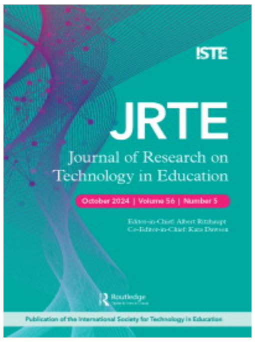

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The effects of practice testing and feedback on learners' performance and persistence in a massive open online course

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ABSTRACT

In this experimental study, we examined the effects of practice tests and feedback on performance and completion in a five-module massive open online course (MOOC). Participants ($N = 6100$) were adults enrolled in the American Museum of Natural History's (AMNH) climate change MOOC. Participants were randomly assigned to one of four conditions. After completing each module, learners in the first treatment group took practice tests without receiving feedback. Learners in the second treatment group took practice tests and received basic (correct/incorrect) feedback. Learners in the third treatment group took practice tests and received detailed feedback. The control group did not take practice tests and, hence, received no feedback. Post-tests were administered after each module. Results indicated that: (1) among all learners in this MOOC, students in the practice test/basic feedback and practice test/detailed feedback conditions outperformed their counterparts in the control and practice test/no feedback conditions; (2) there were no differences in persistence and completion among conditions; (3) conscientiousness was the only predictor of course persistence and completion. These findings offer a new contribution to the assessment and feedback literature and can help to improve self-paced online science courses.

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Introduction

Massive Open Online Courses (MOOCs) have emerged as a transformative force, offering unparalleled accessibility and affordability in educational resources since their inception in 2008 and subsequent popularization in 2012 (O'Connor, 2014; Pappano, 2012). The COVID-19 pandemic further accelerated the widespread adoption of online learning, leading higher education institutions to develop MOOCs as a pragmatic alternative to improvised online sessions, aiming to broaden access to diverse courses in a digital format (Meet & Kala, 2021). With millions of students enrolling in MOOCs and tens of thousands of courses being developed worldwide (McCluskey, 2020; Shah, 2021), the impact of MOOCs on learning outcomes is substantial.

Although MOOCs have played a pivotal role in enhancing learning accessibility (Liang et al., 2014) and contributing to equity and inclusion, they face scrutiny for high drop-out and low completion rates (Lambert, 2020). Recent studies have delved into the self-directed nature of MOOCs, peer assessment, instructional design quality, and their broader implications for higher education (Bozkurt et al., 2017; Doo et al., 2022; Gamage et al., 2021; Margaryan et al., 2015;

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Yuan & Powell, 2013). Despite their widespread adoption and impact, our understanding of learner responses to interventions in this digital landscape remains limited, and strategies effective in traditional settings may not translate seamlessly to MOOCs (Janelli & Lipnevich, 2021). This underscores the critical need for further exploration into the unique instructional mechanisms of MOOCs. In our experimental study, we aim to address this gap by examining the effects of practice testing and feedback on performance, persistence, and course completion in a Coursera MOOC on climate change.

Testing as a strategy for effective learning

Although testing as a method for assessing content knowledge has been subject to criticism (e.g., Ali & Mohsin, 2013; Hamilton et al., 2021; Mandler & Sarason, 1952; Seipp, 1991; Spielberger, 1980; von der Embse et al., 2018; Zeidner, 1998, 2007), testing as a strategy that can boost students' longer term content retention is no longer disputed (Bjork et al., 2013). The use of tests for formative purposes presents an opportunity for both teachers and students to enhance the learning process (Black & Wiliam, 1998). Notably, research on testing effects and retrieval practices extends beyond college students to various populations, including pre-schoolers, elementary school students, middle school students, and adults (e.g., Balota et al., 2006; Bouwmeester & Verkoeijen, 2011; Carpenter et al., 2009; Fritz et al., 2007). Pretests and practice tests have been examined as strategies to promote long-term information retention in students. Understanding how these strategies operate in MOOCs is of great importance to the field of online learning.

Pretesting

Memory retrieval involves actively and repeatedly recalling pertinent information which facilitates memory retention and transfer, and tests are an example of instructional strategies that facilitate this process (Bjork et al., 2011). When information is retrieved from memory, its representation in memory is modified to make it more accessible at a later time (Glover, 1989). Studies (Abbott, 1909; Roediger & Butler, 2011; Rowland, 2014; Yang et al., 2021) support the benefit of the retrieval practice effect or the testing effect and consistently demonstrate the robust advantages of memory retention (e.g., Adesope et al., 2017) and transfer (e.g., Pan & Rickard, 2018) in various educational settings. More durable memories result from retrieval practice compared to passive techniques, such as restudying or re-reading alone (e.g., McDermott et al., 2014; Wang et al., 2023). Furthermore, retrieval practice coupled with tasks related to the generation of new content, such as coming up with examples, can result in more significant learning benefits compared to the use of retrieval only.

Despite the well-researched benefits of pretesting in conventional classroom settings, a study by Janelli and Lipnevich (2021) revealed that pretests negatively affected course persistence in a five-module MOOC on Coursera. The study was one of the first experiments that investigated the effects of automated multiple-choice pretests and different types of feedback on performance, persistence, and course completion in the context of a MOOC (Janelli & Lipnevich, 2021). Interestingly, across the entire sample, there was no effect of either pretest or feedback on student performance on a post-test. A more nuanced glance at the results showed that, compared to learners in the treatment groups, learners in the control group were more likely to persist and complete the course. However, findings also indicated that pretests positively affected achievement for learners who completed all five course modules which hints at the pretest effects on student achievement observed in traditional classrooms (Beckman, 2008; Kornell et al., 2009). Additionally, another study revealed that presenting learning objectives before reading passages improved test performance, especially when paired with pretest questions rather than passive reading or feedback on pretests (Sana et al., 2020). In other words, Janelli and Lipnevich (2021) note, pretests may still work in a MOOC setting, particularly for learners with comparable levels of motivation and similar intentions as those in a traditional classroom.

