



The Effect of Instructional Video Speaking Rate on the Learning Performance of Learners with Different Academic Backgrounds and Ages

Minmin Miao

School of Horticulture and Plant Protection, Yangzhou University, China

mmmiao@yzu.edu.cn

Zhiping Zhang

School of Horticulture and Plant Protection, Yangzhou University, China

Xuehao Chen

School of Horticulture and Plant Protection, Yangzhou University, China

Liangjun Li

School of Horticulture and Plant Protection, Yangzhou University, China

Abstract

In the current study, 120 instructional videos with different speaking rates were selected and the performance of learners with different academic backgrounds and ages were analyzed to investigate the response of different learners to the video speaking rate. The results showed that there was a negative correlation between the learners' age and their preference to videos with high speaking rate. Learner group of 40-50 years old was insensitive to the video speaking rate. We suggested that learners' age is an important factor need to be seriously considered when we prepare educational videos. For learner groups with a wide age range, response sensitivity to speaking rate of social professional learners was higher than that of amateur learners.

Keywords: Speaking Rate, Age, Academic Background, Video, Learning Performance.

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INTRODUCTION

Since 2012 massive open online courses (MOOCs) has attracted global attention from educational institutions, especially in the higher education area of both developing and developed countries (Reich & Ruipérez-Valiente, 2019; Sun & Bin, 2018). Although MOOC provides students the opportunity to access lectures from the world's best teachers and participate in learning more flexibly without being limited by time and space, this distance education system also has many deficiencies that have not been resolved, such as insufficient communication between teachers and students, lack of effective monitoring and restraint online, and low completion rates (Gao & Zhang, 2018). Among MOOCs with different topics, courses in general education area are basically easier to attract learners and with less deficiencies mentioned above than those in natural science and technology area which involving professional knowledge. Among those online courses containing special knowledge, MOOCs about agriculture knowledge seem more boring and always capture fewer learners. In the Chinese University MOOCs platform (<https://www.icourse163.org/>), MOOCs in the agriculture area are less than 100 courses and obtain an average registered student number less than 1000.

Video lecture is the major teaching resources for online learning and its quality is critical to the student learning experience in the current generation of MOOCs (Guo, Kim & Rubin, 2014). It was reported that some characteristics of educational videos such as video length, speaking rate and the gender of instructors have profound impacts on the student performance (Shoufan, 2019). Thus, improving the quality of educational videos through altering these mentioned factors should be beneficial to attract more learners and reduce the dropout rate of current MOOCs, especially those in the agriculture area.

We have run a MOOC in the horticulture area for 4 years on both the Yangzhou University MOOCs platform and the Chinese University MOOCs platform. During this period, we received a considerable amount of recommendations about the speaking rate of our video lectures. We noticed that even to the same video, different learners always have different evaluations about the speaking rate, *i.e.*, some learners felt the instructor talking too fast while others thought he/she talking too slow. Combining our experience and the literature mentioned above together, we consider that video speaking rate is a unique and interesting factors effecting learners' satisfaction. Therefore, in this study, we collected a large number of videos from agricultural MOOCs with different speaking rates and investigated the learner performance of these videos.

RELATED WORKS

Up to date, only a few researches have focused on the speaking rate of educational videos. Williams (1998) investigated general instructional media from the 1950s to 1990s and suggested that 160 words per minute (wpm) is the optimal talking speed for presentations. Guo, Kim and Rubin (2014) collected total 862 videos from the edX MOOC platform and splited those videos into 5 buckets by speaking rate, 48-130 wpm, 130-145wpm, 145-165 wpm, 165-185 wpm and 185-254 wpm. They investigated the student engagement time of videos of each speaking rate buckets and concluded that middle speaking rate (145-165 wpm)

obtained the lowest engagement time while students generally engaged more with videos where instructors spoke faster (185-254 wpm). They analyzed the difference between Williams' data and their own results and suggested that students watching online videos would follow along with faster speaking rates than those attending live lectures. Shoufan (2019) estimated the effect of talking speed on the video cognitive value and found that talking speed played a significant or not significant role in different models. In the significant model, there was a positive relationship between the talking speed and the video cognitive value.

