studies by Duckworth et al. (2011; 2013) showed that MCII had positive effects on high school students' completion of practice questions in

preparation for high stake exams and fifth graders' conduct and punctuality in attending school. Clark, Miller, Berry, and Cheng (2020) compared the effect of MCII to a stress management training and results of the study showed that undergraduates trained in MCII made more progress towards the target goal of increasing study hours. In terms of online learning, Kizilcec and Cohen's (2017) study showed that MCII enhanced course completion of learners from individualistic cultures by 32%. To our knowledge, at present, no studies have examined MCII in a multimedia or video-based learning environment. The only exception is a study by Stalbovs, Scheiter, and Gerjets (2015) examining the effect of II on multimedia learning in a lab setting. They concluded that II was effective given that students who internalized three pre-phrased II (e.g., "If I have opened a new page, then I will carefully study the title first!") performed better than students who internalized three pre-phrased goal intentions (e.g., "I will search every picture for its central elements with regard to content!").

Findings from the studies above suggest that MCII could be an effective strategy for enhancing SRL in online learning environments by stimulating learners to engage in the process of goal setting and planning in the forethought phase. Through MC, the value of the goal (i.e., positive outcomes associated with the goal), and one's self-efficacy (i.e., Am I able to overcome the obstacle that is standing in my way?) can be strengthened. Through II, learners engage in planning by selecting cognitive or metacognitive strategies that will help them to cope with the difficulties that may arise during learning (e.g., "If I am getting bored, then I will pause the video to test myself"). Given that each phase of SRL has an effect on another phase of SRL, we expect that learners who are engaged in goal setting and planning in the forethought phase of SRL through MCII will become not only more active in employing cognitive and metacognitive strategies during learning (i.e., the performance phase), but also become better at assessing their progress towards their goal after learning (i.e., the self-reflection phase).

Given that very few studies were conducted in online contexts, the effect of MCII on online learners' self-motivational beliefs and SRL is not clear. To gain more insight into this, we conducted two studies to examine the effectiveness of MCII, one in a computer lab to examine the effect of MCII in a video-based learning environment and the other as a field study in MOOCs.

2. Study 1: video-based learning

As the use of videos for learning in higher education is becoming increasingly common (e.g., recorded lectures, supplementary resources like Youtube, or free online courses like MOOCs), there is a need to examine the types of SRL support to help learners make good use of the high level of flexibility that such learning environment offer. Several studies showed that prompting learners to self-regulate when watching videos can be an effective way to enhance SRL (Moos & Bonde, 2016; Wong et al., 2021). The study by Stalbovs et al. (2015) showed that II can be effective for enhancing learning with videos. While MCII, to our knowledge, has not been examined in video-based learning environments, studies on MCII in other learning contexts suggest that MC together with II can support the goal setting process and enhance learning in environments that demand SRL (Kizilcec & Cohen, 2017). Drawing from two lines of research (i.e., MCII and prompting SRL), the current study employed a two (MCII, no MCII) by two (SRL prompt, no SRL prompt) experimental design. The experimental design resulted in four conditions: 1) MCII only, 2) prompt only, 3) MCII and prompt, and 4) control condition without MCII and prompt.

The main research question was formulated as.

Does supporting SRL using MCII and prompting SRL, together or individually, have an effect on learners' perceived self-motivational beliefs, perceived SRL, learner engagement, and learning performance?

The first set of hypotheses was formed to examine the effect of MCII and prompting SRL on perceived self-motivational beliefs over time as measured by learners' perceived task value and self-efficacy before MCII

(Time 1), after MCII (Time 2), and at the end of the learning task (Time 3). By asking learners to identify their goals for learning and imagine positive outcomes associated with achieving the goals during MCII, learners would view the task as more important (Hulleman, Kosovich, Barron, & Daniel, 2017). In addition, by asking learners to identify potential obstacles and write plans to overcome the obstacles would increase learners' self-efficacy (Abdulla & Woods, 2021). Therefore, we expected that there would be an interaction effect between time and conditions on perceived task value. Specifically, we hypothesized that learners in the MCII only and MCII and prompt conditions would perceive a higher level of task value than learners in the prompt only and control conditions (Hypothesis 1 A). We also expected that there would be an interaction effect between time and conditions on perceived self-efficacy. Specifically, we hypothesized that learners in the MCII only and MCII and prompt conditions would perceive a higher level of self-efficacy than learners in the prompt only and control conditions (Hypothesis 1 B).

The second set of hypotheses was formed to examine the effect of MCII and prompting SRL on learners' perceived level of SRL measured by persistence, task strategies, self-evaluation, and self-satisfaction. Research suggested that prompting SRL has a positive effect on SRL activities (Wong et al., 2021). Therefore, we hypothesized that the prompt only and MCII and prompt conditions would report a higher level of persistence (Hypothesis 2 A), task strategies (Hypothesis 2 B), self-evaluation (Hypothesis 2C), and self-satisfaction (Hypothesis 2D) than learners in the MCII only and control conditions.

The third set of hypotheses was formed to examine the effect of MCII and prompting SRL on learners' engagement and learning performance. Separate lines of research in MCII and prompting SRL suggested that both approaches had a positive effect on enhancing student engagement and academic performance (Duckworth et al., 2011; Wang et al., 2021; Wong et al., 2019, 2021). Sitzmann and Johnson (2012) found that learners who received a planning intervention in addition to SRL prompts scored five to eight percentage points higher and were less likely to drop out of an online course than learners who received an individual intervention or no intervention at all. Therefore, providing MCII followed by SRL prompt in the online learning environments might be more beneficial than providing the two strategies separately. The average number of clicks and average time spent on the videos were used as indicators of student engagement. We hypothesized that learners in MCII and prompt condition would have the highest average number of clicks (Hypothesis 3 A), average time spent on the videos (Hypothesis 3 B), and the highest score on the quiz (Hypothesis 3C), followed by learners in the MCII only and prompt only conditions, than learners in the control condition.

2.1. Method

2.1.1. Participants

There were 129 psychology undergraduates who participated in the study in exchange for course credits. Two of the participants had to switch computers halfway through the study due to technical issues and one of the participants spent less than 24s watching the content video. The data of the three participants were excluded from the analysis, resulting in a final sample of 126 participants (29 males and 97 females) assigned to one of the four conditions: control ($n = 33$), prompt only ($n = 32$), MCII only ($n = 31$), and MCII and prompt ($n = 30$). Participants are referred to as learners in the rest of the paper.

The mean age of the learners was 21.52 years ($SD = 3.02$) with the majority of them in the first-year bachelor program (69.05%), followed by the second-year program (19.05%), and the third-year program (11.90%). Most of the learners (80.95%) had never taken an online course, while only a small number of learners (10.32%) had taken online courses but never completed them and even fewer (7.94%) had taken online courses and passed at least one of them. To control for prior knowledge, learners were asked if they had ever taken the MOOC, Mind

of the Universe, from which the three content videos used in the study were taken. All learners reported that they had not taken the MOOC before.

2.1.2. Study context: online video-based learning environment

We uploaded three videos from an actual MOOC, Mind of the Universe, to an online platform to create an online video-based learning environment. The length of the first video was 4 min and focused on the topic of *Boggling the imagination*, introducing the role of imagination in becoming a successful scientist and discussing how people translate their imagination into a well-considered research question. The topic of the second video, which lasted 8 min, was *Keep your mind open*. In the second video, the instructor explained the concepts of making use of alternative scenarios when working on possible explanations and contrasts. The third video was 6 min long and focused on *Interdisciplinarity*. The instructor discussed the importance of getting inspired from other domains in scientific research in the video. Altogether, the three videos would require a total viewing time of approximately 18 min. The maximum allotted viewing time for each video was set at twice the duration of each video (e.g., a maximum of 12 min viewing time for a 6-min video) to avoid learners having disproportionate amounts of viewing time and yet still allow students to have ample time to study at their own pace and review (parts of) the videos. The videos (i.e., learning materials) and all instructions were uploaded to an online survey platform and presented to learners as part of a webpage in a browser window on a computer. Learners were free to optimize the viewer to watch the videos as full screen or as part of the webpage.

2.1.3. Materials

The materials can be accessed via the project page created on the Open Science Framework (OSF) (osf.io/hbd2x).