Practice testing

The impact of practice testing on learning has also been substantially researched (e.g., Badali et al., 2023; Bjork et al., 2013; Dunlosky et al. 2013; Rawson & Dunlosky, 2011; Roediger & Butler, 2011; Wang et al., 2023). Practice tests can directly and indirectly benefit learning and retention of the material (Roediger & Karpicke, 2006). Direct advantages include reinforcing learning of the tested content which can improve performance on high-stake tasks, whereas indirect advantages include determining what a student knows and does not know in order to redirect time and effort toward engaging with less familiar information. Students can gain both direct and indirect advantages, especially when they receive feedback, namely, delayed explanatory feedback (Butler et al, 2013; Moreno, 2004; Moreno & Mayer, 2007; Mullet et al., 2014) on their practice tests for better retention (Bjork et al., 2013).

A meta-analysis of retrieval practice in classrooms (Adesope et al., 2017) revealed that students who take practice tests often perform better than students who employ other study strategies. In addition, practice tests involving long-term memory retrieval (e.g., short answer questions) are more effective than recognition-based tests (e.g., multiple-choice questions) (e.g., Carpenter & DeLosh, 2006; Glover, 1989; McDaniel et al., 2007). However, benefits of multiple-choice questions include low levels of cognitive energy compared to short answer problems (Adesope et al., 2017). Hence, the study's recommendation included frequent, low-stakes assessments and other forms of retrieval practice in the classroom, such as self-generated questions, to help students identify gaps and areas of improvement. Additionally, testing can serve as a tool for learning beyond assessment and enhance future retrieval of untested items (Little & Bjork, 2010) along with the opportunity to rectify unsuccessful retrieval efforts and improve future retrieval efforts under specific conditions, such as post-practice test feedback with correct answers (Dunlosky et al., 2013; Dunlosky & Rawson, 2015; Roediger & Butler, 2011). For instance, students may attempt to recall information related to incorrect multiple-choice answers to eliminate them. In particular, competitive yet incorrect answer options on a multiple-choice test can prompt retrieval that enhances learning not only of tested questions and associated information, but also of items associated with incorrect answer choices (Little et al., 2012).

Additionally, the study by Gurung et al. (2012) with 454 students in an introductory psychology course at different institutions replicated a finding that practice exams predicted class performance. In addition to enhancing memory of the tested materials, practice tests enhance the ability to transfer practiced information (Carpenter, 2012). Although studies do show that practice testing is overall productive, coupling practice tests with restudy further promotes learning outcomes when compared to testing or restudying alone (e.g., Agarwal et al., 2008; Butler & Roediger, 2008; Carpenter et al., 2009; Cull, 2000; Pyc & Rawson, 2010). Furthermore, practice tests spaced out with more time are much more productive than practice tests scheduled close together (e.g., Cepeda et al., 2008; Pyc & Rawson, 2009).

Studies also show that in online learning environments, students can benefit not only from frequent, smaller assessments spread throughout the course, but also a range of course assessments, including self-assessments, to help students monitor their progress (Kumar et al., 2019). Integrating automated assessments and offering system feedback can also support online learning. This is particularly beneficial for large courses, especially in fields such as computer science (Ihantola et al., 2010). Synchronous assessment allows for immediate feedback during sessions, unlike asynchronous assessment activities, where feedback is delayed (Moorhouse & Wong, 2022).

The above results come from studies conducted in traditional instructional settings or online learning environments associated with regular courses (e.g., courses offered online or platforms to help students prepare for exams), which may or may not transfer to the unique context of MOOCs. A notable exception is a study by Davis et al. (2016) that investigated the impact of introducing retrieval practice cues after each lecture. In comparison to a control group that did not receive quizzes, the findings revealed no positive effects of retrieval practice on test performance or overall course grades in a MOOC functional programming course. Additionally, another study (Davis et al., 2018) indicated that learning strategies for enhancing retrieval practice, specifically practice quizzes, often used in a physical classroom or laboratory environment, did not affect learning outcomes in MOOCs.

In a different study (Li et al., 2023), successful learners and completers in a computer science MOOC engaged in a structured approach by learning across chapters using quizzes and interacting with both videos and quizzes within chapters. The findings revealed that quizzes played a crucial role in scaffolding and enhancing student motivation, going beyond mere assessment of understanding following video lectures. This suggests that quizzes not only offer extensive information on course content and exams, but also support learners' future learning by providing feedback on their knowledge gaps and skills. Given the abundance of resources, MOOC learners seek streamlined learning, emphasizing the importance of scaffolding role of quizzes in MOOC design. This is further demonstrated in another study (Zhang et al., 2021), which showed that learning analytics revealed quizzes directed learners in deciding which videos to study. Quizzes should be designed to motivate learners and improve learning outcomes. Additionally, feedback from quizzes can minimize cognitive overload (Zhang et al., 2021).

Although online courses can adopt various assessment methods, they often replicate traditional face-to-face assessments. Experts have recommended that both synchronous and asynchronous online course designers adopt more student-focused, authentic assessment methods, such as case analysis, performance-based tasks, and the application of learned skills in new situations (Guerrero-Roldán & Noguera, 2018; Mihret et al., 2017).

