How Rewatching Video Lectures Impacts Students' Performance in Assessments in MOOCs

Dmitry Abbakumov ^{1, 2}, Darja Kravchenko ^{1, 2}, William Kuskin ^{1, 3}, & Alexandra Urban ^{1, 4}

¹ Open Lab for Psychometrics of Digital Learning (www.psychometrics.digital)

² National Research University Higher School of Economics, Moscow, Russia

³ The University of Colorado Boulder, Boulder, USA

⁴ Coursera, Mountain View, USA

Author Note

Corresponding author: Dmitry Abbakumov, mailbox@abbakumov.com

Abstract

Recorded video lectures are a core instructional tool in MOOCs. Students value video lectures and rank rewatching them as an important activity they use to prepare for assessments. Platforms promote rewatching video lectures as an essential instrument of preparation. Despite the widespread use of this strategy, we understand very little about how rewatching video lectures impacts students' performance. In this study, we assess the overall effect of rewatching video lectures on students' performance retaking assessments, and the individual differences among items within the assessment. We use a cross-classification multilevel logistic approach with fixed and random effects of rewatching video lectures and apply the approach to four courses on the Coursera platform. We found that the overall effect varies over courses and among items within an assessment: it can take positive, null, and negative values. Our conclusion is caution: the generalized recommendation that students rewatch videos before they retake a failed assessment is not an absolute truth. Individual students behave differently in a given assessment situation, and more research is needed to better understand student success.

Keywords: effect evaluation, individual differences, psychometrics

How Rewatching Video Lectures Impacts Students' Performance in Assessments in MOOCs

Massive open online courses (MOOCs) are “one of the most significant technological developments in higher education in the past decade” (Deng, Benckendorff, & Gannaway, 2019, p. 48). MOOCs are scaled, internet-based courses developed by universities or industries in partnership with provider platforms such as Coursera and edX. MOOCs originated as entirely open, a designation that is changing within the industry. A typical course consists of a set of pre-recorded video lectures, reading assignments, and various assessments, which all are structured around learning objectives, and forums for communication.

Recorded video lectures are a core instructional tool in MOOCs (Guo, Kim, & Rubin, 2014). Students value video lectures and rank rewatching them as an important activity they use to prepare for assessments (Davies, Cotton, & Korte, 2016). Moreover, the platforms themselves promote rewatching video lectures as an essential instrument of preparation. For instance, Coursera advises course developers to use actionable feedback on question answer options to direct students to relevant video lectures before they retake the assessment. Despite the widespread use of this strategy, we understand very little about how rewatching video lectures impacts students' performance in assessments.

The research on rewatching videos provides conflicting findings on how helpful it is for raising students' assessment scores. Recently, Palmer, Chu, and Persky (2019) and Patel, Yook, Mislan, and Persky (2019) demonstrated that students who rewatched video lectures had better performance in immediate assessment as compared with students who did not. In contrast, Martin, Mills, D'Mello, and Risko (2018) revealed no benefits of rewatching on memory for lecture material. The majority of research on recorded video lectures has, in fact, not focused on their effectiveness at all, but rather on how they are used as a basic learning tool (Davies et al., 2016; Topale, 2016). Interestingly, although students do often use a technique which is similar,

rereading learning materials (Hartwig & Dunlosky, 2012; Karpicke, Butler, & Roediger Iii, 2009; Kornell & Bjork, 2007), there is no generalized evidence of its utility (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013). In preparing this paper, we have found no specific research on rewatching video lectures in MOOCs.

To extend the research literature, this study aims to understand the effects of rewatching video lectures in MOOCs. We propose an approach for evaluating two kinds of effects: the overall effect of rewatching video lectures on students' performance while retaking assessments, and the individual differences in the effect varying among items within the assessment. The approach is based on cross-classification multilevel logistic models presented by Van den Noortgate, De Boeck, and Meulders (2003) which are widely used for explanatory behavior modeling. We apply this approach to four courses in social sciences and math and logic on Coursera platform.