2.1.3.1. Self-motivational beliefs survey. The Online Learning Value and Self-Efficacy Scale (OLVSES; Artino & McCoach, 2008) was used to measure two types of self-motivational beliefs, namely task value and self-efficacy. The task value scale consisted of six items while the self-efficacy scale consisted of five items. Learners were asked to respond to each item on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The task value score measured at Time 1, Time 2, and Time 3 had Cronbach's alpha values of 0.80, 0.91, and 0.91 respectively, indicating that the task value scale had high reliability. Similarly, the self-efficacy score measured at Time 1, Time 2, and Time 3 had Cronbach's alpha values of 0.71, 0.85, and 0.86 respectively, indicating that the self-efficacy scale had high reliability.

2.1.3.2. Self-regulated learning survey. The SRL survey included three scales measuring different SRL processes: persistence, task strategies and self-reflection. The persistence scale containing five items was taken from Jansen, van Leeuwen, Janssen, and Kester's (2017) study. The task strategies and self-reflection scales were adapted from Littlejohn et al.'s (2016) study. The task strategies scale consisted of five items after removing one item from the original task strategies scale that was not relevant in the current context (i.e., I read beyond the core course materials to improve my understanding). The self-reflection scale consisted of two subscales: self-satisfaction (3 items) and self-evaluation (3 items). The Cronbach's alpha values for persistence, task strategies, self-satisfaction, and self-evaluation were 0.85, 0.59, 0.58, and 0.68 respectively.

2.1.3.3. MCII activity. The MCII activity is a written exercise to guide learners through the four steps of MCII using the acronym WOOP that stands for *Wish, Outcome, Obstacle, and Plan*. We developed a guided MCII activity that was adapted from the MCII activity in Saddawi-Konefka et al. (2017) and Oettingen's (2015) studies and the MCII steps provided on a website of Oettingen (<http://woopmylife.org/woop-kit>).

The guided MCII activity consisted of two sections: a training section and an applied section directed at completing the three videos.

In the MCII training section, learners were first prompted to think of an academic *wish* that is challenging but can be reasonably achieved. In a second step learners were prompted to identify a positive *outcome* associated with the wish before imagining the positive outcome. The third step consisted of prompting learners to identify an *obstacle* that stands in their way and imagining how the obstacle will interfere with achieving their goals. Finally, in the fourth step, learners were prompted to identify actions that they could take to overcome the obstacle. Learners were also guided to formulate the obstacle and actions in an if-then plan towards achieving their academic wish. If-then plans related to online learning were used as examples to guide learners in forming their own if-then plans. After completing the MCII practice section, the screen displayed information notifying learners that they had completed a goal-setting technique with the acronym *WOOP* and that they had to apply the technique to set a goal for the learning task (i.e., applied MCII).

In the applied MCII section, learners were asked to choose their wish associated with watching the three content videos from three options: a learning related goal, a performance related goal, or a wish of their own. Most learners chose the learning goal (MCII only condition, $n = 27$; MCII and prompt condition $n = 23$). None of the learners chose to write a wish of their own. The steps in the applied MCII were the same as the MCII practice but with less examples to guide learners. For the conditions without the MCII activity (i.e., prompt only and control conditions), we provided a filler writing activity in which learners were prompted with generic questions about life as a student.

2.1.3.4. SRL prompt video. In Study 1, we provided learners in the prompt only and MCII and prompt conditions with a video prompting SRL strategies. The SRL prompt videos provided learners with three questions to stimulate them to think about their current learning process and three recommendations on SRL strategies that they could use in the learning session. For the conditions without the video prompting SRL (i.e., MCII only and control conditions), we provided a filler video that presented learners with information about the university that produced the content of the videos that they were about to learn.

2.1.3.5. Quiz. We formulated four multiple-choice questions for each video to measure students' understanding of the concepts that were introduced and discussed in each video. The quiz in total consisted of 12 multiple-choice questions with four alternatives each, of which one was the correct answer. One point is awarded for each correct answer. Learners' performance was measured by the scores obtained from all the questions over the three videos (i.e., the minimum score was 0 and the maximum score was 12).

2.1.4. Study Procedure

The experimenter gave a brief explanation of the study and asked

learners to consent to the study before providing them with a pen and paper as optional materials that they could use during the study. Then, the learners were presented with the study materials via an online survey platform, Qualtrics (<https://www.qualtrics.com>). Learners had no access to other webpages to control for the learning experience. The survey platform randomly assigned learners to one of the four experimental conditions based on the 2×2 experimental design (i.e., control, prompt only, MCII only, MCII and prompt). Fig. 1 illustrates the procedure of the study when learners entered the survey platform.

Learners were first presented with an introductory video and a short text about the objectives of the course, the topics to be learned and the structure of the course. Next, they completed the first set of the self-motivational beliefs (T1) survey. Then, learners in the MCII only and MCII and prompt conditions proceeded with the MCII activity whereas the prompt only and control conditions proceeded with a filler activity to write about their university life. After the activity, all learners were asked to complete the second set of self-motivational beliefs (T2) survey. Upon completing the survey, learners in the prompt only and MCII and prompt conditions were shown a video prompting SRL whereas learners in the MCII only and control conditions were shown a filler video that promoted the university. Subsequently, all learners proceeded with the learning phase in which they were given time to watch three videos. Learners were given the options of pausing, playing back or skipping forward parts of each video, and moving forward to the next video whenever they wanted. After the learning phase, learners were asked to complete the third survey measuring self-motivational beliefs and SRL strategies (T3). After completing the survey, learners took a quiz that covered the content of the three MOOC videos. The learners were asked to complete a demographics survey at the end of the study.

2.1.5. Analytical procedure

All analysis were done using the R software. We employed two types of analysis in this study. The first analysis was a mixed-design Analysis of Variance (ANOVA). We conducted separate mixed-design ANOVAs for the two forms of self-motivational beliefs measured in this study, namely task value and self-efficacy. The between-subject factor was Condition with the condition that learners were assigned to as the four levels and the within-subject factor was Time with the three time-points in which task value and self-efficacy were measured as levels. The second analysis involved separate one-way ANOVAs for each SRL process measured (i.e., persistence, task strategies, self-satisfaction, and self-evaluation), engagement behaviors indicated by the log file (i.e., average number of clicks and average time spent on the three videos), and quiz score. We used the non-parametric Kruskal-Wallis test whenever the assumption of normality was violated. The anonymized data and R script for data analysis can be accessed via the project page created on the Open Science Framework (OSF) (osf.io/hbd2x).

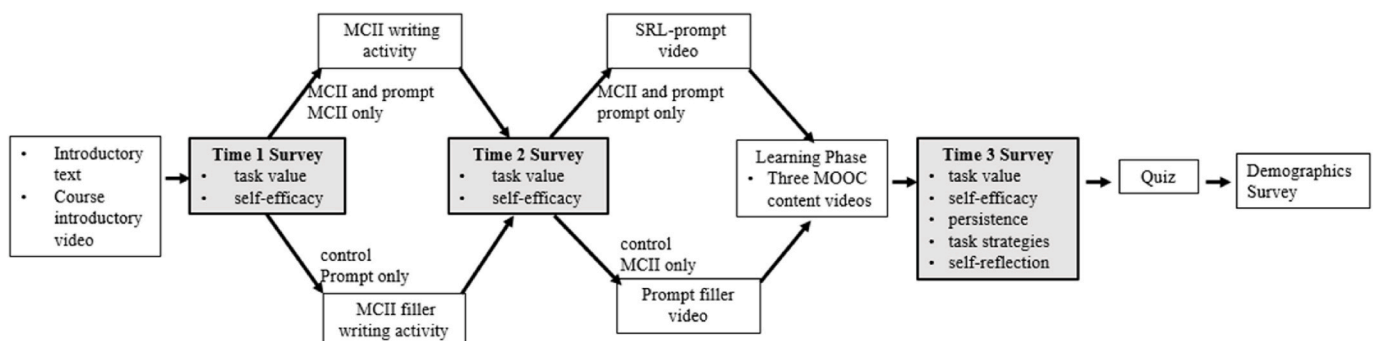


Fig. 1. Presentation of materials in the study procedure.

2.2. Results

2.2.1. Self-motivational beliefs

The self-motivational beliefs as indicated by task value and self-efficacy scores measured at three time points for each of the four conditions can be found in Table 1.