In sum, although the use of practice tests to enhance retention and yield learning benefits in traditional face-to-face educational settings is supported by numerous studies (e.g., Dunlosky & Rawson, 2015; Kornell & Bjork, 2007; Roediger & Karpicke, 2006), the effects of practice tests on meaningful outcomes in the context of MOOCs are far less clear. Thus, our study aims to investigate the effects of practice tests and feedback on the performance and persistence of learners in a MOOC setting.

Feedback as a strategy for effective learning

Countless studies have shown that feedback has a significant impact on students' performance and learning outcomes (e.g., Black & Wiliam, 1998; Hattie & Timperley, 2007). Researchers have examined both feedback delivery (Hattie, 2012; Lipnevich & Smith, 2022; Wiliam, 2018) and feedback uptake (Lipnevich et al., 2021; Nash et al., 2018; Winstone et al., 2017) and the processes and mechanisms that ensure its effective processing.

Although research on feedback supports positive links with academic achievement in a traditional classroom, there is an opportunity for further examination of feedback types, feedback delivery, and feedback uptake in MOOCs (e.g., Hattie, 2012; Smith & Lipnevich, 2018; Winstone et al., 2017). One of the first attempts to study feedback in MOOCs (Suen, 2014) showed that even though students may be dissatisfied with unreliable or cursory peer feedback in MOOCs, it was still beneficial for student learning. Additionally, qualitative analyses of the 4,466 learners' course reflection data from one of ten highly rated MOOCs showed that active learning supported by timely feedback was one of the most enjoyable, beneficial, or motivating components regarding the course design or teaching personnel (Hew, 2018). However, a different study (X. Chen et al., 2022) that used a sentiment analysis of student course review data revealed that instructor feedback had minimal influence on students' perception of learning in MOOCs.

Despite its seemingly relevant objectives, technology-based feedback is not always aligned with educational theories (Munshi & Deneen, 2018). Contrary to the general trend of links between feedback and learning, findings from the study conducted by Janelli and Lipnevich (2021) showed that in a MOOC with low pressure and low completion rates, neither pretests nor feedback affected learning outcomes. Similarly, several other studies (e.g., Butler & Roediger, 2007; Hays et al., 2010; Karpicke & Roediger, 2008) also showed that feedback had no effect on learners' successful retention of information. In particular, feedback on items answered correctly with high levels of confidence by students can take up the time spent on studying and their cognitive resources (Hays et al., 2010; Karpicke & Roediger, 2008). Conversely, a different study revealed that feedback enhanced retention for correctly answered questions on practice tests, particularly when students provided correct responses with low levels of confidence (Butler et al., 2008). Additionally, considering that quizzes serve as scaffolds for dropouts in MOOC settings, feedback on quizzes or tests can provide clear direction, guidance, or navigation through resources to reduce cognitive overload (Zhang et al., 2021).

In an online learning environment different from a MOOC setting, findings from a recent study showed that undergraduate students who received video feedback on their assignments were more successful at using the feedback to improve their work compared to those who received text feedback (Yiğit & Seferoğlu, 2023). Furthermore, to personalize feedback and replicate in-person assessments online, instructors used feedback videos and synchronous lessons to address common errors and to offer praise, while adapting tools like annotation features on customized learning platforms for their assessment and feedback practices (Moorhouse & Wong, 2022). The findings support that audio or video feedback enhances communication although both instructors and learners prefer text-based feedback for its efficiency (Borup et al., 2015). Studies also show that timely and detailed feedback in online settings is related to higher levels of engagement with the instructor and course content (Martin et al., 2018; Shea et al., 2006). In addition, instructors use the automatic grading feature on platforms like *Google Forms*, *Nearpod*, *EdPuzzle*, and *Kahoot* to give students immediate feedback in online learning environments (Moorhouse & Wong, 2022). However, there are still gaps in our understanding of how various online learning contexts and instructional approaches can be effectively and meaningfully integrated into the sequence of learning, and especially in MOOCs.

Although feedback on pretests did not affect learning in the MOOC (Janelli & Lipnevich, 2021), further examination of combined testing and feedback effects is necessary. This study endeavors to contribute to the understanding of this underexplored aspect in the context of MOOCs.

Personality characteristics and MOOC completion

Numerous researchers have questioned the validity of dropout metrics as indicators of MOOC quality, attributing low completion rates to diverse participant intentions, where some learners never intended to complete the MOOC in the first place (Gupta & Maurya, 2022). In her 2021 study, Semenova investigated result-oriented and action-oriented intentions across five MOOCs, discovering an association between strong positive action-oriented intentions (specifically, completing tasks) and course completion. Surprisingly, result-oriented intentions, such as earning a certificate, were deemed less impactful. These findings underscore the necessity for a nuanced understanding of learner intentions in MOOCs. In addition to learners' intentions, personality has emerged as a potential predictor of MOOC completion. Gupta's (2021) study revealed that conscientiousness, openness, agreeableness, and extraversion were positively linked to successful course completion, while neuroticism showed no such effect. In contrast, G. Chen et al. (2016) reported minimal correlations between personality traits and MOOC outcomes.

To further explore the complex interplay between intention and personality in MOOCs, additional studies are crucial. Our research aimed to contribute to this understanding by exploring the link between learners' intentions, personality traits, and MOOC completion, shedding light on the multifaceted factors influencing online learning outcomes.