In China, most researches related to speaking rate focused on the TV news programs. In the "CCTV news" program, it was reported that the average speaking rate of announcers in 1960' was about 180 wpm, while current speaking rate of announcers in this program has been increased to about 280 wpm, indicating that modern people would like to receive audio information with higher speaking rate than past age people (Liu, 2009; Zhong & Chen, 2018). Cui (2018) suggested that the talking speed of 200-250 wpm was optimal for most videos of general education, while in a professional course "Human anatomy", the tested best talking speed of the microlecture video was only 150-200 wpm. The author concluded that professional educational videos need a slower speaking rate than general educational videos to allow learners digesting complicated special knowledge.

METHODS

Sample Videos, Speaking Rate Measurement and Classification

Thirty online courses in agriculture area from the Chinese University MOOC platform (<https://www.icourse163.org/>) were selected randomly. These courses all provided micro videos to learners as the main study materials. Two hundred videos from these courses were selected randomly and the speaking rate of each video were calculated. The value of this variable was determined based on the number of words in the video and the video length taking into account time segments without speech especially at the start and at the end of some videos (Shoufan, 2019). The speaking rate of selected videos ranges from 150 wpm to 240 wpm. To study the effect of speaking rate on the learner performance, we divided these videos into 3 classes according the speaking rate: 150 wpm to 179 wpm, 180 wpm to 209 wpm and 210 wpm to 240 wpm. The distribution of selected videos in 3 classes is shown in Fig. 1. We further selected 40 videos from each class randomly for further study. To exclude the effect of video length on the results, the minutes of all selected videos range from 5 min to 7 min. In addition, no significant correlativity between gender or age and speaking rate were found in these videos (data not shown), therefore the influence of these factors on the results could be eliminated.

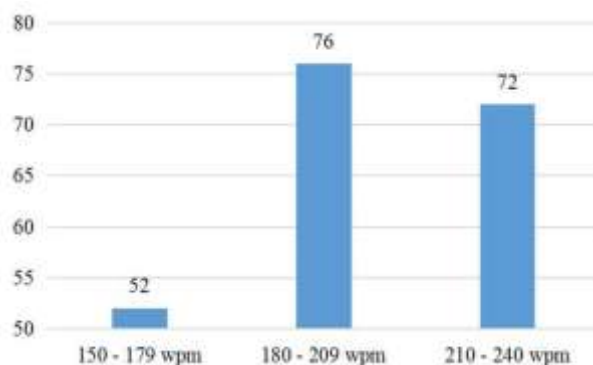


Figure 1: Distribution of speaking rate of selected videos.

Classification of Learners

The numbers of registered learners of selected videos ranged from 562-2389. These videos had three categories of learners. The category 1 (students) was undergraduate students of agriculture universities. These professional courses were often provided to students at the 3rd school year. By then these students had finished prerequisite courses of selected MOOCs, such as physiology or biochemistry. The category 2 (social professional learners) were people engaged in agriculture related works, such as officers in the agricultural administrative departments, administrative personnel or technicians of agricultural enterprises, or big farmers. These agricultural participants always possess certain expertise in certain agricultural area and wish renewing their knowledge through online learning. The category 3 (amateur learners) were agricultural amateurs. They were always lack of professional background knowledge in agriculture and only wish to obtain some useful information about home garden management or pet raising. The identities of learners were easy to be ascertained through their registration information.

To study the effect of age on the learners' response to speaking rate, we collected all learners' age from their registration information. All learners were partitioned into 5 classes according to their age: 18-22, 23-30, 31-40, 41-50 and older than 51 years-old. The age of all university students was located in the interval 18-22. We selected fifty learners completing the certain course randomly from each age interval of each video for further study.

Evaluation of Learner' Performance

Posttest was an essential component of the courses in the Chinese University MOOC platform. As a result, each selected videos in this study had a posttest consisting of 3 to 5 multi-choice questions. Learner performance of each video was estimated as the score shown on the platform after the chapter had finished. The full score was normalized as 10 of each video. It was confirmed that these test questions were designed just for checking if learners watched the video carefully or not, and the answer could be found directly from the videos with no need of any additional professional knowledge. In addition, among 3 categories of learners, students need to complete the posttest to earn the credits, while social professional learners and amateur learners had no pressure to complete these multi-answer questions.

Statistical Analysis

Multi-way ANOVAs were used to determine significances among speaking rates, identity of learners and age of learners in SPSS Statistics 18. The significance of the factor effect was determined using the F-test, and comparisons of means were carried out using the least significant difference (LSD) at the 5% level.

