Which Planning Tactics Predict Online Course Completion?

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ABSTRACT

Planning is a self-regulated learning strategy and widely used behavior change technique that can help learners achieve academic goals (e.g., pass an exam, apply to college, or complete an online course). Numerous studies have tested the effects of planning interventions, but few have examined the content of learners' plans and how it relates to their academic outcomes. Building on a large-scale intervention study, we conducted a qualitative content analysis of 650 learner plans sampled from 15 massive open online courses (MOOCs). We identified a number of *planning tactics*, compared their prevalence, and examined which ones significantly predict course progress and completion using regression analyses. We found that learners whose plans specify a time of day (e.g., morning, afternoon, night) are significantly more likely to complete a MOOC, but only 25% of the learners in our sample used this tactic. The high degree of variation in the effectiveness of planning tactics may contribute to mixed intervention findings in scale-up studies. Models of plan effectiveness can be used to provide feedback on the quality of learners' plans and encourage them to use effective tactics to achieve their learning goals.

CCS CONCEPTS

• **Applied computing → Education**; **Law, social and behavioral sciences**.

KEYWORDS

planning intervention, content analysis, online learning, MOOCs

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1 INTRODUCTION

Self-regulated learning (SRL) theories [45, 62, 66] characterize successful learners as highly motivated, metacognitively skilled, and behaviorally active in their learning process. In practice, however, learners are not always well-equipped to achieve this. Individuals have varying degrees of competence in SRL [36] and use different self-regulation strategies [33]. In informal online education, many learners find themselves in learning environments that are more self-directed than traditional classroom settings, which elevates the role of SRL for achieving good learning outcomes. Learners can benefit from support to develop their self-regulatory skills in such environments [10, 54]. SRL research has long focused on motivational and metacognitive aspects of SRL [44], and recent work is attending to the behavioral aspect of SRL to address issues of attrition, building on behavioral science research. For example, several studies have translated and adapted behavior change interventions for the context of massive open online courses to reduce dropout rates [16]. A common type of behavior change intervention is to ask an individual to write concrete and specific action items for how to achieve a goal (i.e., a planning intervention).

Planning is a behavioral change technique frequently used to promote desirable behaviors in the context of physical activity [11, 39, 46], healthy diets [1, 4], vaccination [38], volunteering [48], voting [41], and exam preparation [23]. Planning is also theorized to be an effective activity in the early "forethought" phase of SRL [67]. While planning in the SRL literature tends to emphasize the strategic selection of sub-tasks to learn specific knowledge or skills, planning in the behavior change literature tends to emphasize behavioral regulation like time management, structuring environments, and habit building. Planning interventions may enhance SRL by helping learners sustain positive learning engagement in online education.

Planning intervention studies demonstrated positive learning outcomes. Yeomans and Reich's study embedded planning prompts at the beginning of MOOCs and found an increase in completion rates across multiple MOOCs [64]. The same year another type of planning intervention tested in two large MOOCs was also found to have significant benefits for course completion, but only in countries with an individualistic culture such as the United States [32]. However, a subsequent scale-up study that tested these interventions across hundreds of courses over three years concluded that they improve engagement in the weeks immediately following the planning intervention, but did not increase course completion rates [34]. However, this scale-up study did not examine the content of the plans and left important questions unanswered: What types of plans do people make? And how effective are different types of plans?

Prior research has investigated ways to enhance the effectiveness of planning interventions. Additional reinforcements, such as sending a reminder, providing guidelines, and monitoring have been proposed as ways to enhance intervention effectiveness (e.g., [29]). But these planning interventions can also be limited by the quality of individuals' plans [40]. Between 20 and 40 percent of study participants have been found to not adhere to planning instructions in prior work (e.g., [19, 37, 51, 56]). Although the act of planning itself may be beneficial (e.g., [6, 27]), it is unclear which kinds of plans are most effective for goal achievement. A few studies have examined the specificity of plans as a measure of plan quality and found more concrete plans to be more effective [18, 43, 65].

Overall, we have little knowledge of how learners plan and how effective their plans are for achieving learning goals. We posit that learners use different planning *tactics*, which we define as strategic approaches to conduct goal-directed behaviors, and that choice of tactics may affect goal achievement. For example, is it more effective for a learner to plan on finishing specific tasks (e.g., to watch the first two lectures this week) or to plan on spending a certain amount of time (e.g., to spend three hours this week)? A better understanding of planning tactics and their relative effectiveness is needed to improve the design of planning interventions (e.g., providing suggestions on effective tactics) and to help learners achieve their goals.

The present study is the first qualitative content analysis of authentic plans to achieve educational goals in the context of online courses. Study plans have been researched mostly in college contexts [22, 30] or younger students [14]. We pose two research questions: What planning tactics do learners use in their plans? And what planning tactics are associated with achieving behavioral course outcomes (i.e., progress and completion)? To answer these questions, we conducted a qualitative content analysis of 650 plans that learners wrote as part of a planning intervention embedded in a wide variety of MOOCs. Here, we first identify 24 tactics from learners' plans (RQ1), and then investigate which tactics are predictive of goal attainment (RQ2).

The contribution of this study is three-fold. First, we provide an in-depth understanding of how learners make plans in a self-regulated learning environment. This is helpful information for instructors and instructional design staff who develop curricula for online courses around the needs of learners (i.e., learner-centered design). Second, our findings offer practical implications for planning interventions. Additional scaffolds can be developed based on our findings, such as examples of effective plans. Third, the findings lay the groundwork for personalized feedback on the plans that learners make. Our study provides a comprehensive coding scheme that applies to plans made for courses in different academic subjects and a range of complexities.