Modeling

To understand the effect of rewatching video lectures on students' performance in assessments, we use a cross-classification multilevel logistic approach to modeling students' responses in assessments. This approach, proposed by Van den Noortgate, De Boeck, and Meulders (2003), understands students' responses on assessment items on the basis of (a set of) person and item effects. In the null model,

$$\text{Logit}(\pi_{ij}) = b_0 + u_{1j} + u_{2i} \text{ and } Y_{ij} \sim \text{Bernoulli}(\pi_{ij}), \quad (1)$$

we have an intercept, b_0 , and two residual terms referring to the student, u_{1j} , and the item, u_{2i} , respectively. As the mean of both residual terms equals zero, the intercept corresponds to the estimated logit of the probability of the correct response for an average student on an average

item. The first residual term $u_{1j} \sim N(0, \sigma_{u_1}^2)$ shows the deviation of the expected logit from student j from the mean logit. The higher this deviation, the higher the expected performance. This residual term can be interpreted as the proficiency of student j . The second residual term shows the deviation of the expected logit from item i from the overall logit. Here, the larger the residual – the higher the probability of the correct response is. In that sense, the residual term $u_{2i} \sim N(0, \sigma_{u_2}^2)$ presents the relative difficulty of item i , compared to the mean difficulty of item b_0 .

Such a modeling approach – considering both items and students as random – allows the addition of predictors without running into computational issues of model identification. The approach leaves degrees of freedom for predictors without running into computational issues of model identification and has been used in various extensions, for instance, for modeling learning effects (Abbakumov, Desmet, & Van den Noortgate, 2019; Kadengye, Ceulemans, & Van den Noortgate, 2014, 2015), effects of interest (Abbakumov, Desmet, & Van den Noortgate, 2020), and explanatory models (Park, Joo, Cornillie, van der Maas, & Van den Noortgate, 2019).

To model the effect of rewatching video lectures, we propose two extensions. In the first, aimed at understanding the general effect,

$$\text{Logit}(\pi_{ij}) = b_0 + b_1 * \text{rewatch}_j + u_{1j} + u_{2i} \text{ and } Y_{ij} \sim \text{Bernoulli}(\pi_{ij}), \quad (2)$$

we have incorporated a binary variable, *rewatch*, indicating whether or not student j rewatched any video lectures before the second attempt of responding on item i ; therefore, b_1 is the overall effect of rewatching video lectures. Thus, the intercept b_0 now corresponds to the estimated logit of the probability of the correct response for an average student on an average item from the second attempt, if this student did not rewatch any video lectures before the second attempt. The

meaning of the residual terms $u_{1j} \sim N(0, \sigma_{u_1}^2)$ and $u_{2i} \sim N(0, \sigma_{u_2}^2)$ remains the same as in Equation 1.

Research on rereading and assessments suggests that the effect of rewatching video lectures may vary from item to item, and thus offers a guide for our research here. For example, Dunlosky and collaborators (2013) summarized that the effects of rereading vary even for similar criteria, for instance, for inference-based questions or fill-in questions. To understand whether the variation exists, we propose the second extension,

$$\text{Logit}(\pi_{ij}) = b_0 + (b_{10} + b_{1i}) * \text{rewatch}_j + u_{1j} + u_{2i} \text{ and } Y_{ij} \sim \text{Bernoulli}(\pi_{ij}), \quad (3)$$

which includes the overall effect of rewatching video lectures, b_{10} , and b_{1i} is a deviation of the effect of rewatching video lectures for item i from the overall effect; u_{2i} and b_{1i} follow a bivariate normal distribution $N(0, \Sigma)$ with Σ as the variance-covariance matrix; while the meaning of the residual terms u_{1j} and u_{2i} does not change.

Method

Data

We studied four courses on the Coursera platform, three from the social sciences and one from math and logic (details presented in Table 1). Each course follows a similar pattern. The courses are composed of modules, structured around cohesive subtopics and typically lasting for one week. These modules consist of a set of lessons. Each lesson contains around 1-2 learning objectives and includes several video lectures. The video lectures last between 4-9 minutes. A module is concluded by a summative assessment, which is realized as a 15-20 item test. The items in these tests are either multiple choice or open-ended questions in which a student is expected to choose an option or options, or insert a number, a sequence, a word, or a phrase. In

our computations, we use the data from one test-based assessment in each course. The dependent variable is students' responses on the assessment items from the second attempt, coded dichotomously, where 1 corresponds to correct response and 0 corresponds to incorrect response. The predictor variable is a binary as well, indicating whether a student rewatched video lectures before the second attempt (value 1) or did not (value 0).