RESULTS

The Effect of Speaking Rate on the Posttest Performance

As shown in Figure 2a, learners generally preferred high speaking rate when they watched educational videos. We further investigated the speaking rate effect among different learner categories. The results indicated that for both students and social professional learners, the order of learning performance of videos with different speaking rates was high speed > medium speed > low speed, while for amateur learners, the order changed to high speed = medium speed > low speed. Although student learners and social professional learners revealed similar pattern of their posttest performance when they watched videos with different speaking rates, the response of student learners was more acute than that of professional learners, *i.e.*, students acquired higher scores for high-speed videos and lower scores for low-speed videos (Figure 2a).

The Effect of Learner Age on the Posttest Performance

As shown in Figure 2b, the posttest performance decreased with the increase of the learners' age. Further analysis indicated that this negative correlation was mainly due to the performance of amateur learners, since for professional learners, no significant difference could be found among different age groups.

The Effect of Learner Identity on the Posttest Performance

The data from Figure 2c suggested that learners with professional background obtained higher posttest scores than amateur learners. To elucidate the difference between students and social professional learners, the performances of learner groups with the same age (18-22 years-old) from both categories were calculated and the results indicated that there was no remarkable difference between university undergraduates and young social agricultural participants (Figure 2d).

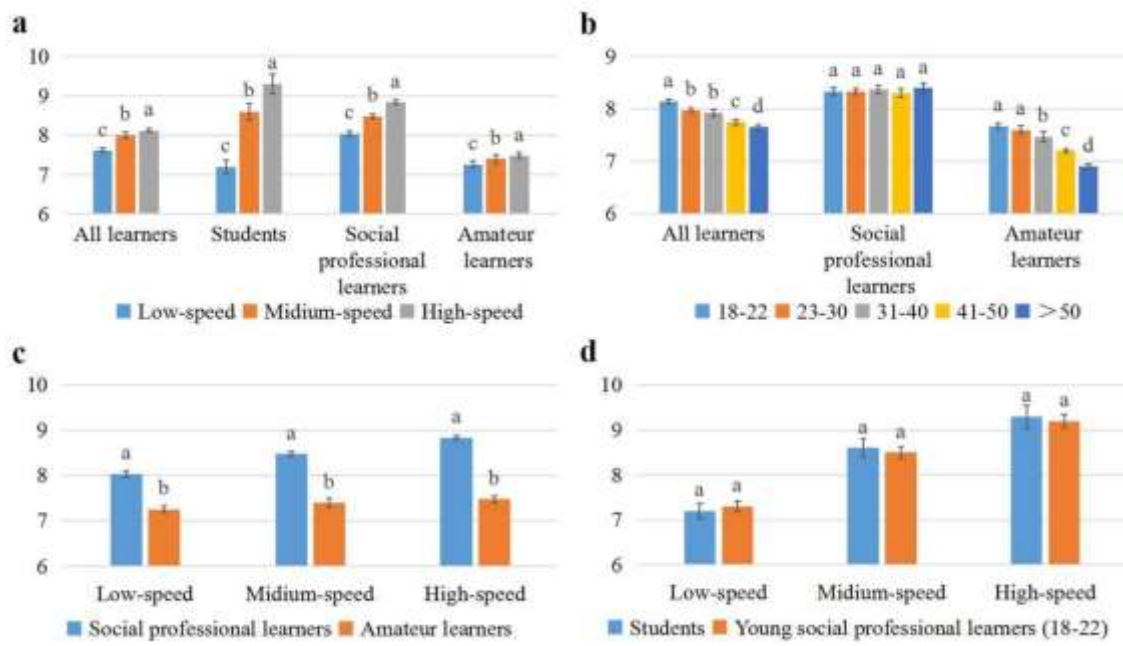


Figure 2 : The effect of speaking rate, learner age and learner identity on the posttest performance. a. Speaking rate. b. Learner age. c. Learner identity. d. The effect of students and social profession learners (18-22 years-old) on the posttest performance. Data are expressed as the means±SD. The different letters indicate significant differences according to Multi-way ANOVAs ($P < 0.05$).