2.2.1.1. Task value. Results of the mixed-design ANOVA revealed significant main effects of time, $F(2, 244) = 3.88, p = .022, \eta_p^2 = 0.031, \eta_G^2 = 0.008$, and condition, $F(3, 122) = 3.06, p = .031, \eta_p^2 = 0.07, \eta_G^2 = 0.054$, which were qualified by a significant interaction between time and condition, $F(6, 244) = 2.16, p = .047, \eta_p^2 = 0.050, \eta_G^2 = 0.013$. This interaction is illustrated in Fig. 2. When comparing task value score of the four conditions measured at each of the three time points, Bonferroni adjusted p-values showed a significant effect of condition at Time 2 ($p = .027$) but not at Time 1 ($p = 1.00$), and Time 3 ($p = .120$). Pairwise comparisons corrected using Bonferroni adjustments at Time 2 showed that the MCII only condition had a higher task value score than the prompt only condition ($p = .012$) and no other significant differences were found between the control and prompt only conditions ($p = 1.00$), the control and MCII only conditions ($p = .173$), the control and MCII and prompt conditions ($p = .887$), the prompt only and MCII and prompt conditions ($p = .104$), and the MCII only and MCII and prompt conditions ($p = 1.00$).

When comparing changes in task value score across time for each group, Bonferroni adjusted p-values showed a significant effect of time on task value scores for the control condition ($p = .024$) but not for the prompt ($p = .292$), MCII only ($p = 1.00$), MCII and prompt only conditions ($p = 1.00$). Pairwise comparisons corrected using Bonferroni adjustments showed that task value scores between Time 1 and Time 2 were significantly different for the control ($p = .019$) and prompt only ($p = .032$) conditions but not for the MCII only ($p = .966$) and MCII and prompt ($p = 1.00$) conditions. For task value scores between Time 1 and Time 3, a significant difference was found only for the control condition ($p = .026$), but not for the prompt only ($p = .306$), MCII only ($p = 1.00$) and MCII and prompt ($p = 1.00$) conditions. There were no significant differences in task value scores between Time 2 and Time 3 for all four conditions ($p = 1.00$). The results suggest that in the two conditions without the MCII activity (i.e., control and prompt only), task value scores appear to decline significantly from Time 1 to Time 2. For the MCII and MCII and prompt conditions, there were no significant changes in task value scores over time.

2.2.1.2. Self-efficacy. Mauchly's test indicated that the assumption of sphericity had been violated for the self-efficacy scores, $\chi^2(2) = 13.97, p = .001$, and therefore degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\epsilon = 0.916$). The results from a mixed ANOVA indicate that there were no significant effects of time, $F(1.83, 223.62) = 2.99, p = .057, \eta_p^2 = 0.024, \eta_G^2 = 0.007$, and condition, $F(3, 122) = 0.96, p = .416, \eta_p^2 = 0.023, \eta_G^2 = 0.016$, and there was also no

significant interaction between condition and time, $F(5.50, 223.62) = 1.56, p = .165, \eta_p^2 = 0.037, \eta_G^2 = 0.011$. The results suggest that the self-efficacy scores did not significantly differ among the four conditions nor did the self-efficacy scores change significantly across the three time points.

2.2.2. Self-regulated learning

Table 2 shows the means and standard deviations for the four perceived self-regulated learning processes (i.e., persistence, task strategies, self-evaluation, and self-satisfaction) per condition. Results of the one-way ANOVA showed that there was no significant effect of condition on perceived task strategies, $F(3, 122) = 1.18, p = .322, \eta_p^2 = 0.028$. Given that the assumption of normality was violated, non-parametric Kruskal-Wallis test was applied to persistence, self-evaluation, and self-satisfaction. Results of Kruskal-Wallis test showed that there were no significant differences among the four conditions for self-evaluation, $H(3) = 1.54, p = .672$, and for self-satisfaction, $H(3) = 2.17, p = .538$. For persistence, Kruskal-Wallis test revealed a significant difference among the four conditions, $H(3) = 9.70, p = .021$. Dunn's pairwise comparisons test with Bonferroni correction showed that the level of persistence in MCII and prompt condition is significantly higher than control condition ($p = .026$). No significant differences were found between control condition and prompt only condition ($p = .954$) or MCII only condition ($p = .094$). There were also no significant differences in level of persistence between prompt only condition and MCII only condition ($p = 1.00$) or between prompt only condition and MCII and prompt condition ($p = .878$), as well as between MCII only condition and MCII and prompt condition ($p = 1.00$).

2.2.3. Engagement-related behavior

Table 3 shows the means and standard deviations of the two types of behaviors identified from the log data (i.e., average number of clicks and amount of time spent watching the three videos). Results from non-parametric Kruskal-Wallis tests revealed no significant effects of condition on average number of clicks, $H(3) = 1.12, p = .773$, and on average time spent on the three videos, $H(3) = 3.58, p = .310$.

2.2.4. Learning performance

The distribution of quiz scores in the prompt condition violated the assumption of normality, and hence, we employed the non-parametric Kruskal-Wallis test to compare the quiz scores obtained in the four conditions: control ($M = 7.24, SD = 1.84$), prompt only ($M = 7.69, SD = 1.77$), MCII only ($M = 8.39, SD = 1.63$), and MCII and prompt ($M = 8.00, SD = 1.55$). Results showed that there were no significant differences in the quiz scores among the four conditions, $H(3) = 7.20, p = .066$.

2.3. Discussion

Our first set of hypotheses focused on the effect of MCII and prompt, together and individually, on self-motivational beliefs. Results showed that learners in the MCII only condition perceived significantly higher task value measure at Time 2 (after completing the MCII activity) than learners in the prompt only condition. However, no significant differences in task value were found between the MCII and prompt condition and prompt only and control conditions nor between the MCII only condition and control condition, failing to support the effect of MCII and prompt on task value (Hypothesis 1 A). Similarly for self-efficacy, no significant differences were found between the conditions, failing to support the effect of MCII and prompt on self-efficacy (Hypothesis 1 B). One possible reason for the lack of findings on task value and self-efficacy could be related to the study population. Learners in Study 1 were psychology undergraduates who were familiar with participating in experiments as part of their psychology program, so it is likely that they viewed themselves as competent in completing the task provided to them in the experiments (i.e., learning from online videos) even though

Table 1

Means and standard deviations of task value and self-efficacy score measured across three time points in the four experimental conditions.

	Time 1		Time 2		Time 3	
	M	SD	M	SD	M	SD
Task Value						
Control	4.86	.88	4.41	1.19	4.33	1.29
Prompt only	4.59	1.14	4.13	1.39	4.30	1.44
MCII only	4.91	.88	5.05	1.11	5.00	1.14
MCII and prompt	4.90	.70	4.84	.85	4.87	.80
Self-efficacy						
Control	4.80	.70	4.92	.86	4.73	1.03
Prompt only	5.03	.66	5.04	.89	5.01	.10
MCII only	4.97	.89	5.14	.94	5.27	1.01
MCII and prompt	4.74	.89	5.03	.88	5.21	1.01

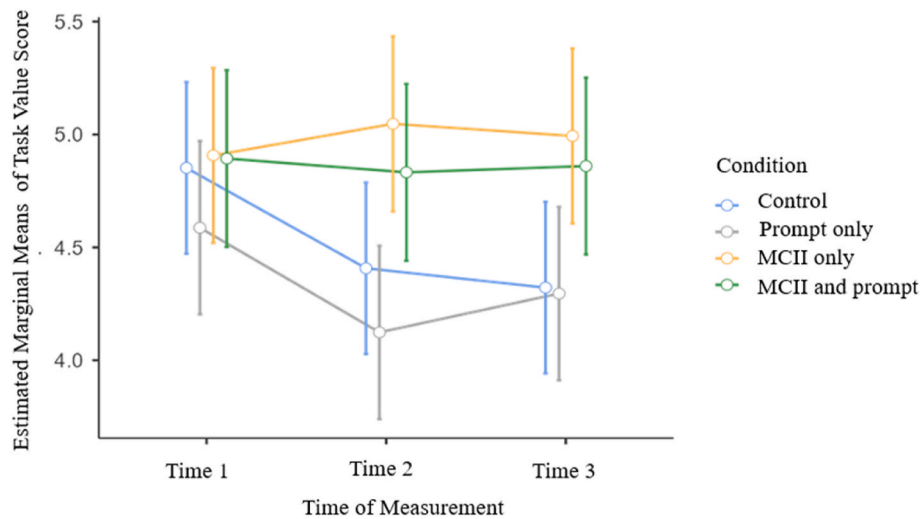


Fig. 2. Mean task value score across the time of measurement for the four conditions.

Table 2

Means and standard deviations of perceived persistence, task strategies, self-evaluation and self-satisfaction measured at the end of the learning phase in the four conditions.