Software

To fit the models, we use the “glmer” function of the “lme4” package (Bates, Mächler, Bolker, & Walker, 2015) of the R language and environment for statistical computing. To assess the model fit, we use the AIC (Akaike, 1974) and cAIC (Vaida & Blanchard, 2005) values; the latter criterion is recommended for models with random effects.

Results

We start with the null model from Equation 1. As shown in Table 2, the estimate of the intercept equals 0.14. The inverse logit, or the anti-logit, of this value is .53, which means that on average, after a wrong response, the expected probability of a correct response from the second attempt is .53. This probability varies among items and among students, which is expressed in item-specific (0.70) and student-specific (0.69) standard deviations from the intercept in Table 2. For instance, after a wrong response, an average student is expected subsequently to succeed on items with the difficulty of one standard deviation lower and with the difficulty of one standard deviation higher than the average with probabilities of .36, which is the antilogit of $(0.14 - 0.70)$, and .70, which is the antilogit of $(0.14 + 0.70)$, respectively. A student of one standard deviation weaker than the average is expected to respond on these items correctly with probabilities of .22, which corresponds to the antilogit of $(0.14 - 0.70 - 0.69)$, and .54, which corresponds to the antilogit of $(0.14 + 0.70 - 0.69)$, respectively. Finally, a student of one standard deviation stronger

than the average is expected to give a correct response on the same items with probabilities of .53, which corresponds to the antilogit of $(0.14-0.70+0.69)$, and .82, which corresponds to the antilogit of $(0.14+0.70+0.69)$, respectively.

Extending the null model by the fixed effect of rewatching videos (Equation 2) reveals the differences in the expected probability of a correct response on the second attempt after the failed first attempt for students who rewatched video lectures and for students who did not. The effect is positive (0.31) and significantly different from zero ($p<.001$). As can be derived from Table 2, on average, a student who did not rewatch videos after a wrong response gives a correct response on the second attempt with expected probability of .52 (the antilogit of 0.07). For a student who rewatched videos, the expected probability is .59, which corresponds to the antilogit of $(0.07+0.31)$.

The effect of rewatching videos is not the same for all items. The second extension, including the random effect varying over items (Equation 3), detects item-specific deviations ($SD=0.32$) from the overall effect of rewatching videos (0.32, $p<.001$). Table 2 shows that for some items there is no effect (*Overall-SD*) or even a negative effect (*Overall-2*SD*) of rewatching videos on the expected probability of correct response on the second attempt. For some items, there are much stronger positive effects (*Overall+SD* and *Overall+2*SD* respectively). To understand the effect size, we can calculate the expected probabilities of correct responses for students with the effect of rewatching videos of one standard deviation lower and one standard deviation higher than the average. Thus, taking into account the item's average difficulty, the probabilities are .51 and .67 which correspond to the antilogits of $(0.06+0.32-0.32)$ and $(0.06+0.32+0.32)$ respectively. For an item with difficulty of one standard deviation higher

than the average, the probabilities are .35 and .5, the antilogits of $(0.06+0.32-0.32-0.70)$ and $(0.06+0.32+0.32+0.70)$ respectively.

According to values of both criteria of model fit (see Table 2), the model including the random effects of rewatching videos ($AIC=34,452$, $cAIC=30,566$) fits the data better than the null model ($AIC=34,605$, $cAIC=30,679$) and the model with only the fixed effect of rewatching videos ($AIC=34,545$, $cAIC=30,710$). At the same time, there is no consensus on whether the model with the fixed effect of rewatching videos has improvement in fit as compared to the null model.

The extension with random effects of rewatching videos (Equation 3) applied to data of the other three courses shows that the overall effect of rewatching videos varies among courses (see Table 3). Interestingly, one course has a negative overall effect (-0.28 , $p=.005$), while the remaining two courses have positive overall effects (0.56 , $p=.005$ and 0.42 , $p<.001$). Importantly, for all of these courses, the effect of rewatching videos varies over items.

Discussion and Conclusion

Research on rewatching video lectures is still emerging. We understand the results of this study in four points: (i.) connections to previous research, (ii.) new findings, (iii.) limitations, and (iv.) impact on practice.