2 BACKGROUND

Most SRL frameworks present a cyclic process of three or four ordered phases, such as goal setting and planning, executing the plans, and evaluating performance [45, 62, 66]. In theory, planning is an important step in most SRL frameworks that prepares for subsequent phases in the process and determines the overall effectiveness of a learning cycle. Yet empirical studies remain inconclusive regarding the impact of planning on learning outcomes. A meta-analysis conducted by Sitzmann and Ely [55] found planning was not a significant predictor of learning outcomes for adult learners. More recent studies conducted in MOOCs showed mixed results: while Davis and colleagues [17] found planning not to be significantly associated with learning outcomes, including course completion and final grades, Kizilcec and colleagues [33] found planning to be positively associated with course completion and other personal learning goals. These inconsistent findings raise questions about how consistent learners are in their plans, and whether individual differences in their approaches to planning could account for this variability in planning effectiveness. Although planning in the SRL literature is concerned with cognitive strategies for reaching a learning goal (e.g., grouping learning tasks by difficulty level, reading a chapter and taking a quiz), it often involves behavioral strategies (e.g., reading every day before going to bed, reviewing during lunch time, going to a quiet study room at a library). The behavioral component of planning grants educators and researchers opportunities to bring perspectives from behavior science to bolster learners' SRL in self-directed learning environments.

The theory of planned behavior posits that people are more likely to engage in a behavior when they intend to do so [2]. Empirical evidence shows that an intention to conduct a behavior is predictive of engaging in the behavior [61]. However, an intention does not automatically give rise to a behavior—a phenomenon known as the intention-behavior gap [52, 53]. The intention-behavior gap implies that merely setting a goal does not guarantee goal achievement; individuals must take goal-directed actions. Planning is a widely used intervention technique to bridge the intention-behavior gap. Different ways of planning have been proposed and found to be effective in promoting goal-directed behaviors [9, 15, 28, 60]. Gollwitzer pioneered the implementation intention strategy, which pairs a specific condition and a goal-directed behavior using an 'if-then' statement [27]. Action planning and coping planning are popular approaches for planning interventions [6, 57]. Action planning is developing a schedule containing a time, a place, and steps to engage in a target behavior. Coping planning is preparing solutions to potential barriers that may deter individuals from conducting planned behaviors. Despite the differences in protocols, these planning methods share similarities in specifying *when*, *where*, and *how* to carry out goal-directed behaviors.

Several studies have tested interventions grounded in the behavior change literature in the context of online education. Yeomans and Reich [64] asked learners at the beginning of the course to write about when, where, and how they plan to complete the course (action planning) as well as how to overcome obstacles (coping planning). This planning activity resulted in a significant increase in course completion and has also been shown to increase completion of extra credit assignments [26]. Kizilcec and Cohen [32] tested a Mental Contrasting with Implementation Intentions intervention at the start of the course, which increased course completion among some learners. These interventions were then tested in a scale-up study with a quarter-million learners across 250 MOOCs [34].

The effect on course completion did not replicate, but there was a short-term effect on engagement in the course (i.e., higher in-course activity in the first two weeks). Others have failed to find overall effects, though some heterogeneity may exist [3].

Prior research suggests that people may not be skillful enough at making plans to fully benefit from planning activities. In a laboratory experiment, Dewitte and colleagues found that not all of the study participants (40% to 64% depending on the type of goal) formed implementation intentions in their plans [21], and those who formed implementation intentions were more likely to perform the planned behaviors. Other studies also found that plans provided by or made with experimenters were more effective in facilitating behavior change compared to participant-generated plans [5, 65]. This implies that planning is a skill that people can acquire. Recently, Bieleke and Keller [13] developed the If-Then Planning Scale (ITPS) to measure individual differences in planning, specifically the process of identifying critical situations and defining goal-directed behaviors. Individuals exhibited varying levels of competence in making plans according to ITPS, and those more competent in planning were also more likely to attain their goals.

Several studies have examined the quality of plans and found it to be positively associated with engaging in goal-directed behaviors. Plan quality has been measured mostly based on the level of specificity, and plan specificity positively influences engagement in planned behaviors [18, 43, 65]. De Vet and colleagues measured quality based on whether a directed behavior was defined and whether the time and the location to conduct the behavior were adequately specified [18]. Ziegelmann and colleagues assessed if a plan includes the time and the place to conduct a planned behavior as well as the frequency and duration of the behavior [65]. Osch and colleagues evaluated the specificity of plans and additionally measured instrumentality, which was assessed by whether a plan was designed for achieving the goal and how feasible the plan was [43]. However, their measure of instrumentality was not significantly associated with behavioral outcomes [43].

Using a bottom-up approach, Yeomans and Reich [64] used natural language processing (NLP) to analyze the content of plans made by learners in MOOCs. They found that course-specific plans were less likely to support course completion. Moreover, heavy use of temporal planning (e.g., more time-related words in plans) and use of concrete time words (e.g., 'Friday') instead of abstract time words (e.g., 'sometime,' 'soon') were associated with a lower likelihood of completion. A follow-up study on concreteness cautions that merely applying pre-existing, domain-general NLP models may provide limited information to researchers and practitioners [63]. Instead, training domain-specific models (e.g., models trained with study plan data in the context of online education) can yield better insights. We therefore rely on a manual coding process instead of general NLP models in this work to identify planning tactics.