The Interaction Among “Speaking Rate”, “Learner Age”and “Learner Identity”

Putting the variables “speaking rate”, “learner age” and “learner identity” together, the data shown in Figure 3 revealed that response of learners to video speaking rate varied depending on their ages, *i.e.*, no matter of the professional background, young learners (18-40 years-old) prefer high-speed videos while old learners (elder than 50) tended to obtain higher posttest scores from the videos with lower talking speed. Interestingly, medium-age learners (40-50 years-old) earned similar performance among all videos with different speaking rates. Among young learners, the younger learners were, the more sensitively they responded to the speaking rate. (Figure 3) Interestingly, we also found that for the social professional learners, all age groups obtained similar posttest scores when the video speaking rate was “medium”, while for the amateur learner category, this universal speaking rate changed to “low”.

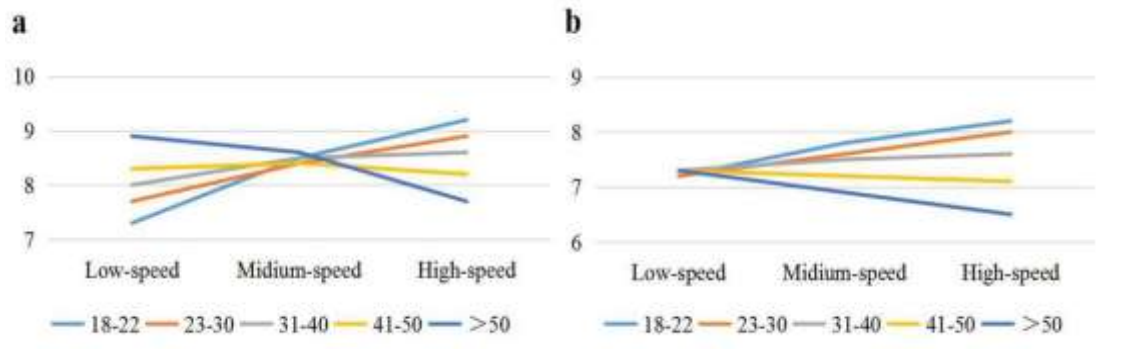


Figure 3: Interaction among learner age, learner professional background and video speaking

rate. a. Social professional learners. b. Amateur learners.

DISCUSSION

The first issue of this study need to be discussed is the methods for evaluating the success of an educational video. Guo, Kim and Rubin (2014) used the length of time that a learner spends on a video as the main proxy to evaluate the student engagement. However, although engagement time was easy to obtain from MOOC platforms, this value cannot identify whether a learner is actively watching the video or just playing it in the background of other tasking. The authors realized that it is infeasible to get the true engagement time without direct observation and questioning, a task which was also unfulfillable at the scale in our study. Several other research groups proposed that the success of MOOCs should be estimated through learner-centered measures such as learner satisfaction or fulfillment of learner intention, rather than completion rates and other teacher-focused measures. (Henderikx, Kreijns & Kalz, 2017; Rabin, Kalman & Kalz, 2019; Reich & Ruipérez-Valiente, 2019). Ten Hove and Van der Meij (2015) defined a metric called popularity rate (PR) to evaluate the acceptance of a video, they formulated this parameter as $PR = (2Lr + V + S) / 4$, whereas V was the number of views, S was the number of shares, and Lr referred to the like ratio. This ratio was defined as $Lr = (L / (L + 2D) \times 100)$, whereas L was the number of likes, D was the number of dislikes. Shoufan (2019) defined a parameter called Video Cognitive Value (VCV) to measure the student's satisfaction of an instructional video. The VCV was formulated as $VCV = W_L \times N_L / N_V \times 10^4$, whereas W_L was the proportion of students who like an educational video due its cognitive value, N_L was the number of likes and N_V was the total number of views. In this study, we adopted the posttest score as an assessment indicator of learner performance of a certain video. Since these multi-choice questions were designed with no need of any additional professional knowledge, and most learners (both social professional learners and amateur learners) had no pressure to complete the course, we believe the score could reflect the attraction of videos to learners or learners' satisfaction to videos. The similar performance of university students (need to complete the course) and social profession learners (with no any mandatory constraint to complete the course) further confirmed that the constraint of completing course was not a factor to impact the posttest scores in this study. Li (2019) also reported that students' satisfaction in learning is often positively correlated with learning outcomes. Guo, Kim and Rubin (2014) tried to use the attempt rate of the posttest (usually a multiple-choice question) to estimate students' engagement. In our study, the posttest of each video consisted of 3-5 multi-choice questions, which should be more accurate to evaluate the learners' performance than only one question.