Connections to Previous Research. Although students who rewatch video lectures before retaking an assessment have a statistically significant benefit in comparison to other students, which supports the findings of Palmer, Chu, and Persky (2019) and Patel, Yook, Mislan, and Persky (2019), the final effect of rewatching video lectures varies. For some courses, the effect might be negative. Studies on a larger number of MOOCs is needed to understand the more generalized effect.

New Findings. The novel contribution to the field in this study lies in its revelation of individual differences in the effect of rewatching videos. While the overall effect of rewatching video lectures is positive, for some items within one assessment it might be null or even negative. Knowing this should stimulate continuing research into these differences, for instance, by explaining them using item properties such as item type or its location within assessment.

Limitations. The study does, however, have limitations. It does not reveal the causes of the differences and similarities in the effects of rewatching video lectures on the course and item levels. These differences and similarities might be desirable to the practice. Further, it is based on test-based assessments only, and thus its results cannot be generalized to other types of assessments in MOOCs. Both limitations are directions for future research.

Impact on Practice. Finally, from the perspective of practice, this study shows that the generalized recommendation to direct students to relevant video lectures before they retake the assessment should be used with caution. At the least, the practitioner should consider the overall effect of rewatching video lectures before providing actionable feedback to students. A balanced solution is to take into account the individual effect for each item in the assessment and provide actionable feedback only after items with positive values of the effect.

This study continues the recent expansion of the field of psychometrics into the study of MOOCs. The psychometrics of MOOCs combines a century-old heritage of study (Borsboom, 2005) with modern sources of large data sets. This combination will allow us to find an answer to the question of when and why learning happens in MOOCs, and how scaled digital learning products allow individuals to achieve success.

Table 1

Description of the courses

	Course 1	Course 2	Course 3	Course 4
Field	Social Science	Math and Logic	Social Science	Social Science
Discipline	Economics	Math	Sociology	Finance
Language	English	Russian	Russian	Russian
Number of enrollments	87,700	45,444	11,259	40,657
Completion rate, %	4.8	5.1	16.9	10.0
Top five countries by number of students, %	USA, 19	Russia, 68	Russia, 78	Russia, 69
	India, 9	Ukraine, 11	Ukraine, 6	Ukraine, 7
	Russia, 9	Kazakhstan, 3	Kazakhstan, 2	Kazakhstan, 3
	UK, 4	Belarus, 3	Belarus, 2	China, 3
	Brazil, 4	USA, 2	USA, 1	Belarus, 2
Female Students, %	48	46	54	42

Table 2

Model parameters estimates for Course 1

			Null	Fixed Effect	Random Effect
Fixed	Intercept		0.14 (0.18)	0.07 (0.18)	0.06 (0.20)
	Video			0.31 (0.04)	0.32 (0.09)
Random	Intercept	Student	0.69	0.68	0.68
		Item	0.70	0.70	0.75
	Video	Item			0.32
cAIC			30,679	30,710	30,566
AIC			34,605	34,545	34,452

Note: The number of students was 5,156, the number of items in assessment was 15. For fixed effects, the standard error is presented in parentheses. For random effects the standard deviation is presented.

Table 3

Parameters estimates for the model with random effects of rewatching videos for Courses 2, 3, and 4

			Course 2 N=3,957 20 items	Course 3 N=775 12 items	Course 4 N=4,016 20 items
Fixed	Intercept		0.65 (0.14)	-0.16 (0.13)	0.50 (0.16)
	Video		-0.28 (0.10)	0.56 (0.20)	0.42 (0.10)
Random	Intercept	Student	1.03	1.16	0.78
		Item	0.58	0.38	0.71
	Video	Item	0.20	0.46	0.34

Note: For fixed effects, the standard error is presented in parentheses. For random effects the standard deviation is presented.