3 METHODS

3.1 Data and Context

We used data that was originally collected in a large-scale intervention experiment in MOOCs offered by Harvard University, MIT, and Stanford University [34]. The original study reported findings from data collected over 2.5 years across 247 MOOCs and included over a quarter-million people from nearly every country. The interventions were implemented in a standardized survey at the start of the course. Learners were randomly assigned to different kinds of interventions, including a planning intervention. For the present study, we use data collected as part of this original study (same study design), but we restrict our sample to HarvardX MOOCs and plans written in the planning intervention condition. We also use data collected from courses that were offered after the original study was published until 2021. All in all, 132k learners were assigned to the planning intervention condition between 2017-21 across 384 MOOCs offered by HarvardX. We sampled courses and written plans as explained below. The planning intervention asked learners to formulate a concrete plan for how to complete the course (i.e. long-term planning); specifically, the planning prompt read:

Please write down a clear, concrete plan to follow through on your goals in the course. Planning can be a helpful tool in MOOCs! Successful students in previous courses have made detailed plans for how they will engage throughout the course. In the text boxes below, write out your plans to complete your work for the course. Please be as specific as you can! Write clearly, in full sentences, so that someone else could understand what you mean.
1. When and where do you plan to engage with the course content?
2. What specific steps will you take to ensure you complete the required coursework?

3.2 Qualitative Content Analysis

We qualitatively analyzed learners' written responses to each of the two planning questions above: (1) the *when and where* question, and (2) the *how* question. In three stages, we randomly sampled responses without replacement in selected courses, excluding previously sampled plans. As illustrated in Figure 1, we expanded our selection of courses strategically over three stages to cover a diverse set of courses. In the third stage, we sampled more responses from data science and economics courses to approximate the proportions of course enrollments on the platform. We conducted a qualitative content analysis of responses to each of the planning questions separately using an inductive approach [24, 31]. Following best practices [25], two co-authors from different countries and with a high familiarity with MOOCs coded responses to the two questions independently in three stages. They discussed codes until they agreed and refined the coding scheme in cases of disagreement (e.g., for *how* planning, the 'setting deadlines,' 'monitoring,' and 'time commitment' codes were refined by adding details to the code book). Before sampling and coding, we excluded data points where the length of the written plan was under 10 characters in either of the *where & where* or the *how* prompts.

In the first stage, we developed a general understanding of the plans learners make based on a small set of plans written in an introductory data science MOOC offered in the second term of 2020. This course was chosen because of its popularity with a wide audience, including students, researchers, and working professionals. We randomly sampled 56 from 2,846 learner plans (4,636 learners were assigned to the planning condition in this course but many did not write a plan). Plans were read by the researchers multiple times, divided into condensed meaning units to extract important information, and developed into codes that describe the important

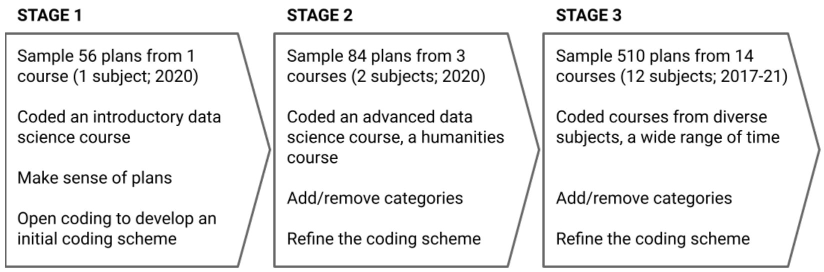

Figure 1: Three-stage Process of Sampling Plans and Qualitative Content Analysis.

information. Finally, the researchers organized these codes into categories.

In the second stage, the coding scheme was refined using another sample of plans drawn from three intentionally selected MOOCs offered in 2020: the same introductory data science MOOC from the first stage, a more advanced data science MOOC, and a humanities MOOC (see Table 1). We randomly sampled an equal number of plans from each of the three courses (28 plans out of 2,846, 333, and 988 after exclusions, respectively). Two co-authors coded the plans independently with the first-stage coding scheme and discussed conflicting or questionable plans until they reached a consensus for each one. Following best practices in qualitative research methods, we opted for detailed discussion between coders to develop a precise and generalizable coding scheme, rather than focusing on inter-coder reliability [8]. This stage improved our initial coding scheme such that it could be applied to courses of varied difficulty levels (introductory and advanced levels) and different academic subjects (data science and humanities subjects).

In the third stage, we finalized the coding scheme by applying it to a larger dataset sampled from a wider pool of academic subjects offered between 2017 to 2021 (Table 1). We intentionally selected 14 out of the 384 courses with this process: 1) we excluded courses with less than 5,000 learners assigned to the planning intervention, 2) we focused on courses that were offered at least three times between 2017 to 2021, 3) we included courses for beginner-level learners or broad audience, 4) we included courses from diverse academic subject areas (including architecture, business, data science, education, English literature, and humanities such as theology). Then, we randomly sampled 510 plans from 47,802 plans written in the 14 selected courses. The range of courses and times allowed us to gain insights into a more diverse array of planning behaviors by MOOC learners: in particular, we noticed plans varied considerably when comparing plans made before vs. during the pandemic. Following the same procedure as in the second stage, we independently coded plans with the coding scheme and resolved any disagreements in stage three. The level of agreement between the two coders was high even before reaching full agreement through discussion, as indicated by a Kappa coefficient of 0.99 for 'when & where' plans and 0.82 for 'how' plans. Most disagreements for 'how' planning arose for the 'setting deadlines,' 'monitoring,' and 'time commitment' codes which we refined by adding details to the codebook.

3.3 Regression Analysis

3.3.1 Dataset. We investigated how planning tactics are associated with learners' behavioral outcomes in the course using the 510 plans from 14 courses coded in the third stage of the content analysis (Table 1). These plans were written by a diverse sample of learners, described in Table 2: 263 (52%) male, 246 (48%) female, and 1 non-binary learner; and an average age of 33 at the time of course enrollment (sd=12, min=15, max=81, median=33). Only 124 learners (24%) enrolled in the course live in the United States; others live in 77 different countries, including India (n = 47, 9%), Brazil (n = 33, 6%), and the United Kingdom (n = 27, 5%). Based on the Online Learning Enrollment Intentions (OLEI) scale [35], learners were enrolled in the course for various reasons (Table 2). The majority of the learners reported that they planned to take this course from start to finish (n = 462, 91%), and only a few reported that they planned to take some parts (n = 12, 2%), just browse (n = 7, 1%), or have no clear idea (n = 30 5%). Learners also indicated how many hours they plan to spend on the course per week and the average was 6.3 hours (sd=4.8; min=1, max=48, median=5).