SRL processes	Control		Prompt only		MCII only		MCII and prompt	
	M	SD	M	SD	M	SD	M	SD
Persistence	4.36	1.11	4.68	1.14	5.05	1.03	5.12	.89
Task strategies	4.98	.94	5.29	.90	5.31	.64	5.07	.87
Self-evaluation	4.72	1.08	4.74	1.05	5.03	.90	4.98	.64
Self-satisfaction	4.92	1.15	5.02	1.14	5.13	.98	4.77	1.02

they had little or no online learning experience.

To examine the second set of hypotheses, we compared learner's SRL in terms of perceived persistence, task strategies, self-evaluation, and self-satisfaction. The results showed that only learners who received the MCII and prompt perceived higher persistence than learners in the control condition who did not receive MCII nor the prompt. Therefore, the results suggest that MCII combined with SRL prompt has a positive effect on learners' persistence but not prompt alone, partially supporting Hypothesis 2A. The items measuring persistence are related to the obstacles that learners commonly face in online learning (e.g., when my mind starts to wander and when I am feeling bored). Therefore, it is likely that MCII is reinforced by prompting SRL to prepare learners for the obstacles and the actions that they can take to overcome the obstacles, enhancing learners' persistence when learning from videos. We did not find any significant effect of MCII and prompt, together or individually, on other aspects of SRL, failing to support Hypothesis 2B (task strategies), 2C (self-evaluation), and 2D (self-satisfaction). We observed that learners' self-reported task strategies, self-evaluation, and self-satisfaction across all conditions were close to a mean score of 5 out of a maximum score of 7. One possible reason could be that learners in the study, being undergraduates, were well-versed in using effective strategies and engaging in the process of self-reflection (i.e., self-evaluation and self-satisfaction). Therefore, MCII nor prompt,

individually or together, had any additional effect on these already highly perceived SRL strategies with regard to using task strategies and self-reflecting when learning from videos.

Similarly, we did not find any support for the third set of hypotheses in relation to learners' engagement and learning performance when learning from videos. There were no significant differences in average number of clicks (Hypothesis 3 A), average time spent on the videos (3 B), and learning performance (3C) between the four experimental conditions (i.e., MCII and prompts, MCII only, prompt only, and control condition). We noticed that learners across all conditions took less than the required time to watch all three videos and most of them made use of the optional pen and paper to make notes when learning from the videos. This could indicate that learners are skilled in identifying key information from videos and skipped over less relevant content in the videos. Another reason could be that the current learning task is one-off and deals with a topic that is not too difficult for the study population. Accordingly, a certain level but not a great extent of SRL is needed to succeed in the task. Therefore, goal setting and planning through MCII may be helpful but is not vital in enhancing learners' engagement and performance.

Given that Study 1 was conducted online in a controlled lab environment where learners could only access the webpage with the three videos and no other webpages, it is not clear whether MCII might be more effective in enhancing SRL in actual online learning environments where learners have more autonomy in deciding when to study and what to study. Furthermore, the student population in Study 1 consisted of only psychology undergraduates. Therefore, more studies are needed to examine the effectiveness of MCII in actual online learning environments and with other student populations.

3. Study 2: Massive Open Online Courses

To examine the effect of MCII in a more ecologically valid learning environment, we implemented MCII in MOOCs that were hosted on Coursera (<https://www.coursera.org/>), a MOOC platform. Study 2 differed from Study 1 in two important ways. The first difference was the

Table 3

Means and standard deviations of engagement in video measured by average number of clicks and average time spent on the three videos in the four conditions.

Learning behavior	Control		Prompt only		MCII only		MCII and prompt	
	M	SD	M	SD	M	SD	M	SD
Average number of clicks	2.04	3.28	1.59	1.91	1.79	3.52	2.94	4.68
Average time spent on the videos (secs)	416.00	98.47	418.22	75.11	452.47	97.31	430.62	68.61

personal value of the learning task to the learners. Study 1 was conducted in a more controlled environment where learners were taking part in the study for course credits and not for learning the content of the three videos. Therefore, while completing the videos might have been interesting for them, the videos had no direct personal relevance to the learners. While MOOC learners have diverse reasons for taking a specific MOOC, these reasons are usually of certain personal significance (Hew & Cheung, 2014; Littlejohn et al., 2016). The second difference was the duration of the learning task. In Study 1, learners were setting goals for watching three videos that could be completed in approximately half an hour in one study session. Learning in MOOCs typically stretches across multiple study sessions and weeks. Furthermore, in addition to watching a large number of videos, learning in MOOCs also includes other course activities such as participating in discussions, reading texts, and completing assessments (e.g., quizzes and assignments). Therefore, in Study 2, we examined the effect of MCII as a tool for supporting goal setting and planning to support learning in MOOCs with learning spanning across multiple sessions as opposed to one study session. Furthermore, based on the findings in Study 1 which showed that MCII and MCII with prompting did not differ from each other, Study 2 was set up to focus mainly on the effect of MCII as a tool to support goal setting and planning. Given that MOOC learners are likely to be more diverse than the learners who participated in Study 1 and less likely to finish the whole MOOC, we were also interested in goal attainment as an indicator of success.

Study 2 contained three experimental conditions: MCII only, goal only, and control. The first condition was the MCII condition where learners received an MCII activity that was modified from Study 1's MCII activity to cater to the MOOC learners. One of the two modifications of the MCII activity was adapting the step on identifying goals to capture the diverse personal goals that learners might have for taking the MOOCs (Littlejohn et al., 2016). In a MOOC, learners have greater autonomy over what they want to learn and the activities that they want to engage in. While watching lectures could be considered as one of the main learning activities in MOOCs, the intention to watch most lectures would be dependent on whether the content in the lectures were aligned to what the learners wanted to learn. Besides, some MOOC learners might only be interested in a subset of the content within the MOOC, and as such, they might not have the intention to watch most of the lectures in the course (Wang & Baker, 2018). Therefore, in Study 2, we guided learners in setting two types of goals: a participation goal (to what extent do you wish to complete the activities) and a learning module completion goal (i.e., what do you wish to learn). The other modification concerned cutting down on the guidance and instructions of the MCII activity that was used in Study 1. Studies showed that MOOC learners' compliance to interventions are low (Wong et al., 2021). Therefore, to increase learners' chances of completing all the steps of MCII, we condensed the MCII activity by integrating the information that we provided in the training section as examples in the actual MCII section. By doing so, the MCII activity in Study 2 was more concise but still offered learners the same level of guidance through the extended examples.

The second condition was the goal only condition in which learners were asked to select a participation goal and a learning module completion goal (i.e., Step 1 of the MCII activity in the MCII condition). The goal only condition was used as an active control group. By asking learners to indicate their goals for the MOOC, we were able to measure goal attainment as an indicator of learner success in addition to the final grades that they obtained in the course. The third condition was the pure control condition in which learners were not asked to select any goals nor were they exposed to the MCII activity.

The main research question for Study 2 was formulated as.

Does MCII have an effect on learners' perceived self-motivational beliefs (i.e., task value and self-efficacy), SRL-related behavior, course engagement and performance, and goal attainment in MOOCs?

The first set of hypotheses was formed to examine the effect of MCII

on self-motivational beliefs as measured by perceived task value and self-efficacy. In Study 1, perceived task value was sustained over time for learners who completed the MCII activity, suggesting that the MCII activity likely safeguarded one's perceived task value during learning. Given that it is mostly out of personal and diverse interest that one enrolls in MOOCs, getting learners to think of positive outcomes associated with their goal in MCII might help learners to become more aware of the personal benefits and value of taking the MOOC. Therefore, we hypothesized that learners in the MCII condition would perceive higher task value than learners in the goal only and control conditions (Hypothesis 1 A). Even though there was no significant effect of MCII on perceived self-efficacy in Study 1, considering the differences in the study environment and population between Study 1 and 2, we maintained our hypothesis that learners in the MCII condition would perceive higher self-efficacy than learners in the goal only and control conditions (Hypothesis 1 B). Given the close relationship between self-efficacy and goal setting, it was expected that MOOC learners who are more aware of the personal obstacles and have plans to overcome the obstacles through MCII would perceive themselves as more self-efficacious (Webb & Sheeran, 2008).