The current study

The current study is a randomized experiment designed to examine the effects of practice tests and differential feedback (i.e., no feedback, basic feedback, elaborate feedback) on the outcome variables of performance, persistence, and course completion among a sample of adults enrolled in a science MOOC. We also examined whether learners' intention to complete the course and their personality explained differences in the outcome variables. Data were collected from the course *Our Earth's Future* offered by the American Museum of Natural History on the Coursera platform. Research questions that guided our study were:

1. Is there an effect of practice tests and feedback on learners' performance on the final test? (RQ1)
2. Is there an effect of practice tests and feedback on learners' persistence in the course? (RQ2)
3. Does the initial intention to complete the course and learners' personality predict student course completion? (RQ3)

Method

Course background

Our Earth's Future comprises five modules dedicated to the exploration of climate change. Crafted collaboratively by a team of scientists, educators, instructional designers, videographers, and graphic designers, the course employs a diverse range of resources, including essays, images, videos, and tests. Designed for a global audience, the course aims to educate individuals worldwide on the compelling evidence supporting the reality of climate change. Each weekly module culminates in a post-test, urging participants to assess their understanding. This study introduces a unique approach, incorporating a practice test with varied feedback formats. This intervention occurs after learners have engaged with all course materials and precedes their final test, aiming to enhance the learning experience and reinforce knowledge acquisition. To incentivize course completion, we provided learners with a $50 waiver to cover the cost of their course completion certificate.

Participants

The sample consisted of 6,100 participants who registered for the MOOC. Participants over the self-reported age of 18 were included in the analysis. Participants consented to having their data used for the study. Data from the following participants were excluded: (1) individuals younger than 18; (2) learners who took the post-tests before the practice tests; (3) those who took the practice tests but not the corresponding post-tests, and vice versa.

Demographic data were collected from a pre-course survey administered by AMNH and from a demographic survey administered by Coursera, with a very limited response rate. Out of 80 people who chose to disclose their sex, 49.9% participants were male and 50.1% were female. Respondents came from the United States (20.2%), Canada (16.2%), the United Kingdom (11.1%), France (6.5%), Mexico (6.5%), Portugal (5.0%), and Switzerland (3.0%). The remaining 9.3% of respondents reported that they live in ten other countries.

Procedure

After enrolling in the course, participants were randomly assigned to one of four conditions: (1) practice tests with no feedback; (2) practice tests with basic (correct/incorrect) feedback; (3) practice tests with detailed feedback (correct/incorrect and detailed explanations for why a specific option was correct); or (4) the control group (no practice tests or feedback). Participants in the three treatment groups took the practice test after completing each of the five course modules, prior to taking post tests for each module. All participants took module-level post-tests. The practice tests were not identical to the post-tests, but both tests were organized around the key concepts that served as the framework for the course. Items were selected from the general pool of items for each module. See the Appendix for an example of a practice test question with feedback and a corresponding post-test question.

The practice tests had four main features: (1) each question had one correct answer and three lures; (2) test results were available immediately after answers were submitted; (3) to avoid test-taking fatigue, practice tests had five questions whereas post-tests had ten questions.

Additionally, all participants indicated their intention to complete the course. Participants' intention to complete the study was measured with the following question: "Do you intend to complete this course." Responses to this question were either Yes or No.

In addition to assessing learners' intentions, personality factors were evaluated using the Big 5 personality assessment (BFI), a 44-item inventory measuring the dimensions extraversion, agreeableness, conscientiousness, neuroticism, and openness (Goldberg, 1992). Responses were rated on a scale of 1 to 5 (1 = strongly disagree, 5 = strongly agree), and composite scores for each personality factor were calculated by summing the respective responses.

Data analysis plan

The dependent variables were post-test composite scores, post-test scores across all five modules, course persistence, and course completion. Course persistence was indexed by the number of modules completed, whereas course completion was indicated by the submission of post-tests for each of the five modules. Descriptive statistics, including mean, median, and standard deviations, were computed to derive the final test score results for each experimental condition at every module of the course. To answer RQ1, hierarchical linear modeling (HLM) was employed, exploring the connection between experimental conditions and test scores across modules. A level 2 random intercept only model was implemented for RQ1. Level 1 predictor included personality factors and experimental condition assignment. At level 2, a random intercept of participant id to account for the repeated measures for participants at each module. We accounted for the variance in test scores explained by repeated measures for each participant while controlling for personality factors. Standardized grand mean centering was conducted on continuous predictors to avoid converge issues in HLMs due to different scaling in predictors. To address RQ2 and RQ3, multiple binary logistic regression was employed, investigating the relationships between the initial intention to complete the course, student personality and the impact of experimental conditions on overall course persistence. Survival analysis (Kaplan-Meier) was used to determine whether there were differences in survival (retention) rates at each module based on the participants' experimental group and Cox regression was used to assess how personality factors are associated with survival rates. All data analyses were performed using the R statistical software (R Core Team, 2023).

Results

Descriptive results

The initial sample size for this study consisted of 6100 participants that were randomly assigned into one of the four experimental conditions: control group ($n = 1448$, 23.7%), practice test basic feedback group ($n = 1481$, 24.3%), practice test detailed feedback group ($n = 1574$, 25.8%), and practice test no feedback group ($n = 1597$, 26.2%). At the end of the last module in the course 1702 (27.9%) of the sample remained. Each experimental condition has over a 70% attrition rate by the last module of the course. Further descriptive information regarding academic performance and attrition rate for all four experimental conditions at each module is presented in Tables S1–S4 in the supplementary material. In addition, Figure S1 in the supplementary material shows the attrition rate for each experimental condition for each module.