3.3.2 Behavioral Outcomes. We use two behavioral outcome measures obtained from the course data exports: (1) course completion and (2) course progress. Course completion is presented as the focal goal in the planning intervention; learners are asked to "write out your plans to complete your work for the course." To complete a course, learners need to satisfy all course requirements (e.g., final project, quizzes). In our final sample, 95 learners (19%) completed the course they enrolled in; we do not use course performance (e.g., grades) as an outcome because requirements vary substantially across courses. Course progress is considered a goal-directed behavior as it is essential to achieve the end goal (course completion). We operationalize progress here by the number of unique video lectures that a learner watched (mean=2.5, sd=6.37, min=0, max=38, median=1.0).[1]

3.3.3 Analytic Approach. We use regression models to examine which planning tactics significantly explain each behavioral outcome measure to gain correlational insights about effective planning tactics. We separately analyzed tactics employed in the *when* and

[1] We additionally confirmed that our results are robust to converting the number of videos into a percentage of videos (normalizing by the total number of videos in the course), which yielded the same significant predictors. However, we use the absolute instead of relative definition due to the noise that arises from miscellaneous videos in the course that a learner does not need to watch (e.g., how-to guides, tutorials, recordings of office hours).

Table 1: Courses Sampled in Each Stage of Qualitative Content Analysis

Stage (Sample Size)	Courses Sampled	Plans Sampled (%)
Stage 1 (56 learners)	Data Science: R Basics	56 (100%)
Stage 2 (84 learners)	Data Science: R Basics	28 (33.3%)
	Fundamentals of TinyML	28 (33.3%)
	Justice	28 (33.3%)
Stage 3 (510 learners)	Data Science: R Basics	158 (31.0%)
	Justice	17 (3.3%)
	Visualization	21 (4.2%)
	Machine learning	10 (2.0%)
	Introduction to Digital Humanities	10 (2.0%)
	The Architectural Imagination	41 (8.0%)
	CitiesX: The Past, Present and Future of Urban Life	15 (2.9%)
	Entrepreneurship in Emerging Economies	101 (19.8%)
	Christianity Through Its Scriptures	7 (1.4%)
	Modern Masterpieces of World Literature	1 (0.2%)
	Improving Your Business Through a Culture of Health	20 (3.9%)
	American Government: Constitutional Foundations	11 (2.2%)
	Leaders of Learning	42 (8.2%)
	Rhetoric: The Art of Persuasive Writing & Public Speaking	56 (11.0%)

Table 2: Information about Learners in the Sample

Demographic background	n (%)	Enrollment and completion intentions	n (%)
Female	246 (48%)	Enrolled for relevance to school or degree program	464 (91%)
≥ 30 years old	275 (54%)	Enrolled for career change	428 (84%)
Employed	269 (53%)	Enrolled for fun and challenge	344 (67%)
High school degree or higher	291 (57%)	Enrolled to improve English skills	215 (42%)
Lives in USA	124 (24%)	Intended to complete the course	462 (91%)

where plan and the *how* plan (Table 3). Course completion is predicted as a binary outcome (19% positive cases[2]) and we use logistic regression to analyze this outcome. Course progress is predicted as the log-transformed number of lecture videos watched due to its long-tailed distribution (skew = 2.91) and we use OLS regression to analyze this outcome. All models include course fixed effects, which mean-centers all outcome measures within courses, and standard errors are clustered at the course level. We use the specific codes for tactics as predictors instead of higher-order themes given the exploratory goals of this regression analysis. We confirmed that tactics were not strongly correlated with each other (i.e., multicollinearity; all VIF scores are below 2). We add two covariates to the regression model: first, a binary indicator that a learner intends to complete the course ("I plan to take this course from start to finish" in the survey) since the original study found this to be a predictive covariate [34]. Second, plan length in terms of the number of characters in the plan is added as a continuous variable to control for general motivation and specificity. Learners wrote 72 characters on average (sd=68.6, min=10, max=746, median=53) for the *when* and *where* question, and 75 characters on average (sd=62.3, min=10, max=640, median=60.5) for the *how* question.

[2]The course completion rate for learners in our sample is relatively high for MOOCs because they were motivated enough to enter the course, open the optional survey, progress far enough in the survey to reach the planning intervention, and write a plan.

4 RESULTS

4.1 Planning *When* and *Where* to Engage in the Course

A total of 314 (62%) plans contain a location and 401 (79%) plans include at least one temporal planning tactic. Temporal planning is central to our analysis because 38% of plans lack locations and provided locations show not much variation. Most are 'home,' 'office,' and 'desk,' therefore we simply code if a location is provided. Thus, we find one location tactic and nine tactics for temporal planning (26% Frequency; 25% Time; 22% Sequence; 16% Day; 11% Present; 7% Noncommittal; 3% Clock; 2% Period; 1% Date), which can be grouped into five themes: frequency-based planning, time-based planning, event-based planning, present-oriented planning, and noncommittal planning.[3]

In Table 3, *time* is a significant positive predictor of course completion. Learners who write plans that specify the time of day are more likely to complete the course (odds ratio = 2.0). Other tactics

[3]A plan can fit more than one category. For instance, "I plan to study from home, in the afternoon from 1p.m to 3p.m." has three tactics: (*location*) for 'from home,' (*time*) for 'afternoon,' and (*clock*) for 'from 1p.m to 3p.m.' Frequency-based planning is often coupled with a time-based planning tactic. For example, "Every Saturday evening" contains (*day*) for 'Saturday' and (*time*) for 'evening,' in addition to *frequency*. Another example, "On Wednesdays for two hours at home and on Sundays for two hours [. . .]" is coded both as *frequency* and *day* as it specifies which days of the week, Wednesdays and Sundays, to engage in learning.

are not significant predictors of course completion; none of the tactics is significantly associated with lectures watched (i.e., course progress).