A number of studies have focused on the effect of learners' academic background or prior knowledge on their learning outcomes in MOOCs (Lee & Choi, 2011). Among which most scholars found that high level of previous knowledge was needed to be successful in a MOOC (Santos, Costa, & Aparicio, 2014; Kennedy, Coffrin, DeBarba, & Corrin, 2015). Generally, more experienced learners showed better mastery and usage of effective learning strategies and were easy to earn certificates for completing MOOCs (Vermunt & Vermetten, 2004; Christensen et al., 2013; Daily, 2014; Guo & Reinecke, 2014; Hansen & Reich, 2015; Koller, Ng, Chuong, & Zhenghao, 2013). However, DeBoer et al. (2013) suggested that learners' educational attainment, rather than their prior knowledge of the course topic was a

significant predictor for success. In our study, we also found the social professional learners caught better posttest performance of selected videos than amateur learners. In addition, we did not find significant difference of academic degree level between professional and amateur learners (from the registration information of learners, data not shown), indicating it is the prior knowledge, rather than the academic degree, contributing to the learning performance. Up to date, little is known about the effect of learners' academic background on their response to the speaking rate, our data indicated that the sensitivity order of response to the speaking rate among 3 learner categories was students > social professional learners > amateur learners (Figure 2b), if all learners in each category were considered as a unit.

Age is another factor having long been studied for relationships with many aspects of MOOCs. Lan (2005) and Colorado and Eberle (2012) found that older learners tended to be more self-regulated in learning, and used more advanced strategies to monitor their own learning behaviors and used more frequently than younger students. Vermunt and Vermetten (2004) reported that older learners showed better mastery and usage of effective learning strategies. Guo and Reinecke (2014) suggested a positive correlation between age and MOOC learning grades. In an examination of completion rates, Morris et al. (2015) found that course completers were on average older, while those who dropped out at the beginning stage of the course were on average the youngest group. Zhang et al. (2019) also stated that older participants (age > 50 years-old) have higher probability of completing the MOOC. However, Law et al. (2008) did not find significant different self-regulated strategy usage between students of different ages, Breslow et al. (2013) also found there was not a correlation between age and learning grades. Although the impact of learners' age on the MOOC performance were well studied as mentioned above, the response of learners with different ages to the speaking rate still remained unclear. In this study, the results strongly suggested that older learners preferred lower speaking rate when they watch an instructional video, no matter of their academic backgrounds. Since gender was also a frequently investigated variable in MOOC studies, we also analyzed the posttest scores of learners with different genders. No significant differences of the response to speaking rate of male and female learners were observed in this study (data not shown).

Since different languages have different characteristics, some people think the optimal video speaking rate tested with one language could be of no help to guide producing educational videos with other languages. However, if we selected some "standard speaking rate" of two different languages (for example, current average speaking rate in CCTV news" is about 280 wpm while in news program of the" Voice of America" is about 160) (Liu, 2009; Zhong & Chen, 2018), and normalized the speaking rate each other, the research result about speaking rate drawn from one language may have some reference value to MOOCs education with another language. In addition, some researches indicated that learners with different culture backgrounds may have different perceptions towards learning (Purdie & Hattie, 1996; Li, 2005), does culture background play a role in the speaking rate response need further study.

CONCLUSION

Due to its openness, MOOC always has very diverse learner characteristics. Our results

showed that no matter the academic background, there was a significant negative correlation between the learner age and the preference to the high speaking rate videos (Figure 3). Therefore, when MOOC teachers produced their instructional videos and decide the speaking rate, it is important to consider the audience's age carefully. In addition, the data shown in Figure 2b indicated that for learners with professional background, we could manage to keep similar learning performance among different age groups if we choose right speaking rates for certain groups, while for amateur learners, the learning outcome would decrease inevitably with the learner age increase. Another interesting result we obtained from this study is that the learning performance of the age group of 40-50 years old was not sensitive to the video speaking rate, indicating there is a wide range of video talking speed we can choose for this age group. Finally, our results suggested that the response sensitivity to speaking rate of social professional learners was higher than that of amateur learners (Figure 2a). As a result, when instructional videos are prepared for professional learners with a wide range of ages, a high speaking rate should be selected. However, if we select videos for amateur learners, a looser criterion of speaking rate could be adopted.

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