Differences among conditions in performance (RQ1)

Hierarchical linear modeling was used to examine if there were differences in performance for learners in different experimental conditions for each module while controlling for personality factors (openness, conscientiousness, extraversion, agreeableness, and neuroticism). The resulting model could significantly explain variance in the outcome ($LR(12) = 80.86, p < .001, marginal\ R^2 = .03, Conditional\ R^2 = .52, ICC = .50$). However, the interaction between the module and the experimental condition was not statistically significant. There were significant main effects for the experimental conditions *Practice Test with Basic Feedback*(*b = .03, p = .037*) *and Practice Test with Detailed Feedback* (*b = .05, p < .001*) in comparison to the control group, and module (*b* = *–0.01, p =.008*). Post-hoc analysis with Benjamini-Hochberg *p*-value adjustment was conducted to examine if there were any significant pairwise comparisons in test scores between experimental conditions. The post-hoc results revealed that *Practice Test with Basic Feedback* group ($M = .68, SD = .20$) and the *Practice Test with Detailed Feedback* group ($M = .67, SD = .20$) had statistically higher test performance scores than the control group ($M = .63, SD = .21$). *The Practice Test with Basic Feedback* group had statistically higher test scores than the *Practice Test with No Feedback* group (*M* = .66, *SD* = .20). See Table 1 for further information on the multilevel linear model results. See Table 2 for the descriptive results for each condition and Figure 1 for visual representation of group differences.

RQ2 and RQ3 results

Binary Logistic Regression was conducted to examine whether participants' initial intention to complete the course and their experimental condition groups were statistically associated with their course completion while controlling for personality factors. The variance in the outcome could be significantly explained $\left(LR\chi^2(9) = 41.30, p < .001\right)$. Neither experimental condition nor learners' initial intention were statistically associated with course persistence. Conscientiousness

Table 1. Multilevel linear regression table of predicting final test performance.

Predictor	Beta	*SE*	*t*	*df*	*p*	95% CI for Beta		Partial R^2
Intercept	0.70	0.01	70.11	3,943.52	<.001***	0.68	0.72	
Openness	0.02	0.01	2.91	1,646.95	.004**	0.01	0.04	0.01
Conscientiousness	0.02	0.01	3.59	1,669.32	<.001***	0.01	0.04	0.01
Extraversion	−0.02	0.01	−3.09	1,674.70	.002**	−0.04	−0.01	0.01
Agreeableness	−0.02	0.01	−3.26	1,649.79	.001**	−0.04	−0.01	0.00
Neuroticism	−0.01	0.01	−1.21	1,652.93	.227	−0.02	0.00	0.00
Practice Test Basic Feedback	0.03	0.01	2.08	3,930.30	.037*	0.00	0.06	0.00
Practice Test Detailed Feedback	0.05	0.01	3.64	3,958.96	<.001***	0.02	0.08	0.00
Practice Test No Feedback	0.02	0.01	1.25	3,966.83	.211	−0.01	0.04	0.00
Module	−0.01	0.00	−2.63	4,370.34	.008**	−0.01	−0.00	0.00
Practice Test Basic Feedback *Module	0.00	0.00	0.44	4,370.37	.658	−0.01	0.01	0.00
Practice Test Detailed Feedback Group *Module	−0.00	0.00	−0.27	4,402.26	.787	−0.01	0.01	0.00
Practice Test No Feedback Group*Module	0.00	0.00	0.29	4,398.90	.770	−0.01	0.01	0.00

Note. *p < .05, **p < .01, ***p < .001.

was found to be a significant positive predictor of course persistence (*OR* = 1.64, CI 95%[1.37, 1.97], p < .001). Please see Table 3 for further information.

Further, a survival analysis (Kaplan-Meier) was used to determine whether there were differences in survival rates at each module based on the participants' experimental group. The results of the log-rank test showed that there was no significant difference in the survival rates depending on the intervention groups. Please see Table S5 in the supplementary material for the results of the survival analysis for each experimental group and Figure 2 for the pictorial representation of these results. Finally, a Cox proportional hazard regression was conducted to examine whether experimental groups and personality factors were associated with the survival (or retention) of participants during the five modules. A significant regression model was found ($LRT(8) = 39.84, p < .001$). Conscientiousness (HR = −0.29, [CI 95%: −0.41. −19], p <.001) was found to be statistically associated with lower hazard odds of dropping out. All other included predictors did not significantly predict whether participants dropped out. Please see Table 4 for further information.

Discussion

The goal of this study was to investigate the effects of practice tests and different types of feedback on students' tests performance and course completion in a large MOOC. Further, we

Table 2. Descriptive table of final test performance for each module.

Condition		Mod 1	Mod 2	Mod 3	Mod 4	Mod 5
Control	N	1448	978	611	499	456
	M	0.67	0.59	0.61	0.64	0.64
	SD	0.19	0.21	0.22	0.22	0.21
Practice Test Basic Feedback	N	1481	945	583	473	420
	M	0.71	0.63	0.66	0.67	0.69
	SD	0.18	0.21	0.20	0.21	0.20
Practice Test Detailed Feedback	N	1574	996	628	504	466
	M	0.71	0.64	0.65	0.67	0.67
	SD	0.18	0.21	0.21	0.21	0.21
Practice Test No Feedback	N	1597	995	592	478	438
	M	0.69	0.61	0.63	0.67	0.66
	SD	0.18	0.20	0.21	0.22	0.20

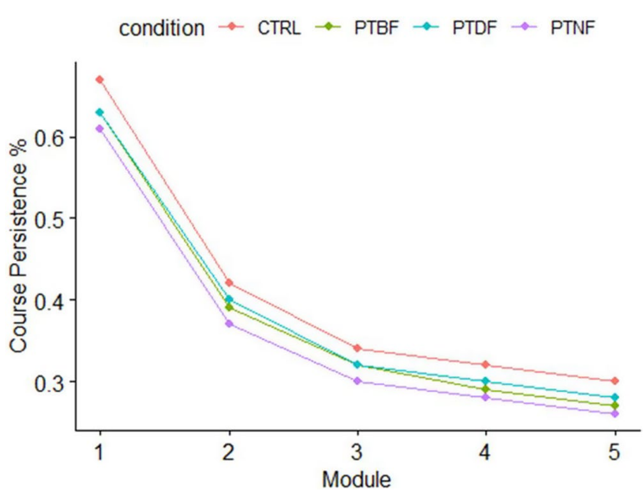

Figure 1. Boxplot of test performance by condition for all modules. *Note*. PTDF = Practice Test Detailed Feedback Group, PTBF = Practice Test Basic Feedback Group, PTNF = Practice Test No Feedback Group, CTRL = Control Group.