Frequency-based planning refers to setting task duration or the number of times per day or per week (or weekend). A total of 134 (26%) plans include a frequency-based planning tactic. This theme has one category, ***frequency***. Some learners assign a certain amount of time per day; for example, learners write, "Daily basis, for 2-3 hours" and "[. . .] I'm going to spend at least 2 hours each day." Others make learning plans to engage in the course regularly, not necessarily on a daily basis. For example, "I will set a fixed (repeating) day for every week." and "[. . .] 1 hour during the week and 1 hour on weekends."

Time-based planning refers to making a plan with specific times. A total of 231 (45%) plans include at least one time-based planning tactic. This theme comprises four tactics. First, ***date*** specifies a date like "I engage this course content from May 13, 2019 to June 31, 2019." Second, ***day*** mentions day(s) of the week, including any weekdays or weekends. Examples include, "I will follow the course from home during the weekend [. . .]," "On Sundays at home," "Monday - Friday." Third, ***time*** selects a time of a day. Plans with this category include keywords 'morning,' 'afternoon,' and 'night.' Example plans include, "At home in the morning," "Every evening [. . .]," and "from home at nights." Fourth, ***clock*** specifies a clock time. For example, "[. . .] between 6-8."

Event-based planning refers to arranging a learning time on the basis of an event. A total of 125 (25%) plans include at least one time-based planning tactic. This theme consists of two tactics: *sequence* and *period*. ***Sequence*** refers to planning with a sequence or occurrence of potential, everyday events or tasks. For example, plans with this tactic contain phrases like, "After work," "After my school,""[. . .] during my lunch break at work," and "[. . .] after finishing family-related activities." ***Period*** is planning to engage in the course over a period of an event or specific time. For instance, "As right now my college is closed due to COVID-19, [I] will take the course at home during the quarantine," "During spring festival," "During summer."

Present-oriented planning is planning to work immediately or soon after today. This theme has one category, ***present***. A total of 125 (25%) plans contain present-oriented planning. Learners plan to engage with the coursework today or tomorrow. For example, "I am planning to engage today with the course content." and "I plan to start from tomorrow [. . .]" Another pronounced group of plans is to work on the coursework immediately, like these plans, "as soon as possible," and "soonest within this week."

Noncommittal planning refers to planning without providing any details, including a specific time. This theme has one category, ***noncommittal***. A total of 35 (7%) plans contain noncommittal planning. Learners write that they will engage in the coursework anytime or in their spare time. For example, "Anytime I'm free [. . .]," "I plan to engage with the content whenever I have free time [. . .]," "As often as my schedule permits," and "As often as possible [. . .]."

4.2 Planning *How* to Engage in the Course

We find 477 plans (93.5%) contain at least one **how** tactic; 33 (6%) plans are either irrelevant to course-taking (coded as 'other') or say 'no plans'. The qualitative content analysis identified 14 tactics: 38% Time commitment, 21% Utilizing tools, 15% Self-reliance, 14% Task commitment, 14% Meta-planning, 12% Learning strategies, 11% Setting deadlines, 7% Support-seeking, 5% Coupling, 4% Setup, 4% Monitoring, 3% Routine making, 2% No plans, 2% Prioritizing.[4] Most plans contain only one tactic ($n = 306, 60\%$), but 36% ($n = 184$) contain multiple tactics (mean=1.46, sd=0.86, min=0, max=5).

In Table 3, *routine-making* and *prioritizing* tactics are significant negative predictors of course completion (OR = 0.16 and 0, respectively): learners whose plans used either tactic were less likely to complete the course. However, both tactics are used in only 2-3% of plans. None of the tactics were significant predictors of course progress.

Time commitment is making a time-based commitment. A total of 192 (38%) plans include this tactic. learners plan to spend a certain amount of time daily, such as "Dedicate 2 hours of learning everyday," and "Taking 2 - 3 hours per day." There are also less concrete plans, like, "I plan to access and work on this course EVERYDAY even if it's for few minutes," "Do a small amount consistently each day," and even "Learn each day." Some learners make weekly commitments, and their specificity also varies: "I will study about 2 - 4 hours each week," "spending required hours for completion of the course every week," and "Spend time consistently and doing assignments [on] weekly basis." Another line of plans is characterized by showing willingness to spend time to complete the course instead of committing time regularly, "If extra time is required, I will wake up early in the morning to complete the work." Plans with any time dedication are marked despite their ambiguity. For example, "Spending [a] good amount of time [. . .]" and "I would ensure that I am available for all my classes." Likewise, plans related to time scheduling for class are also marked. Examples are "Schedule a specific time to study everyday [. . .]" and "Plan a specific time just to it."