The second set of hypotheses focused on examining the effect of MCII on SRL-related behavior measured from the log data. Based on Zimmerman's model of SRL and previous studies (Jansen et al., 2020; Wong et al., 2021), we identified five SRL-related behaviors: planning, self-monitoring of grades, persistence, time-management, and self-reflection. The first SRL-related behavior was planning operationalized by the average number of times learners viewed the course overview page and weekly course information page (Jansen et al., 2020). You (2016) suggested that viewing course information pages was related to course achievement. These course pages provided learners with information on the topics to be covered and the course activities to be completed for the whole course and in each week. Therefore, we hypothesized that learners in the MCII condition would visit these pages more often as part of their planning process when learning in a MOOC than learners in the goal only and control conditions (Hypothesis 2 A). The second SRL-related behavior was self-monitoring of grades and was operationalized as number of views of the grade information page (Jansen et al., 2020). We expected that learners who are committed to completing certain modules in the MOOC would be monitoring the grades they achieved when taking the module. Therefore, we hypothesized that learners in the MCII condition would view the grade information page more often as part of self-monitoring of grades than learners in the goal only and control condition (Hypothesis 2 B). The third SRL-related behavior was operationalized by the proportion of course activities that were completed (Jansen et al., 2020). Learning in a MOOC requires learners to engage in a number of course activities (e.g., watching videos and participating in discussions). In Duckworth's (2011) study, students in the MCII condition completed more practice questions than students in the control condition. Therefore, we hypothesized that learners in the MCII condition would be more persistent as manifested by completing a greater proportion of course activities than learners in the goal only and control conditions (Hypothesis 2C). The fourth SRL-related behavior was time-management as indicated by the proportion of course activities that were completed on time (Wong et al., 2021). Studies by Oettingen et al. (2015) and Saddawi-Konefka et al. (2017) showed that learners in the MCII condition scheduled more time for learning. Therefore, we hypothesized that learners in the MCII condition would be better at managing their time as manifested by completing a greater proportion of course activities on time than learners in the goal only and control conditions (Hypothesis 2D). The final behavior of interest in Study 2 was related to self-reflection in SRL (Wong et al., 2021). Learners who are better at SRL are more likely to revisit course materials (Kizilcec et al., 2017). Therefore, we hypothesized that learners in the MCII condition would engage in the process of self-reflection to a greater extent, and as such, revisit a greater proportion of course materials than learners in the goal only and control

conditions (Hypothesis 2 E).

The third set of hypotheses formed to examine the effect of MCII on course engagement and performance. As mentioned in the introduction, learners have a high level of autonomy in MOOCs. Therefore, learners who are more involved in their learning would access more course activities, log on to the course more often, and work on more graded assessments. Previous studies suggested that MCII has potential to improve grades and attendance for students in middle school (Duckworth et al., 2013). We hypothesized that learners in the MCII condition would access more course activities (Hypothesis 3 A), be active on more days over the duration of the course (Hypothesis 3 B), and achieve higher course grades (Hypothesis 3 C) than learners in the goal only and control conditions.

The fourth set of hypotheses was formed to examine the effect of MCII on goal attainment. Studies suggest that not all learners have the intention to complete a MOOC as a whole and might be seeking parts of the course as a form of upskilling (Henderikx, Kreijns, & Kalz, 2017). Therefore, we measured two types of learners' goal intention in two conditions (i.e., goal only and MCII): participation goal and module completion goal. Participation goal referred to the extent to which learners intended to participate in the course while module completion goal referred to the modules in the MOOC that learners intended to complete. We hypothesized that learners in the MCII condition would have higher participation goal attainment (Hypothesis 4 A) and module completion goal attainment (Hypothesis 4 B) than learners in the goal only condition.

3.1. Method

3.1.1. Participants

We collected 625 survey responses. After linking the learner id in the log data with the survey data and removing incomplete survey responses based on the data cleaning process described in the analytical procedure, the final data set consisted of 194 learners. Two learners did not report their demographics. Based on the completed demographics, 34.5% was between 25 and 34 years old, 23.2% was between 18 and 24 years old, 18.6% was between 35 and 44 years old, and 13.4% was between 45 and 54 years old. Only a small number of learners reported an age below 17 years old (2.6%) and above 55 years old (6.7%). There were 97 learners who identified as female, 94 learners identified as male, 1 learner did not specify, and 2 learners did not answer the question. In terms of education level, a large proportion of the learners had a higher education degree (36.6% had a master's degree, 32% had a bachelor's degree, and 10.3% had a doctoral or professional degree). Less than a quarter of the learners (20.2%) did not have a higher education degree. Most of the learners (46.4%) had previously taken and passed at least one online course, followed by 36.6% who had not taken any online courses before, and 16% who had taken online courses but had not finished a single course. The distribution of learners in the three experimental conditions across the five MOOCs is provided in Table 1 of the supplementary file (Appendix 1 Table 1).

3.1.2. Study context: MOOCs

We conducted the study in five MOOCs offered on the MOOC platform Coursera. A MOOC could be taken at any time of the year and when learners enrolled in a MOOC, they were enrolled in an active cohort. We collected data over three consecutive cohorts for each MOOC. The number of modules and graded and non-graded activities are provided in Table 2 of the supplementary file (Appendix 1 Table 2). The MOOCs differed in the number of modules. Two of the MOOCs had eight modules and learners were given 12 weeks to complete the eight modules (i.e., from the start date of the MOOC enrolment till the end date of the MOOC). In other words, each round of the MOOC lasted 12 weeks. For the MOOC with seven modules, learners had 11 weeks to complete the MOOC. For the MOOC with 6 modules, learners had 10 weeks to complete and for the MOOC with 5 modules, learners had 9 weeks to

complete the MOOC. The number of course activities (e.g., videos, reading, discussion) varied between the courses.

3.1.3. Materials and procedure

Learners were invited to participate in the survey via the course enrolment email that was sent to the learners after enrolment and Week 1 course email that was sent at the start of first week of the MOOC. In the emails, learners were provided with an embedded link that would direct them to a pre-MOOC survey created on a survey platform (Qualtrics; <https://www.qualtrics.com>). At the start of the pre-MOOC survey, learners were first asked to give their consent for the collection and use of their data for research purposes. The pre-MOOC survey was set up to randomly assign learners to one of the three conditions (i.e., control, goal, MCII). Learners in the control condition received a set of questions measuring their self-motivational beliefs, course intentions, and demographics. Learners in the goal condition received two additional questions to set their goals for participation and course module completion. Learners in the MCII condition received the extended pre-MOOC survey that consisted of the set of questions in the control condition, the two questions for participation and course module completion, and the guided MCII activity. All learners proceeded with taking the MOOCs as they typically would. A post-MOOC survey was sent at the end date of each respective MOOC to learners who provided us with their email addresses in the pre-MOOC survey. The post-MOOC survey was intended to measure self-motivational beliefs at the end of the course. Given that we only received 16 survey responses in the post-MOOC survey, the post-MOOC survey responses were not analyzed. The questions used in the survey and the measures are described in the following subsections. The materials can be accessed via the project page created on the Open Science Framework (OSF) (osf.io/hbd2x).

3.1.3.1. Self-motivational beliefs. The Online Learning Value and Self-Efficacy Scale (OLVSES; Artino & McCoach, 2008) measuring task value and self-efficacy used in Experiment 1 was also used in Experiment 2. In the pre-MOOC self-motivational survey, the six items measuring task value had a Cronbach's alpha of .89 and the five items measuring self-efficacy had a Cronbach's alpha of .80, indicating that both scales are reliable measures of task value and self-efficacy, respectively.

3.1.3.2. Course intentions. Given the varied intentions of learners in MOOCs, we included two questions that were taken from previous research to measure learners' course intentions in the form of likelihood to complete the course and how important it was to complete the course. Learners were asked to respond on a scale from 1 (not likely at all, not important at all) to 5 (extremely likely, extremely important).

3.1.3.3. Participation and completion goals. Only the goal setting and MCII conditions were asked to set participation and course module completion goals. To ensure that the participation goal was measurable, we asked learners to identify the extent to which they would like to participate in the course by selecting one of the four participation levels (i.e., less than 25%, above 25%, above 50%, and above 75%). Attainment of participation goal was defined as course activities accessed by the learners as measured from the log data matched or exceeded the level of participation that the learners indicated to achieve.

Similarly, to make course module completion goals measurable, we provided learners with the main objectives of each module and asked learners to select the module(s) that they would like to complete. We considered learners as having attained a module when they had completed at least 75% of the activities in the module that they have selected. Course module completion goal attainment was defined as the proportion of modules attained (i.e., sum of modules attained divided by number of modules selected).