Table 3. Binary logistic regression table of experimental condition and initial persistence predicting course persistence.

Term	OR	*SE*	Wald	*p*	95% CI for OR	
Intercept	0.19	1.01	−1.63	.103	0.02	1.36
Openness	0.84	0.11	−1.58	.115	0.68	1.04
Conscientiousness	1.64	0.09	5.34	<.001***	1.37	1.97
Extraversion	0.87	0.10	−1.44	.151	0.72	1.05
Agreeableness	1.08	0.10	0.72	.472	0.88	1.31
Neuroticism	1.00	0.08	0.06	.956	0.86	1.17
Practice Test Basic Feedback	1.04	0.15	0.27	.791	0.78	1.38
Practice Test Detailed Feedback Group	0.91	0.14	−0.65	.518	0.69	1.21
Practice Test No Feedback Group	0.91	0.14	−0.64	.522	0.69	1.21
Intention to Complete Course	1.66	0.74	0.69	.491	0.40	8.25

Note. ***$p < .001$.

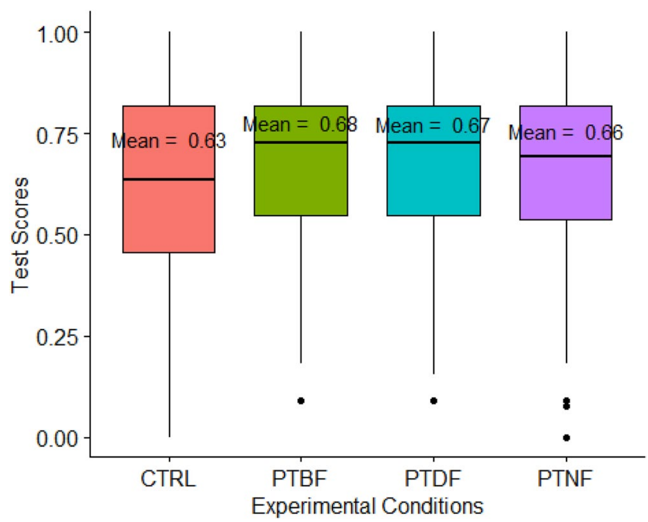

Figure 2. Survival plot of dropout rates for each intervention. *Note*: PTDF = Practice Test Detailed Feedback Group, PTBF = Practice Test Basic Feedback Group, PTNF = Practice Test No Feedback Group, CTRL = Control Group.

examined whether intention to complete the course as well as student personality predicted their performance and course completion. The study revealed intriguing results.

First, we found a significant improvement in test scores for students in the *Practice Test with Basic Feedback* and *Practice Test with Detailed Feedback* groups compared to those in the control group, with the former group performing significantly better than the *Practice Test with No Feedback* group. Second, neither the experimental condition nor the initial intention to complete the course were associated with course persistence, except for conscientiousness being a positive predictor. Furthermore, the results highlight that conscientiousness was the only personality factor found to be significantly associated with a lower hazard of dropping out. Interestingly, the survival analysis did not demonstrate any significant differences in dropout rates among the experimental groups. Let us closely examine the obtained results.

Performance on the test

Students in the *Practice Test with Basic Feedback* and *Practice Test with Detailed Feedback* groups attained higher test scores when compared to the control group. In particular, students in the *Practice Test with Basic Feedback* and *Practice Test with Detailed Feedback* groups outperformed

Table 4. Cox regression table of intervention groups and personality factors predicting dropout rates.

Term	HR	SE	Wald	*p*	95% CI for Beta	
Practice Test Basic Feedback	0.03	0.10	0.31	.759	−0.16	0.22
Practice Test Detailed Feedback Group	0.12	0.09	1.29	.197	−0.06	0.31
Practice Test No Feedback Group	0.11	0.09	1.21	.225	−0.07	0.30
Openness	0.12	0.07	1.75	.080	−0.01	0.26
Conscientiousness	−0.29	0.06	−4.97	<.001***	−0.41	−0.18
Extraversion	0.11	0.06	1.68	.092	−0.02	0.24
Agreeableness	−0.05	0.07	−0.69	.490	−0.17	0.08
Neuroticism	0.04	0.05	0.79	.432	−0.06	0.14

Note. ***$p < .001$.

those in the control group. Additionally, students in the *Practice Test with Basic Feedback* group demonstrated significantly higher test scores compared to those in the *Practice Test No Feedback* group. In other words, practice tests on their own did not result in improved performance for any of the five modules.

On the other hand, practice tests, whether paired with basic or detailed feedback, have contributed to students' improved performance by engaging participants in an iterative learning and retrieval process (Rawson & Dunlosky, 2012). This retrieval practice may have improved retention and enhanced students' understanding of the course material, allowing them to address gaps in their knowledge (Adesope et al., 2017). This is consistent with studies conducted in traditional settings that show that frequent testing (and retrieval, associated with it) not only improved the retention of tested materials but also had a positive effect on recalling untested content (for a meta-analysis, see Yang et al., 2021).