Utilizing tools refers to using tools, technology, or any aids for a task and/or time management. A total of 107 (21%) plans include this tactic. Reminders appear most frequently, "Set auto-reminder for the date and time," "I'll put reminders on my phone," "Push notification on phone to remind me of the studying," and "I will set an alarm to remind me daily about the course." Another frequently used tool is a list, such as a checklist, a to-do list, and an agenda. These are the examples: "[I] will have a checklist for my day," "Keeping a to do list," "[. . .] I will stay organized using my agenda [. . .]." Calendars also appear frequently, "Setting timed slots in my work calendar," and "I added an appointment to my calend[a]r." Likewise, multiple plans also mention a timetable like,"I will make a time table [. . .]." This category also includes aids (e.g., "SMART goals," which is a technique to set a goal) and actions of

[4]Some plans reveal more than one tactic about how learners will engage with the course. Take this plan as an example, "To ensure that I will complete the coursework, I will spend time ingraining a habit of working on it every morning, after I have my bath and for 6 hours, reminding myself of the benefits of completion and priding myself on being the kind of person who does what he sets out to do." Three planning tactics are used: the learner states that they will not only spend time (*time commitment*) but also develop a learning habit (*routine making*) and fully mobilize personal willpower (*self-reliance*).

Table 3: Regression Results for Tactics in *When* and *Where* Planning (left) and *How* Planning (right). Tactics are coded binary (if a plan contains the tactic). Logistic regression is used for the binary completion outcome; OLS regression is used for the continuous progress outcome. Course IDs are included as fixed effects and standard errors (in parentheses) are clustered at the course level. Intention to complete the course (binary) and plan length in characters are included as covariates. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

When/Where Plans	Completion	Progress	How Plans	Completion	Progress
Location	0.02	0.05	Coupling	1.05	−0.03
	(0.31)	(0.12)		(0.54)	(0.33)
Frequency	0.22	0.26	Routine making	-1.86^{*}	−0.06
	(0.29)	(0.15)		(0.75)	(0.34)
Day	−0.43	−0.02	Self-reliance	0.26	0.13
	(0.52)	(0.23)		(0.37)	(0.19)
Time	0.71^{*}	0.25	Learning strategies	−0.10	−0.04
	(0.35)	(0.13)		(0.39)	(0.16)
Clock	−0.06	−0.53	Setup	−1.05	−0.16
	(0.83)	(0.35)		(0.91)	(0.37)
Date	0.05	1.15	Support seeking	0.19	0.08
	(1.07)	(0.67)		(0.48)	(0.23)
Sequence	−0.01	0.10	Utilizing tools	0.02	−0.01
	(0.34)	(0.18)		(0.31)	(0.18)
Period	1.33	0.60	Setting deadlines	0.40	0.08
	(0.79)	(0.61)		(0.47)	(0.22)
Present	0.24	−0.08	Time-based commitment	−0.35	−0.15
	(0.41)	(0.19)		(0.34)	(0.13)
Noncommittal	0.11	0.35	Task-based commitment	0.05	−0.19
	(0.64)	(0.22)		(0.32)	(0.19)
Plan length	0.00	0.00	Meta-planning	−0.34	−0.31
	(0.00)	(0.00)		(0.46)	(0.21)
Intent to complete	1.28	0.18	Prioritizing	-17.23^{***}	−1.00
	(0.66)	(0.17)		(0.54)	(0.43)
			Monitoring	−0.65	−0.40
				(0.60)	(0.31)
			No Plan	0.34	0.22
				(0.93)	(0.41)
			Plan length	0.00^{*}	0.00
				(0.00)	(0.00)
			Intent to complete	1.26^{*}	0.14
				(0.62)	(0.18)
(Pseudo-)R^2	0.14	0.25	(Pseudo-)R^2	0.17	0.24
Sample Size	510	510	Sample Size	510	510

making a list or writing down tasks (e.g., "make a list of what's required each week" and "I will diari[z]e what needs to be done by when ....") because they are considered instruments for managing time and tasks.

Self-reliance is relying on one's willpower, values, personality, and attitude. A total of 78 (15%) plans include this tactic. Some learners focus on overcoming a negative attitude: "Not be lazy.", "by getting rid of laziness.", and "Making sure not to procrastinate." Most learners emphasize a positive attitude: "Work hard and stay motivated.", "to be consistent, to be motivated.", and "discipline, hardwork, and attitude." Some of the plans are more explicit about the self. For example, "I'll be consistent," and "I have a good discipline to take courses [...]." Personal values are also mentioned, either abstractly, like "Use personal motivation [...]," or more concretely, like "[...] reminding myself of the benefits of completion and priding myself on being the kind of person who does what he sets out to do." In the plans of this category, learners share their determinedness; "I will make sure that I follow every course seriously [...].", " I know I will complete it.", "Whatever it takes, [I] will try to do my best.", and "As much as [I] can [I] put my complete effort to complete this course."

Task commitment is making a task-based commitment. A total of 73 (14%) plans include this tactic. Learners plan to engage in the course on a regular basis, but these plans are varying levels of specificity; while some plans specify the number of tasks to do each day, such as "Making sure I take the one lesson per day," and "I'll try to complete at less 10 activities everyday," others are not concrete, "Make sure that all daily tasks are done promptly," or even "do the work in regular intervals." Learners also describe learning activities. For example, "I'll watch the videos [...]," "complete assignments and review," and "finish all lectures and assignments," Furthermore, there is a portion of plans where learners claim they will do all required tasks for completion, “Do all suggested work. Complete all assignments. Pass the tests,” and “all steps that could I will need.”

Meta-planning is planning to make a plan by setting a goal regularly, managing time, and scheduling without explicitly committing a certain amount of time to specific tasks. A total of 70 (14%) plans include this tactic. Goal setting is pronounced in the plans. Learners make daily goals, such as “write goals each day,” and “By making daily goals to be achieved which will eventually help in completing the course on time." They also make weekly goals, like “setting up weekly targets,” and “I’ll always make goals for a week and follow and make sure I complete the weekly targets.” Furthermore, learners often mention time management, “Manage my time wisely,” and “I am going to organi[z]e my week[ly] schedule in a way that I will be able to study [. . .]." This category also includes abstract plans about planning and scheduling that lack concrete steps, “Create a pacing plan for myself,” and “scheduling and planning."