3.1.3.4. MCII activity. The MCII activity from Study 1 was adapted for

Study 2 to suit the learning context of MOOCs. We displayed the participation and learning goals that learners had identified earlier on in the survey and asked learners to imagine and write about the positive outcomes that came to their mind relating to achieving the goals that they had identified. Then, learners were asked to identify an obstacle that might interfere with achieving the goal and imagine how the obstacle stands in their way of achieving the goal. The last part of the MCII activity guided learners in identifying three actions that they can take to overcome their obstacle. The first action that learners were asked to identify were specific to when and where they plan to engage in the course activities. Learners were given examples of if-then plans and were asked to form their if-then plans based on their obstacle and actions identified. On average, learners in the MCII condition spent 16.3 min on the page with the MC activities (i.e., imagine positive outcome, identify obstacle, and imagine how the obstacle stand in the way) and 4.8 min on the page with II activities (i.e., identify three actions and form three if-then plans).

3.1.3.5. SRL-related behavior. We identified five proxies for SRL-related behaviors from the log data that were used in previous studies (Jansen et al., 2020; Kizilcec et al., 2017; Wong et al., 2020; You, 2016). Planning was operationalized by the number of course overview and weekly course page views divided by the number of course weeks. Self-monitoring of grades was operationalized by the number of page views to the grade information page. Persistence was operationalized by the proportion of course activities that were completed. Time-management was operationalized by the proportion of course activities that were completed on time. Finally, self-reflection was operationalized by the proportion of completed course activities that were revisited.

3.1.3.6. Course engagement-related behavior. We defined engagement based on two types of behavior. The first behavior was the proportion of accessed course activities. Accessing a course activity could mean that learners started the activity but did not complete the activity or they started and completed the activity. The proportion of accessed course activities was calculated by dividing the total number of accessed course activities by the number of course activities in the MOOC. The other engagement-related behavior was defined as the proportion of active days in the MOOC. Active days referred to the days in which the learners accessed at least one course activity. We calculated the proportion of active days by dividing the total number of active days learners had in a MOOC by the duration of the course in days (i.e., date in which the course was open for enrollment till the end date of the MOOC).

3.1.3.7. Course performance. The course grade table obtained from Coursera provided learners' grades for the MOOC calculated based on the weightage given to the graded course activities in the MOOC. For example, in the MOOC on Driving Business towards Sustainable Development Goals, there were 10 quizzes and each quiz contributed for 10% to the overall course grade.

3.1.4. Analytical procedure

We collected and matched four sources of data for the analyses: survey data, learner's course grade, log data on learner's interactions with the course activities, and log data on learners' page views in the MOOC. All analyses were done using the R studio software. The first phase of the analytical procedure was to clean the log data for each MOOC. For the survey data, we removed data of learners' who did not consent to the study and data of learners who did not meet the criteria for the experimental conditions. We first removed all learners who did not indicate their likelihood and importance of completing the MOOC. For the goal only condition, we also removed all learners who did not select a participation and a learning module completion goal. For the MCII condition, we also removed learners who did not state a positive

outcome associated with the goals and learners who did not provide at least one action to overcome the obstacle.

For the log data on learner's interactions with the course materials and page views, we used the `crsra` package developed by Hadavand, Muschelli, and Leek (2019) to import the data tables into R studio. Then, we selected data of learners who were enrolled in only one cohort of the MOOC during the period of data collection. MOOC learners continued to have access to the course materials even after the cohort of the MOOC that they were enrolled in ended. Therefore, we removed learners' interactions with the course activities and page views that were made after the end date of MOOC for each specific cohort to create a comparable set of data (i.e., learners' interactions with course activities from the date when the enrolment began for the cohort till the date when the MOOC ended for the cohort).

In the second phase, we processed the data to calculate the outcome variables (e.g., proportion of course items completed on time) based on our operationalization. For example, to get the proportion of accessed course activities in Enjoyable Econometrics MOOC, we divided each learners' total number of accessed course activities by 25 (i.e., the number of course activities in the MOOC). Then, in the third phase, we joined the two data sets in each MOOC using learners' ID (i.e., survey and log data) and removed learners' data whose ID in the survey data failed to match the log file. The last step in the data processing phase was to combine the data sets across the five MOOCs.

The final phase of the analytical procedure was the data analysis computed across the five MOOCs. We first checked the data for the assumption of normality and homogeneity. Given that the assumption of normality was violated, we used the non-parametric Kruskal-Wallis test to examine whether there were differences in the outcome variables between the three conditions. When examining the number of page views to the grade information page and the course grade, we excluded the data from the Enjoyable Econometrics MOOC because the MOOC did not have any graded assessments. For the fourth set of hypotheses, we were interested in participation and learning module completion goal attainment in the MOOCs. Only learners in the goal only and MCII only conditions were asked to indicate the extent to which they would like to participate in the MOOC and the modules that they would like to learn. Therefore, comparisons were made only between the goal only and MCII only conditions. Participation goal was defined as a dichotomous variable (whether or not the learner attained the level of participation that they indicated). Therefore, we used a Chi-squared test to examine whether goal only and MCII only conditions differed in the number of learners who attained their participation goal. Learning goal attainment was defined as a continuous variable (the proportion of selected modules that were completed). Given the non-normal distribution of the data, we used the non-parametric Mann-Whitney *U* test to examine whether learning goal attainment differed between the goal only and MCII only conditions.

The anonymized data and R script for data analysis can be accessed via the project page created on the Open Science Framework (OSF) (osf.io/hbd2x).

3.2. Results

Table 4 provides the means and standard deviations of all outcome variables across the three conditions.

3.2.1. Pre-MOOC self-motivational beliefs

As shown in Table 4, learners in all three conditions reported considerably high self-efficacy and task value scores measured by a 7-point Likert scale at the start of the MOOC. Results of the Kruskal-Wallis test showed that there were no significant differences in perceived self-efficacy, $H(2) = 2.20, p = .334$, and perceived task value, $H(2) = 0.14, p = .934$, among the three experimental conditions.

Perceived likelihood to complete the MOOC and perceived importance to complete the MOOC were measured on a 5-point Likert scale.

Table 4

Means and Standard Deviations of Outcome Variables across the three conditions.

	Control <i>n</i> = 78		Goal Only <i>n</i> = 77		MCII <i>n</i> = 39	
	M	SD	M	SD	M	SD
<i>Pre-MOOC motivational beliefs</i>						
Self-efficacy	5.15	.94	5.26	1.05	5.33	.74
Task value	5.56	.93	5.47	1.09	5.55	.96
Likelihood to complete	3.82	.85	4.00	.80	3.92	.70
Importance to complete	3.58	.96	3.62	.93	3.82	1.02
<i>SRL-related behaviors</i>						
Average page views for course overview and weekly course pages	2.33	6.01	2.26	3.59	2.61	4.63
Proportion of course items completed	.33	.36	.37	.38	.34	.37
Proportion of course items completed on time	.28	.33	.33	.36	.28	.34
Proportion of completed course items that were repeated	.02	.06	.02	.03	.02	.02
Number of page views to grade information page*	1.04	2.74	1.46	3.60	1.06	2.03
<i>Course engagement</i>						
Proportion of course items accessed	.34	.36	.38	.38	.34	.37
Proportion of active days	.08	.10	.08	.10	.09	.10
<i>Course performance</i>						
Course grade*	.22	.38	.27	.41	.24	.41

*The Enjoyable Econometric MOOC was excluded from the analysis as the MOOC did not have any graded course items. Therefore, in these analyses the sample size in the three conditions was reduced (i.e., control, *n* = 69; goal only, *n* = 69; MCII, *n* = 35).

On average, learners reported that they were moderately likely to complete the MOOC and that completing the MOOC was of moderate importance to them. Results of the Kruskal-Wallis test showed that there were no significant differences in likelihood to complete, $H(2) = 1.76$, $p = .415$, and importance to complete, $H(2) = 1.89$, $p = .388$, among the three experimental conditions.

3.2.2. SRL-related behavior

Results of the Kruskal-Wallis test showed no significant differences among the three conditions across all proxies of SRL-related behavior: Planning operationalized by the average number of page views for course content overview and weekly information pages, $H(2) = 0.39$, $p = .822$; persistence operationalized by the proportion of course items completed in the course, $H(2) = 0.62$, $p = .735$; time-management operationalized by the proportion of course items in the course that were completed on time, $H(2) = 0.560$, $p = .756$; and self-reflection operationalized by the proportion of completed course items in the course that were repeated, $H(2) = 0.198$, $p = .906$.