References

- Abbakumov, D., Desmet, P., & Van den Noortgate, W. (2019). Measuring growth in students' proficiency in MOOCs: Two component dynamic extensions for the Rasch model. *Behavior Research Methods*, 51(1), 332-341. doi:10.3758/s13428-018-1129-1
- Abbakumov, D., Desmet, P., & Van den Noortgate, W. (2020). Rasch Model Extensions for Enhanced Formative Assessments in MOOCs. *Applied Measurement in Education*, 33(2), 113-123. doi:10.1080/08957347.2020.1732382
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716-723. doi:10.1109/TAC.1974.1100705
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. 2015, 67(1), 48. doi:10.18637/jss.v067.i01
- Borsboom, D. (2005). Measuring the Mind: Conceptual Issues in Contemporary Psychometrics. Cambridge: Cambridge University Press.
- Davies, T. L., Cotton, V. K., & Korte, L. (2016). Student Usage And Perceptions Of The Value Of Recorded Lectures In A Traditional Face-To-Face (F2F) Class. *Journal of College Teaching & Learning (TLC)*, 13(3), 85-94. doi:10.19030/tlc.v13i3.9714
- Deng, R., Benckendorff, P., & Gannaway, D. (2019). Progress and new directions for teaching and learning in MOOCs. *Computers & Education*, 129, 48-60. doi:10.1016/j.compedu.2018.10.019
- Dunlosky, J., Rawson, K. A., Marsh, E. J., Nathan, M. J., & Willingham, D. T. (2013). Improving Students' Learning With Effective Learning Techniques: Promising

Directions From Cognitive and Educational Psychology. *Psychological Science in the Public Interest*, 14(1), 4-58. doi:10.1177/1529100612453266

Guo, P. J., Kim, J., & Rubin, R. (2014). *How video production affects student engagement: an empirical study of MOOC videos*. Paper presented at the Proceedings of the first ACM conference on Learning @ scale conference, Atlanta, Georgia, USA.
doi:10.1145/2556325.2566239

Hartwig, M. K., & Dunlosky, J. (2012). Study strategies of college students: Are self-testing and scheduling related to achievement? *Psychonomic Bulletin & Review*, 19(1), 126-134.
doi:10.3758/s13423-011-0181-y

Kadengye, D. T., Ceulemans, E., & Van den Noortgate, W. (2014). A generalized longitudinal mixture IRT model for measuring differential growth in learning environments. *Behavior Research Methods*, 46(3), 823-840. doi:10.3758/s13428-013-0413-3

Kadengye, D. T., Ceulemans, E., & Van Den Noortgate, W. (2015). Modeling Growth in Electronic Learning Environments Using a Longitudinal Random Item Response Model. *The Journal of Experimental Education*, 83(2), 175-202.
doi:10.1080/00220973.2014.907226

Karpicke, J. D., Butler, A. C., & Roediger Iii, H. L. (2009). Metacognitive strategies in student learning: Do students practise retrieval when they study on their own? *Memory*, 17(4), 471-479. doi:10.1080/09658210802647009

Kornell, N., & Bjork, R. A. (2007). The promise and perils of self-regulated study. *Psychonomic Bulletin & Review*, 14(2), 219-224. doi:10.3758/BF03194055

- Martin, L., Mills, C., D'Mello, S. K., & Risko, E. F. (2018). Re-watching lectures as a study strategy and its effect on mind wandering. *Experimental Psychology*, 65(5), 297-305. doi:10.1027/1618-3169/a000412
- Palmer, S., Chu, Y., & Persky, A. M. (2019). Comparison of Rewatching Class Recordings versus Retrieval Practice as Post-Lecture Learning Strategies. *Am J Pharm Educ*, 83(9), 7217. doi:10.5688/ajpe7217
- Park, J. Y., Joo, S.-H., Cornillie, F., van der Maas, H. L. J., & Van den Noortgate, W. (2019). An explanatory item response theory method for alleviating the cold-start problem in adaptive learning environments. *Behavior Research Methods*, 51(2), 895-909. doi:10.3758/s13428-018-1166-9
- Patel, B., Yook, G., Mislan, S., & Persky, A. M. (2019). Exploring the Consequences on Memory of Students Who Know They Have Access to Recorded Lectures. *Am J Pharm Educ*, 83(5), 6958. doi:10.5688/ajpe6958
- Topale, L. (2016). The strategic use of lecture recordings to facilitate an active and self-directed learning approach. *BMC Medical Education*, 16(1), 201. doi:10.1186/s12909-016-0723-0
- Vaida, F., & Blanchard, S. (2005). Conditional Akaike Information for Mixed-Effects Models. *Biometrika*, 92(2), 351-370. Retrieved from www.jstor.org/stable/20441193
- Van den Noortgate, W., De Boeck, P., & Meulders, M. (2003). Cross-Classification Multilevel Logistic Models in Psychometrics. *Journal of Educational and Behavioral Statistics*, 28(4), 369-386. doi:10.3102/10769986028004369