Learning strategies is writing about strategies related to learning in general or an academic topic of the course in which the learner enrolled. A total of 63 (12%) plans include this tactic. Any study strategies, such as taking notes and reviewing, are marked. For example, “The steps that I will take to ensure the completion of this course include: extensive research of relevant topic, taking down notes, reviewing lessons, and reading of relevant materials to understand and give answers to inquiries.”, “Read the content, translate the unknown words and interpret the content to complete the lessons.” and “Listen to the course, write main concepts and study.” Some plans are more specific to an academic subject. For example, a plan for a data science course includes installing software, “[. . .] Dow[n]load the r program to practice.”

Setting deadlines is setting a deadline or following the course schedule or a self-imposed timeline on time. A total of 54 (11%) plans include this tactic. Some learners utilize the course syllabus or schedule to set deadlines for themselves. For example, “I will keep an eye on deadlines for assignments and exams. I will schedule my study time as per the deadline.” Other learners set deadlines on their own, like “Set course milestones on my calendar,” and “Attend lectures and complete quizzes within set timeline.” Many plans are about keeping up with the schedule; learners write, “[. . .]stay on track,” “Will do assignment or frameworks on time,” and simply “Stick to the plan.”

Support-seeking is seeking social support from employers, family, and fellow course takers. A total of 36 (7%) plans include this tactic. In workplace settings, learners negotiate with their employers,“[. . .] I will agree with my manager to allow me this time at work” and organize study groups, “Formed study group at work for the 9-course series.” Some learners plan to update their families and/or friends on their learning progress. For example, “I will tell my wife all about I’ve learned from every content.”, “I will hold myself accountable by sending a photo to my friend who is also taking the course when I submit anything.”, and “I will share with others that I am doing it so I have to keep my words.” Also, learners seek support from a learning community, for example, collaborating with fellow course takers: “Maintain constant communication with all EdX representatives, officials, lecturers, professors and tutors [. . .] in order to be successful in this course,” and “I hope to pair up with a fellow course mate, whom I will be accountable to.”

Coupling is pairing a planned learning behavior with another goal or activity to motivate oneself. A total of 23 (5%) plans include this tactic. Learners tie completing the MOOC with career development, ranging from improving their credentials, “My intention is to work on the area and to have a certificate from Harvard. it will have a big impact on my career [. . .],” to work performance, “Try and implement the course work in my work," and “the knowledge offered by the course can be of great use to me during my next years as a professional.” Some learners who are assumed to be students also connect course taking with school projects and exams, like, “While learning the course here, [I] will also be doing my semester project [aligning] the course so this makes me up to date about the course.” They also draw a link between the MOOCs and their personal growth, “I’m doing it so I can become better at my blog and future creative writing pursuits - the visualization of my dream blog and essay are keeping me motivated."

Setup is setting up a study environment by avoiding or removing distractions and/or preparing oneself to be in good condition for learning. A total of 29 (4%) plans include this tactic. Most learners strategize about handling distractions: “Sit down and take away anything that will distract me.", “Wait for the kids to go to bed.", “Close my office to avoid interruptions.” and “Turn off the TV and social media." Some learners prepare themselves with good conditions for learning. For example, “I will make sure that I have a better internet connection throughout the course [. . .]," and “I will go to places every evening where I can focus to this course.”

Monitoring is observing or documenting the progress of course-taking behaviors or/and learning outcomes. A total of 18 (4%) plans include this tactic. Importantly, this tactic does not include the act of keeping track of tasks to do, as it is more of task management. Examples of plans are the following: “I will keep track of my progress manually[. . .]." and “record how many hours a week I am spending on the course so I can get an inference as to how much time is needed to complete the course material.”

Routine making is developing a routine or habit to engage in learning regularly. A total of 16 (3%) plans include this tactic. Learners explicitly write that they will develop a routine or a habit. For example, “I intend to carry out the activities every day at the same time, in order to create a habit and a discipline [. . .]." and “I will spend time ingraining a habit of working on it every morning, after I have my bath and for 6 hours." Some learners are implicit about making a routine for learning by writing, “[. . .] include this course into my daily schedule."

No plans refer to stating having no plan. Learners write that they don’t know what to plan yet; for example, “I don’t know," “I do not have specific steps yet . . . , "“This I will determine when I know about the nature of assignments, which I currently do not yet oversee." Some learners imply that planning is not necessary because they will complete the course anyhow. Their plans look like, “not much specific yet. but I gonna do this.” and “none. I know I will complete it."

Prioritizing is making learning as a priority. A total of 11 (2%) plans include this tactic. Some learners write the course as their priority; “[. . .] this course for me is my priority in this moment.”, and “[. . .] Treat it as a priority." Learners also sacrifice their routine activity for the course; “I will remember that it’s better to do this for an hour each night instead of watching TV.” and “By making sure

I don't sleep till I'm done with it." They also defer other activities for learning, "[. . .] Will not fix any other program by that time of the day," "I will ensure I don't make any plans during the time I have allocated to complete course content. [. . .]," and "Blocked all Sunday evenings in my agenda."

5 DISCUSSION

We investigated the content and behavioral correlates of plans made by people as part of a planning intervention in MOOCs. Plans in this context comprise two parts: (1) *when* and *where*, and (2) *how* to engage in coursework to complete the course. For *when* and *where* planning, we identify nine temporal planning tactics. A quarter of all plans use the *time* tactic, which is to specify a time of the day (e.g., morning, afternoon, evening), and this is the only tactic that is positively associated with course completion in our analysis. Temporal tactics are not found to be significant predictors of course progress. For planning *how*, we identify fourteen tactics. Consistent with prior work [64], we find that *time commitment* is most frequently used but not positively associated with behavioral outcomes. The use of *routine making* and *prioritizing* tactics, albeit rare in our sample, predicts lower course completion but not progress.