The Enjoyable Econometrics MOOC did not have any graded course activities and was excluded from the analysis to examine the number of page views on grade information page as a proxy for self-monitoring of course grades. Results of Kruskal-Wallis test again showed that there were no significant differences in the number of page views on grade information page among the three conditions, $H(2) = 1.83$, $p = .40$.

3.2.3. Course engagement

Results of the Kruskal-Wallis test showed no significant differences in course engagement operationalized by the proportion of course activities accessed in the course, $H(2) = 0.56$, $p = .755$, and the number of active days for the duration of the course, $H(2) = 0.81$, $p = .666$.

3.2.4. Course grades

Results from a Kruskal-Wallis test showed no significant differences in learners' course grade across the three conditions, $H(2) = 0.42$, $p = .811$.

3.2.5. Participation and module completion goal attainment

Table 5 shows the number of learners who achieved the passing criteria (i.e., passed all graded assessments and obtained 80% of the course grade) and learners' attainment of their participation and learning module completion goals. The frequencies showed that while the number of learners did not meet the passing criteria and attained their goals outweigh the number of learners who met the passing criteria and attained their goals, the number of learners who did attain their participation goal seems to be slightly higher. By considering attainment or participation and learning module completion goal, we gain an additional perspective to learner success in MOOCs.

3.2.5.1. Participant goal attainment. We first looked at the distribution of learners according to the participation goals that they had selected. Most of the learners (65.5%) intended to complete at least 75% of the MOOC. About a quarter of the learners (27.6%) intended to complete at least 50% of the MOOC. Only a small number of learners selected a low goal of completing at least 25% of the MOOC (5.2%) and completing less than 25% of the MOOC (1.7%). In general, learners selected a high goal with the intention of participating in most of the course activities. Results of the Chi-squared test revealed no significant differences in the number of learners who attained their participation goals between the goal only and MCII only condition, $\chi^2(1, n = 116) = 0.38$, $p = .537$.

3.2.5.2. Learning module completion goal attainment. Learners could complete more than or less than the number of modules that they had selected. Therefore, when dividing the number of modules that the learners completed by the number of selected modules, we obtained a continuous variable ranging from 0 to 6, with scores less than 1 indicating that learners completed less than the number of modules that they had selected. Results of a Mann-Whitney *U* test showed no significant differences in the attainment of learning module completion by the goal only condition ($M = 0.50$, $SE = 0.79$, $Mdn = 0.20$) and the MCII only condition ($M = 0.38$, $SE = 0.44$, $Mdn = 0.14$), $U = 1387$, $p = .498$.

3.3. Discussion

Study 2 was set up to examine the effectiveness of MCII to support goal setting and planning as an approach to enhance SRL, course engagement and performance, and goal attainment in MOOCs. Results showed that the MCII activity did not increase SRL-related behaviors, course engagement and performance, nor goal attainment, failing to support any of our hypotheses. In contrast to previous studies, results from Study 2 do not support the effectiveness of MCII in enhancing academic achievement (Duckworth et al., 2011, 2013) and SRL (e.g., time management; Oettingen et al., 2015) in MOOCs. Our results are aligned with results from a recent large-scale study conducted by Kizilcec et al. (2020) where MCII increased students' engagement only in Week 1 of

Table 5

Number of Learners in the Goal only and MCII Conditions who Met the Passing Criteria and Attained the two types of Goals.

	Passed Course		Participation Goal		Learning Module Completion Goal	
	Not Passed	Passed	Not Attained	Attained	Not Attained	Attained
Goal only (<i>n</i> = 77)	60	17	53	24	58	19
MCII only (<i>n</i> = 39)	31	8	29	10	31	8
Total	91 (78.4%)	25 (21.6%)	82 (70.7%)	34 (29.3%)	89 (76.7%)	27 (23.3%)

the MOOCs but the positive effect diminished by Week 2, and overall, there was no significant effect on MOOC completion rates. Given the non-significant results of MCII in MOOCs, we propose several reasons as to why the MCII intervention used in Study 2 might fall short in enhancing SRL and academic performance in MOOCs.

Firstly, the effect of MCII might be dependent on the characteristics of the goals that learners set. Learners were asked to select from a set of possible goals that were pre-defined based on the log data in MOOCs to facilitate the analysis of goal attainment. For example, learners were asked to set a goal for their level of participation for the whole MOOC (e.g., browse and explore; less than 25% of the activities). Setting a goal for the whole MOOC can be considered a long-term goal and require sustained effort to attain the goals (Kizilcec et al., 2020). In addition, the goals are pre-defined and can be viewed as somewhat restrictive. Learners might have other goals that are more personally relevant but less measurable from the log data, for instance, I want to be able to apply new knowledge in my job. Future studies are therefore necessary to examine how the types of goals that learners are asked set may influence the effectiveness of MCII. For example, whether the effect of MCII depends on the time it takes to attain the goal (e.g., goal for the learning session compared to goal for the whole MOOC) and the personal relevance of the goals (e.g., open-ended goals compared to predefined goals).

Another reason concerns the timing of the MCII. In Study 2, the MCII activity was provided only at the beginning of the MOOCs. Learners' situation can change over the duration of the course and affect their original goals and plans, for example, a learner might receive an extra job assignment in the second week of the course or have other social obligations (Kizilcec et al., 2020). In Study 1 where the learning task can be completed within one study session, learners in the MCII condition reported higher level of persistence than learners in the control condition. Therefore, it could be that for MCII to be effective, the activity has to be completed or reviewed at a study session level and not at the course level. This would allow learners to adapt and adjust their goals and plans according to the changing situation.

The third reason concerns the measurement of the outcomes. We examined only a small set SRL and engagement-related behaviors in the Study and operationalized the behaviors over the span of the whole MOOC (i.e., proportion of completed activities). Kizilcec et al. (2020) found the benefits of planning prompts diminished by Week 2 of the course. In the current MCII activity, we explicitly asked learners to plan when and where to engage with the course materials as part of process of II. Therefore, it could be that the effect of MCII is manifested in other forms of behaviors that were not included in the analysis. For example, it would be interesting to follow up the current analysis by examining the log data at a more comprehensive level (e.g., weekly activities) and also to examine whether learners' followed their plans, which could provide insight into whether learners who planned to log on to a MOOC twice a week actually did so.

4. General discussion

The benefits of online learning environments are built on the premise that learners are capable of self-regulating their learning. However, research suggest that many learners struggle with SRL and supporting SRL can enhance SRL and increase student success (Azevedo & Feyzi-Behnagh, 2011). In the present study, we examined the effect of MCII as an approach to enhance SRL by supporting goal setting and planning in two studies. While the results from both studies provide little to no support for the robust findings of the effectiveness of MCII in enhancing SRL and academic performance, differences in the findings between Study 1 and Study 2 as well as between the two studies and previous research provide several insights.

One of the differences between Study 1 and Study 2 is the frequency and duration of the learning sessions. In Study 1, the learning session was a one-off event that consisted of watching three videos that would

not take more than an hour. In Study 2, we used MOOCs and learning in MOOCs typically takes place across multiple learning sessions (i.e., weeks). The positive effects of MCII on task value and persistence in learning obtained in Study 1 suggest that MCII might be more effective when it is used for a specific learning session rather than for setting goals and plans across learning sessions. Research suggests that MOOC learners' session learning behavior, for example the duration and frequency in which they engaged in uninterrupted study (e.g., watching a series of videos) are related to SRL (de Barba et al., 2020). MOOC learners who reported higher level of time management and effort regulation had longer and more sessions over the duration of a MOOC. Therefore, future research could explore how MCII can be used to enhance session-specific SRL. Instead of providing the MCII activity only at the start of learning, learners may be directed to use MCII multiple times throughout the course of learning (Wang et al., 2021).

Another difference between Study 1 and 2 is learners' perceived task value. The primary goal of the learners in Study 1 was to earn course credits for their undergraduate course. Therefore, they did not choose to watch the three videos because of their interest in the content of the videos. Learners in Study 2 were invited to participate in the study after they enrolled in the MOOCs. Therefore, the primary goal of the learners in Study 2 was most likely related to their interest in the content of the MOOCs. As shown in the results, the task value reported by learners at the start in Study 2 is higher than in Study 1, suggesting that the task value of the MOOC learners who took part in the study was already high. Therefore, it was unlikely that MCII would have any additional effect on learners' task value.