However, unlike in studies conducted in formal instructional settings, we observed no effect of practice testing without feedback on students' performance. Our results support the findings of Davis et al.'s (2016) study, who also revealed no effect of testing on student performance in a MOOC. It is possible that due to the format of MOOCs, which for the most part rely on solitary engagement with the content, practice tests do not motivate students enough to mindfully engage with the material to correctly answer practice test questions. Receiving no indication of whether the answers are correct may prevent learners from reinforcing their storage and retrieval pathways.

Moreover, no differences were found between basic feedback and detailed feedback conditions. In traditional contexts, the literature consistently underscores the beneficial impact of detailed feedback that not only corrects errors but also provides detailed explanations of correct and incorrect answers (Dunlosky et al., 2013; Dunlosky & Rawson, 2015; Roediger & Butler, 2011). This pedagogical approach is rooted in the idea that detailed explanations foster deeper understanding and facilitate re-learning, thus strengthening both storage and retrieval.

Contrastingly, our study revealed that learners exhibited comparable levels of performance when exposed to basic feedback that simply communicates correctness or incorrectness. The lack of discernible differences between the basic and detailed feedback conditions in our MOOC setting raises intriguing questions about the extent to which MOOC learners engage in practices, such as re-studying that are traditionally associated with detailed explanations. The autonomy of MOOC learners from the conventional need for elaborate feedback warrants further scrutiny, as it challenges preexisting assumptions about the pedagogical strategies most conducive to online learning environments. As we unravel these findings, we not only contribute to the understanding of MOOC dynamics but also prompt a reevaluation of the role and necessity of detailed feedback in the context of MOOC.

Course persistence and completion

When it comes to course persistence and completion, MOOCs have historically grappled with high dropout rates, with the typical attrition rate reaching over 90% (Borrella et al., 2022).

The high dropout rate in MOOCs is influenced by various factors, including psychological, course-related, personal, social, and external factors. Among these, psychological factors (e.g., motivation) and course-related factors (e.g., course design) are identified as particularly prominent contributors (for a bibliometric review, refer to W. Wang, Zhao, Wu, et al., 2023). However, our study presented a notable departure from this trend, retaining a quarter of participants—an unexpected and positively surprising outcome. The unique circumstances surrounding the timing of our data collection shed light on potential explanations for this higher-than-anticipated completion rate.

Our data collection coincided with the onset of the COVID-19 pandemic. At a time when educational institutions worldwide faced closures, learners from diverse geographic locations sought high-quality instructional materials to supplement their disrupted learning. This demand, paired with the extended time availability afforded by the pandemic-related disruptions, likely contributed to the enhanced completion rate observed in our study. The unforeseen interplay of global circumstances and the specific educational needs arising from the pandemic underscores the complexity of factors influencing MOOC engagement and completion.

In our study, neither the experimental condition nor the initial intention to complete the course showed a statistically significant relationship with course persistence or completion. The complexity of students' experiences in a MOOC context may encompass various individual factors, such as cognitive abilities, emotions, learning behaviors (e.g., Huang et al., 2023), that were not accounted for in the experimental conditions or initial intentions. These results are different from those reported in Janelli and Lipnevich (2021) that revealed higher dropout rates for students who took pretests, compared to those in the control group. Taking tests on material to which the learners have not been exposed was a deterrent to their persistence. In our study, practice tests followed learner engagement with the course content and thus were likely to elicit motivation to find out the level of their understanding. Further, due to the context of the pandemic, some students enrolled in this class to satisfy course or professional development requirements. Hence, they took it much more seriously. This highlights the nature of student engagement and suggests additional elements that warrant further investigation in understanding their impact on course persistence in the MOOC.

Additionally, our findings revealed that individuals with higher conscientiousness were more likely to persist in the course. Conscientious individuals exhibit higher diligence, organization, and work ethic - traits that might contribute to a higher likelihood of persisting in an online course (e.g., Abdullatif & Velázquez-Iturbide, 2020; Gupta, 2021). Conversely, students' intention to complete the course had no relation to persistence or completion. This is contrary to studies that reveal that intention is one of the strongest predictors of behaviors, as described by the Theory of Planned Behavior (Ajzen, 1991; Lung-Guang, 2019; Sommer, 2011; Y. Wang et al., 2020). Likewise, individuals who initially planned to complete the course were more likely to obtain a certificate (Greene et al., 2015), which demonstrates the relationship between intention and behavior in MOOCs (e.g., Robinson et al., 2016). Upon further examination of students' responses to the question capturing their intention to complete, we found that the vast majority of learners fully endorsed their high intention to complete all five modules. Future studies could examine whether this trend is common for MOOC studies or whether this finding pertains to our specific context of a MOOC occurring during a pandemic. Additionally, different types of intentions in MOOC settings could be further investigated as findings from a different study (Semenova, 2022) demonstrated that action-oriented intention or intention to accomplish short-term outcomes (e.g., watching all lectures or completing all tasks) (Gollwitzer, 1993; Sheeran, 2002; Verplanken et al., 1998) had a stronger effect on course completion than result-oriented intention or the intention to complete the course. Thus, this study underscores the significance of individual characteristics in predicting students' commitment and engagement to the learning process.

Practical implications

Our findings suggest that incorporating practice tests with basic feedback in course design can significantly enhance student performance. Instructional designers can leverage this insight to improve learning experiences by integrating assessment strategies, namely, those providing basic feedback. In STEM courses, such as MOOCs for programming, where standardized and clear-cut answers are common, auto-graded selected-response and short-answer questions with feedback provide an efficient way for larger classes to check in on their academic progress (Najafi et al., 2017). In this context, learners have several opportunities to submit formative exercises, allowing them to identify gaps and manage their learning outcomes.