We suspect that *time* is the only significant factor positively associated with course completion because it is a readily available cue [12, 49, 50]. Gollwitzer [27] postulates that automating the process of taking actions is the key to achieving a goal and thereby suggests pairing an action with an accessible cue when making a plan. Times of the day, like morning, afternoon, and night serve as more accessible cues than the others. They are relatively effortless to spot compared to an event (e.g., after kids go to bed) or non-specific time (e.g., anytime, free time). They are available more often compared to less frequent time-based tactics like days of the week (e.g., weekends), more flexible than a clock time but more stable than a sequenced event (e.g., 'after work') for being less influenced by other social factors. Additionally, other tactics, *date*, *period*, and *present*, are planning to engage in learning one time or just for a specific period; therefore, they may not function as sustainable cues for conducting a long-term behavior.

The negative relationship between *prioritizing* and behavioral outcomes is possibly explained by the challenging nature of the tactic to sustain over a long period. Prioritizing is accompanied by sacrificing other routine activities, which requires more effort to follow through than other tactics that merely arrange certain behaviors, such as *setting deadlines*, *monitoring*, and *meta-planning*, or express intention, such as *self-reliance*, *time commitment*, and *task commitment*. For a similar reason, *routine making* is effortful to realize. Our results are consistent with prior findings that show adverse consequences of setting an ambitious challenge (e.g., [42, 59]). It is possible that learners who plan to prioritize or make a routine exhaust themselves early in the course and drop out.

Our findings have several implications for planning interventions in self-directed learning settings, including MOOCs. First, breaking down the end goal (e.g., course completion) into a series of sub-goals may improve learners' planning behavior. We find learners write about their tactics–approaches to goal striving–rather than specific steps as instructed in the *how* plan. This may be because people tend to make action plans for more proximal goals instead of longer-term goals [20]. Planning prompts could provide or ask individuals to set their sub-goals to increase learners' persistence in goal striving (e.g., [47, 58]). Moreover, this highlights the importance of setting milestones and formative assessments for online course instructors and administrative staff. Instruction teams of online courses need to consider how to better design course schedules and materials to help learners set sub-goals and readily plan their learning.

A second implication of our findings is that more scaffolds may be necessary to increase the efficacy of a planning intervention for goal achievement. Our content analysis yields findings that are consistent with prior work that shows that many people do not follow the planning instructions [19, 37, 51, 56]. As seen in previous studies (e.g., [5, 65]), learners may not be proficient in making plans, and therefore coaching on how to make a better plan will increase follow-through behaviors and, subsequently, goal achievement. For example, based on our findings, the intervention can provide examples of good plans or instructions for using effective tactics (e.g., specifying a time of day). The instruction teams of online courses can also consider referring to the findings of our study to remind learners that there are various planning tactics; they can use different ones to make a more suitable plan for themselves.

This study has limitations and suggests directions for future work. First, we coded plans in the context of a MOOC platform that mostly offers STEM courses. This affects the generalizability of our findings to courses on different topics with other assignment structures (e.g., humanities courses that emphasize written reflection, discussion, and design). Although MOOCs are a popular option for self-directed learning, future studies could investigate if learners use similar planning tactics in other contexts (e.g., high school, higher education, and educational games). Second, as the effect of action planning is known to last for only a short period (e.g., [29]), the long-term behavioral outcomes used in this study may not fully capture the efficacy of planning tactics in a self-directed learning environment. Future studies may investigate how planning tactics are associated with short-term behavioral outcomes, such as week-long learning behaviors after planning. Third, our findings on the link between certain tactics and behavioral outcomes should be interpreted with caution. Not only are some of the categories sparsely represented in the dataset, but the regression results we present do not have causal interpretations: the use of a certain tactic may correlate with learner characteristics (e.g., motivation or conscientiousness) that are strong correlates of our behavioral outcomes themselves. Regression adjustment methods can account for some variance associated with such confounders but do not guarantee unconfoundedness. Future research should examine the causal effects of planning tactics on learning outcomes by nudging learners to utilize promising tactics in an encouragement design. Fourth, our English-language intervention may inherently favor English-speaking learners. While we selected courses to be inclusive of academic subjects and the time of offering (before and after the pandemic), we cannot formally check if the sample is representative of the MOOC learner population in demographics or performance. Future research can identify planning tactics from other non-English courses and compare them with our findings. Lastly, this study does not consider specificity (how concrete a plan is), which is known to predict follow-through behaviors (e.g., [18, 43, 65]). Future studies may examine the effect of planning tactics combined with the concreteness of plans on behavioral outcomes [63].

The main contribution of the present study is that we lay the groundwork for developing effective and scalable interventions to promote learning behaviors in self-directed online learning settings. The identified tactics and their relation to learning behaviors can help enhance intervention designs targeted to promote self-regulated learning (e.g., [7, 17]). Models of plan effectiveness can be developed to detect tactics from learners' plans and provide tailored feedback that encourages them to use effective tactics to achieve their learning goals. Based on the planning tactics we identified, feature engineering and prediction modeling can help forecast MOOC learners' course completion. By combining NLP techniques, future learning analytic studies can develop new predictors (the number of planning tactics, continuity of planning tactics, etc.) of not only learning outcomes but also learners' preparedness for persisting in the face of challenges. Furthermore, researchers and educators can utilize the planning tactics presented in this work to design personalized guidance for individual learners tailored to the planning tactics adopted by each learner. Our coding scheme can be scaled up (e.g., to analyze a larger dataset) as we developed it from plan texts sampled from a wide variety of courses, learner backgrounds, and plan texts in terms of their length and specificity.

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