The third difference between Study 1 and Study 2 is learners' experience with the learning task. Most learners in Study 1 reported that they did not have prior experiences with taking an online course, whereas almost half of the learners in Study 2 had taken and passed at least one online course. Learners in Study 1 also reported a slightly lower self-efficacy measured at the start of the study than learners in Study 2. The greater familiarity with online learning and feelings of competence could have provided MOOC learners in Study 2 with more favorable perceptions of themselves, thereby for example overestimating the ability to self-regulate one's learning (van Halema, van Klaveren, Drachsler, Schmitz, & Cornelisz, 2020). That is, learners who have previously successfully completed one MOOC might not perceive potential obstacles as real threats to their learning success for a more challenging MOOC. Also, they might rely on previous learning experiences when planning without considering that they might face a new set of challenges. Therefore, future studies should examine whether learners' initial self-efficacy and prior experiences influence how learners define their obstacles and handle them during goal setting and planning.

Besides differences between the two studies in our paper, we also identified differences between the two studies and previous studies in terms of study context, type of MCII intervention, and additional support combined with MCII. Wang et al. (2021) conducted a meta-analysis on 21 empirical studies on MCII across study contexts (i.e., academic, health, personal and relationship). Results of the meta-analysis showed that the positive effect of MCII in the academic domain is the lowest, suggesting that other goal setting and planning approaches might be as effective, if not more effective than MCII. The findings are supported by Abdulla and Woods' (2021) study in which MCII was compared to two other approaches on supporting secondary students' goal progress: solution-focused planning and autonomous planning. The study showed no significant differences between MCII and the other two approaches. Similarly, in Study 1, no significant differences were found between MCII and SRL prompt. However, as Abdulla and Woods (2021) observed, there are very few studies that compared MCII with action-oriented approaches that are ecologically valid. Therefore, more studies are needed not only to examine whether there are other approaches comparable to MCII in supporting goal setting and planning, but also how MCII can be better designed and implemented to increase

its effectiveness.

Besides study contexts, the type of MCII intervention across studies was identified as a significant moderator of the effect of MCII on goal attainment (Wang et al., 2021). MCII interventions that were implemented in the form of a document as in the format used by the two studies in the current paper had significant lower effect sizes than when the MCII interventions were implemented by experimenters (i.e., face to face). One possible reason is that the interpersonal relationship between the experimenters and participants could have promoted the effectiveness of the MCII. Another reason is that experimenters could provide additional and targeted guidance to help participants formulate higher quality goals and plans when needed. While less effective, MCII interventions in the format of a document are more cost effective and more scalable, making it easier to implement. Future studies can examine whether pedagogic conversational agents as a way to provide a scalable and affective model to implement MCII would enhance the effectiveness of MCII.

Additional support in combination with MCII might be needed to increase the effectiveness of MCII and provide a more comprehensive SRL support. For example, supporting learners in monitoring their goals and plans. Giasiranis and Sofos (2020) followed up the MCII in each week of the MOOC with instructions to self-record aspects of one's learning and achievement towards the goal. Their study showed that learners in the MCII application group perceived higher SRL at the end of the MOOC, specifically in metacognitive activities after learning, persistence, and help-seeking, than learners who did not receive the MCII application. In Saddawi-Konefka et al.'s (2017) study, learners were asked to report the weekly amount of time they spent studying towards their goals. These studies suggest that activities that promote self-observation towards achieving the stated goal in MCII might increase the effectiveness of MCII. According to the SRL cycle, goal setting in the forethought phase influence self-monitoring in the performance phase, and subsequently self-evaluation in the self-reflection phase. In turn, self-evaluation in the self-reflection phase can influence the goals and plans in the next cycle of forethought phase. Therefore, besides supporting self-monitoring of goals and plans, future studies may explore the design of an adaptive MCII that allows learners to set new goals or make changes during learning to account for the SRL cycle. Learning analytics could be a potential area of research to enhance MCII by supporting learners in monitoring their progress towards goal attainment and adapting their learning activities (Giasiranis & Sofos, 2020; Jivet et al., 2021, pp. 416–427).

4.1. Limitations

We recognize several limitations in our study. Firstly, this concerns the generalizability of the findings in both studies. Study 1 was a controlled experiment in a lab with a rather homogeneous population. In Study 1, learners were provided with the same set of videos that are of similar video length, in the same sequence, on the same type of computer screen in a lab setting. In actual study environments, learners might need to read or use other learning materials in addition to watching videos. Therefore, we are unable to generalize the findings to authentic study environments where learners are learning from video as part of a regular course. Given that the use of videos as an instructional medium is becoming more common in higher education, it is important to examine whether MCII can benefit learners in university courses where their study sessions might include watching video lectures. Study 2, on the other hand, is a field experiment that was conducted in several MOOCs. The MOOCs differed not only in the disciplines (e.g., Business and Economics), but also in the way the course activities were organized in the MOOCs, the length of the MOOCs, and the type and number of assessments. It is not clear whether the differences could have an impact on the effectiveness of MCII. For example, MCII might be beneficial for a MOOC with weekly deadlines. Future studies should work towards accounting for the differences in the MOOCs when examining the effect of

an intervention.

Secondly, only a small number of learners who enrolled in the MOOCs in Study 2 clicked on the survey link. Furthermore, only 40% of the learners who clicked on the survey completed the survey questions. Similar to previous studies in MOOC, the compliance rate of MOOC learners is a challenge to experimental studies in MOOCs (Jansen et al., 2020). One of the reasons could be that the survey was sent via the course emails to learners during enrollment and the first week of the course. Therefore, the survey link could be easily missed if learners do not open their course emails. Another reason could be that learners were less interested in completing a peripheral activity outside the MOOC even though the activity could have been helpful. Besides, the MCII activity required learners to put aside time to think about the positive outcome and obstacles and to write the if-then plan. Therefore, future studies in MOOCs should work towards implementing an intervention that can be easily accessed within the MOOC platform itself. Another method is to incorporate the intervention as part of the MOOC so that learners are more likely to be exposed to the intervention. Integrating the intervention with the MOOC will also help learners to make a closer connection between the study materials (i.e., MCII activity) and their learning process in the MOOC. Designing such a study will require an interdisciplinary team involving MOOC instructors, programmers, and web designers.

Thirdly, we did not examine the effect of MCII on subpopulations (e.g., culture and courses with global achievement gap) (Kizilcec et al., 2020). For both studies, the sample size was considerably small. Therefore, further categorizing learners in each condition by their culture or by their countries' level of development, or even the MOOC that they were enrolled in would not have allowed us to conduct a reliable analysis. To look into the effect of MCII on subpopulations or the effect of individual MOOCs, future studies can aim to collect data from a larger sample size. It is also necessary to conduct research on other methods to reach a wider range of learners to avoid selection bias (i.e., learners who choose to comply with the intervention) and to benefit learners who are in need of additional support (Azevedo & Feyzi-Behnagh, 2011).

Finally, while log data on learners' use of the learning materials in an online environment provided opportunities for us to understand the learning process, a lot more research is needed to better relate the behavioral indicators that can be obtained from data mining with the constructs in (self-regulated) learning. We operationalized SRL-related behaviors from the log data at a generic course level based on work from previous studies. However, the instructional design of the MOOCs can vary from MOOC to MOOC (e.g., some MOOCs can have graded assessments each week and some MOOCs have more readings). Learners' behaviors are tied to the learning context (Giasiranis & Sofos, 2020). Therefore, follow-up studies would be needed to examine the effect of learning context on learner behavior and whether MCII facilitates adaptive learning behavior to enhance course engagement and performance.

5. Conclusion

Despite the limitations, our study adds to the field by examining MCII as an approach to support goal setting and planning in a video-based learning environment and in MOOCs. Our results showed that MCII sustained task value over the duration of a learning session and enhanced learners' persistence to learn in a video-based learning environment. However, MCII did not benefit learning in MOOCs. One of the major limitations is the low study participation in Study 2. Given the multitude of activities in MOOCs, it is necessary for research on supporting learning in MOOCs to develop interventions that would appeal to learners, especially those who are less engaged to begin with.

CRedit author statement

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Acknowledgments

The authors would like to thank Drs. K. Stabel, Dr. T. K. de Mey, and the MOOC instructors of the five MOOCs examined in this study for their support in the implementation of the study. The study is funded by the Leiden-Delft-Erasmus Centre for Education and Learning (LDE-CEL).

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chb.2021.106913>.

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