A significant association between personality traits and a learner's intention to complete a MOOC exists (Gupta, 2021), suggesting compelling trends for future research. Hence, understanding the key role of conscientiousness in course persistence is valuable for educators and course designers striving to increase student engagement and retention. Learners categorized as committed outperformed those in the three other learner types (negative, mid-term dropout and early dropout; W. Wang, Zhao, Cao, et al., 2023). Furthermore, studies (e.g., Ogunyemi et al., 2022) have found a link between learners' engagement patterns and their intent to complete a MOOC. Many studies have been exploring differences in demographics and cognitive abilities between completers and dropouts (e.g., Al-Shabandar et al., 2017; El Said, 2017; Gomez-Zermeno & de La Garza, 2016), particularly by employing machine learning (e.g., Lai et al., 2020; Narayanasamy & Elçi 2020; Panagiotakopoulos et al., 2021) as a way to identify learners who need extra support. This proactive and predictive approach enables educational interventions to be implemented early, addressing the challenge of high dropout rate in MOOCs.

In addition, the observed lower attrition rate in the MOOC in the current study could be influenced by external factors, such as the impact of the COVID-19 pandemic, indicating the need for adaptive strategies in course design to address evolving learning environments and student needs. Given the shifting educational landscape that provides students with more flexibility and less structure compared to traditional classrooms, it is crucial to explore how and when students effectively learn in MOOCs (Carpenter et al., 2022). Thus, our study examined the effectiveness of well-researched educational interventions, testing and feedback, in the context of a MOOC.

Limitations and future directions

The current study acknowledges several limitations and suggests potential directions for future research. First, our study focused on a single science course. It is important for future studies to replicate the research across diverse MOOCs, spanning various domains and including for-credit course contexts. Second, we were unable to capture substantial information about student background. Future investigations should examine relations between student individual characteristics, prior knowledge, and performance in MOOCs. Finally, the impact of variations in individual student study habits and time devoted to engaging with course materials on performance in MOOC could be closer examined in future investigations.

Conclusion

In this large experimental study, we explored the influence of practice tests and differential feedback on students' test performance and course completion within the context of a MOOC. Additionally, we investigated whether students' initial intention to complete the course and their personality characteristics could serve as predictors for their performance and course persistence. The outcomes of the study present compelling insights.

To begin, higher test scores were evident among students in both the *Practice Test with Basic Feedback* and *Practice Test with Detailed Feedback* groups compared to the control group. Notably, the former group exhibited significantly superior performance when compared to the *Practice Test with No Feedback* group. This offers insights for MOOC designers and shows concrete strategies that help to improve student performance. Moving on to the factors influencing course persistence, neither the experimental conditions nor the initial intent to complete the course demonstrated a clear association with the course completion. The only notable exception was conscientiousness, which emerged as a positive predictor. Conscientiousness, in particular, was identified as the sole personality factor significantly linked to a reduced likelihood of learners' dropping out. In light of these findings, it is important for future studies to further examine the interplay of practice tests, feedback types, and learner characteristics in MOOCs. This not only contributes to refining theoretical frameworks but also offers insights for educators, instructional designers, and policymakers seeking to optimize online learning experiences.

Ethical approval

Ethical approval was obtained: protocol number QC-345789NH.

Disclosure statement

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Appendix

Module One Practice Test Question with No Feedback

Why are the tropics warmer than the poles all year long?

1. The angle of sunlight is more direct in the tropics.
2. The equator is closer to the sun, so more sunlight hits the tropics.
3. Higher albedo at the poles means they absorb less sunlight.
4. The atmosphere is higher at the tropics than the poles, so there are more greenhouse gases to trap outgoing heat.

Module One Practice Test Question with Basic (Correct/Incorrect) Feedback

Why are the tropics warmer than the poles all year long?

5. The angle of sunlight is more direct in the tropics.
   a. Option 1 feedback: Correct!
6. The equator is closer to the sun, so more sunlight hits the tropics.
   a. Option 2 feedback: Incorrect
7. Higher albedo at the poles means they absorb less sunlight.
   b. Option 3 feedback: Incorrect
8. The atmosphere is higher in the tropics than the poles, so there are more greenhouse gases to trap outgoing heat.
   c. Option 4 feedback: Incorrect

Module One Practice Test Question with Elaborate Feedback

Why are the tropics warmer than the poles all year long?

9. The angle of sunlight is more direct in the tropics.
   d. Option 1 feedback: Correct!
10. The equator is closer to the sun, so more sunlight hits the tropics.
    e. Option 2 feedback: The size of the Earth is so small compared to the Sun-Earth distance that there is no appreciable difference.
11. Higher albedo at the poles means they absorb less sunlight.
    f. Option 3 feedback: This is a true statement but doesn't answer the question. The cooling due to higher polar albedo is a smaller effect than the tilt of the Earth.
12. The atmosphere is higher at the tropics than the poles, so there are more greenhouse gases to trap outgoing heat.

Option 4 feedback: It is true that the atmosphere is higher at the tropics, but that doesn't influence the greenhouse effect.

Module One Post-test Question

What is the main reason that, year-round, the tropics are warmer than polar regions?

1. The equator is closer to the sun, and since energy decreases with distance, sunlight is stronger in the tropics.
2. The atmosphere in the tropics contains higher levels of greenhouse gases, trapping more heat energy and warming the air.
3. Sunlight strikes Earth more directly in the tropics and at more of an oblique angle in the polar regions, so sunlight is more concentrated in the tropics. (correct response)
4. Tropical rainforests are darker and absorb lots of sunlight, or heat energy, while the bright, snow-covered polar regions reflect sunlight.